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Biomedical Signal Processing Project

A comprehensive evaluation of the effects of alcohol on sustained attention, reaction times, and stress response in a testing environment

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Info-Bionics Engineering MSc

2025

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Contents

Chapter 1

Introduction

Biomedical signal processing plays a central role in extracting meaningful information from complex physiological data and is fundamental to both modern medical research and cognitive science. This project draws on these principles to examine the psychophysiological effects of alcohol consumption. Alcohol as a beverage is a widely used psychoactive substance, and although its general effects are well known, its impact on cognitive performance and autonomic regulation remains nuanced.

The study combines a standardized neuropsychological assessment, the Sustained Attention to Response Task (SART) [1], [2], with continuous heart rate monitoring to create an integrated methodological approach. This design produces a dataset that reflects both behavioral performance and physiological activity. Using a within-subjects experimental framework, participants are assessed across three conditions: a sober baseline, after consuming one standard drink, and after consuming two standard drinks. This structure enables a controlled examination of dose-dependent effects on attention based control, response latency, and stress reactivity.

The project involves developing a complete pipeline for signal acquisition, preprocessing, and statistical analysis. The expected findings aim to deepen our understanding of how incremental alcohol intake affects performance in tasks that rely on sustained attention and rapid motor responses. These insights have potential relevance for real-world contexts in which such abilities are essential.

Chapter 2

Aims

The primary technical aim is to develop a complete, reproducible data processing pipeline. This involves the synchronized acquisition of behavioral and physiological data, followed by systematic preprocessing to clean the heart rate signal and structure the performance metrics. The entire workflow will be implemented using an open-source programming language (Python 3.12), to ensure transparency and reproducibility. The comprehensive analysis shall include deriving relevant features from the physiological signal, conducting statistical comparisons across experimental conditions, and exploring potential correlations between autonomic activation and behavioral performance.

The core scientific objective is to test the dose-dependent impact of alcohol; we seek to determine whether increasing consumption leads to measurable degradation in sustained attention, prolongation of motor reaction times, and a heightened physiological stress response during a cognitively demanding task.

Finally, the project aims to synthesise the entire process and its outcomes into a coherent, professional format. This includes comprehensive technical documentation, clearly showing the aims, methodology, results, and their significance.

Chapter 3

Methods

3.1. Data Acquisition

The final dataset comprised nine participants. Two individuals were excluded from the analysis. One participant was unable to complete the protocol for the second drink condition. The second participant utilized a personal smartwatch for heart rate monitoring; as this device was incompatible with our standardized data collection pipeline, their physiological data were deemed unsuitable for inclusion. For all remaining participants, heart rate data were acquired using our standardized hardware: a Garmin HRM-Dual chest strap transmitter paired with a Garmin Edge 530 cycling computer [3].

ID	Age	Weight (kg)	Heigth (cm)	Consumed alcohol after 1st measurement (ml/kg)	Consumed alcohol after 2nd measurement (ml/kg)
0	23	85	193	0,24	0,47
1	22	85	168	0,24	0,47
2	23	70	174	0,29	0,57
3	23	78,6	179,5	0,25	0,51
4	23	54	158	0,37	0,74
5	25	95	187	0,21	0,42
6	24	87	164	0,23	0,46
7	23	50	159	0,40	0,80
8	24	65	175	0,31	0,62
9	22	70,7	157	0,28	0,57

Table 3.1: Numerical physiological data collected from participants; amount of alcohol consumed in ml per body weight in kg.

All participants were asked to complete the Sustained Attention to Response Task (SART) [1], [2] three times – once sober, after one drink, then finally after two drinks have been consumed. One drink was set to be 500 ml of beer, 4% alcohol by volume (ABV). During each iteration of the task, real-time heart rate (HR) measurements were taken for every subject via a chest strap. Further physiological data of the participants, such as weight, height, and age, were collected through a questionnaire, as can be seen in Table 3.1.

3.1.1 What is SART

The Sustained Attention to Response Task is a well-established cognitive test used to assess vigilance and sustained attention. Its design explores the conflict between automatic motor responding and controlled inhibition. Participants are presented with a continuous stream of digits and are instructed to press a key for each common digit (the "Go" trials) but to withhold that press when a single, pre-specified rare digit appears (the "No-Go" or target trial). The high frequency of Go trials establishes a strong response habit, making failures of sustained attention evident as errors of commission (responding to the target) or errors of omission.

For this study, the task was administered using the web-based PsyToolkit platform. We specifically employed the publicly available SART demonstration from the PsyToolkit experiment library. This standardised version of the task was used to collect all behavioral performance data. Results of the SART test were outputted in .txt files, which included the following metrics in each column:

- Name of block (training or test)
- Number of the block
- Go (1) or no-go trial (0)
- Digit (1-9)
- Size of stimulus (values between 1 and 5, from smallest to highest)
- Response outcome (0 is error, 1 is correct)
- Reaction time in milliseconds.

3.2. Data Processing

The initial phase established a structured workflow for transforming raw experimental data into an analyzable format. Behavioral metrics were derived from SART task files, with parsing focused on extracting reaction times exclusively from correct 'Go' trials alongside commission and omission error counts. Variability in reaction time was captured through multiple dispersion measures, including variance, standard deviation, and median absolute deviation. Physiological data were processed from TCX-formatted heart rate recordings. The heart rate time series was extracted, timestamps were normalized to seconds, and the data were trimmed to the precise duration of the cognitive task. From each resulting series, summary statistics were generated.

Next, the individual data streams were combined. Behavioral performance summaries, reaction time variability metrics, and heart rate features were merged into a single dataset. Participant information was appended, incorporating calculated Body Mass Index (BMI) and exact dosage per body mass. To facilitate direct comparison of within-subject changes across experimental conditions, z-score normalization was applied to mean reaction time and mean heart rate across the full sample. The application of signal smoothing was considered. While a moving average filter was implemented and demonstrated on a sample heart rate trace, illustrating noise reduction principles, the technique was deliberately withheld from the analytical pipeline. This decision was methodological, as applying smoothing would have artificially attenuated the high-frequency and beat-to-beat variability, thereby compromising the integrity of the primary heart rate variability analysis.

3.3. Data Evaluation

The analytical evaluation began with a comprehensive descriptive overview and diagnostic assessment of data distributions. For each dependent variable-mean reaction time, reaction time variance, mean heart rate, and the RMSSD-like metric-summary statistics were computed per condition. Distributions were visually inspected via histograms.

Formal assessment of the normality assumption was then conducted using the Shapiro-Wilk test, applied to each dependent variable within every condition. The results from these tests were documented and informed subsequent methodological choices. Statistical hypothesis testing proceeded with the Friedman test for repeated measures, which was

selected based on the study design and the distribution characteristics observed in the previous steps. This test was applied separately to each of the four primary dependent variables to evaluate for overall differences across the three experimental conditions.

For variables where the Friedman test returned a statistically significant result, a secondary investigative stage was implemented. This involved post-hoc pairwise comparisons between conditions using the Wilcoxon signed-rank test. To control for the increased risk of Type I error, p-values obtained from these pairwise tests were adjusted using the Holm-Bonferroni correction method.

A separate exploratory analysis investigated potential associations between the collected physiological and behavioral metrics and participant Body Mass Index (BMI). This analysis was performed by calculating correlation coefficients and creating corresponding scatterplots with data points visually differentiated by experimental condition.

Visualization techniques were used throughout the analysis process. The distribution of each primary variable was represented using boxplots with overlaid stripplots, illustrating central tendency, spread, and individual data points. Individual trajectories across conditions for reaction time variance and mean were plotted on spaghetti plots. To enable direct comparison of normalized scores, dedicated visualisations were created for the z-scored reaction time and heart rate data.

The entire data processing and evaluation pipeline was carried out in the Google Colaboratory environment, to facilitate cooperation.

Note: The entire project was completed in full cooperation between team members. All members contributed their individual expertise to all steps during the data acquisition, data processing, and documentation development phases, each bringing a unique viewpoint to the table. During the preparation of this work, various artificial intelligence tools such as ChatGPT [4] and DeepSeek [5] were used, for language refinement, code troubleshooting and debugging, proofreading, etc. All generated content was thoroughly reviewed and edited by the authors, who take full responsibility for the final documentation and code submissions, as available on GitHub [6].

Chapter 4

Results

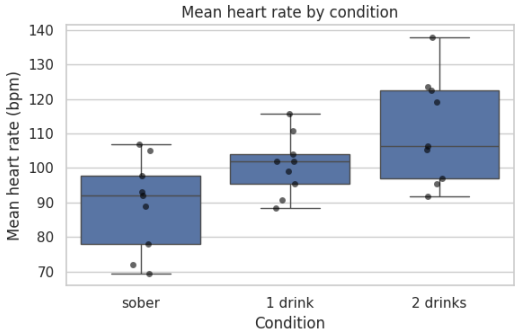

Figure 4.1: Mean heart rate by condition

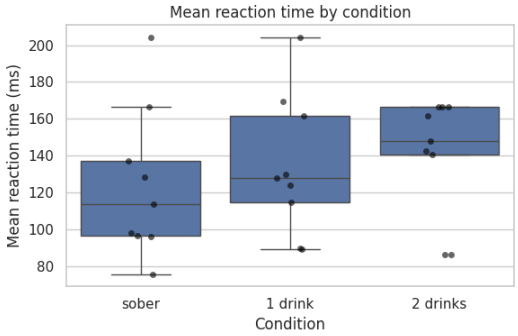

Figure 4.2: Mean reaction time by condition

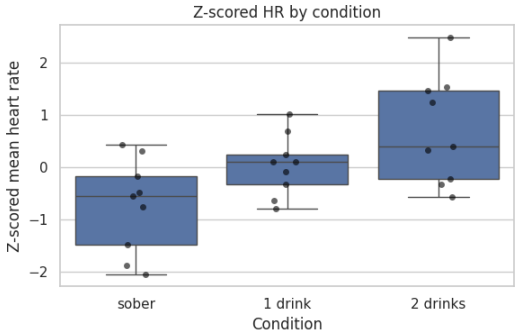

Figure 4.3: Z-scored HR by condition

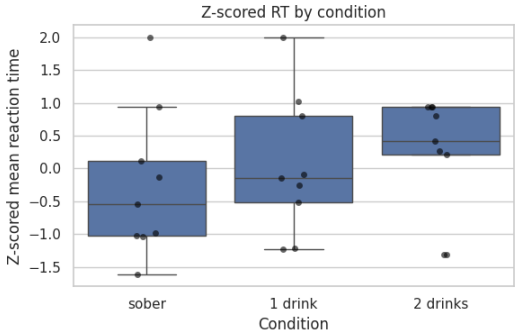

Figure 4.4: Z-scored RT by condition

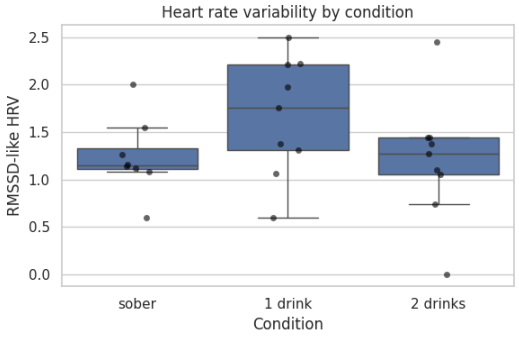

Figure 4.5: Heart rate variability by condition

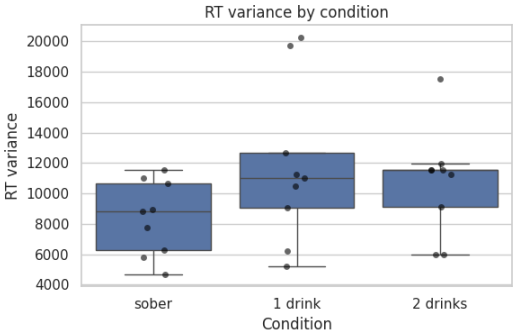

Figure 4.6: RT variance by condition

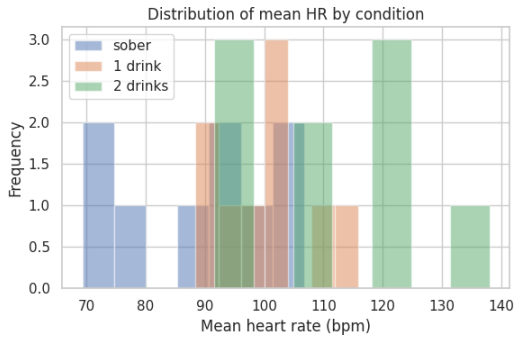

Figure 4.7: Distribution of mean HR by condition

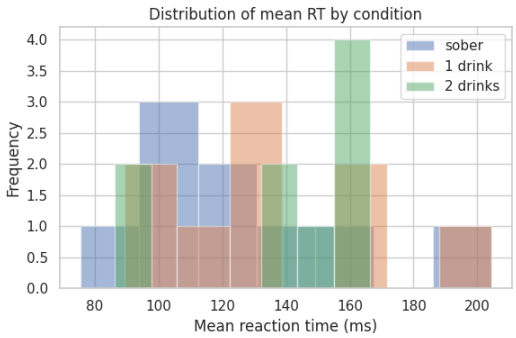

Figure 4.8: Distribution of mean RT by condition

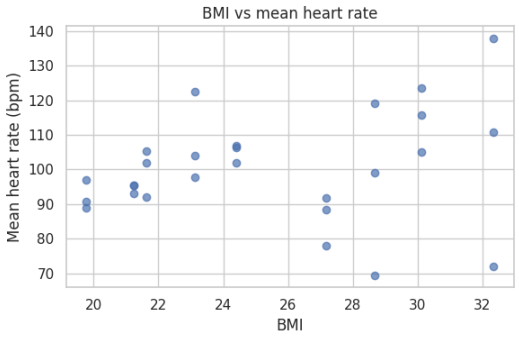

Figure 4.9: BMI vs mean heart rate

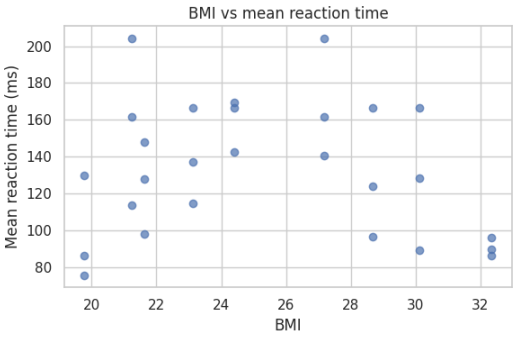

Figure 4.10: BMI vs mean reaction time

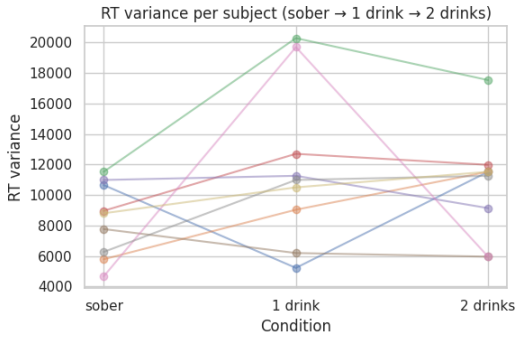

Figure 4.11: RT variance per subject (with condition tracking)

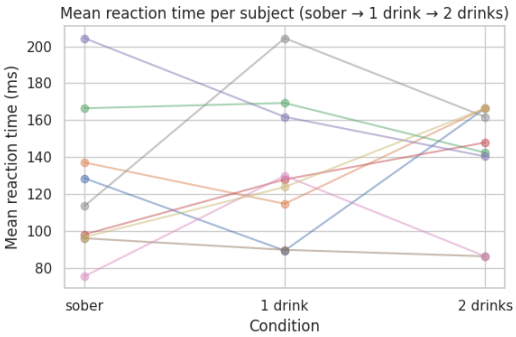

Figure 4.12: Mean reaction time per subject (with condition tracking)

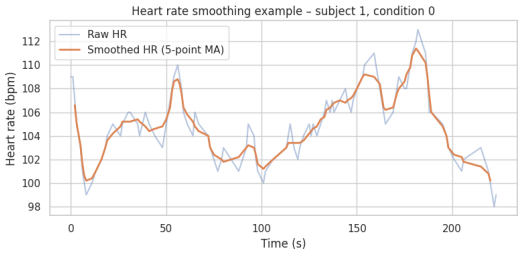

Figure 4.13: Heart rate smoothing example

Chapter 5

Discussion

5.1. Expected results

The main hypothesis suggests a two-phase, dose-dependent effect of alcohol. After a low dose (one drink), alcohol was theorised to have an anti-anxiety effect in some cases. This should reduce the physiological stress response, while leaving key cognitive abilities such as sustained attention and reaction time largely unchanged.

With a higher dose (two drinks), the hypothesis was that the effects of alcohol consumption move beyond a beneficial range and reach a level that causes noticeable cognitive decline. This was expected to appear as a statistically significant rise in SART errors together with slower reaction times. At the same time, the stress response and thus heart rate were predicted to increase.

Overall, the results are expected to map a shift from reduced stress with roughly intact performance to a state of clear neurocognitive impairment.

5.2. Actual results

The descriptive plots in Figures 4.1 to 4.6 show how the main behavioural and physiological measures changed across the three alcohol conditions. Mean heart rate increased steadily from the sober condition to one drink and then to two drinks (Figure 4.1). The same ordering was still present after z-score normalisation (Figure 4.3). This pattern points to a clear group-level effect of alcohol on physiological arousal.

Mean reaction time showed a weaker and less consistent change. In Figures 4.2 and 4.4, reaction times were on average slightly longer after drinking compared to sobriety, but the spread across participants was large and the condition ranges overlapped strongly. This suggests that alcohol affected reaction time less than it affected heart rate in this sample.

Heart-rate variability (RMSSD-like) and reaction-time variance followed a similar subtle direction (Figures 4.5 and 4.6). Both measures tended to be higher after alcohol, yet the distributions overlapped widely and individual differences were noticeable. The histograms in Figures 4.7 and 4.8 support this view, showing gradual shifts rather than clear separation between conditions, with all three conditions covering broadly similar value ranges.

The statistical tests align with these descriptive trends. Shapiro–Wilk tests did not show strong evidence of non-normality. However, because the sample size was small, non-parametric repeated-measures methods were used. The Friedman test indicated a significant condition effect only for mean heart rate. Post-hoc Wilcoxon tests with Holm correction showed that each pairwise comparison of heart rate was significant. In contrast, none of the behavioural measures (mean reaction time, reaction-time variance, RMSSD-like variability) differed significantly across conditions.

Figures 4.9 and 4.10 report an exploratory check of BMI effects. The correlations with mean heart rate ($r \approx 0.2$) and mean reaction time ($r \approx -0.14$) were weak, and given the limited sample size they should be treated as tentative.

Finally, Figure 4.11 shows participant-level trajectories for reaction time variance. Variability was often higher after alcohol, but the size and direction of change differed across individuals. This is reinforced by its counterpart, Figure 4.12, which shows the progression of mean reaction times per subject. Figure 4.13 illustrates the application of a simple moving-average filter to one heart-rate trace, included as an example of a possible preprocessing step.

5.3. Methodological considerations and limitations

Several practical and methodological factors influenced the analysis and interpretation of the data. Although we had exported mainly TCX files and one pair of JSON files, only the TCX files were used. The JSON files contained mainly daily summary metrics and lacked the time-resolved heart-rate signal needed for HR- and HRV-related analyses. The TCX files, in contrast, included second-by-second HR data, which allowed for isolation of the SART task period and computation of meaningful physiological features.

Moreover, some TCX recordings were missing for specific subject–condition combinations. These cases could not be included in the physiological analyses, slightly reducing the within-subject sample size. As the project required demonstrating signal preprocessing steps (e.g., noise reduction), a simple moving-average filter was applied to one HR time series as an example. The entire dataset was not smoothed as filtering can distort HRV-like measures. [7] All statistical analyses therefore used the original HR signal.

Finally, the relatively small sample size and some non-normal variable distributions limited the statistical power. For this reason, non-parametric tests (Friedman, Wilcoxon) were used, and z-scoring was applied for more interpretable visual comparisons.

Chapter 6

Conclusion

Figures 4.11 and 4.12 clearly present findings for different subjects across their various conditions, with each subject compared to their own baseline. The statistics show that alcohol consumption affected different individuals in markedly different ways.

Based on our initial assumptions, reaction time was expected to increase between the sober state, the first and the second drink conditions. The interesting phenomenon is that for some individuals reaction time showed deterioration between the sober state and the state after one drink, while for others the exact opposite was true. In a few participants these tendencies continued after their second drink was consumed, however, not in all cases.

Several potential biases could have occurred in our measurements, which can be attributed to the influence of various factors. The results of our subjects may have been influenced by the imperfect test environment, as the measurements did not take place in a laboratory setting. Furthermore, the human factor may also have influenced our measurement results: participants declared their sober state on a trust basis beforehand, without a confirmatory breathalyzer test. Another aspect of the human factor is the differences in alcohol metabolism across individuals. Although the test was standardized, our subjects produced varied results. While they received a verbal briefing regarding the nature of the experiment, participants were not familiarized with the test in advance; their sober state measurements represent their first encounter with the testing procedure. Finally, the small sample size reduces the statistical power of the analysis and increases the influence of individual variability on the overall results.

All aims of the project as outlined in Chapter 2 of this documentation were met in full.

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