From Cheers to Tears:

Comparing Cognitive Impairments for Acute Alcohol Intoxication and Hangover

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ABSTRACT. This study investigated the differential effects of alcohol intoxication and hangover on cognitive processing using a perceptual decision-making task. Twelve participants completed a moving dot task under two conditions: alcohol intoxication and hangover. Results indicated that acute alcohol intoxication significantly impaired performance, evidenced by slower reaction times and increased errors compared to the hangover condition. Drift Diffusion Model (DDM) analysis revealed a lower drift rate during intoxication, reflecting impaired sensory evidence accumulation, while hangover exhibited greater variability in drift rates, potentially due to individual differences in metabolism speed. These findings suggest that alcohol intoxication has a more pronounced negative impact on cognitive processes than hangover. Future research should incorporate residual blood alcohol concentration (BAC) levels and a baseline condition to further elucidate the differential effects of alcohol intoxication and hangover on cognitive performance.

KEYWORDS: Alcohol, hangover, DDM

1. Introduction

Alcohol use is widespread, impacting lives on a social, economic, and health level globally. It has been well established that alcohol affects cognitive functions, including reaction time (RT) and decision-making processes (e.g., Weissenborn & Duka, 2003; McKinney et al., 2012; Grange et al., 2016). During intoxication, alcohol typically leads to slower RTs and impaired decision-making abilities corresponding with altered neural activity in areas such as the Anterior Cingulate Cortex (Anderson et al., 2010; Marinkovic et al., 2011). Previous studies posit that the effects of alcohol occur through the interference with top-down regulatory processes that facilitate goal-directed behavior (Marinkovic et al., 2011). Anderson and colleagues (2011) proposed that the level of alcohol intoxication (high/moderate) could impact regulatory processing to a different extent. They found that for high doses of alcohol, reaction time and errors increased. For lower alcohol levels, no significant effect on reaction time was found. However, they did find an increase in errors. Based on their study, they concluded that acute alcohol intoxication hinders cognitive control by reducing cortical activation in a dose-dependent manner.

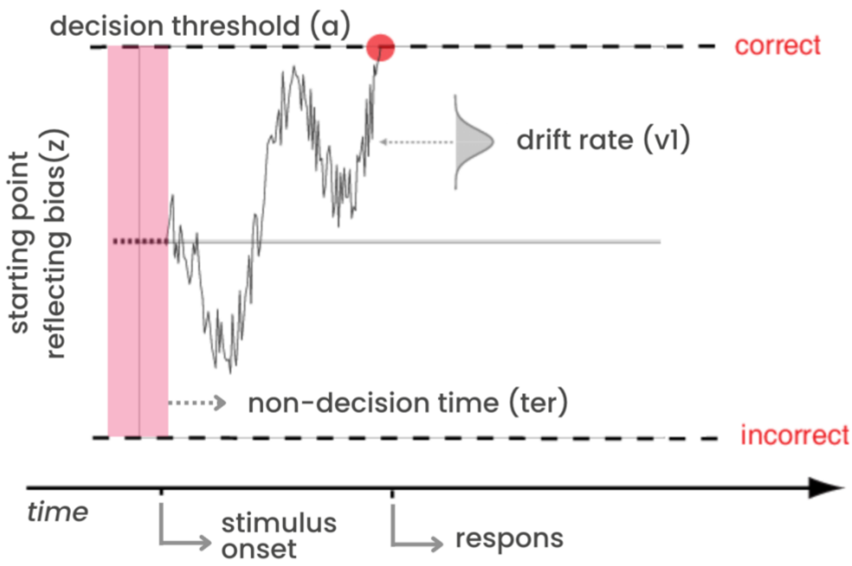
Next to the acute effects of alcohol intoxication, the effects of alcohol the following day when the blood alcohol concentration (BAC) has reached 0, also negatively impact cognitive processing (Grange et al., 2016). Whether these effects are caused directly through the effects of alcohol, or indirectly (e.g. sleep) is still poorly understood (Finnigan et al., 2005). Moreover, hangover effects have received far less attention in scientific research and reveal inconsistent findings (Grange et al., 2016). Studies comparing the effects of acute alcohol intoxication with next-day alcohol effects are even more scarce.

The impact of alcohol on cognitive processes could be investigated through the use of a Drift Diffusion Model (DDM). The DDM provides a robust framework for explaining the cognitive processes underlying decision-making (Ratcliff, 1978; Evans & Wagenmakers, 2020). It posits that decision-making can be understood as a noisy, evidence-accumulation process, where information is integrated over time until a decision threshold is reached. This model uniquely stands out as it not only accounts for RTs but includes parameters such as drift rate, starting point, making it a powerful tool for dissecting the cognitive processes influenced by different states, such as alcohol intoxication and hangover (Van Ravenzwaaij et al., 2011; Grange et al., 2016).

Key components of the DDM include the drift rate, decision threshold, non-decision time, and bias (Ratcliff, 1978; Evans & Wagenmakers, 2020). Drift rate (v), which represents the speed and direction of evidence accumulation, reflect both someone's task ability as well as the ease with which the task is being performed. In contrast, the decision threshold (A), representing the amount of information required to make a decision, reflects cautiousness in decision strategy. Non-decision time (T_{er}) accounts for processes like stimulus encoding and motor execution. During this time span, no evidence accumulation occurs. Lastly, the starting point of the accumulation process (z) reflects the tendency to choose one response over the other (i.e., a priori bias). Figure 1 illustrates the DDM model, highlighting the key components and their influence on the decision-making process.

Figure 1

Drift Diffusion Model



The aim of our current study was to assess the differential effects of alcohol intoxication and hangover on a perceptual decision-making task. Furthermore, by implementing a DDM, we want to investigate whether these changes were due to altered sensory evidence accumulation (drift rate; v), biased responses (starting point; z), and/or response cautiousness (threshold; A). The implementation of a DDM in alcohol-induced states has been done before. However, to our knowledge, a direct comparison between the two states (i.e., acute alcohol intoxication and hangover) using DDM is still lacking.

Based on previous research, we hypothesized that acute alcohol intoxication will lead to poorer performance compared to the hangover condition as reflected by slower RTs and lower response accuracy. More specifically, we posit that found differences between the two conditions could be accounted for by considering the drift rate, reflecting impaired information processing in acute alcohol intoxication condition in comparison to the hangover condition (e.g., Anderson et al, 2011).

When looking at response cautiousness, we do not expect to find any significant differences between alcohol intoxication and hangover conditions. Previous research has shown acute alcohol intoxication to be associated with an increase in impulsivity, which could be reflected through a lower decision threshold (Ravenzwaaij et al., 2012). Similar results have been found in hangover conditions compared to control groups (Grange et al., 2016). Therefore, it could be possible that by comparing the two groups, no significant effect of response cautiousness on cognitive performance will be found. Similarly, we do not expect to find a difference in response bias.

2. Methods

2.1. Participants

Our data included 12 participants that were repeatedly tested in two separate conditions: (1) evening session under the influence of alcohol, and (2) a morning session during the hangover.

2.2. Conditions

The aim of the experiment was to assess the differential effects of alcohol intoxication and hangover on a perceptual decision-making task using a within-subject design. The design included two conditions:

1. *Alcohol Intoxication*: Participants were administered alcohol to raise their blood alcohol concentration (BAC) to 80 mg/dL.
2. *Hangover*: Participants performed the same task under hangover conditions the following morning.

2.3. Moving Dot Task

During both sessions, the participants completed a perceptual decision-making task that was presented to them on a computer screen. More specifically, the participants were administered a moving dot task with two blocks of 200 trials per session, adding up to a total of 800 trials tested per participants (400 per session). On each trial, participants were presented with a noisy visual stimulus consisting of a field of randomly moving dots, where a small proportion of dots moved consistently in one direction. Participants were then instructed to indicate the direction of the coherently moving dots (left/right) by pressing one of two buttons. To assess performance, we measured both reaction time in milliseconds (ms), and accuracy (correct/incorrect).

2.4. Computational Modelling

We fit our data using a Drift Diffusion Model (DDM; (Ratcliff, 1978). The DDM is used to simulate decision-making processes, describing how evidence accumulation occurs over time until a decision boundary is reached. The basic DDM equation is as follows:

$$a_t = a_{t-1} + (I_A - I_B) + N(0, \sigma)$$

where α_t is the accumulated evidence at timepoint *t, I* represents the evidence for each alternative (*A* and *B*), and $N(0, \sigma)$ accounts for Gaussian distributed noise. Model fitting will result in the estimation of five key parameters: drift rate (v), threshold (A), starting point (z), and non-decision time (Ter). Next to the key parameters, we will also inspect the distribution of drift rate between conditions. The parameters were estimated for each participant in each condition, resulting in a total of 24 parameter estimations.

2.4.1. Cost Function

The cost function evaluates how well the model fits the observed data. Essentially, we want to compare the modeled RTs and accuracies to the observed RTs and accuracies.
In this study we calculated the likelihood of the observed data given the model parameters. The following code snippet within the 'obj' function was used to obtain the negative log-likelihood for the fit:

```
preds=getpreds(I1=I1,I2=I2,sdI=sdI,x0max=x0max,Ter=Ter,chi=chi, pred=pred,dat=dat,qps=qps,nc=nc)
[…]
tmp=-sum(dat$pb*log(pmax(preds$q,1e-10)))
```

2.4.2. Parameter Optimization

To find the optimal parameters based on the likelihood for the fit, we used an optimization algorithm. The main fitting function iteratively optimizes the models' parameters until convergence using the function 'optim'. Initial parameter values were based on the data and optimized through several iterations. The code snippet below displays the key lines used for parameter optimization within the fitter function:

```
tmp=optim(fn=obj,par=par,control=list(maxit=maxit[fitnum],parscale=par),
dat=dat,qps=qps,trace=trace,nc=nc)
out<-par<-tmp$par
```

2.4.3. Model Fitting

Parameter estimates were retrieved with the fit_data function, using code displayed below. All found parameters were stored in a data frame for further analyses.

```
for (subject in n_subjects) {
  for (condition in conds) {
    print(paste("participant", subject, "condition", condition))

    results <- if(condition == 1){
      print(fit_data(subset(filtered_data, ID==subject & condition==1)))
    } else {
      print(fit_data(subset(filtered_data, ID==subject & condition==2)))
    }
    df <- rbind(df, c(subject, condition, results))}}
```

2.4. Statistical analysis

2.4.1. Outliers

Outliers on RT will be removed from our dataset for all analyses, as to not influence subsequent conclusions. The upper and lower bounds for outliers will be defined by multiplying the Inter-Quartile Range (IQR) with 1.5 (see code snippet below).

```
lower_bound <- Q1 - 1.5 * IQR
upper_bound <- Q3 + 1.5 * IQR
```

2.4.2. Reaction Time and Accuracy

To compare the differential effects of each condition on RT (continuous), a paired-sample t-test will be performed. Since we are dealing with Gaussian distributed data (due to RT), we will aggregate the data by subject using the median. Differential effects of each condition on accuracy (dichotomous) will be tested with a chi-square test.

2.4.3. Model Parameters

To compare model parameters for each condition obtained from the DDM, we will perform a paired sample t-test separately for each parameter. Since we are testing five hypotheses (i.e., v, standard deviation of v, A, z, and Ter), we will use a Bonferroni correction when interpreting the obtained test results ($\alpha_{corrected} = .01$).

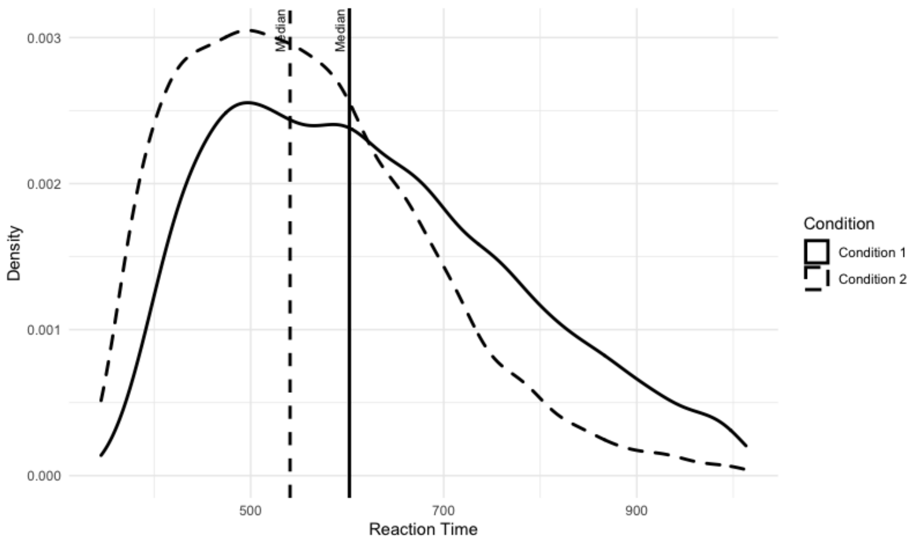
3. Results

3.1. RT performance

Prior to conducting our analyses, we removed all outliers on the variable RT based on IQR (refer to *2.4. Statistical analyses*). Once our data was filtered, we proceeded with our analyses. The paired-sample t-test showed a significant difference in median response times between the alcohol intoxication and hangover condition (t (11) = 13.807, p <.001). The results indicated that the responses were significantly slower during acute alcohol intoxication condition compared to the hangover condition (see Figure 2) with a mean difference of 64.04 ms, 95% confidence interval (53.83 – 74.24 ms). These findings suggest a greater impact of acute alcohol intoxication as compared to a hangover on reaction time.

Figure 2.

Density plot for reaction time distribution per condition.



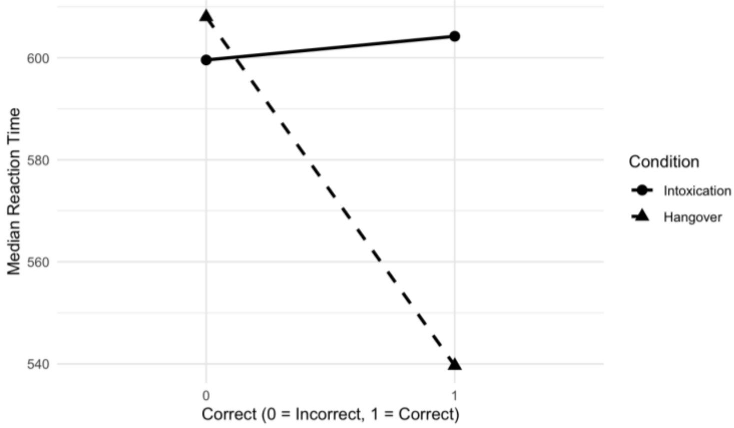
Note. Condition 1 = Alcohol intoxication; condition 2 = hangover.

3.2. Accuracy

Inspection of the data showed that accuracy was higher in the hangover condition (98.09%) as compared to the alcohol intoxication condition (68.36%). This effect was found to be significant, χ (1) = 1488.5, p <.001. Interestingly, visual inspection of a profile plot showed that for alcohol intoxication RT did not seem to differ much between correct and incorrect responses (see Figure 3). In contrast, a large difference in RT could be seen for the hangover group where correct answers were given at a faster rate compared to incorrect answers.

Figure 3.

Median Reaction Time by Accuracy and Condition



3.3. Diffusion modelling

The DDM was fitted per participant for each condition separately. It became evident that the rate of accumulating sensory evidence was slower for acute alcohol intoxication (M_v = .588, SD_v = .0335) compared to hangover conditions (M_v = .946, SD_v = .142). This effect was found to be significant, t (11) = -9.0658, p <.001, suggesting a differential effect of alcohol intoxication and hangover on the drift rate parameter.

Furthermore, the distribution of drift rates also appeared to differ significantly between conditions (t (11) = -4.4758, p<.001), with the hangover condition showing greater variability (M = .217) as compared to acute alcohol intoxication (M = .133). These effects remained significant even after Bonferroni correction for multiple testing (α = .01).

Inspection of the remaining parameters did not reveal any significant differences between the two conditions (see Table 1).

Table 1. *Parameter estimates*

	Intoxication (1)		Hangover (2)			
	M	SD	M	SD	*t*	*p*
Drift rate	.588	.0335	.946	.142	-9.0658	<.001
SD drift rate	.133	.0375	.217	.0522	-4.4758	<.001
Bias	301	32	313	56.1	-.60076	.5602
Non-decision time	248	146	260	70.1	-.23948	.8151
Threshold	393	61.9	417	29.2	-1.0625	.3108

Note. Degrees of freedom for every test equals 11

4. Discussion

The main aim of this study was to investigate the differential effects of alcohol intoxication and hangover on cognitive processing using a perceptual decision-making task. As hypothesized, our study showed that acute alcohol intoxication led to worse performance compared to hangover, as reflected by slower reaction times and increased errors. This finding could reflect the increased interference with top-down regulatory processes that has been found when investigating increased levels of alcohol intoxication (e.g., Anderson et al., 2011; Marinkovic et al., 2011).

We further investigated these differential findings by fitting a Drift Diffusion Model (DDM) to see whether changes could be explained by either altered sensory evidence accumulation (drift rate), biased responses (starting point), and response cautiousness (threshold). Fitting the DDM showed that for alcohol intoxication drift rate was significantly lower compared to hangover, possibly reflecting increased top-down interference (Anderson et al., 2011).

Interestingly, we found that for the hangover condition, the distribution of drift rates was significantly higher. As hangover effects are essentially the next-day alcohol effects, variability in drift rates might also reflect individual differences in metabolism speed. This might also reflect why previous literature seems to be somewhat inconsistent when considering the effects of hangover on cognitive performance (Grange et al., 2016; McKinney et al., 2012). Future research that accounts for residual BAC levels when investigating next-day alcohol effects is warranted. Incorporating BAC levels might account for individual differences and the increased variability that was observed in the hangover group. Lastly, future research could benefit from including a baseline condition to gain further insight into the differential effects between alcohol intoxication and hangover.

4.1. Conclusion

This study investigated the effects of alcohol intoxication and hangover on cognitive processing using a perceptual decision-making task. Results showed that alcohol intoxication significantly impaired performance, with slower reaction times and more errors compared to hangover, likely due to increased interference with top-down processes. Fitting a Drift Diffusion Model indicated lower drift rates for intoxication, reflecting this interference, while hangover showed greater variability in drift rates, possibly due to individual differences in metabolism. Future research should consider residual BAC levels and include a baseline condition to better understand these effects.

5. Appendix

Data analysis, model fitting, and parameter optimization was performed in R (Version 2024.04.1+748) using the *fit_data* function. All R code and raw data can be found in the GitHub repository, available at: https://github.com/RoosBoender/DDM_RLDM.git

6. References

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