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Careless Responding in Online Studies Is Associated With Alcohol Use: A Mega-Analysis

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Objective: The prevalence of research conducted online in the addiction field has increased rapidly over the past decade. However, little focus has been given to careless responding in these online studies, despite the issues it may cause for statistical inference and generalizability. Our aim was to examine whether alcohol use is associated with careless responses. ***Method:*** Raw data were requested from online studies examining alcohol use and related problems which also addressed careless responding. We obtained 13 data sets of 12,237 participants (M_{age} = 42.16, SD = 15.65, 50.5% female). The sample had an average Alcohol Use Disorders Identification Test (AUDIT) score of 10.88 (SD = 7.77). Predictors included demographic information (age, gender) and AUDIT total scores. The primary outcome was whether an individual was classed as a careless responder, for example, by failing an explicit attention check question. ***Results:*** AUDIT total scores were associated with careless responding (OR = 1.07, 95% CI [1.06, 1.08], $p < .001$). Hazardous drinking or worse was associated with 2.21 greater odds (OR = 2.21, 95% CI [1.81, 2.71] of careless responding, whereas harmful drinking or worse was associated with 3.43 greater odds (OR = 3.43, 95% CI [2.83, 4.17]) and probable dependence was associated with 3.63 greater odds (OR = 3.63, 95% CI [2.95, 4.48]). ***Conclusions:*** Alcohol use and related problems are positively associated with careless responding in online research. Removal of individuals identified as careless responders may lead to issues of generalizability, and more care should be taken to identify and handle careless responder data.

Public Health Significance Statement
This mega-analysis demonstrates a robust relationship between alcohol use (defined by the Alcohol Use Disorders Identification Test) and careless responding in online studies. The findings suggest that the typical removal of careless responders from analyses in online alcohol studies is insufficient at best and at worst leads to issues with statistical inference and generalizability.

Keywords: Alcohol Use Disorders Identification Test, alcohol use, attention, careless responding, online research

Supplemental materials: https://doi.org/10.1037/adb0000924.supp

Conducting research online brings several benefits, including the recruitment of many participants quickly and efficiently, which greatly reduces the "cost per observation" of studies. It allows for the recruitment of diverse and underrepresented samples, and overcomes geographical barriers (Jones et al., 2022). Studies assessing alcohol or other substance use online, as opposed to in-person, also benefit from the ability to measure consumption and behavior without impression management concerns, or fear of stigmatization

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Analysis scripts and data can be found here at https://osf.io/49e5x/.

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(Groh et al., 2009). These benefits have led to a massive increase in research conducted online in psychology, but also specifically addiction-related research (Strickland & Stoops, 2019).

One potential limitation of online research is the increased likelihood of careless responding (also known as "insufficient effort responding"), which can be defined as intentional or unintentional responding that is not reflective of a participant's true nature. Careless responding by individuals can have detrimental consequences across studies, biasing effect size estimates, incorrectly categorizing individuals with a psychiatric disorder (reducing specificity), and generally increasing noise within the data (Jones et al., 2022). In response to this, researchers have attempted to identify careless responders using "attention checks," such as asking participants a question with one clear answer and several impossible answers (e.g., "Which planet do you live on?"). In this case, if participants chose anything other than "Earth" they are classified as careless responders and likely removed from inferential analyses. Other methods also exist, such as infrequency scales, in which participants respond to statements such as "I am answering a survey right now" using a Likert scale with response options such as *strongly disagree* to *strongly agree* (Kim et al., 2018). For these methods, responses that occur infrequently (*strongly disagree* relative to *strongly agree*) are used to infer carelessness.

In a recent meta-analysis (Jones et al., 2022), we demonstrated that careless responding was prevalent in online studies examining alcohol use, with ~12% of participants (across 51 studies) being identified as careless. We examined various study-level predictors and demonstrated that only the number of careless response techniques used was a significant predictor of increased carelessness across studies, suggesting that more attempts to identify carelessness increase the detection of carelessness. However, it is likely that various individual differences also contribute to carelessness within online studies, and it is important to isolate these to assess their influence on data quality.

Previous research has demonstrated that personality characteristics such as conscientiousness and agreeableness are negatively associated with carelessness (Bowling et al., 2016). Sociodemographic characteristics have also been identified as correlates of carelessness. For example, Berry et al. (2019) demonstrated that male participants were more likely to be careless responders (but see Ashley & Shaughnessy, 2021) and Nichols and Edlund (2020) demonstrated further that being male, younger, and college-educated were significant predictors of increased carelessness. However, there is a lack of evidence as to whether *individual differences* in alcohol-related variables are associated with careless responses. One USA based study (Agley et al., 2022) conducted via Amazon Mechanical Turk (MTurk) demonstrated significant differences in Alcohol Use Disorders Identification Test (AUDIT) scores from a sample arm with no quality control ($M_{AUDIT} = 13.6$, $SD = 10.2$) compared with a sample arm with the addition of attention checks ($M_{AUDIT} = 9.3$, $SD = 8.1$, Cohen's $d = 0.47$). Assuming the initial randomization was successful, these findings suggest that individuals who were removed by these attention checks had higher AUDIT scores. A substantial reduction in the proportion of participants meeting the cutoff for probable dependence was also identified between the two arms (30% vs. 14.4%), and there was an increased negative skew in the arm with attention checks. The authors suggest that individuals who fail quality control checks do not input random data but are more likely to report higher AUDIT scores.

However, it is also possible that careless responding may happen in several pseudorandom ways. First, individuals may respond uniformly (selecting each possible response with a similar probability); consistently (selecting the same response over several questions, known as long-string responding, which would be uniform if it was across the whole questionnaire); or even in a pattern (selecting "a," then "b," then "c," and repeating this pattern; see Kim et al., 2018). Both uniform and long-string responding have been shown to cause an overinflation of associations between variables. To highlight this in the addictions field, King et al. (2018) used a large publicly available data set and replaced varying amounts of data (2.5%, 5%, and so on) with uniform or long-string random responses. They demonstrated even small amounts of random data could inflate a "true" correlation between past-year alcohol use and closeness to their mother from $r = .012$ to .24 with long-string responding and to $r = .18$ with uniform responding. Similar findings were also shown by Credé (2010) who demonstrated even 5% of random responding can substantially inflate correlations.

It is therefore important to determine the cause and consequence of careless responses in relation to an individual's alcohol use. Should carelessness be nonrandom (e.g., a function of increased alcohol use) this raises concerns about excluding these individuals from alcohol-related research, as it creates data missing not at random, which can bias predictive models, excludes the very population of interest in many alcohol studies, and, in turn, reduces the generalizability of any findings. Should carelessness be random, this can potentially inflate estimates or scores on diagnostic tests (Meyer et al., 2013), especially if the true distribution is positively skewed (larger number of lower values, King et al., 2018), as well as the correlations between alcohol and other variables of interest.

Therefore, the aim of this mega-analysis was to examine the predictors of careless responses in online studies examining alcohol use. Specifically, we preregistered two main research questions: (a) do increased AUDIT scores predict an increased likelihood of careless responding; (b) do demographic variables (e.g., age, gender) increase the likelihood of careless responding within alcohol-related studies.[1] Our preregistration can be found here at https://aspredicted.org/8mx7y.pdf.

Method

Participants and Statistical Power

We aimed to obtain individual participant data from studies that were conducted online, measured alcohol consumption, and implemented a measure of careless responding. As a formal systematic review was not feasible, we first extracted data from studies conducted in our own laboratory. Second, we emailed corresponding authors from our recent meta-analysis of careless responses in alcohol use (Jones et al., 2022) and requested the raw data. Finally, we conducted further scoping searches via Google Scholar searching the first 100 hits for ("careless responding" OR "attention check") AND (alcohol OR "Alcohol Use Disorder Identification Task") AND (online OR MTurk OR Qualtrics OR Prolific).

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study. We

[1] Note—we also hypothesized testing for mental health problems but too few studies had this information for it to be estimated reliably.

conducted a post hoc power calculation using a subset of the data used for the final analyses with the "simR" package (Green & MacLeod, 2016) in R. Using data from five studies (1,860 participants total) we observed a significant effect of AUDIT scores on careless responding (b = .07, 95% CI [.05, .09]). With this information, we determined that we had 95% power, 95% CI [88.7, 98.4] to detect this effect with a = .05. However, given the issues with typical post hoc power calculations (Heckman et al., 2022), we examined the sensitivity of our statistical power by simulating the inclusion of data from another five studies and re-estimating the statistical power. Doing so increased the statistical power to 99.9% [96.4%, 100%], assuming similar sample sizes of these studies. Therefore, we aimed to include 10 studies at a minimum for our data analyses. We searched in December 2021–January 2022, and then reran searches in December 2022 after the peer review process, identifying two further articles (Copeland et al., 2023; Davies et al., 2022). The analysis script for our power calculation can be found here at https://osf.io/49e5x/.

In total, we obtained 13 data sets with 12,237 participants (see Table 1). On average, participants were 42.16 years old (SD = 15.65), 50.5% female and had an average AUDIT score of 10.88 (SD = 7.77). All studies were recruited in the U.K./United States.

Measures

Demographic Questions

Where available, we extracted the age, gender, education level, and ethnicity of each participant within each study. With regards to gender, a small number of individuals identified as nonbinary (N = 29, <0.1%); however, this was not enough to create a statistically meaningful comparison group, and these were therefore removed from all our primary analyses (however, in online Supplemental Materials, we included them in a male vs. other categories—notably the pattern of results was unaffected). For education level, there was considerable heterogeneity across studies in how this was measured; therefore, we manually coded this to reflect higher (university/college degree or above) versus lower (educated to less than degree level), similar to previous research (Robinson et al., 2022). For our outcome of carelessness, we created a binary variable (noncareless responder vs. careless) based on whether participants had been identified as careless in the original studies (e.g., failed an attention check).

Data Reduction and Analysis

To maximize the sample size, we applied several models to examine our hypotheses. First, in Model 1, we analyzed age and gender as predictors of careless responding. In Model 2, we included education (below undergraduate degree vs. degree and above) and ethnicity (White vs. non-White). In Model 3 (testing our confirmatory hypothesis), we included age, gender, and total AUDIT scores. In exploratory models (Models 4–6), we used AUDIT cutoffs to examine whether there were greater odds of careless responding in hazardous drinking or worse (AUDIT > 7: Model 4) versus not; harmful drinking or worse (AUDIT > 15: Model 5) versus not; and probable dependence (AUDIT > 19: Model 6) versus not. We removed ethnicity and education from Models 3–6 as their inclusion greatly reduced the available data.

Each model was analyzed using a multilevel logistic regression, with a random intercept for the study to adjust for dependent data points within individual studies. Across all models, there was limited evidence of multicollinearity (Variance Inflation Factors < 1.05). Intraclass correlation coefficients were calculated as Level 2 variance/(Level 2 variance + 3.29), and interpreted as the proportion of variance that is attributable to systematic differences between studies (Sommet & Morselli, 2017). We also computed the marginal R^2 of each model (variance explained by the fixed effects) using the "sjPlot" package (Lüdecke, 2022).

In exploratory analyses, we visually examined the distribution of AUDIT scores separately for careless and noncareless responders, but also compared the distribution of careless and noncareless responders using a Kolmogorov–Smirnov test. Where question-level data were available for the AUDIT, we computed the long-string index for the first eight items (which all have similar response options 0–4). Long-string index (Johnson, 2005) is the longest consecutive number of the same response, for example, in the sequence of responses "1," "2," "1," "3," "3," "3," "3," "1," the long-string index would be 4 (four consecutive "3" responses). A rule of thumb is that individuals who have a long-string response greater than half the length of the scale are considered careless. We also calculated the intraindividual response variability (IRV; Dunn et al., 2018), which is the within-person standard deviation of the raw scores. A small IRV is indicative of consistent responding (similar to long-string responding); however, a larger IRV may also be considered as highly random responding. We used the "careless" R package (Yentes & Wilhelm, 2021) to compute these scores. Here, we removed any participants who only provided a positive score on the final two items of the AUDIT as these may reflect individuals who no longer drink but have been injured or had advice to cut back in the past. In this case, they would have a maximum long-string score (=8) but be a truthful responder.[2] In each case, we compared careless versus noncareless responders on the long-form and IRV scores, but also correlated these scores with total AUDIT scores.

Analysis scripts and data can be found here at https://osf.io/49e5x/.

Results

Across all models, age was a negative predictor of careless responding, suggesting that younger participants were more likely to carelessly respond. In Models 1 and 2, gender was a significant predictor; female participants had lower odds of careless responding compared to male participants. When AUDIT scores were included in the model, gender was no longer a significant predictor. Male participants had significantly higher AUDIT scores than female participants (male = 12.12, SD = 8.15, female = 9.55, SD = 7.66, t[4,684] = 11.53, p < .001, d = 0.33, 95% CI [0.28, 0.39]).

Overall, total AUDIT scores were associated with careless responding (OR = 1.07: Model 3). Hazardous drinkers or worse (AUDIT > 7) had 2.21 greater odds of careless responding (Model 4). Harmful drinkers or worse (AUDIT > 15) had 3.43 greater odds of careless responding (Model 5). Individuals with probable dependence (AUDIT > 19) had 3.63 greater odds of careless responding (Model 6; see Table 2).

[2] Indeed, Copeland et al. (2023) specifically recruited individuals who had reduced their drinking in the previous months.

Table 1
Description of Studies and Data That Were Used Within Our Analyses

Study ID	Description	Sample	Measure(s) of carelessness	No. of careless (% of sample)
Angus et al. (2021)	Study examined whether framing of the research on a MTurk influenced self-reported problem drinking or gambling severity in participants. U.S. sample	N = 1,010 recruited M_{age} = 36.1 (11.6) M:F = 520:485 Ethnicity = NA Education = 668 degree or above, 342 below degree M_{AUDIT} = 8.4 (7.9)	"Three attention check items consisted of simple probe questions (e.g., To continue, select *strongly agree*")	N = 89 (8.81%)
Baines and Jones (2021) Experiment 1	Study examined the relationship between cognitive processes and alcohol use, using an online convenience sample. U.K. sample recruited via opportunity sampling	N = 108 recruited M_{age} = 24.1 (8.5) M:F = 26:82 Ethnicity = NA Education = NA M_{AUDIT} = 10.4 (5.7)	"If you are paying attention leave this question blank": with the answers No, Yes but not in the last year and Yes during the last year	N = 3 (2.78%)
Baines and Jones (2021) Experiment 2	Study examined the relationship between cognitive processes and alcohol use, using an online convenience sample. U.K. sample recruited via opportunity sampling	N = 116 recruited M_{age} = 22.00 (6.1) M:F = 53:63 Ethnicity = NA Education = NA M_{AUDIT} = 13.0 (6.2)	"If you are paying attention leave this question blank": with the answers No, Yes but not in the last year and Yes during the last year	N = 3 (2.59%)
Blackwell et al. (2020)	Study was a randomized controlled trial examining the impact of availability on alcoholic drink selection. U.K. sample, recruited via Prolific	N = 812 recruited M_{age} = 37.9 (12.3) M:F = 607:533 Ethnicity = NA Education = 757 degree or above, 390 below degree M_{AUDIT} = 9.7 (5.4)	"When was the last time you flew to Mars? ('never'; 'a few days ago'; 'weeks ago'; 'months ago')"	N = 4 (0.49%)
Clarke et al. (2021)	Study was a factorial experimental design examining the effect of warning labels on alcohol selection. U.K. sample recruited via Qualtrics	N = 6,198 recruited M_{age} = 49.1 (15.5) M:F = 3,131:3,059 Ethnicity = 5,784 White, 414 other Education = 3,056 degree or above, 3,126 below degree M_{AUDIT} = NA	Inattentive participants were screened out via an attention check embedded in the study (those not answering "never" to the question: "When did you last fly to Mars?"	N = 174 (2.81%)
Copeland et al. (2023)	Study examined the behavioral economic differences in heavy drinkers and people who have reduced their consumption.	N = 120 recruited M_{age} = 36.56 (13.05) M:F = 60:59 Ethnicity = 112 White, 8 other Education = 57 degree or above, 63 below degree M_{AUDIT} = 15.00 (6.83)	Eight attention checks in total, including; this is an attention check question. Please select "Can't Say True or False," and "This is an attention check question." Please select "Monthly"	N = 14 (11.67%)
Davies et al. (2022)	Study examined the framing of messages on alcohol labels (positive, negative, neutral) on drinking intentions. U.K. sample recruited via a university course. Note—Data from only "University 2" is included.	N = 302 recruited M_{age} = 30.10 (15.80) M:F = 74:227 Ethnicity = 277 White, 25 other Education = 88 degree or above, 214 below degree M_{AUDIT} = 10.56 (6.22)	"Two attention check questions were included in the version of the survey implemented at University 2"	N = 26 (8.61%)

(*table continues*)

Table 1 (*continued*)

Study ID	Description	Sample	Measure(s) of carelessness	No. of careless (% of sample)
Jones et al. (2020)	Study examined the prevalence of negative outcomes experienced following alcohol use. U.K. sample recruited via university course credits and opportunity sampling.	N = 299 recruited M_{age} = 24.3 (10.7) M:F = 87:211 Ethnicity = NA Education = NA M_{AUDIT} = 11.3 (5.9)	"To ensure you are paying attention leave this question blank" with four response options.	N = 9 (3.01%)
McPhee et al. (2020)	Study examined the changes in alcohol use and outcomes after the introduction of COVID-19 social distancing. U.S. sample recruited via MTurk	N = 1,127 recruited M_{age} = 40.2 (10.3) M:F = 739:381 Ethnicity = 737 White, 386 other Education = NA M_{AUDIT} = 13.3 (9.4)	"Five attention check questions were interspersed throughout the survey as a means of detecting random responding."	N = 481 (42.68%)
Robinson et al. (2020)	Study examined lifestyle related changes following the introduction of COVID-19 lockdowns. U.K. sample recruited via Prolific	N = 902 recruited M_{age} = 30.6 (9.7) M:F = 296:587 Ethnicity = 705 White, 176 other Education = 558 degree or above, 322 below degree M_{AUDIT} = NA	"Two attention checks were included in the survey (e.g., 'have you ever been to the planet Mars?')"	N = 33 (3.66%)
Strickland, Hill, et al. (2019)	Study tested the feasibility and acceptability of delivering cognitive training interventions via crowdsourcing. U.S. sample recruited via MTurk	N = 476 recruited M_{age} = 34.1 (9.8) M:F = 236:240 Ethnicity = 370 White, 106 other Education = 244 degree or above, 232 below degree M_{AUDIT} = 12.6 (7.3)	One or more attention checks were used throughout the study.	N = 32 (6.72%)
Strickland, Alcorn, and Stoops (2019)	Study examined the predictive relationship between behavioral economic demand, delay discounting and alcohol reinforcement and alcohol use. U.S. sample recruited via MTurk	N = 307 recruited M_{age} = 35.5 (10.7) M:F = 136:171 Ethnicity = 251 White, 56 other Education = 155 degree or above, 152 below degree M_{AUDIT} = 10.4 (7.8)	One or more attention checks were used throughout the study.	N = 30 (9.77%)
Strickland and Bergeria (2020)	Study aimed to examine the association between concurrent choice tasks and alcohol. U.S. sample recruited via MTurk	N = 125 recruited M_{age} = 34.8 (11.1) M:F = 64:61 Ethnicity = 94 White, 31 other Education = 73 degree or above, 52 below degree. M_{AUDIT} = 6.5 (6.0)	Checks included: (a) comparisons of age and gender at two points across the survey, (b) an item that instructed participants to select a particular response, (c) recall of a single digit number presented earlier in the survey that participants were instructed to remember, and (d) an item that asked if participants had been attentive and that their data should be used	N = 17 (13.60%)

Note. MTurk = Amazon Mechanical Turk; M = male; F = female; AUDIT = Alcohol Use Disorders Identification Test; NA = not applicable.

Table 2

Multilevel Binomial Regression Models Examining the Association Between Sociodemographic Characteristics, Alcohol Use, and Careless Responding

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	OR [95% CI]	*OR* [95% CI]	*OR* [95% CI]	*OR* [95% CI]	*OR* [95% CI]	*OR* [95% CI]
Age	0.969 [0.962, 0.975]**	0.959 [0.950, 0.968]**	0.991 [0.982, 1.000]	0.989 [0.980, 0.998]*	0.989 [0.980, 0.998]*	0.988 [0.979, 0.997]**
Gender	0.674 [0.575, 0.789]**	0.611 [0.485, 0.769]**	0.952 [0.780, 1.162]	0.895 [0.735, 1.088]	0.894 [0.734, 1.089]	0.879 [0.722, 1.070]
Ethnicity		0.996 [0.721, 1.377]	—	—	—	—
Education		1.376 [1.088, 1.738]**	—	—	—	—
AUDIT total			1.071 [1.060, 1.083]**	—	—	—
AUDIT hazard				2.211 [1.807, 2.713]**	—	—
AUDIT harmful					3.434 [2.829, 4.172]**	—
AUDIT prob dep						3.633 [2.946, 4.481]**
Model information						
No. of total/study total	11,756/13	8,353/7	4,660/11	4,660/11	4,660/11	4,660/11
AIC	4,902	2,569	2,908	3,017	2,914	2,923
ICC	0.29	0.06	0.30	0.32	0.30	0.29
Marginal R^2	.056	.132	.063	.040	.065	.052
Careless *N* (%)	909 (7.7%)	324 (3.9%)	678 (14.3%)	678 (14.3%)	678 (14.3%)	678 (14.3%)

Note. CI = confidence interval; *OR* = odds ratio; AUDIT = Alcohol Use Disorders Identification Test; prob dep = probable dependence; AIC = Akaike's information criterion; ICC = intraclass correlation coefficient.
* $p < .05$. ** $p < .01$.

Across the whole sample which included demographic information, the removal of careless responders reduced the AUDIT score from 10.87 (*SD* = 7.76) to 10.03 (*SD* = 7.06). The AUDIT score for individuals identified as careless responders was 15.82 (*SD* = 9.69).

Exploratory Analyses of Carelessness

In line with the prediction that careless responding may follow a uniform distribution (e.g., equal likelihood of responding of AUDIT total scores from 0 to 40), we examined the distribution of AUDIT total scores in careless versus noncareless responders (see Figure 1). Distributions for the AUDIT total scores were visibly different, with careless responders having a more uniform distribution and noncareless responders having a skewed positive distribution as expected (King et al., 2018). A Kolmogorov–Smirnov test demonstrated a significant difference between the distributions ($D = .33$, $p < .001$). Note, that a Kolmogorov–Smirnov test was also significant when comparing the careless responders to several randomly simulated uniform distributions (all *p*s < .001).

Exploratory Analysis: Long-String Responding

We computed long-string scores for the first eight items of the AUDIT. There was a significant difference in that noncareless responders had longer long-string scores ($M = 3.75$, $SD = 1.78$) compared to careless responders ($M = 3.16$, $SD = 1.90$, $t[884] = 7.53$, $p < .001$, $d = 0.33$, 95% CI [0.25, 0.41]). Across the complete sample, the correlation between long-string score and total AUDIT was significant, $r(4,427) = -.59$, $p < .001$. This suggests that increased AUDIT scores were associated with less consistent responses. Finally, we examined a cutoff of 4 (half the scale length) as a measure of carelessness. Those measured as careless had lower odds of long-string responding greater than the cutoff ($OR = 0.607$, 95% CI [0.511, 0.722], $p < .001$) compared to noncareless responders.

Exploratory Analysis: Intraindividual Response Variability

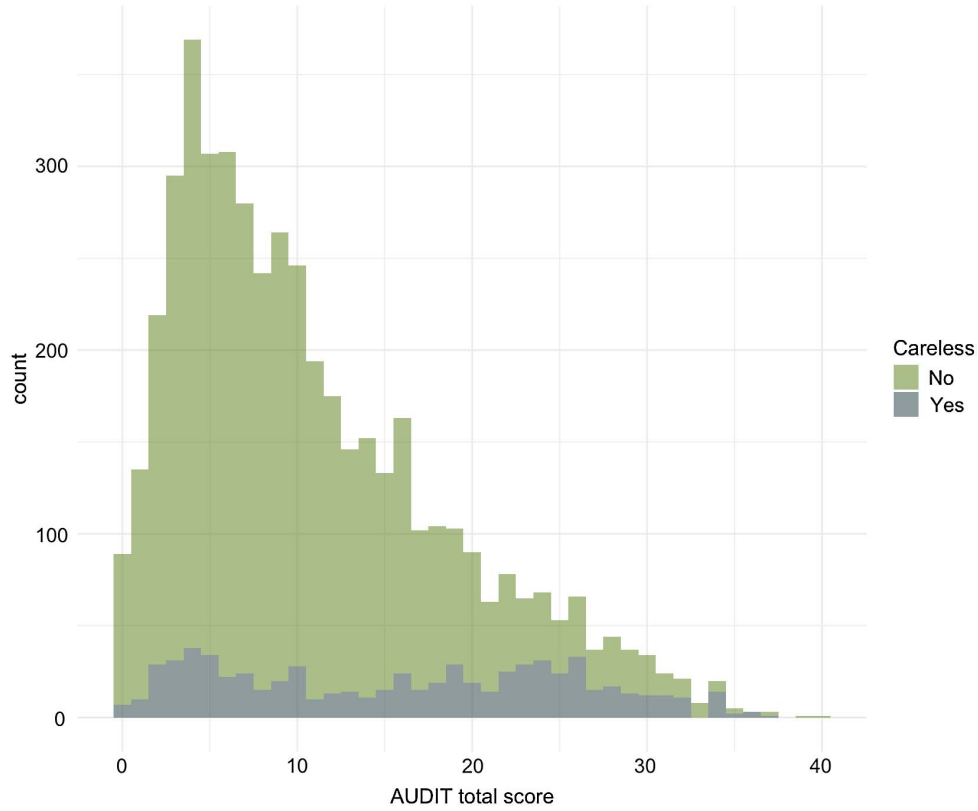
We computed the IRV for the first eight items of the AUDIT. There was a significant difference in that careless responders had lower IRV scores ($M = 0.85$, $SD = 0.33$) than noncareless responders ($M = 1.03$, $SD = 0.34$, $t[949] = 13.56$, $p < .001$, $d = 0.55$, 95% CI [0.46, 0.63]). Across the complete sample, the correlation between IRV and total AUDIT was significant, $r(4,427) = .07$, $p < .001$. This suggests that increased AUDIT scores were associated with increased variability in responses across the individual AUDIT questions; however, the size of this association was small.

Discussion

We conducted a mega-analysis on online studies examining alcohol use and related problems which also addressed careless responding. Across 13 studies with >12,000 participants, we demonstrated a robust association between careless responding and alcohol use and related problems (AUDIT scores). We were also able to replicate previous findings suggesting that male (vs. female) and younger participants are more likely to be careless responders (see Berry et al., 2019; Nichols & Edlund, 2020).

Figure 1

Histogram of AUDIT Total Scores for Careless Versus Noncareless Responders



Note. AUDIT = Alcohol Use Disorders Identification Test. See the online article for the color version of this figure.

We demonstrated a reliable association between careless responding and AUDIT scores across multiple models. Specifically, hazardous drinkers had >2 odds increase of being a careless responder, while harmful drinkers and those with probable dependence had >3 times the odds. In line with data from Agley et al. (2022), this may be explained in one of two ways: (a) individuals with higher levels of alcohol use are more inattentive during online surveys or (b) careless respondents do not add random noise to the data, but instead, bias estimates of alcohol consumption upward. In support of the former explanation, there is evidence to suggest that higher levels of alcohol use are associated with poor attention, impulsivity, and a general lack of cognitive abilities (Martins et al., 2018), and general cognitive abilities are negatively associated with careless responding ($r = -.38$; Huang & DeSimone, 2021); however, this casual pathway needs testing directly in future studies.

Our exploratory analyses provide some tentative support for the latter explanation, however. First, we observed clear differences in the distribution of total AUDIT scores between careless and noncareless responders, with careless responders having a much more uniform distribution, and noncareless responders having a somewhat positively skewed distribution, as expected (Kehoe et al., 2012). While a completely uniform distribution should lead to an average AUDIT total score of ~20, the AUDIT score of our careless responders (~16) was lower than that but significantly higher than noncareless responders. This supports observations across other studies suggesting that careless responders bias survey scales upward (Meyer et al., 2013), but also inflate correlations between measures (Credé, 2010; King et al., 2018).

The exploratory data-driven estimates of carelessness (long-string responding and IRV) led to somewhat different conclusions. We observed individuals identified as careless via individual study methods (attention checks) were much less likely to respond consistently but also had lower variability in responses. These counterintuitive observations suggest that neither measure in isolation is particularly useful in identifying careless responders (Hong et al., 2020), or that the AUDIT, being fairly short and not having any negatively worded items is not suitable for such methods (Curran, 2016; Schroeders et al., 2022).

The identification of the robust relationship between careless responses and alcohol use has wider ramifications for online alcohol-related research. In most studies with measures of careless responding, identified individuals are removed from subsequent analyses (Jones et al., 2022). In this case, researchers who assume carelessness is randomly distributed throughout their sample may be inadvertently constraining their analytic sample to individuals with lower alcohol consumption. This has been described as "tantamount to survey nonresponse" (Dunn et al., 2018) and has implications for the interpretation of data, which would appear unlikely to be missing at random. In addition, heavier drinkers are the population of interest in many alcohol studies and their exclusion can therefore impact the

generalizability of study findings. In these instances, we reiterate calls from researchers to thoroughly and transparently examine both the causes of missing data, but also to discuss how the exclusion of this data might influence both descriptive and inferential analyses (Agley et al., 2022; Curran, 2016; Jones et al., 2022). Indeed, future research could also examine whether the inclusion or removal of careless responders has amplified or attenuated reported effects in previous studies.

Strengths and Weaknesses

Strengths of these analyses are that we included data from several different studies using different sampling techniques from different online platforms and different countries (see Table 1). We had high statistical power (>95%) to detect the effects, suggesting these findings are robust. For our confirmatory model, we had a similar percentage of carelessness (14.3%) to our recent meta-analysis which included 48 studies and more than 75,000 participants (11.7%, 95% CI [7.6%, 16.5%]; Jones et al., 2022). We examined multiple forms of carelessness, including individual question failures, long-string index, and intraindividual response. However, as this was a secondary analysis, we were unable to determine the precise careless measures used and included in the individual studies (which were all "attention check" failures). Given discrepancies between different methods, true careless responding may be difficult to diagnose, and failure on a single item (a zero-tolerance approach) is perhaps too conservative (Kim et al., 2018). This would be true if carelessness was akin to a lapse in attention which may be momentary, rather than across the duration of a study. Furthermore, not all measures of carelessness are equal; it has been shown that some measures of careless responding perform better than others, and some measures may inappropriately categorize an individual as careless (Curran & Hauser, 2019). For example, statements such as "All my friends say I would make a great poodle" lead to high false positive rates of careless responding, as conscientious responders can provide rational answers ("Friends say I share a dog-like personality"). Researchers are now moving beyond the individual item(s) approach to more sophisticated approaches (e.g., latent profiles of carelessness across multiple methods; Brühlmann et al., 2020). Finally, data from our own laboratory made up a large proportion of the overall data. However, we made multiple attempts to obtain data from elsewhere to attempt to overcome this, with limited success (Wicherts et al., 2006).

In conclusion, careless responding presents a significant challenge in online alcohol research. Here, we have demonstrated that careless responses and heavier alcohol use are positively associated; however, the causal pathway remains unknown. Increased alcohol use may lead to more careless responding, but alternatively careless responding may bias estimates of alcohol use upward. Regardless of this causal path, researchers should carefully consider how to measure carelessness and the ramifications of removing careless responders for the statistical inferences and the generalizability of their findings.

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References marked with an asterisk indicate studies included in the meta-analysis.

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