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**Raising the Bar: Improving Methodological Rigour in Cognitive Alcohol Research**

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**Funding:** None.  
**Conflict of Interest:** None to declare.

**Journal:** *Addiction*

**Article Type:** *Methods & Techniques*

**Abstract**: 249 words

**Article:** 3210 words

**Supporting Information:** All materials associated with this manuscript are publicly available on the Open Science Framework: <https://osf.io/x7gcq/>

**CRediT Contribution**

*Conceptualization:*CRP;*Methodology:*CRP, DJS, AJ;*Validation:*CRP, AJ;*Formal Analysis:*CRP, AJ;*Investigation:*CRP, DJS, AJ, JEB, AC;*Data Curation:*CRP, DJS, AJ;*Writing – Original Draft:* CRP, AJ, JEB, AC; *Writing – Review & Editing Preparation:*CRP, DJS, AJ, JEB, AC;*Supervision:*CRP**;** *Project Administration:*CRP.

**Abstract**

**Background & Aims:** A range of experimental paradigms claim to measure the cognitive processes underpinning alcohol use, suggesting that heightened attentional bias, greater approach tendencies and reduced cue-specific inhibitory control are important drivers of consumption. This paper identifies substantial methodological shortcomings within this broad domain of research, however, and exemplifies them in studies focused specifically on alcohol-related attentional bias. **Argument/Analysis:** We highlight five main methodological issues: (i) the use of inappropriately matched control stimuli; (ii) opacity of stimulus selection and validation procedures; (iii) a credence in noisy measures; (iv) a reliance on unreliable tasks; and (v) variability in design and analysis. This is evidenced through a review of alcohol-related attentional bias (64 empirical articles, 68 tasks), which reveals the following: only 53% of tasks utilise appropriately matched control stimuli; as few as 38% report their stimulus selection and 19% their validation procedures; less than 28% used indices capable of disambiguating attentional processes; 22% assess reliability; and under 2% of studies were preregistered. **Conclusions:** Substantial improvements are required to improve the methodological rigour of cognitive alcohol research. To facilitate this, we provide a practical guide for future research: we advocate the use of well-matched and validated experimental stimuli, the development of reliable cognitive tasks and explicit assessment of their psychometric properties, and careful consideration of behavioural indices and their analysis. Further, we discuss open science principles that can facilitate replication and reproducibility in alcohol research, thereby enhancing trust in a field that has significant implications for public health and policy.

**Key words:** Alcohol; addiction; cognition; attentional bias; methodology; reliability; open science

**ALCOHOL-RELATED COGNITIONS AND THEIR IMPORTANCE**

Dual-process models of addiction propose that the loss of control over alcohol consumption results from an imbalance between two competing systems: an automatic ‘impulsive’ system triggered by substance-related cues, and a more controlled ‘reflective’ system underpinned by executive functioning (1–3). According to these models, alcohol misuse develops when the impulsive system becomes hyper-sensitive through repeat exposure to the rewarding effects of alcohol, which compromises self-control and leads to dysregulated approach bias towards alcohol-related cues (4).

There is considerable interest in identifying and measuring the cognitive processes that drive alcohol (mis)use, not least because this might tell us how alcohol use disorders develop and persist. A wealth of research suggests that heightened *attentional bias,* greater *approach tendencies,* and reduced cue-specific *inhibitory control* are important drivers of alcohol consumption and related behaviours (e.g., substance seeking; 4–6). These distinct but interrelated processes have been shown to predict progression from heavy drinking to dependency (7–9), and the likelihood of relapse following treatment (10,11; but see 12). Moreover, rather than representing stable traits, they appear to fluctuate in response to internal and environmental demands (13,14). At first glance, these findings have clear health implications; interventions that target these fluctuations effectively might mitigate alcohol-related harm (15).

Importantly, however, several methodological shortcomings cast doubt over the robustness of findings from cognitive alcohol research. In this *Methods & Techniques* article, we draw attention to five main issues: (i) a frequent use of inappropriately matched control stimuli; (ii) the opacity of stimulus selection and validation procedures; (iii) a credence in noisy measures; (iv) a reliance on unreliable tasks; and (v) considerable variability in design and analysis. To exemplify this, we systematically review the last 10-years of literature on one specific sub-domain of cognitive alcohol research; namely, alcohol-related attentional bias (*n* = 64 articles, 68 tasks; <https://osf.io/x7gcq/>). As shown in Figure 1, this revealed that these issues were present in the majority of synthesised studies. After discussing their respective impact, we then present an easy-to-implement practical guide with a view to establishing gold standards for future research. It is important to stress that many of the issues highlighted in the sections below are applicable beyond the field of cognitive alcohol research and have been discussed within psychological science more generally (e.g., 16–20). However, it is important to look critically at our own specific field(s) to highlight particular areas in need of methodological reform, and to promote best practices going forward.

[FIGURE 1 HERE]

**METHODOLOGICAL ISSUES  
*USE OF INAPPROPRIATELY MATCHED CONTROL STIMULI***

To investigate alcohol-related cognitions, researchers typically employ experimental paradigms that contrast responses to two categories of stimuli: alcohol-related versus alcohol-unrelated. In our review of alcohol-related attentional bias, for example, 61.76% employed the Addiction Stroop (21) or Visual Probe Task (VPT; 22). The former is an adaptation of the emotional Stroop task (23), whereby individuals are required to identify the colour of words that are semantically related or unrelated to alcohol. When colour identification is slower for alcohol-related compared to -unrelated words, this is interpreted as heightened attentional capture by alcohol-related cues (24–26). During the VPT, individuals are required to respond to a neutral cue (probe) that appears in a location occupied previously by alcohol-related or -unrelated pictorial stimuli. Faster responses to probes appearing in the same location as the former stimulus category are interpreted as attentional bias towards alcohol (27–29). Both tasks appear to demonstrate construct validity; they generate indices of attentional bias that are associated with individual differences in self-reported alcohol consumption and transient changes in drinking motivation (30–32).

In order to claim that preferential responses toward alcoholic cues on these tasks reflect *alcohol-specific* attentional bias, it is necessary to employ appropriately matched control stimuli – that is, a category of non-alcoholic substances with some degree of incentive value (e.g., soft drinks). However, our focused review of alcohol-related attentional bias revealed that, of those papers reporting explicitly the stimuli employed within tasks, 35.29% used unmatched non-appetitive control stimuli. For instance, responses toward pictorial alcohol-related stimuli were compared frequently against those to household objects or office stationery (e.g., 33–35), thereby confounding the incentive value of alcoholic and non-alcoholic appetitive substances. Similarly, although researchers take care with certain validation procedures in the Addiction Stroop task, such as ensuring that word length, syllables and frequency of use are matched between experimental and control stimuli, many compare responses between alcohol-related (e.g., VODKA) and non-appetitive words (e.g., CHAIR; 36–38). One study even reports that they employed office stationery purposefully “so that participants would not be distracted by the control category stimuli in any way” (39, pp. 2). While these studies have provided important contributions by demonstrating attentional bias towards alcohol-related relative to non-appetitive stimuli, differential responding between these stimulus categories might simply reflect a general (alcohol-unspecific) bias to appetitive stimuli (40,41). Comparisons among such stimuli that differ markedly in terms of their incentive value therefore make it impossible to isolate the precise mechanisms driving alcohol (mis-)use and may inflate effect size estimates (41–43).

***OPACITY OF STIMULI SELECTION & VALIDATION***

A related but separate issue that casts doubt over the robustness of findings in alcohol research generally is the failure of many studies to report the selection and validation of experimental stimuli. Our review of alcohol-related attentional bias revealed that 11.76% of articles do not describe control stimuli with sufficient detail to evaluate their appropriateness, instead using ambiguous terms such as ‘neutral’ stimuli. Of the articles that do report such information, only 38.24% disclose the source from which their stimuli were selected and just 19.12% report a validation procedure. Moreover, despite the availability of validated image databases, such as the Amsterdam Beverage Picture Set (44), our review indicates that these were utilised by only 15.38% of the studies reporting their source.

Instead, the majority (61.54%) report using stimuli from previous studies but neglect to detail any validity checks. This creates a ‘rabbit-hole’ problem for researchers in the many instances where materials are not openly available. As one example, the authors of a study published in 2019 cited their previous 2015 article as the origin of the alcohol stimuli, but that article then cites Hogarth et al. (45) who employed *smoking* cues. Such dead-ends stifle progress within this research field; researchers are unable to use the same stimuli in order to build upon prior findings, and direct replications are impossible if researchers are forced to develop their own stimuli. Others report using internet image searches to develop stimulus sets, with no information provided about their visual properties (e.g., luminosity) or, therefore, the equivalence between experimental and control stimuli. It is well known that the visual characteristics of stimuli can influence general cognitive processing (28,46), meaning it is important to standardise stimulus sets in order to reduce noise from these factors. Just as the lack of transparency constrains progress, the frequent disregard for stimulus validation limits the evidential value of cognitive alcohol research.

***A CREDENCE IN NOISY MEASURES***

Researchers often rely on measurement indices from raw behavioural data, such as average reaction times (RT) or choice accuracy. For example, our review reveals that behavioural RT was the primary index for 72.06% of measures of attentional bias (with the remaining 27.94% utilising eye-tracking methodology that can disambiguate attentional processes). This assumes that systematic differences in RT are driven *only* by attentional bias, but there is a general understanding that RT measures are affected by several cognitive and motor processes simultaneously (47,48). Specifically, a participant must first encode the stimulus, process information needed to make a decision, and then execute an appropriate motor response (e.g., key press). Measurement noise is exacerbated by the fact that common experimental tasks are often unable to account sufficiently for speed-accuracy trade-offs (SATOs; 49,50); while some people will respond faster at the cost of being less accurate, others will respond slower to increase their accuracy (51). By failing to account for SATOs, inferences drawn from raw behavioural data might lack insight into important aspects of the decision-making process (e.g., response caution; 49).

Another issue is the reliance on subtraction methods (e.g., difference scores) to index alcohol-related cognitions, and assess their associations with other variables of interest (e.g., subjective craving). Difference scores appear to be a simple and effective method of controlling for general RT and isolating signal in the noise. Unfortunately, however, there is a fundamental shortcoming in the use of difference scores; as the correlation increases between two component measures (e.g., RTs to alcohol-related and -unrelated stimuli), the reliability of their difference score decreases proportionately (49) and potentially meaningful associations with other variables are weakened (17). Together then, RTs and difference scores are contaminated by factors extraneous to the cognitive mechanism of interest. Since the use of such measures constitutes a norm in this domain, these issues question the extent to which existing research can be viewed as obtaining precise, interpretable, and sensitive measures of alcohol-related cognition.

***UNRELIABLE TASKS = UNRELIABLE INFERENCES***

Variability in the stimulus sets used across studies, the number of stimuli and their repetitions, and the use of noisy measures of response bias will all impact on the reliability of experimental tasks and the replicability of research findings. Increasing the number of stimuli is believed generally to increase the internal consistency of a task (52), and a large number of stimuli will help to reduce any habituation effect (53). This is critical, since the stimuli used in alcohol cognition tasks are assumed to evoke an implicit response (e.g., alcohol-related cues should ‘grab’ attention). Despite this, some tasks used commonly in alcohol (and addiction) research fail to achieve acceptable levels of internal reliability (54,55); for example, Ataya et al. (54) report alarmingly low estimates for the VPT (*a* = .00-.50, mean = .18), and although the Stroop task outperformed this in a handful ofstudies, there was marked variability (*a* = .00-.98, mean = .74). Others have confirmed these findings and suggest that such variability might be attributable to specific task features, namely differences in the stimuli used, procedural flexibility (e.g., randomised vs. blocked designs, number of stimuli), and serial versus multiple stimulus presentations (56).

Despite its integral role in effect size estimates and reproducibility (57), reliability was assessed for only 22.06% of the reviewed attentional bias tasks – 13.24% reported internal reliability, 10.29% split-half, and 8.82% test-retest (some report a combination). Perhaps most strikingly, out of the 68 tasks employed, 47.06% were the VPT (18.75% eye tracking) and a further 14.71% the Addiction Stroop, with only 4.41% reporting acceptable reliability explicitly. The poor psychometric properties of some cognitive measures pose a serious issue for the interpretation of research findings and, again, may hamper scientific progress in this field (see 58). Without investigating and reporting transparently the reliability of cognitive tasks, it is impossible to delineate whether findings from this field are robust or a result of measurement error (16).

***VARIABILITY IN EXPERIMENTAL DESIGN & ANALYSIS DECISIONS***

There is substantial variability and opacity in the measures used to operationalise alcohol-related cognition, and many intricate design decisions that affect this further. The Addiction Stroop task, for example, can differ in the way it is administered (paper-pencil vs. computerised), the response type measured (key press vs. verbal), the number and type of stimuli presented, and the design (block vs. mixed). Unless reported transparently, such flexibility in methodological choice is likely to restrict the generalisability of findings across studies. Further, seemingly subtle design modifications can impact upon the psychometric properties of a task (59) and statistical power (60).

Alongside heterogeneous stimuli presentation protocols, there is also evidence to suggest a lack of prescriptive analysis strategies across studies. Jones et al. (61) noted considerable flexibility in the way that RT outliers were handled in the VPT. In addition, they demonstrated that analysing the same data using different cut-off values led to different estimates of internal consistency and test-retest reliability. Similarly, Jones et al. (62) conducted a systematic review of analysis decisions within alcohol and smoking Stroop studies and estimated that over 7000 analysis pipelines could be attempted. Although these issues extend to the paradigms and techniques employed in other research domains (e.g., fMRI; 63), such flexibility is associated with increased false-positive findings, particularly when paired with selective reporting and publication bias (64,65). Indeed, Jones et al. (62) found that key aspects of design and analysis decisions were not disclosed when employing the Addiction Stroop task, and our review of the alcohol-attentional bias literature indicates that only one study (1.56%) reported design and analysis decisions a priori through study preregistration.

**RAISING THE BAR: RECOMMENDATIONS FOR RESEARCHERS**

We have identified numerous shortcomings in the methods employed commonly within studies of not only alcohol-related attentional bias, but cognitive alcohol research more generally. In pursuit of enhancing methodological rigour in this field, we now propose several easy-to-implement practical recommendations. Table 1 provides a summary.

[TABLE 1 HERE]

First, we recommend the use of appropriately matched and validated experimental stimuli to assess alcohol-related cognitions. Control stimuli must be able to isolate the specific cognitive mechanism(s) under investigation; if the aim is to capture individual differences in alcohol-*specific* cognitions, we recommend that researchers employ matched alcohol-related and *appetitive* alcohol-unrelated stimuli (e.g., soft drinks). In situations where attentional bias is believed to be unspecific to alcohol, it might be more suitable to employ both appetitive *and* non-appetitive control stimuli (see 40). In either case, there needs to be a clear rationale behind stimulus selection. Furthermore, researchers should report stimulus validation procedures routinely. Where possible, researchers can make use of existing validated stimulus sets (44,66–69) and in situations where this is inappropriate (e.g., cultural differences in drinking preferences, brand familiarity), available guidelines (see 44) should be utilised to develop new sets.

Second, we recapitulate calls for a standard practice of reporting the reliability (and validity) of cognitive tasks (16) within alcohol research. This is essential given that reliability estimates differ between samples, experimental task parameters and measures. A helpful guide is provided by Parsons et al. (16) who suggest that permutation split-half reliability should be estimated for individual trial-level data and test-retest reliability when assessing trait constructs. We encourage a focus on improving the reliability of certain experimental paradigms, such as the VPT and Addiction Stroop task (56,70), with a view to developing consensus guides outlining optimal task parameters (e.g., 18). It is notable, however, that one study reports failed attempts to improve both the test-retest and internal reliability of the VPT based upon empirical recommendations (61). If a task consistently demonstrates sub-optimal psychometric properties, then it should be abandoned in favour of alternative reliable tasks (e.g., visual search and free-viewing tasks; 42,58,71). Furthermore just because a cognitive task is reliable does not necessarily mean that it is a valid measure of the construct under investigation; some tasks will be better at providing mechanistic insights into the cognitive processes that drive alcohol (mis)use, and it is these tasks that we should seek to optimise (see 72).

Third, researchers should explore different ways of analysis which might overcome the limitations inherent in the use of raw RTS and difference scores (see 49 for suggested alternatives). Another option is the application of computational modelling (51,73) to alcohol research. One example is the drift-diffusion model (DDM; 74,75), which performs a principled reconciliation of RT and accuracy data to provide accurate estimates of dissociable cognitive and motor processes (e.g., 76,77). Empirical research demonstrates that the DDM provides more reliable indices of attentional bias (towards threat) derived from the VPT (78) and new interpretations of previous experimental findings (79). Interestingly, it has also been shown that researchers can benefit from increased statistical power by applying such decision models to experimental designs, without requiring more trials or participants (76). Although these techniques are yet to be tested empirically within cognitive alcohol research, a recent theoretical review (80) outlines their potential contribution to this field.

**A CASE FOR OPEN SCIENCE**

Many of the issues highlighted above are compounded by the non-disclosure of important study characteristics (e.g., stimuli selection, analytic decisions), which threaten replicability and reproducibility. This can be improved simply by the implementation of open science practices. There are several excellent guides to adopting open science (81–83), so we focus herein on solutions that are relevant particularly to the field of alcohol research.

One solution to the lack of transparency around stimulus sets and task parameters is a move to *open materials.* Currently, reviews of biomedical and addiction sciences indicate that just 1-3% of articles share their methods or protocols through public repositories (84,85), with higher (yet far from optimal) estimates of 14% in psychology (86). Moreover, a standard practice of *open data* (where ethically permissible) will allow findings and inferences to be verified and new models to be applied to advance knowledge. We recommend use of the Open Science Framework ([www.osf.io](http://www.osf.io)), a platform which permits the storage of materials, experimental scripts and data with a CC BY licence so that any reuse is attributed to the original author(s). Indeed, it has been shown consistently that articles adopting open research practices receive more citations and lead to research collaborations (87–89).

Rigor in alcohol research can also be enhanced through *study preregistration* – a time-stamped proposal that makes transparent all key experimental design and analysis decisions in advance, thereby reducing many researcher degrees of freedom. Preregistration can be initiated for both confirmatory and exploratory research. Current rates of preregistration within the addictive behaviour literature are worryingly low; Adewumi et al. (84) report that just 3% of articles in addiction medicine were preregistered, and our own review of empirical research on alcohol-related attentional bias revealed only onepreregistered study. Despite the benefits, preregistration is not a panacea and requires careful oversight by authors, editors, and reviewers.

Their extension is a Registered Report (RR), whereby authors complete a stage-one submission outlining their planned methods and analyses. Should this receive approval through the peer-review process, researchers then receive an ‘In Principle Acceptance’; so long as the authors adhere closely to their protocol, the journal agrees to publish the article regardless of the results. Despite recommendations to implement RRs more widely in this specific research domain (90), at the time of this review, only four of the 288 journals offering this publishing format focus primarily on alcohol and substance-use research.Even in their nascent stage, initial evidence suggests that RRs reduce publication bias (91) and enact higher levels of open data and computational reproducibility (92). Furthermore, RRs receive more citations than would be expected given the impact factor of the journal in which they are published (93,94).

Overall, then, the adoption of open science is likely to increase replication and reproducibility in alcohol research (see 95).

**CONCLUSIONS**

Methodological shortcomings weaken the robustness of cognitive alcohol research. We provide an easy to implement guide to enhance rigour in this field; this includes the use of appropriately matched and validated experimental stimuli, a renewed focus on the development and refinement of reliable experimental tasks, and careful consideration of behavioural indices and their analysis. Moreover, we stress the importance of transparent reporting aided by open science principles: stimulus selection, task reliability and validation procedures should be disclosed as standard practice, and study preregistration, open materials and data should be implemented wherever possible. Establishing these recommendations as a gold-standard will facilitate replication and reproducibility, thereby increasing trust in a field that proffers important implications for public health and policy.

*Figure 1.* Percentage of tasks (total *n* = 68) that met the proposed methodological standards. Note: AB = attentional bias.

Table 1. *Summary of recommendations for improving the methodological rigour of cognitive alcohol research.*

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| --- | --- | --- |
|  | **Recommendations** | **Resources** |
| **Stimuli** | * Matched appropriately (luminosity; valence). * Clear rationale behind selection. * Use existing validated stimulus sets where appropriate. * Use existing instructions to develop and validate new stimulus sets. | (44,66–69)  S1 File of (44) provides instructions for developing new stimulus sets. |
| **Head with gearsTask** | * Assess factors contributing to reliability. * Develop and refine tasks with acceptable psychometric properties and avoid those with poor reliability. * Use tasks with demonstrated reliability. * Develop consensus guides with recommendations for optimal task parameters. | (18,42,58,61,70–72) |
| **StopwatchMeasures** | * Justify choice of measures according to established consensus. * Explicitly acknowledge the limitations of certain indices. | (17,47–50) |
| **Bar graph with downward trendAnalysis** | * Include complementary analysis techniques (e.g., modelling) that can afford greater reliability and offer new insights. | (51,73–80) |
| **DocumentDisclosure** | * Report stimuli selection, validation and reliability as standard practice. * Report design and analysis decisions through study preregistration or Registered Reports. * Make materials, scripts and data openly available. | (16,81–83)  [www.osf.io](http://www.osf.io) |

**References**

1. Di Lemma LCG, Field M. Cue avoidance training and inhibitory control training for the reduction of alcohol consumption: a comparison of effectiveness and investigation of their mechanisms of action. *Psychopharmacology*. 2017;234(16):2489–98. Available from: https://doi.org/10.1007/s00213-017-4639-0

2. Wiers RW, Stacy AW. Implicit cognition and addiction: An introduction. *Current Directions in Psychological Science*. 2005;15(6):1–9. Available from: https://doi.org/10.1111/j.1467-8721.2006.00455.x

3. Wiers RW, Bartholow BD, van den Wildenberg E, Thush C, Engels RCME, Sher KJ, et al. Automatic and controlled processes and the development of addictive behaviors in adolescents: A review and a model. *Pharmacology Biochemistry & Behavior*. 2007;86(2):263–83. Available from: https://doi.org/10.1016/j.pbb.2006.09.021

4. Fleming KA, Bartholow BD. Alcohol cues, approach bias, and inhibitory control: Applying a dual process model of addiction to alcohol sensitivity. *Psychology of Addictive Behaviors*. 2014;28(1):85–96. Available from: https://doi.org/10.1037/a0031565

5. Jones A, Robinson E, Duckworth J, Kersbergen I, Clarke N, Field M. The effects of exposure to appetitive cues on inhibitory control: A meta-analytic investigation. *Appetite.* 2018;128:271–82. Available from: https://doi.org/10.1016/j.appet.2018.06.024

6. Field M, Munafò MR, Franken IHA. A meta-analytic investigation of the relationship between attentional bias and subjective craving in substance abuse. *Psycholological Bulletin*. 2009;135(4):589–607. Available from: https://doi.org/ https://dx.doi.org/10.1037%2Fa0015843

7. Rubio G, Jiménez M, Rodríguez-Jiménez R, Martínez I, Ávila C, Ferre F, et al. The role of behavioral impulsivity in the development of alcohol dependence: A 4-year follow-up study. *Alcohol: Clinical & Experimental Research*. 2008;32(9):1681–7. Available from: https://doi.org/10.1111/j.1530-0277.2008.00746.x

8. van Hemel-Ruiter ME, Wiers RW, Brook FG, de Jong PJ. Attentional bias and executive control in treatment-seeking substance-dependent adolescents: A cross-sectional and follow-up study. *Drug & Alcohol Dependence*. 2016;159:133–41. Available from: https://doi.org/10.1016/j.drugalcdep.2015.12.005

9. Wiers CE, Stelzel C, Park SQ, Gawron CK, Ludwig VU, Gutwinski S, et al. Neural correlates of alcohol-approach bias in alcohol addiction: The spirit is willing but the flesh is weak for spirits. *Neuropsychopharmacology*. 2014;39(3):688–97. Available from: https://doi.org/10.1038/npp.2013.252

10. Garland EL, Franken IHA, Howard MO. Cue-elicited heart rate variability and attentional bias predict alcohol relapse following treatment. *Psychopharmacology*. 2012;222(1):17–26. Available from: https://doi.org/10.1007/s00213-011-2618-4

11. Rupp CI, Beck JK, Heinz A, Kemmler G, Manz S, Tempel K, et al. Impulsivity and alcohol dependence treatment completion: Is there a neurocognitive risk factor at treatment entry? *Alcoholism: Clinical & Experimental Research.* 2016;40(1):152–60. Available from: https://doi.org/10.1111/acer.12924

12. Christiansen P, Schoenmakers TM, Field M. Less than meets the eye: Reappraising the clinical relevance of attentional bias in addiction. *Addictive Behaviors*. 2015;44:43–50. Available from: http://dx.doi.org/10.1016/j.addbeh.2014.10.005

13. Field M, Werthmann J, Franken I, Hofmann W. The role of attentional bias in obesity and addiction. *Health Psychology*. 2016;35(8):767–80. Available from: https://psycnet.apa.org/doi/10.1037/hea0000405

14. Jones A, Tiplady B, Houben K, Nederkoorn C, Field M. Do daily fluctuations in inhibitory control predict alcohol consumption? An ecological momentary assessment study. *Psychopharmacology.* 2018;235(5):1487–96. Available from: https://doi.org/10.1007/s00213-018-4860-5

15. Field M, Christiansen P, Hardman CA, Haynes A, Jones A, Reid A, et al. Translation of findings from laboratory studies of food and alcohol intake into behavior change interventions: The experimental medicine approach. *Health Psychology*. 2020. Available from: https://doi.org/10.1037/hea0001022

16. Parsons S, Kruijt A-W, Fox E. Psychological science needs a standard practice of reporting the reliability of cognitive-behavioral measurements. *Advances in Methods & Practices in Psychological Science*. 2019;2(4):378–95. Available from: https://doi.org/10.1177%2F2515245919879695

17. von Bastian CC, Blais C, Brewer GA, Gyukovics M, Hedge C, Kałamała P, et al. Advancing the understanding of individual differences in attentional control: Theoretical, methodological, and analytical considerations. 2020; Available from: https://doi.org/10.31234/osf.io/x3b9k

18. Verbruggen F, Aron AR, Band GPH, Beste C, Bissett PG, Brockett AT, et al. A consensus guide to capturing the ability to inhibit actions and impulsive behaviors in the stop-signal task. *eLife*. 2019;8:1–26. Available from: https://doi.org/10.7554/eLife.46323

19. Munafò MR, Nosek BA, Bishop DVM, Button KS, Chambers CD, Percie Du Sert N, et al. A manifesto for reproducible science. *Nature Human Behavior*. 2017;1(1):1–9. Available from: http://dx.doi.org/10.1038/s41562-016-0021

20. Silberzahn R, Uhlmann EL, Martin DP, Anselmi P, Aust F, Awtrey E, et al. Many analysts, one data set: Making transparent how variations in analytic choices affect results. *Advances in Methods & Practices in Psychological Science*. 2018;1(3):337–56. Available from: https://doi.org/10.1177%2F2515245917747646

21. Cox WM, Fadardi JS, Pothos EM. The addiction-stroop test: Theoretical considerations and procedural recommendations. *Psychological Bulletin*. 2006;132(3):443–76. Available from: https://doi.org/10.1037/0033-2909.132.3.443

22. MacLeod C, Mathews A, Tata P. Attentional bias in emotional disorders. J*ournal of Abnormal Psychology*. 1986;95(1):15–20. Available from: https://doi.org/10.1037//0021-843x.95.1.15

23. Stroop JR. Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*. 1935;18(6):643–62. Available from: https://doi.org/10.1037/h0054651

24. Field M, Christiansen P, Cole J, Goudie A. Delay discounting and the alcohol Stroop in heavy drinking adolescents. *Addiction*. 2007;102(4):579–86. Available: https://doi.org/10.1111/j.1360-0443.2007.01743.x

25. Flaudias V, Brousse G, de Chazeron I, Planche F, Brun J, Llorca PM. Treatment in hospital for alcohol-dependent patients decreases attentional bias. *Neuropsychiatric Disease & Treatment*. 2013;9:773–9. Available from: https://doi.org/10.2147/NDT.S42556

26. Spanakis P, Jones A, Field M, Christiansen P. A Stroop in the hand is worth two on the laptop: Superior reliability of a smartphone based alcohol Stroop in the real world. *Substance Use & Misuse*. 2019;54(4):692–8. Available from: https://doi.org/10.1080/10826084.2018.1536716

27. Manchery L, Yarmush DE, Luehring-Jones P, Erblich J. Attentional bias to alcohol stimuli predicts elevated cue-induced craving in young adult social drinkers. *Addictive Behavior*. 2017;70:14–7. Available from: http://dx.doi.org/10.1016/j.addbeh.2017.01.035

28. Miller MA, Fillmore MT. Persistence of attentional bias toward alcohol-related stimuli in intoxicated social drinkers. *Drug & Alcohol Dependence*. 2011;117(2–3):184–9. Available from: http://dx.doi.org/10.1016/j.drugalcdep.2011.01.016

29. Ramirez, J. J., Monti, P. M., & Colwill RM. Brief and extended alcohol-cue-exposure effects on craving and attentional bias. *Experimental & Clinical Psychopharmacology*. 2015;23:159–67. Available from: https://doi.org/10.1037/pha0000018

30. Díaz-Batanero C, Domínguez-Salas S, Moraleda E, Fernández-Calderón F, Lozano OM. Attentional bias toward alcohol stimuli as a predictor of treatment retention in cocaine dependence and alcohol user patients. *Drug & Alcohol Dependence*. 2018;182:40–7. Available from: https://doi.org/10.1016/j.drugalcdep.2017.10.005

31. Gladwin TE, Vink M. Alcohol-related attentional bias variability and conflicting automatic associations. *Journal of Experimental Psychopathology*. 2018;9(2):1-14. Available from: https://doi.org/10.5127/jep.062317

32. Monem R, Fillmore MT. Alcohol administration reduces attentional bias to alcohol-related but not food-related cues: Evidence for a satiety hypothesis. *Psychology of Addictive Behaviors*. 2019;33(8):677–84. Available from: https://doi.org/10.1037/adb0000522

33. Ghiţă A, Porras García B, Moreno M, Monras M, Ortega L, Mondon S, et al. Attentional bias assessment in patients with alcohol use disorder: An eyetracking study. A*nnual Review of CyberTherapy & Telemedicine*. 2019;17:83–7.

34. Wilcockson TDW, Pothos EM. Measuring inhibitory processes for alcohol-related attentional biases: Introducing a novel attentional bias measure. *Addictive Behavior*. 2015;44:88–93. Available from: http://dx.doi.org/10.1016/j.addbeh.2014.12.015

35. Kim J, Marciano MA, Ninham S, Zaso MJ, Park A. Interaction effects between the cumulative genetic score and psychosocial stressor on self-reported drinking urge and implicit attentional bias for alcohol: A human laboratory study. *Alcohol & Alcoholism*. 2019;54(1):30–7. Available from: https://doi.org/10.1093/alcalc/agy065

36. Luehring-Jones P, Louis C, Dennis-Tiwary TA, Erblich J. A single session of attentional bias modification reduces alcohol craving and implicit measures of alcohol bias in young adult drinkers. *Alcoholism: Clinical & Experimental Research*. 2017;41(12):2207–16. Available from: https://doi.org/10.1111/acer.13520

37. Rettie HC, Hogan LM, Cox WM. Negative attentional bias for positive recovery-related words as a predictor of treatment success among individuals with an alcohol use disorder. *Addictive Behavior*. 2018;84:86–91. Available from: https://doi.org/10.1016/j.addbeh.2018.03.034

38. Snelleman M, Schoenmakers TM, van de Mheen D. Attentional bias and approach/avoidance tendencies do not predict relapse or time to relapse in alcohol dependency. *Alcoholism: Clinical & Experimental Research*. 2015;39(9):1734–9. Available from: https://doi.org/10.1111/acer.12817

39. Brown CE, Wilcockson TDW, Lunn J. Does sleep affect alcohol-related attention bias? *Journal of Substance Use*. 2020;25(5):515–8. Available from: https://doi.org/10.1080/14659891.2020.1736670

40. Monk RL, Qureshi A, Pennington CR, Hamlin I. Generalised inhibitory impairment to appetitive cues: From alcoholic to non-alcoholic visual stimuli. *Drug & Alcohol Dependence*. 2017;180:26–32. Available from: http://dx.doi.org/10.1016/j.drugalcdep.2017.07.038

41. Pennington CR, Qureshi AW, Monk RL, Greenwood K, Heim D. Beer? Over here! Examining attentional bias towards alcoholic and appetitive stimuli in a visual search eye-tracking task. *Psychopharmacology*. 2019;236(12):3465–76. Available from: https://doi.org/10.1007/s00213-019-05313-0

42. Pennington CR, Shaw DJ, Adams J, Kavanagh P, Reed H, Robinson M, et al. Where’s the wine? Heavy social drinkers show attentional bias towards alcohol in a visual conjunction search task. *Addiction*. 2020;115(9):1650–9. Available from: https://doi.org/10.1111/add.14997

43. Versace F, Engelmann JM, Deweese MM, Robinson JD, Green CE, Lam CY, et al. Beyond cue reactivity: Non-drug-related motivationally relevant stimuli are necessary to understand reactivity to drug-related cues. *Nicotine & Tobacco Research*. 2017;19(6):663–9. Available from: https://doi.org/10.1093/ntr/ntx002

44. Pronk T, van Deursen DS, Beraha EM, Larsen H, Wiers RW. Validation of the Amsterdam Beverage Picture Set: A controlled picture set for cognitive bias measurement and modification paradigms. *Alcoholism: Clinical & Experimental Research*. 2015;39(10):2047–55. Available from: https://doi.org/10.1111/acer.12853

45. Hogarth L, Dickinson A, Duka T. Detection versus sustained attention to drug cues have dissociable roles in mediating drug seeking behavior. *Experimental & Clinical Psychopharmacology*. 2009;17(1):21–30. Available from: https://doi.org/10.1037/a0014957

46. Harrison NR, McCann A. The effect of colour and size on attentional bias to alcohol-related pictures. *Psicológica*. 2014;35(1):39–48. Available from: https://doi.org/ https://dx.doi.org/10.1111%2Fj.1360-0443.2009.02860.x

47. Hedge C, Powell G, Bompas A, Vivian-Griffiths S, Sumner P. Low and variable correlation between reaction time costs and accuracy costs explained by accumulation models: Meta-analysis and simulations. *Psychological Bulletin*. 2018;144(11):1200–27. Available from: https://doi.org/10.1037/bul0000164

48. Miller J, Ulrich R. Mental chronometry and individual differences: Modeling reliabilities and correlations of reaction time means and effect sizes. *Psychonomic Bulletin & Review*. 2013;20(5):819–58. Available from: https://doi.org/10.3758/s13423-013-0404-5

49. Draheim C, Mashburn CA, Martin JD, Engle RW. Reaction time in differential and developmental research: A review and commentary on the problems and alternatives. *Psychological Bulletin*. 2019;145(5):508–35. Available from: https://doi.org/10.1037/bul0000192

50. Heitz RP. The speed-accuracy tradeoff: History, physiology, methodology, and behavior. *Frontiers in Neuroscience*. 2014;8:1–19. Available from: https://doi.org/10.3389/fnins.2014.00150

51. Dutilh G, Annis J, Brown SD, Cassey P, Evans NJ, Grasman RPPP, et al. The quality of response time data inference: A blinded, collaborative assessment of the validity of cognitive models. *Psychonomic Bulletin & Review*. 2019;26(4):1051–69. Available from: https://doi.org/10.3758/s13423-017-1417-2

52. Hoekstra R, Vugteveen J, Warrens MJ, Kruyen PM. An empirical analysis of alleged misunderstandings of coefficient alpha. *International Journal of Social Research Methodology*. 2019;22(4):351–64. Available from: https://doi.org/10.1080/13645579.2018.1547523

53. Hall G, Rodríguez G. Habituation and conditioning: Salience change in associative learning. *Journal of Experimental Psychology: Animal Learning & Cognition*. 2017;43(1):48–61. Available from: https://doi.org/10.1037/xan0000129

54. Ataya AF, Adams S, Mullings E, Cooper RM, Attwood AS, Munafò MR. Internal reliability of measures of substance-related cognitive bias. *Drug & Alcohol Dependence*. 2012;121(1–2):148–51. Available from: http://dx.doi.org/10.1016/j.drugalcdep.2011.08.023

55. Field M, Christiansen P. Commentary on Ataya et al. (2012), Internal reliability of measures of substance-related cognitive bias. *Drug & Alcohol Dependence*. 2012;124(3):189–90. Available from: http://dx.doi.org/10.1016/j.drugalcdep.2012.02.009

56. Christiansen P, Mansfield R, Duckworth J, Field M, Jones A. Internal reliability of the alcohol-related visual probe task is increased by utilising personalised stimuli and eye-tracking. *Drug & Alcohol Dependence*. 2015;155:170–4. Available from: http://dx.doi.org/10.1016/j.drugalcdep.2015.07.672

57. Baugh F. Correcting effect sizes for score reliability. *Journal of Applied Psychology*. 2002;62(2):254–63. Available from: https://doi.org/10.1177/0013164402062002004

58. Soleymani A, Ivanov Y, Mathot S, de Jong PJ. Free-viewing multi-stimulus eye tracking task to index attention bias for alcohol versus soda cues: Satisfactory reliability and criterion validity. *Addictive Behaviors*. 2020;100:106117. Available from: https://doi.org/10.1016/j.addbeh.2019.106117

59. Cooper SR, Gonthier C, Barch DM, Braver TS. The role of psychometrics in individual differences research in cognition: A case study of the AX-CPT. *Frontiers in Psychology*. 2017;8:1–16. Available from: https://doi.org/10.1016/j.drugalcdep.2011.08.023

60. Baker DH, Vilidaite G, Lygo FA, Smith AK, Flack TR, Gouws AD, Andrews, TJ. Power contours: Optimising sample size and precision in experimental psychology and human neuroscience. *Psychological Methods*. 2020. Available from: http://dx.doi.org/10.1037/met0000337

61. Jones A, Christiansen P, Field M. Failed attempts to improve the reliability of the Alcohol Visual Probe Task following empirical recommendations. *Psychology of Addictive Behaviors*. 2018;32(8):922–32. Available from: https://doi.org/10.1037/adb0000414

62. Jones A, Duckworth J, Christiansen, P. May I have your attention, please? Methodological and analytical flexibility in the Addiction Stroop. 2020. *PsyArXiv*. Available from: https://doi.org/10.31234/osf.io/ws8xp

63. Botvinik-Nezer R, Holzmeister F, Camerer CF, Dreber A, Huber J, Johannesson M, et al. Variability in the analysis of a single neuroimaging dataset by many teams. *Nature*. 2020;582(7810):84–8. Available from: https://doi.org/10.1038/s41586-020-2314-9

64. Simmons JP, Nelson LD, Simonsohn U. False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological Science*. 2011;22(11):1359–66. Available from: https://doi.org/10.1177%2F0956797611417632

65. Young NS, Ioannidis JPA, Al-Ubaydli O. Why current publication practices may distort science. *PLoS Medicine*. 2008;5(10):1418–22. Available from: https://doi.org/10.1371/jounral.pmed.0050201

66. Peterson H, Simpson SL, Laurienti PJ. Wake Forest Alcohol Imagery Set: Development and validation of a large standardized alcohol imagery dataset. *Alcoholism: Clinical & Experimental Research*. 2019;43(12):2559–67. Available from: https://doi.org/10.1111/acer.14214

67. Onie S, Gong S, Manwaring E, Grageda D, Webb K, Yuen WS, et al. Validation of the Australian beverage picture set: A controlled picture set for cognitive bias measurement and modification paradigms. *Australian Journal of Psychology*. 2020;72(2):223–32. Available from: https://doi.org/10.1111/ajpy.12272

68. López-Caneda E, Carbia C. The Galician Beverage Picture Set (GBPS): A standardized database of alcohol and non-alcohol images. *Drug & Alcohol Dependence*. 2018;184:42–7. Available from: https://doi.org/10.1016/j.drugalcdep.2017.11.022

69. Stauffer CS, Dobberteen L, Woolley JD. American Alcohol Photo Stimuli (AAPS): A standardized set of alcohol and matched non-alcohol images. *American Journal of Drug & Alcohol Abuse*. 2017;43(6):647–55. Available from: https://doi.org/10.1080/00952990.2016.1253093

70. Grafton B, Teng S, MacLeod C. Two probes and better than one: Development of a psychometrically reliable variant of the attentional probe task. *Behaviour Research & Therapy*. 2021;138:103805. Available from: https://doi.org/10.1016/j.brat.2021.103805

71. Heitmann J, Jonker NC, Jong PJ De, Gladwin TE. A promising candidate to reliably index attentional bias toward alcohol cues: An adapted Odd-One-Out Visual Search Task. *Frontiers in Psychology*. 2021;12:1–11. Available from: https://doi.org/10.3389/fpsyg.2021.630461

72. Hedge C, Bompas A, Sumner P. Task reliability considerations in computational psychiatry. *Biological Psychiatry: Cognitive Neuroscience & Neuroimaging*. 2020;5(9):837–9. Available from: https://doi.org/10.1016/j.bpsc.2020.05.004

73. Guest O, Martin AE. How computational modeling can force theory building in psychological science. *Perspectives on Psychological Science*. 2021. Available from: https://doi.org/10.1177%2F1745691620970585

74. Ratcliff R, McKoon G. The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation*. 2008;20(4):873–922. Available from: https://doi.org/10.1162/neco.2008.12-06-420

75. Ratcliff, R, Smith PL, Brown SD, McKoon G. Diffusion Decision Model: Current issues and history. *Trends in Cognitive Sciences*. 2016;20(4):260–281. Available from: https://doi.org/10.1016/j.tics.2016.01.007

76. Stafford T, Pirrone A, Croucher M, Krystalli A. Quantifying the benefits of using decision models with response time and accuracy data. *Behavior Research Methods.* 2020; 1-14. Available from: https://doi.org/10.3758/s13428-020-01372-w

77. Lerche V, Voss A. Retest reliability of the parameters of the Ratcliff diffusion model. *Psychological Research*. 2017;81(3):629–52. Available from: https://doi.org/10.1007/s00426-016-0770-5

78. Price RB, Brown V, Siegle GJ. Computational modeling applied to the Dot-Probe Task yields improved reliability and mechanistic insights. *Biological Psychiatry*. 2019;85:606–12. Available from: https://doi.org/10.1016/j.biopsych.2018.09.022

79. Pirrone A, Dickinson A, Gomez R, Stafford T, Milne E. Understanding perceptual judgment in autism spectrum disorder using the drift diffusion model. *Neuropsychology*. 2017;31(2):173–80. Available from: https://doi.org/10.1037/neu0000320

80. Field M, Heather N, Murphy JG, Stafford T, Tucker JA, Witkiewitz, K. Recovery from addiction: Behavioral economics and value-based decision making. *Psychology of Addictive Behaviors*. 2020;34(1):182–93. Available from: https://doi.org/10.1037/adb0000518

81. Kathawalla U-K, Silverstein P, Syed M. Easing into open science: A guide for graduate students and their advisors. *PsyArXiv.* 2020;1–34. Available from: https://doi.org/10.31234/osf.io/vzjdp

82. Soderberg CK. Using OSF to share data: A step-by-step guide. *Advances in Methods & Practices in Psychological Science*. 2018; 1:115-120. Available from: https://doi.org/10.1177/2515245918757689

83. Kiyonaga A, Scimeca JM. Practical considerations for navigating Registered Reports. *Trends in Neuroscience*. 2019;42(9):568–72. Available from: https://doi.org/10.1016/j.tins.2019.07.003

84. Adewumi MT, Vo N, Tritz D, Beaman J, Vassar M. An evaluation of the practice of transparency and reproducibility in addiction medicine literature. *Addictive Behaviors.* 2021;112:106560. Available from: https://doi.org/10.1016/j.addbeh.2020.106560

85. Iqbal SA, Wallach JD, Khoury MJ, Schully SD, Ioannidis JPA. Reproducible research practices and transparency across the biomedical literature. *PLoS Biology.* 2016;14(1):1–13. Available from: https://doi.org/10.1371/journal.pbio.1002333

86. Hardwicke T, Thibault R, Kosie J, Wallach J, Kidwell M, Ioannidis J. Estimating the prevalence of transparency and reproducibility-related research practices in psychology (2014-2017). *MetaArXiv*. 2020. Available from: https://doi.org/10.31222/osf.io/9sz2y

87. Allen C, Mehler DMA. Open science challenges, benefits and tips in early career and beyond. *PLoS Biology*. 2019;17(12):1-14 (e3000246) Available from: https://doi.org/10.1371/journal.pbio.3000246

88. Piwowar HA, Vision TJ. Data reuse and the open data citation advantage. *PeerJ*. 2013;2013(1):1–25. Available from: https://doi.org/10.7717/peerj.175

89. McKiernan EC, Bourne PE, Brown CT, Buck S, Kenall A, Lin J, et al. How open science helps researchers succeed. *eLife*. 2016;5:1–19. Available from: https://doi.org/10.7554/eLife.16800

90. Gorman DM. Use of publication procedures to improve research integrity by addiction journals. *Addiction*. 2019;114(8):1478–86. Available from: https://doi.org/10.1111/add.14604

91. Scheel A, Schijen M, Lakens D. An excess of positive results: Comparing the standard Psychology literature with Registered Reports. *PsyArXiv*. 2020;1–14. Available from: https://doi.org/10.31234/osf.io/p6e9c

92. Obels P, Lakens D, Coles NA, Gottfried J, Green SA. Analysis of open data and computational reproducibility in Registered Reports in Psychology. *Advances in Methods & Practices in Psychological Science*. 2020;3(2):229–37. Available from: https://doi.org/10.31234/osf.io/fk8vh

93. Chambers C. The registered reports revolution: Lessons in cultural reform. *Significance*. 2019;16(4):23–7. Available from: https://doi.org/10.1111/j.1740-9713.2019.01299.x

94. Chambers C, Tzavella L. Registered Reports: Past, Present and Future. *MetaArXiv*. 2020. Available from: https://doi.org/10.31222/osf.io/43298

95. Protzko J, Krosnick J, Nelson L, Nosek B, Axt J, Berent M, Buttrick N, DeBell M, Ebersole C, Lundmark S, MacInnis B, O’Donnell M, Perfecto H, Pustejovsky J, Roeder S, Walleczek J, Schooler JW. High replicability of newly-discovered social-behavioral findings is achievable. *PsyArXiv*. 2020. Available from: <https://doi.org/10.31234/osf.io/n2a9x>