Poor and Ponderous Decisions;

Negative Effects of Implicit Time Pressure

on Evidence Accumulation in Decision-Making

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Reinforcement Learning & Decision Making

Date: 13–06–2024

Word count: 4040

Abstract

This paper investigated the effects of implicit time pressure on decision making, using a computational drift diffusion model (DDM) to estimate the parameters underlying these processes. Results for the decision-making task showed slower and less accurate responses in the high time pressure condition, indicating that both aspects of the speed-accuracy trade-off are negatively affected by time pressure. Additionally, significant differences were found for the drift rate parameter and its standard deviation, reflecting a slower evidence accumulation process under time pressure. Further research is necessary for more conclusive results on the effects of a priori response biases and response caution during decision making under pressure.

Introduction

In everyday life many decisions have to be made within a certain time frame; we only have so much time before we are forced to make a decision, a choice-alternative disappears, or the choice gets made for us instead. Time pressure can therefore significantly alter our decisions and the underlying decision-making processes leading up to it.

This paper will discuss the influence of implicit time pressure on decision making and studied this effect with an experimental decision-making task. The decision-making process has been modelled with a computational drift diffusion model (DDM), investigating the effects of time pressure on the parameters estimating a priori response bias (starting point), evidence accumulation (drift rate), and response caution (threshold).

A drift diffusion model (DDM) predicts the processes underlying decision-making by computing parameters estimating various elements impacting the time necessary to make and execute a decision. The most commonly used parameters estimate the a priori bias for decision alternatives, the accumulation of evidence, the decision thresholds, as well as the sensory encoding and behavioural execution of the decision response (Harris & Hutcherson, 2021; Kloosterman et al., 2019).

The a priori bias is reflected in the starting point of evidence accumulation, indicating a bias or expectation leading to being more likely to choose the option for which the threshold is closer to the starting point. The accumulation of evidence represents the learning of information that weighs into the decision-making process; more information for one choice alternative confirms the "correctness" of this option, making it the better alternative, and therefore supporting the choice to pick this option. The speed at which this accumulation of information happens is described in the drift rate, as the information accumulation “moves” (drifts) away from the starting point towards the choice alternative that will be chosen. The drift rate moves towards the threshold of the choice alternative, and once this threshold is crossed, a decision is made. The height or distance of this threshold from the starting point reflects the speed-accuracy trade-off, since a lower threshold results in faster but more incorrect responses, while a higher threshold encourages caution. Lastly, the time it takes to make choices is not only affected by these processes directly involved with the choosing between options, but also involves non-decision time. This is the time that is required to be able to process the information or stimuli that serve as choice alternatives or feed into the information accumulation. Once the decision has been made, it additionally takes time to be able to convert this into a motor action to be able to indicate the choice physically (for example with a button press in experimental designs).

Depending on the circumstances—both internal and external contexts—these parameters can differ or reflect biases, which affect the underlying processes involved in decision making. Implicit time pressure is one of these contextual factors that could possibly affect a priori biases, evidence accumulation, or response caution.

Previous literature has indicated that implicit time pressure can affect decision making processes by influencing the speed-accuracy trade-off, by encouraging faster responses, and therefore likely increasing the number of errors made. This trade-off can be effectively estimated by altering the parameters in a drift diffusion model.

Faster decision making could be reflected in an a priori bias, which would indicate an altered starting point for the information accumulation process. If a certain outcome is expected—meaning that one choice alternative is preferred before the stimulus is even presented—the starting point could be moved closer to the decision boundary of that option. This preference could be due to a variety of reasons, such as the decision that was made in the previous trial, or an arbitrary bias of the participant to prefer one side of the visual field or motor response. Although this increased pre-stimulus baseline activation has been widely hypothesised and tested, the evidence is inconclusive and does not always outweigh biases in other parameters (Harris & Hutcherson, 2021; Kloosterman et al., 2019).

An alternative reason for the increased decision speed under time pressure could be as a result of altered sensory evidence accumulation, represented in the drift rate parameter. It has been found that a drift bias model can accurately predict decision making in this context, as has been hypothesised to reflect increased neural excitability leading to biased evidence accumulation for one of the decision boundaries (Kloosterman et al., 2019). Another study supported this with evidence for enhanced drift rates under speed pressure reflecting increased sensory evidence accumulation. However, they do acknowledge that there is still ongoing debate within the literature, and that the faster responses are also partially attributable to shortened non-decision times (Kelly et al., 2021).

Lastly, a possible consequence of implicit time pressure could be the lowering of decisional thresholds. There is much debate about this parameter in the literature, as some studies have found that thresholds change as a result of time pressure, while others have not found support for this (Dambacher & Hübner, 2015; Harris & Hutcherson, 2021). Lowered bounds during the information accumulation process lead to a faster crossing of the threshold to make a decision, meaning that the perceptual information is not filtered as much and will lead to more impulsive—and therefore also more erroneous—decision making (Dambacher & Hübner, 2015). It has even been hypothesised that collapsing bound could be a possibility. Collapsing bounds describe the lowering of decision thresholds dynamically during a trial, meaning that evidence strength might be considered differently and given a different weight within an ongoing trial, depending on how fast the deadline of the limited time frame is approaching (O'Connell et al., 2018).

Due to the inconclusive literature regarding the affected parameters when under time pressure, this paper aimed to investigate this further. The effects of implicit time pressure on decision making processes were tested with a within-subjects decision-making task, including a high and low time pressure condition. The response times of participants were used to computationally model the parameters of a drift diffusion model (DDM). In particular, focus was placed on the parameters estimating a priori response biases (starting points), evidence accumulation (drift rate), and response caution (threshold).

It was expected that the time-accuracy trade-off would differ between the two conditions, with speed being prioritised in the high time pressure condition. As a result, participants should have lower reaction times and more incorrect responses in the high time pressure condition. For the DDM parameters, it was hypothesised that a priori response biases would be present in the high time pressure condition, therefore showing increased starting point parameter values. In addition, increased drift rates were expected in the high time pressure condition, as a result of faster evidence accumulation. Lastly, it was hypothesised that decision thresholds would be decreased in the high time pressure condition to be able to make a decision faster.

Methods

To be able to test the effects of implicit time pressure on decisions making, a within-subjects decision-making task was used. Twelve participants were recruited who completed two sessions in the lab. The participants engaged in a decision-making task, in which on every trial a noisy visual stimulus appeared, consisting of a field of randomly moving dots. Participants had to indicate the consistent direction that a small proportion of the dots moved in, with the left or right arrow keys on a keyboard. Each session contained 400 trials. During the sessions a ticking clock was heard during the presentation of the stimulus. In the low time pressure condition, this clock ticked at a slow frequency of 0.5 Hz. In the high time pressure condition, the clock ticked at a much faster rate of 3 Hz. This ticking clock was used to induce a sense of implicit time pressure for the participants, while they were trying to decide on the direction of the moving dots.

The participants' reaction times were recorded from the moment of stimulus onset until the button-press, as well as the number of (in)correct responses they made throughout the trials. To be able to answer the hypotheses, a DDM model was computed, and paired samples t-tests were performed on the reaction times, (in)correct responses, and DDM parameters between-conditions.

Model simulation

A generalised DDM model was simulated (see the code in Appendix A), but was eventually not used to produce the parameters applied to the dataset. Instead, a pre-made dataset was received and used for the analyses.

Model fitting

The DDM parameters were estimated using the reaction times of the twelve subjects for each of the two time pressure conditions. After initial inspection of the data, outliers above the 75th and below the 25th percentile were removed, since these reaction times were too fast and too slow to be considered related to the presented stimulus.

The DDM model fitted five parameters to each individual subject for each condition. The estimated parameters were: the upper limit of the starting point (A), the drift rate (v1) and its standard deviation (s), the decision threshold (b), and the non-decision time (ter). The subject's ID, the condition number, and the parameter values for each subject–condition interaction were saved in a data frame. The code used for this is stated below.

```
#Removing outliers
quartiles <- quantile(dataset8$rt, probs=c(.25, .75), na.rm = FALSE)
IQR <- IQR(dataset8$rt)
Lower <- quartiles[1] - 1.5*IQR
Upper <- quartiles[2] + 1.5*IQR
data_no_outlier <- subset(dataset8, dataset8$rt > Lower & dataset8$rt <
Upper)
dim(data_no_outlier)

#Selecting the subject ID's and the conditions
n_subjects <- unique(data_no_outlier$ID)
conds <- unique(data_no_outlier$condition)

#Creating a dataframe and saving the outcomes as numerical values
data_no_outlier <- as.data.frame(data_no_outlier)

df <- data.frame(ID=numeric(),
                 condition=numeric(),
                 s=numeric(),
                 A=numeric(),
                 ter=numeric(),
                 b=numeric(),
                 v1=numeric())

#Fitting the DDM model
for (subject in n_subjects) {
  for (condition in conds) {

    #fit data of participant for condition
    print(paste("participant", subject, "condition", condition))

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

#Giving the columns in the dataframe appropriate names
names(df) <- c("ID", "condition", "s", "A", "ter", "b", "v1")
View(df)
```

Results

Firstly, overall patterns of the raw data were explored, before fitting the DDM model or applying statistical analyses to the parameters.

To be able to visually inspect the raw data, a histogram of the reaction times of all participants across both conditions were plotted. In the histogram some extreme outliers are visible with very slow reaction times (Figure 1). Since reactions times delayed to the extent that they are no longer related to the presented stimulus can interfere with the association between the predictors and outcomes, the outliers above the 75th and below the 25th percentile were removed. The histogram of the data without the outliers looks better distributed and displays a skewness commonly found in reaction time plots (Figure 2).

```
#Histogram of frequency of reaction times in raw data
ggplot(rawdata, aes(x=rt)) + geom_histogram(binwidth=.5) + xlim(0, 3000)
+ labs(title = "Histogram of raw data", x = "Reaction time", y =
"Frequency")

#Removing outliers
quartiles <- quantile(rawdata$rt, probs=c(.25, .75), na.rm = FALSE)
IQR <- IQR(rawdata$rt)
Lower <- quartiles[1] - 1.5*IQR
Upper <- quartiles[2] + 1.5*IQR
data_no_outlier <- subset(rawdata, rawdata$rt > Lower & rawdata$rt <
Upper)
dim(data_no_outlier)

#Histogram of frequency of reaction times in data without outliers
fortify(data_no_outlier)
ggplot(data_no_outlier, aes(x=rt)) + geom_histogram(binwidth=.5) +
labs(title = "Histogram of data without outliers", x = "Reaction time", y
= "Frequency")
```

Figure 1

Histogram of frequency of reaction times in raw data

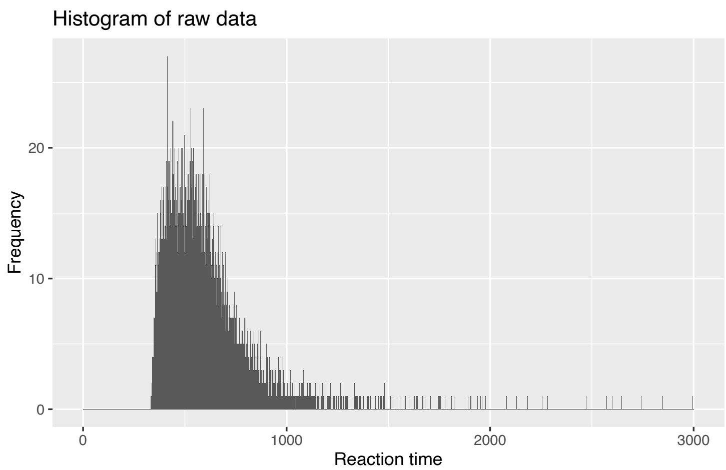
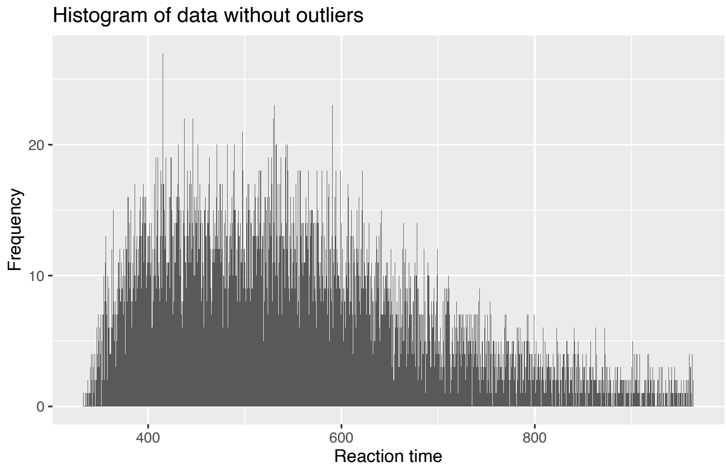


Figure 2

Histogram of frequency of reaction times in data without outliers

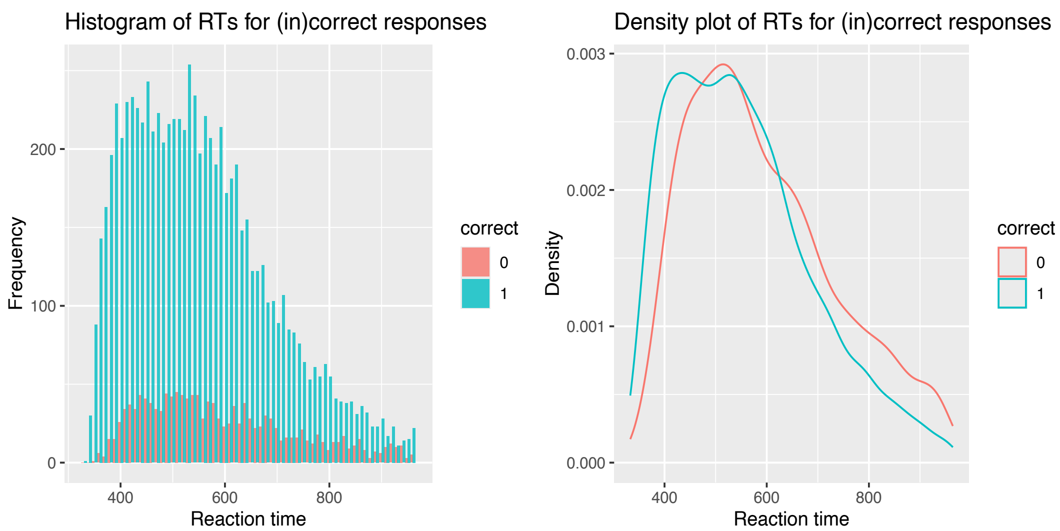


Visual inspection of the amount and density of correct and incorrect answers for all subjects and conditions in the new outlier-free dataset are plotted in Figure 3. In the legend "0" represents an incorrect answer, whereas "1" represents a correct answer. There are clearly far more correct than incorrect responses across all participants and conditions.

```
#Histogram for correct and incorrect
ggplot(data_no_outlier, aes(x=rt, fill=correct)) +
  geom_histogram(binwidth=10, alpha=0.8, position="dodge") +
  labs(title = "Histogram of RTs for (in)correct responses", x =
"Reaction time", y = "Frequency")

ggplot(data_no_outlier, aes(x=rt, colour=correct)) + geom_density() +
  labs(title = "Density plot of RTs for (in)correct responses", x =
"Reaction time", y = "Density")
```

Figure 3

Histogram and density plot of reaction times for incorrect (0) and correct (1) responses



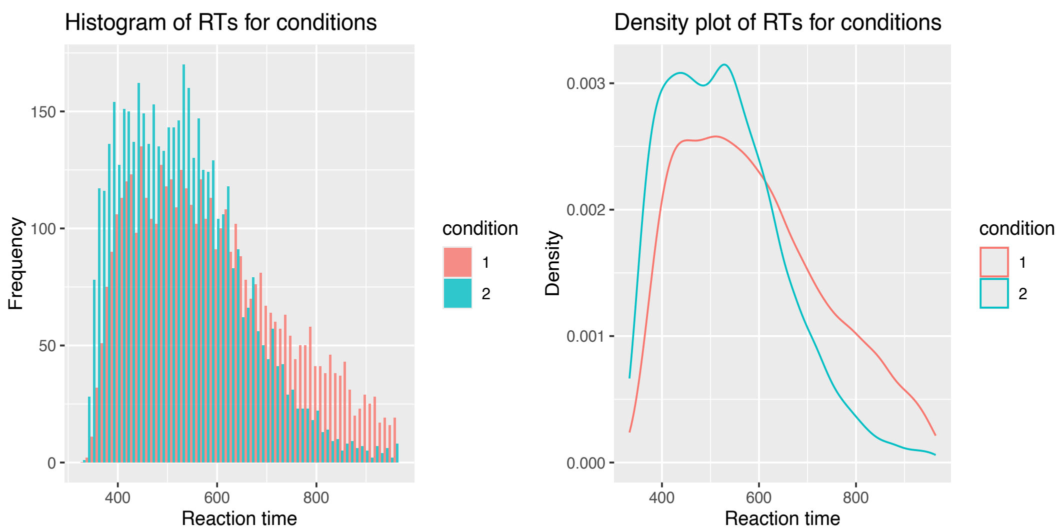
The differences in reaction times between the low and high time pressure conditions were also plotted, and are presented in Figure 4. In the legend, condition "1" represents the high time pressure condition with the fast ticking clock, and condition "2" represents the low time pressure condition with the slow ticking clock.

In condition 1 there seems to be a higher frequency of longer reaction times, and in condition 2 there are more faster reaction times. At face value, this appears to be contrary to the hypothesis that speed would be prioritised in the high time pressure condition.

```
#Histogram for condition 1 vs condition 2
ggplot(data_no_outlier, aes(x=rt, fill=condition)) +
  geom_histogram(binwidth=10, alpha=0.8, position="dodge") +
  labs(title = "Histogram of RTs for conditions", x = "Reaction time", y
= "Frequency")

ggplot(data_no_outlier, aes(x=rt, colour=condition)) + geom_density() +
  labs(title = "Density plot of RTs for conditions", x = "Reaction time",
y = "Density")
```

Figure 4

Histogram and density plot of reaction times for condition 1 (high time pressure) and 2 (low)

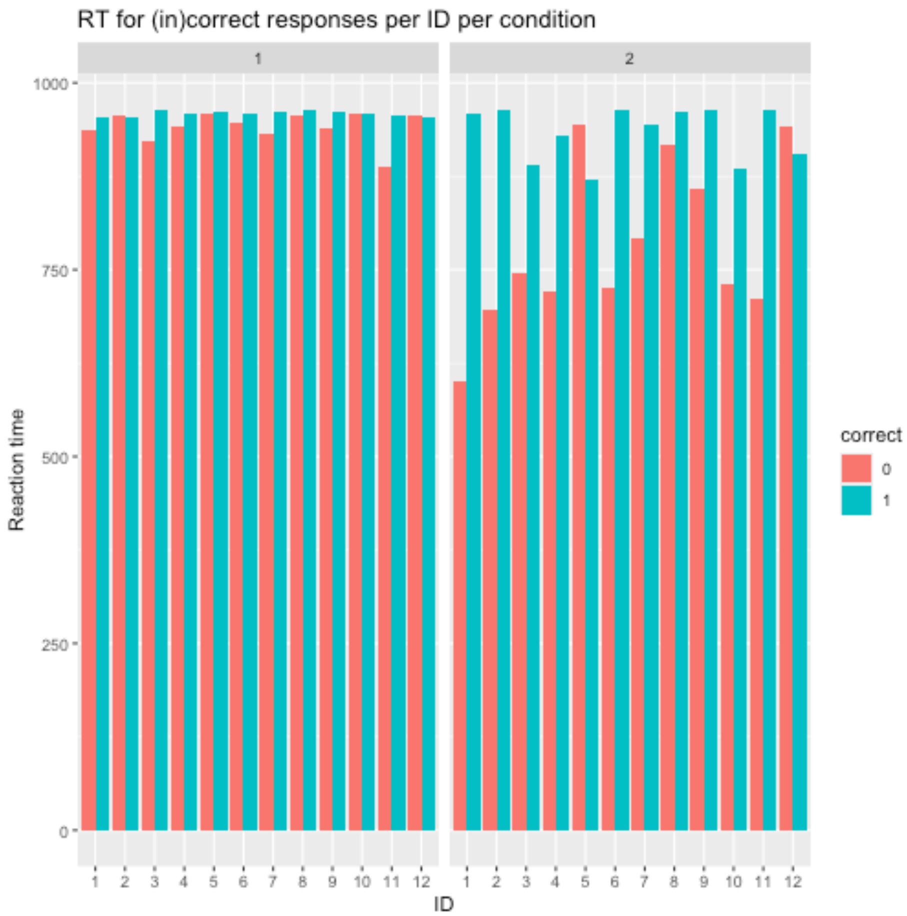


Lastly, all variables were combined into one plot to be able to compare all measures visually. Figure 5 displays bar charts for each subject (on the x-axis), plotted against the reaction times (y-axis). The left plot displays the values for condition 1 (high time pressure), and the right plot for condition 2 (low time pressure). The red bars indicate the incorrect responses, and the blue bars the correct responses. In the plot it appears that in the high time pressure condition, most participants needed a similar amount of time to determine the direction of the dots regardless of whether they answered correctly or not. In the low time pressure condition, there is some variation between participants, but most participants responded much faster on trials where they answered incorrectly.

```
#Bar graph for subject, reaction time, condition, (in)correct repsonse
library(magrittr)

data_no_outlier %>%
  ggplot(aes(ID, rt)) +
  geom_col(aes(fill = correct), position=position_dodge()) + xlab("ID") +
ylab("Reaction time") +
  ggtitle("RT for (in)correct responses per ID per condition") +
facet_wrap( ~ condition)
```

Figure 5

Reaction times for each subject's (in)correct responses per condition (left = condition 1: high time pressure, right = condition 2: low time pressure)



From Figure 5, it appears that for most of the participants the reaction times differ between the two time pressure conditions. Therefore, the significance of this difference was tested with a paired samples t-test. To do this, the dataset was first aggregated to compute summary scores for the participants' reaction times. The median was used for this, due to the skewness in reaction times. These summary scores are presented in Table 1.

```
#Paired t-test over RT data by condition
aggregated_output = aggregate(data_no_outlier$rt ~ data_no_outlier$ID *
data_no_outlier$condition, data=data_no_outlier, FUN=median)
aggregated_output

t.test(aggregated_output$`data_no_outlier$rt` ~
aggregated_output$`data_no_outlier$condition`, data = data_no_outlier,
paired = TRUE)

aggregated_output <- as.data.frame(aggregated_output)
mean(aggregated_output$`data_no_outlier$rt`[1:12])
mean(aggregated_output$`data_no_outlier$rt`[13:24])
```

Table 1

Aggregated (median) reaction times for each participant per condition

ID	condition	rt	ID	condition	rt
1	1	565.7479	1	2	522.5024
2	1	564.1055	2	2	511.2140
3	1	573.0660	3	2	508.1174
4	1	567.2788	4	2	522.7325
5	1	570.4822	5	2	522.6183
6	1	569.9050	6	2	506.3632
7	1	550.9582	7	2	508.5651
8	1	569.3834	8	2	520.6430
9	1	574.3720	9	2	520.8683
10	1	577.7631	10	2	525.0928
11	1	571.2155	11	2	522.6332
12	1	561.0248	12	2	520.8820

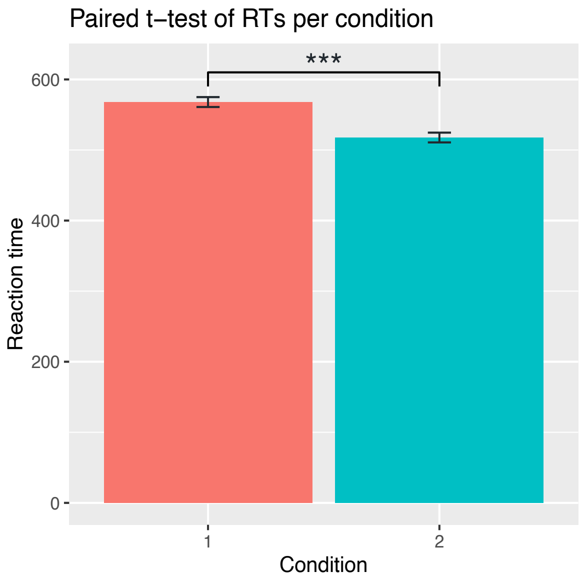
The paired samples t-test gave a highly significant result, with: $t(11) = 22.267$, $p < .001$, $CI_{95} = [45.288, 55.223]$. This indicates that the reaction times between the two conditions significantly differ, and that therefore implicit time pressure significantly affects reaction times in decision making. The reaction times for condition 1 (the high time pressure condition) are significantly higher ($M = 567.94$, $SD = 7.03$) than in condition 2 (the low time pressure condition; $M = 517.69$, $SD = 6.92$). The differences are represented visually in Figure 6.

```
#Bar graph for paired t-test over reaction time by condition
library(tidyverse)
glimpse(aggregated_output)
```

```
bars <- aggregated_output %>%
  group_by(`data_no_outlier$condition`) %>%
  summarise(
    mean_rt = mean(`data_no_outlier$rt`),
    sd_rt = sd(`data_no_outlier$rt`))

p_value <- tibble(
  x = c("1", "1", "2", "2"),
  y = c(590, 610, 610, 590))

bars %>%
  ggplot(aes(`data_no_outlier$condition`, mean_rt)) +
  geom_col(aes(fill = `data_no_outlier$condition`)) +
  geom_errorbar(aes(ymin = mean_rt - sd_rt, ymax = mean_rt + sd_rt),
                color = "#22292F", width = .1) +
                guides(fill=FALSE) + xlab("Condition") +
                ylab("Reaction time") +
                ggtitle("Paired t-test of RTs per condition") +
                geom_line(data = p_value, aes(x = x, y = y, group = 1)) +
                annotate("text", x = 1.5, y = 620, label = "***",
                         size = 6, color = "#22292F")
```

Figure 6

Results of paired t-test of reaction times per condition

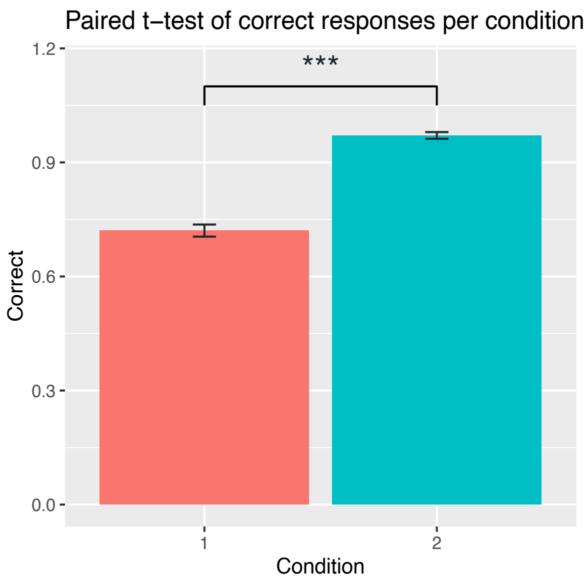


A paired samples t-test for the differences in correct scores for the two conditions was calculated, which was highly significant: $t(11) = -50.803$, $p < .001$, $CI_{95} = [-0.261, -0.239]$. The results are visualised in Figure 7. In condition 1 subjects had a significantly lower ($M = 0.72$, $SD = 0.02$) mean number of correct responses over all trials than in condition 2 ($M = 0.97$, $SD = 0.01$). This indicates that in the high time pressure condition 1 participants made significantly more mistakes than in condition 2 with the low time pressure, indicating that implicit time pressure can have an effect on accuracy in a decision-making task.

```r
#Paired t-test over correct responses by condition
data_no_outlier$correct <- as.numeric(data_no_outlier$correct)
agg = aggregate(data_no_outlier$correct ~data_no_outlier$ID *
data_no_outlier$condition, data=data_no_outlier, FUN=mean)
agg

t.test(agg$`data_no_outlier$correct` ~ agg$`data_no_outlier$condition`,
data = data_no_outlier, paired = TRUE, var.equal=FALSE)

#Bar graph for paired t-test over correct repsonses by condition
agg$`data_no_outlier$condition` <-
as.factor(agg$`data_no_outlier$condition`)

bar <- agg %>%
  group_by(`data_no_outlier$condition`) %>%
  summarise(
    mean_cor = mean(`data_no_outlier$correct`),
    sd_cor = sd(`data_no_outlier$correct`))

p_v <- tibble(
  x = c("1", "1", "2", "2"),
  y = c(1.05, 1.1, 1.1, 1.05))

bar %>%
  ggplot(aes(`data_no_outlier$condition`, mean_cor)) +
  geom_col(aes(fill = `data_no_outlier$condition`)) +
  geom_errorbar(aes(ymin = mean_cor - sd_cor, ymax = mean_cor + sd_cor),
                color = "#22292F", width = .1) +
  guides(fill=FALSE) + xlab("Condition") +
  ylab("Correct") +
  ggtitle("Paired t-test of correct responses per condition") +
  geom_line(data = p_v, aes(x = x, y = y, group = 1)) +
  annotate("text", x = 1.5, y = 1.15, label = "***",
           size = 6, color = "#22292F")
```

Figure 7

Results of paired t-test of correct responses per condition



After the initial exploration of the data and testing the differences between the reaction times and correct responses, the drift diffusion model (DDM) was finally fitted to the participants' data. The parameters were estimated as described in the methods. The parameter values for each participant and condition are presented in table 2.

Table 2

Parameter values for each participant and condition

ID	condition	A	v1	s	b	ter
1	1	241.0854	0.6253139	0.2039193	364.2577	206.8566
	2	389.4486	1.1248751	0.2545946	401.8589	340.3213
2	1	269.3846	0.5893848	0.1632118	404.2936	164.6975
	2	348.6782	1.0925319	0.3405161	394.4849	310.1442
3	1	288.2408	0.6050990	0.1796017	398.7590	193.0259
	2	250.6246	0.8700672	0.2044790	354.8009	245.5854
4	1	333.7036	0.6609065	0.2465478	334.8724	368.7883
	2	301.2819	0.9069071	0.1835765	374.4766	279.5285
5	1	308.8380	0.6021257	0.1180152	379.4677	253.7677
	2	299.2797	0.9257701	0.2116857	353.5236	297.8727
6	1	283.1530	0.6077793	0.1779399	364.3373	251.1784
	2	380.9013	1.1416932	0.3434664	419.1285	311.5307
7	1	288.3260	0.6089402	0.1929031	357.9577	263.4071
	2	282.2517	0.8871486	0.2261928	391.7838	231.3837
8	1	288.0015	0.6119702	0.1489467	377.2155	233.1570
	2	381.3185	1.0787475	0.3041672	401.5246	329.1396
9	1	317.6381	0.6124275	0.1368066	358.3741	311.4749
	2	331.7434	0.9540737	0.2440995	360.2392	317.9173
10	1	327.1102	0.6576067	0.1725205	327.8963	379.8948
	2	321.6473	0.9588885	0.2156120	350.0229	322.6956
11	1	262.6339	0.5987497	0.1775171	357.1645	241.6785
	2	365.0837	1.0556086	0.2083823	377.8172	338.4731
12	1	289.7073	0.6305255	0.2194671	349.4308	285.9292
	2	274.3984	0.8777439	0.2031009	325.8166	304.6202

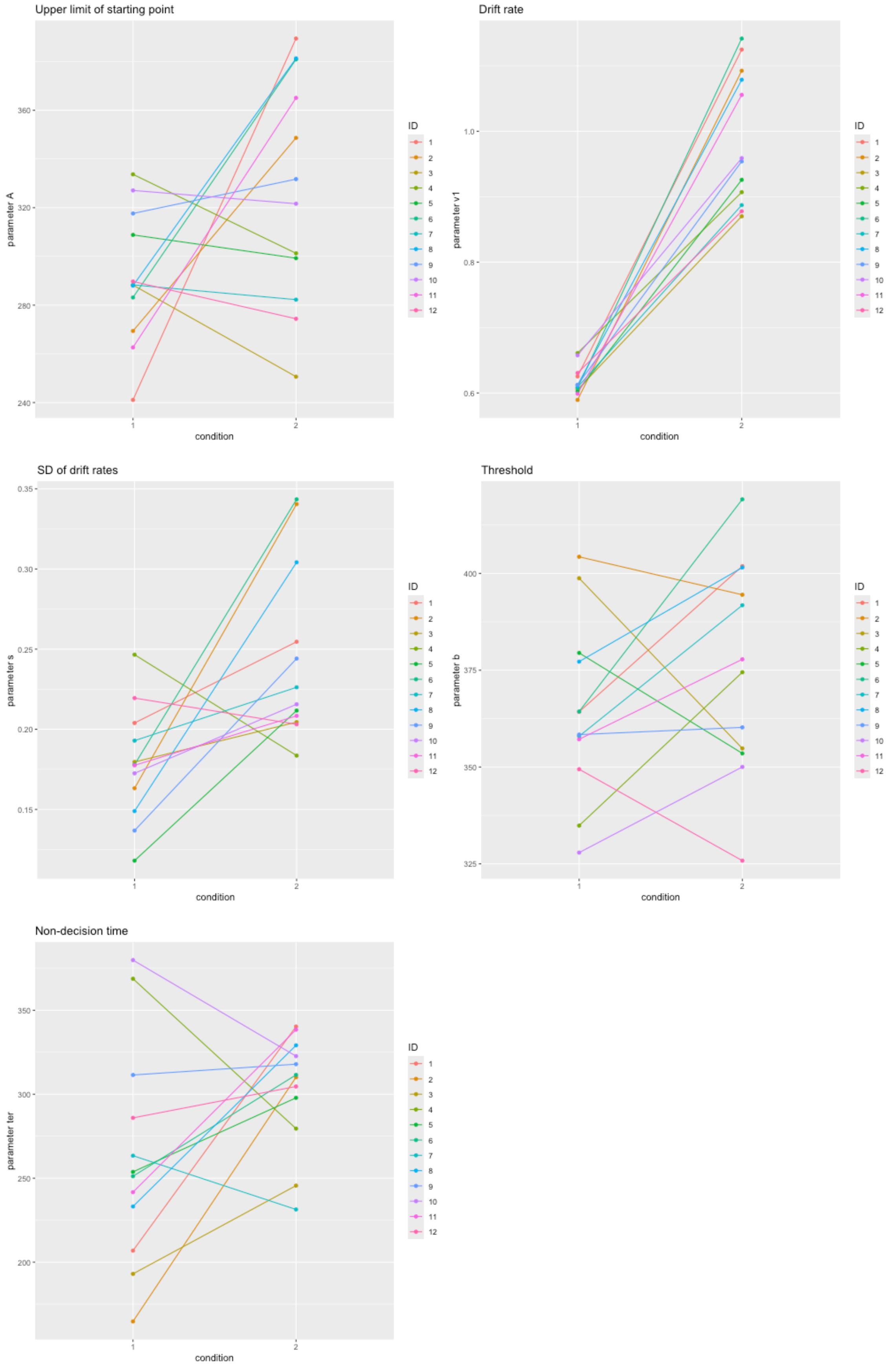
The parameter values are visualised in Figure 8, with the parameter values on the y-axis, the condition on the x-axis, and each line representing an individual participant.

For the parameter estimating the upper limit of the starting point value there seems to be no clear pattern between the conditions, as approximately half of the participants' values increase for condition 2, whereas they decrease for the other half of the participants. For the drift rate parameter there is a very clear pattern for all participants, as the values for this parameter are higher in condition 2 than in condition 1 for everybody. Most participants also have a higher value for the standard deviation of the drift rate in condition 2 than in condition 1, except for participants 4 and 11 who have a lower value in condition 2. Most participants' threshold parameter value is a bit higher in condition 2 than in condition 1, although this is not the case for participants 2, 3, 5, and 12. The non-decision time decreases in condition 2 for most participants, although this is not the case for participants 10, 4, and 7.

```
df$condition <- as.factor(df$condition)
df$ID <- as.factor(df$ID)

#Line graph for parameter "A" = upper limit of starting point
plot_A <-
  ggplot(data=df, aes(x=condition, y=A, group=ID, col = ID)) +
  geom_line() + ylab("parameter A") +
  ggtitle("Upper limit of starting point") + geom_point()
plot_A

#Line graph for parameter "v1" = drift rate
plot_v1 <-
  ggplot(data=df, aes(x=condition, y=v1, group=ID, col = ID)) +
  geom_line() + ylab("parameter v1") +
  ggtitle("Drift rate") + geom_point()
plot_v1

#Line graph for parameter "s" = SD of drift rates
plot_s <-
  ggplot(data=df, aes(x=condition, y=s, group=ID, col = ID)) +
    geom_line() + ylab("parameter s") +
    ggtitle("SD of drift rates") + geom_point()
plot_s

#Line graph for parameter "b" = threshold
plot_b <-
  ggplot(data=df, aes(x=condition, y=b, group=ID, col = ID)) +
  geom_line() + ylab("parameter b") +
  ggtitle("Threshold") + geom_point()
plot_b

#Line graph for parameter "ter" = non-decision time
plot_ter <-
  ggplot(data=df, aes(x=condition, y=ter, group=ID, col = ID)) +
  geom_line() + ylab("parameter ter") +
  ggtitle("Non-decision time") + geom_point()
plot_ter
```

Figure 8

Line graphs for the five estimated parameter values of the DDM for each participant



After this exploratory visual inspection of the differences in parameter values between participants, the differences between the two conditions were tested to see if implicit time pressure affects the parameters underlying decision making processes. Paired samples t-tests were performed to see if there were significant differences between the parameter values within-participants between-conditions.

```
#"A" upper limit of starting point
t.test(df$A ~ df$condition, data = df, paired = TRUE)

#"v1" drift rate
t.test(df$v1 ~ df$condition, data = df, paired = TRUE)

#"s" SD of drift rates
t.test(df$s ~ df$condition, data = df, paired = TRUE)

#"b" threshold
t.test(df$b ~ df$condition, data = df, paired = TRUE)

#"ter" non-decision time
t.test(df$ter ~ df$condition, data = df, paired = TRUE)
```

Firstly the a priori bias parameter was tested, estimated by the upper limit of the starting point (A). This parameter did not significantly differ between the two conditions: $t(11) = -1.94$, $p = .078$, $CI_{95} = [-76.280, 4.807]$. The parameter value for condition 1 was slightly lower ($M = 291$, $SD = 27.0$) than for condition 2 ($M = 327$, $SD = 46.5$).

The drift rate and its standard deviation were significant. The drift rate parameter (v1) was highly significant: $t(11) = -11.595$, $p < .001$, $CI_{95} = [-0.442, -0.301]$. For this parameter the values in condition 1 were lower ($M = 0.62$, $SD = 0.02$) than in condition 2 ($M = 0.99$, $SD = 0.10$). The standard deviations of the drift rate parameters (s) were also significant: $t(11) = -3.114$, $p = .010$, $CI_{95} = [-0.114, -0.020]$. Here the values in condition 1 were also lower ($M = 0.18$, $SD = 0.04$) than in condition 2 ($M = 0.25$, $SD = 0.06$).

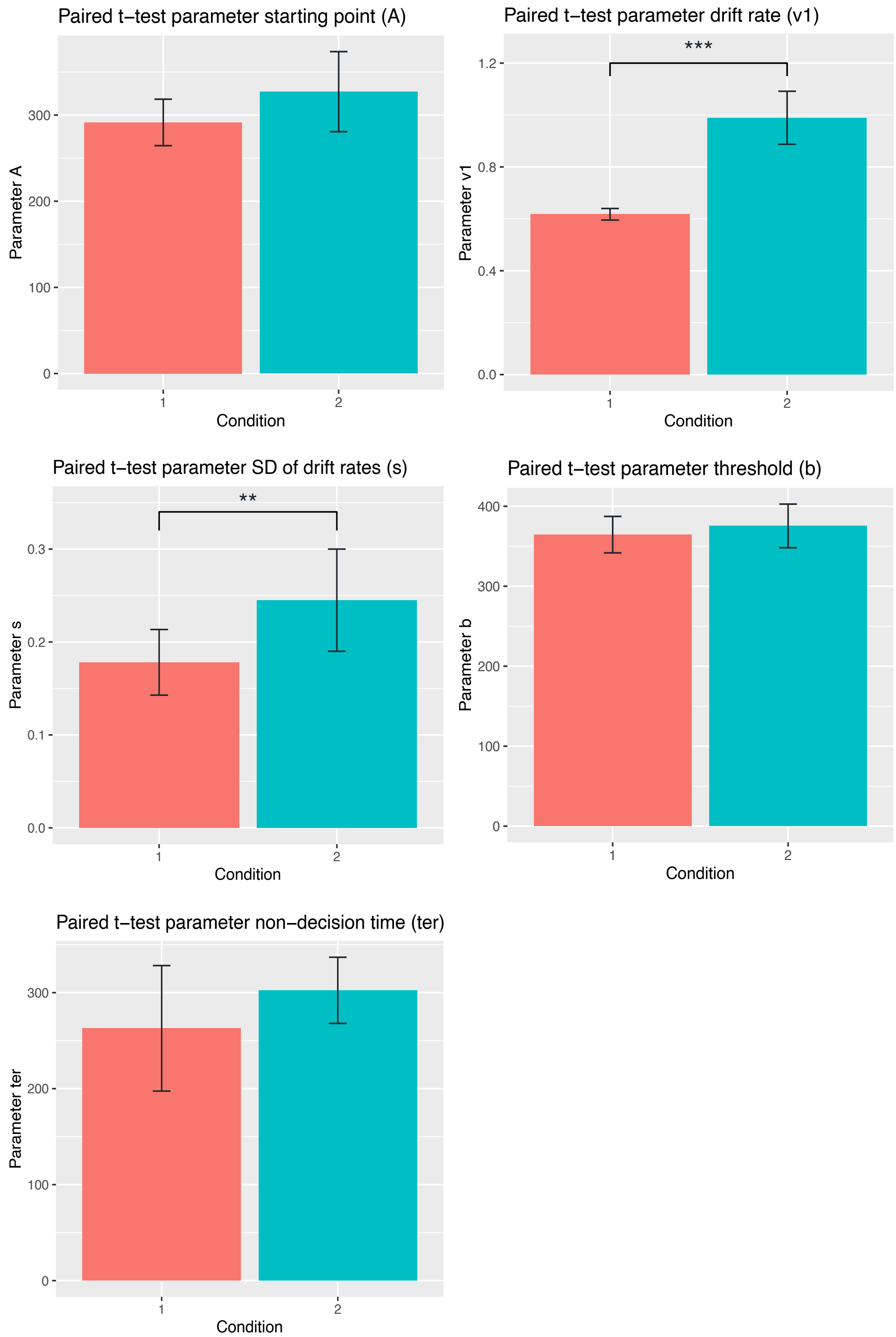
The parameter estimating response caution was not significant: $t(11) = -1.231$, $p = .244$, $CI_{95} = [-30.546, 8.637]$. The threshold values (b) in condition 1 were slightly lower ($M = 365$, $SD = 22.8$) than in condition 2 ($M = 375$, $SD = 27.3$).

Lastly, the parameter for the non-decision time (ter) was not significantly different between the two conditions: $t(11) = -1.862$, $p = .089$, $CI_{95} = [-86.430, 7.204]$. The values were lower in condition 1 ($M = 263$, $SD = 65.4$) than in condition 2 ($M = 302$, $SD = 34.5$).

The five parameter values and their differences between the two conditions are visualised in Figure 9, the code for these bar graphs can be found in Appendix B.

Figure 9

Bar charts of the five parameter estimates compared between conditions



Discussion

Implicit time pressure encourages speed in the speed-accuracy trade-off in decision-making processes, which can be estimated and modelled with parameters in a drift diffusion model (DDM). In this study a high and low time pressure condition were compared to see what their effects would be on reaction times, accuracy, and five parameter estimates. The model estimated parameter values for the upper limit of the starting point (A), the drift rate (v1) and its standard deviation (s), the decision threshold (b), and the non-decision time (ter). Particular focus for the hypotheses were on the a priori response biases reflected in the starting point, evidence accumulation reflected in the drift rate, and speed of decision making reflected in the thresholds.

It was predicted that in the high time pressure condition participants would have faster reaction times and more incorrect responses. For the DDM parameters increased starting points, increased drift rates, and decreased thresholds were expected in the high time pressure condition.

The results for the paired samples t-test comparing the reaction times of participants between the two conditions showed highly significant results ($p < .001$). Participants had significantly higher reaction times in the high time pressure condition (1), meaning that they responded slower. This indicates that implicit time pressure slows down decision making processes, which is contrary to what was hypothesised.

The results also showed highly significant ($p < .001$) differences in accuracy between the conditions. Participants had a significantly lower mean number of correct responses in the high time pressure condition (1), indicating that implicit time pressure leads to more errors, and therefore negatively affects accuracy. This is in line with the hypothesis.

In terms of the speed-accuracy trade-off, the results indicate that implicit time pressure during a decision-making task decreases both speed and accuracy. This is unexpected, since it is usually theorised that when one aspect of the speed-accuracy trade-off is prioritised, the other aspect is neglected.

For the DDM parameter estimates, significant results were found for the drift rate and its standard deviation, the other parameter values were not significantly different between the conditions.

The drift rate parameter was highly significant ($p < .001$), with lower scores in the high time pressure condition, which is contrary to the hypothesis. This result indicates that implicit time pressure leads to a slower accumulation of evidence. Although the literature has not yet reached consensus regarding the influence of time pressure on the drift rate parameter, these results do contradict some previous results that have been found (Kelly et al., 2021; Kloosterman et al., 2019). It was hypothesised that time pressure would lead to an altered filtering of sensory information, meaning that more information of lesser quality would be used to reach the decision threshold faster. However, as the results have indicated that this is not the case and that time pressure actually slows reaction times and evidence accumulation, it is possible that time pressure might actually interfere with the evidence accumulation process and introduce additional noise, meaning that the available information is more difficult to interpret or distinguish, and therefore slows the decision-making process down.

The parameter estimating the standard deviations of the drift rates was also significant ($p = .010$), with lower values in the high time pressure condition. Since this parameter does not have an easily interpretable cognitive mapping, it will not be further interpreted. *(In the assignment code it said that this parameter would not differ between conditions, but it does?)*

It was hypothesised that there would be an a priori response bias in the high time pressure condition, leading to increased starting point values. However, the results do not support this, as these parameter values do not significantly ($p = .078$) differ between the conditions. These results are however in line with the inconclusive findings within the wider literature (Harris & Hutcherson, 2021; Kloosterman et al., 2019).

Lastly, it was hypothesised that implicit time pressure would lead to faster decision making, reflected in decreased decisional thresholds. Considering that the reaction times were slower under time pressure, it makes sense that the differences between the conditions for the threshold parameter were not significant ($p = .244$). For this parameter there is once again a lot of debate within the literature due to contradictory findings (Dambacher & Hübner, 2015; Harris & Hutcherson, 2021). While these results do not support the theory that time pressure could accelerate the crossing of the decisional threshold by lowering it, the results are in line with the consequence of more erroneous decision making in this condition, reflecting a decreased response caution (Dambacher & Hübner, 2015).

As no hypotheses were made for the non-decision time and these parameter values did not significantly differ between the conditions, they will not be further discussed.

To summarise, the results from this experiment indicate that implicit time pressure slows down decision making, increases inaccuracy, and is influenced by a decreased drift rate parameter value. Although more research is necessary to determine the robustness of these findings, they do indicate an influential role of implicit time pressure on the underlying process of evidence accumulation in decision making.

The real-world implications of these results could warrant further research into potential buffering factors for the lowered accuracy resulting from implicit time pressure. As many everyday decisions are made under time pressure, investigating potential variables that buffer or even reverse this effect might have practical value. Future research could also consider potential interaction effects with implicit time pressure that might result in the negative performance, such as investigating the effects of explicit instructions to respond as accurately as possible, or testing multiple decision tasks differing in difficulty.

Computational models such as the DDM are useful for experiments such as these, in which limited data has been collected; only reaction times and response accuracy. The DDM parameters significantly improve the description of the findings and their potential underlying processes. In addition, these parameters estimating the quality of the evidence could be used in future research to look into the underlying causes of individual differences in performances on decision-making tasks (Ratcliff et al., 2016).

Computational modelling approaches can provide valuable additional evidence when investigating the processes underlying decision making, and should be carefully considered when accounting for the effects of contextual factors on decision making performances.

Conclusion

A decision-making task was used to investigate the effects of implicit time pressure on the speed-accuracy trade-off. A drift diffusion model (DDM) was computed to estimate the parameters underling decision-making processes. The results indicated that implicit time pressure negatively affects both aspects of speed and accuracy, since slower and less accurate responses were observed in the high time pressure condition. The only significant DDM parameters were for the drift rate and its standard deviation, indicating that time pressure slows down the accumulation of evidence during decision making. Contrary to the hypotheses, no significant differences were found for the starting point and threshold parameters, meaning that results remain inconclusive for the possible effects of time pressure on a priori response biases and response caution.

Generative AI

I have not made use of generative AI for this assignment, neither for the code nor the writing.

References

Dambacher, M., & Hübner, R. (2015). Time pressure affects the efficiency of perceptual processing in decisions under conflict. *Psychological Research*, *79*(1), 83–94. https://doi.org/10.1007/s00426-014-0542-z

Harris, A., & Hutcherson, C. A. (2021). Temporal dynamics of decision making: A synthesis of computational and neurophysiological approaches. *Wiley Interdisciplinary Reviews. Cognitive Science*, *13*(3), 1–20. https://doi.org/10.1002/wcs.1586

Kelly, S. P., Corbett, E. A., & O'Connell, R. G. (2021). Neurocomputational mechanisms of prior-informed perceptual decision-making in humans. *Nature Human Behaviour*, *5*(4), 467–481. https://doi.org/10.1038/s41562-020-00967-9

Kloosterman, N. A., De Gee, J. W., Werkle-Bergner, M., Lindenberger, U., Garrett, D. D., & Fahrenfort, J. J. (2019). Humans strategically shift decision bias by flexibly adjusting sensory evidence accumulation. *eLife*, *8*, 1–27. https://doi.org/10.7554/elife.37321

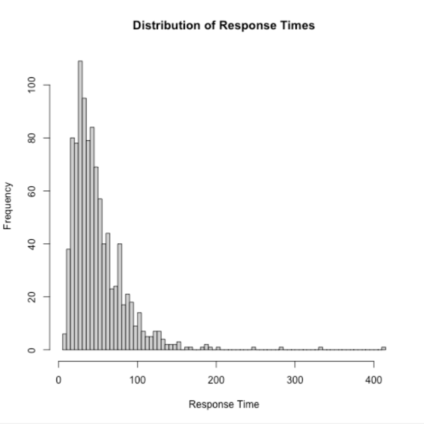
O'Connell, R. G., Shadlen, M. N., Wong-Lin, K., & Kelly, S. P. (2018). Bridging neural and computational viewpoints on perceptual Decision-Making. *Trends in Neurosciences*, *41*(11), 838–852. https://doi.org/10.1016/j.tins.2018.06.005

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion Decision Model: Current issues and history. *Trends in Cognitive Sciences*, *20*(4), 260–281. https://doi.org/10.1016/j.tics.2016.01.007

Appendix A

Attempt at simulating a drift diffusion model (DDM)

```
act = 0
threshold1 = 10
threshold2 = -10
threshold_reached = FALSE

# Define Racemodel function
Racemodel <- function(threshold1 = 10, threshold2 = -10, evidence1 = 0.2,
evidence2 = 0.1, noise = 1.0) {
  current_evidence1 <- 0
  current_evidence2 <- 0
  time <- 0

  while (current_evidence1 < threshold1 && current_evidence2 >
threshold2) {
    time <- time + 1
    current_evidence1 <- current_evidence1 + evidence1 + rnorm(1, mean =
0, sd = noise)
    current_evidence2 <- current_evidence2 + evidence2 + rnorm(1, mean =
0, sd = noise)}

  chosen_alternative <- ifelse(current_evidence1 < current_evidence2,
"Alternative1", "Alternative2")
  return(list(chosen_alternative = chosen_alternative, response_time =
time))}

# Number of simulations
num_simulations <- 1000

# Vector to store response times
response_times <- numeric(num_simulations)

# Run simulations
for (i in 1:num_simulations) {
  result <- Racemodel(threshold1 = 10, threshold2 = -10, evidence1 = 0.2,
evidence2 = 0.1, noise = 1.0)
  response_times[i] <- result$response_time}

# Plot histogram of response times
hist(response_times, main = "Distribution of Response Times", xlab =
"Response Time", ylab = "Frequency", breaks = 100)
```



Appendix B

Code for the bar graphs visualising the differences in parameter values between the two time pressure conditions.

```
#bar graph A (starting point)
bar_A <- df %>%
  group_by(condition) %>%
  summarise(
    mean_A = mean(A),
    sd_A = sd(A))

bar_A %>%
  ggplot(aes(condition, mean_A)) +
  geom_col(aes(fill = condition)) +
  geom_errorbar(aes(ymin = mean_A - sd_A, ymax = mean_A + sd_A),
                color = "#22292F", width = .1) +
  guides(fill=FALSE) + xlab("Condition") +
  ylab("Parameter A") +
  ggtitle("Paired t-test parameter starting point (A)")


#bar graph v1 (drift rate)
bar_v1 <- df %>%
  group_by(condition) %>%
  summarise(
    mean_v1 = mean(v1),
    sd_v1 = sd(v1))

p_v1 <- tibble(
  x = c("1", "1", "2", "2"),
  y = c(1.15, 1.2, 1.2, 1.15))

bar_v1 %>%
  ggplot(aes(condition, mean_v1)) +
  geom_col(aes(fill = condition)) +
  geom_errorbar(aes(ymin = mean_v1 - sd_v1, ymax = mean_v1 + sd_v1),
                color = "#22292F", width = .1) +
  guides(fill=FALSE) + xlab("Condition") +
  ylab("Parameter v1") +
  ggtitle("Paired t-test parameter drift rate (v1)") +
  geom_line(data = p_v1, aes(x = x, y = y, group = 1)) +
  annotate("text", x = 1.5, y = 1.25, label = "***",
           size = 6, color = "#22292F")


#bar graph s (SD of drift rate)
bar_s <- df %>%
  group_by(condition) %>%
  summarise(
    mean_s = mean(s),
    sd_s = sd(s))

p_s <- tibble(
  x = c("1", "1", "2", "2"),
  y = c(0.32, 0.34, 0.34, 0.32))

bar_s %>%
  ggplot(aes(condition, mean_s)) +
  geom_col(aes(fill = condition)) +
  geom_errorbar(aes(ymin = mean_s - sd_s, ymax = mean_s + sd_s),
```

```
                 color = "#22292F", width = .1) +
  guides(fill=FALSE) + xlab("Condition") +
  ylab("Parameter s") +
  ggtitle("Paired t-test parameter SD of drift rates (s)") +
  geom_line(data = p_s, aes(x = x, y = y, group = 1)) +
  annotate("text", x = 1.5, y = 0.35, label = "**",
            size = 6, color = "#22292F")


#bar graph b (decision threshold)
bar_b <- df %>%
  group_by(condition) %>%
  summarise(
    mean_b = mean(b),
    sd_b = sd(b))

bar_b %>%
  ggplot(aes(condition, mean_b)) +
  geom_col(aes(fill = condition)) +
  geom_errorbar(aes(ymin = mean_b - sd_b, ymax = mean_b + sd_b),
                 color = "#22292F", width = .1) +
  guides(fill=FALSE) + xlab("Condition") +
  ylab("Parameter b") +
  ggtitle("Paired t-test parameter threshold (b)")


#bar graph ter (non-decision time)
bar_ter <- df %>%
  group_by(condition) %>%
  summarise(
    mean_ter = mean(ter),
    sd_ter = sd(ter))

bar_ter %>%
  ggplot(aes(condition, mean_ter)) +
  geom_col(aes(fill = condition)) +
  geom_errorbar(aes(ymin = mean_ter - sd_ter, ymax = mean_ter + sd_ter),
                 color = "#22292F", width = .1) +
  guides(fill=FALSE) + xlab("Condition") +
  ylab("Parameter ter") +
  ggtitle("Paired t-test parameter non-decision time (ter)")
```