Master Thesis

The Effects of Sense of Agency on Motivation: An EEG Study

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Abstract

The sense of agency (SoA) describes the feeling of control over actions and their outcomes and is a crucial factor influencing individuals to pursue their goals. This study examines the influence of outcome controllability in the form of feedback reliability on motivation. Furthermore, we were interested in how a change in motivation influences the use of proactive control during task performance. Using an electroencephalogram, we observed the contingent negative variation to examine an increase or decrease in task preparation. A total of 39 people (18 female) between the ages of 18 to 35 (M = 25.59, SD = 3.8) participated and completed a colour perception task. Overall, the results indicate that higher outcome controllability increases motivation and task preparation, which ultimately leads to shorter response times. Against our expectations, response accuracy was not significantly affected by changes in SoA.

Contents

Introduction

Everyday life consists greatly of human decision-making, often coupled with specific goals in mind. However, we do not always act according to the goals we want to achieve. Imagine you are a student wanting to reach a higher grade in a particular subject. One thing you might consider is your chances of actually reaching a higher grade. If you see a realistic chance of reaching that grade, your motivation increases, and you put more effort into studying to reach your goal. If, however, you are certain that the teacher does not like you and will give you a low grade regardless of your effort, you will feel like you have no control over your academic outcome. In that case, your motivation to reach the goal decreases and you lower your effort in studying. This shows that sometimes individuals do not act by their goals, for example, when they feel they have no control over the outcome. This study aims to further investigate the relationship between perceived control and motivation.

The feeling of control over actions and their outcomes is called the sense of agency (SoA) (Haggard & Tsakiris, 2009), and is widely discussed in research (e.g., Karsh & Eitam, 2015; Van den Bussche et al., 2020; Sperduti et al., 2011). According to van den Bussche et al. (2020), the key to a feeling of agency is the connection between voluntary action and the resulting outcome. That can be as simple as turning the light switch, and seeing the light turned on. By making that connection to '*I caused this*', we can differentiate if an event was caused by our own or an external action (Sperduti et al., 2011). On the other hand, in the scenario above, the student does not perceive a connection between their performance and academic outcome but sees the teacher as the external factor 'controlling' the grade. Hence, to feel SoA, some kind of outcome control must be perceived (van den Bussche et al., 2020) by which individuals can determine their capabilities of impacting their environment (Jeannerod, 2003; Sperduti et al., 2011).

One of the most influential models regarding the sense of agency is the comparator model. According to the model, the perception of agency a person has is based on a comparison between the estimated and actual outcomes of their actions. When an action is initiated, the brain creates an efference copy of this action command and the action outcomes are estimated (Frith et al., 2000). For example, when an individual operates the light switch, an efferent copy of the action is made, and the predicted outcome is 'The light will turn on'. The sensory feedback acquired during action performance (reafference) is then compared to the predicted outcome. Based on a match or mismatch of the efferent copy and incoming sensory feedback, the brain determines if the outcome is caused by the action. If it matches, the individual feels a strong SoA, while a mismatch undermines SoA (Knoblich & Kirchner, 2004; Oishi et al., 2018; Sato & Yasuda, 2005). Hon et al. (2015) concluded that a manipulation of the relationship between the expected and actual outcomes in basic motor tasks is known to influence SoA.

Subsequently, if an individual determines their control to be high, they will perceive an overall higher motivation to act and reach their goals. In previous research, a connection between control over the environment and motivation has been revealed, where mere outcome controllability can be a motivator to initiate action (Karsh & Eitam, 2015; Ren et al., 2023). Ren et al. (2023) argued that the feeling of controllability can be perceived as a form of intrinsic reward that increases motivation. It is notable that outcome controllability in this context does not equal controllability over the *desired* outcome, but the feeling that it was *me* causing the outcome.

Motivation can be measured by both self-reports and performance behaviours. For one, a motivation score can be obtained by directly asking about perceived motivation in a situation (Touré-Tillery & Fishbach, 2014). However, other subjective measures, such as mind wandering and focus during task performance can be indicators of motivation. Mind wandering describes the switch of attention from the task at hand to something unrelated, for example, what to cook for dinner (Smallwood & Schooler, 2006). While mind wandering is a normal process that happens regularly and is even considered the default mode (Thompson et al., 2015), it has been shown that higher motivation can suppress mind wandering to an extent (He et al. 2023; Seli et al. 2015). He et al. (2023) have shown that focus is a mediating factor between motivation and mind wandering. That is because cognitive resources must be divided between mind wandering and task completion, and increased focus helps redirect the mind back to the task (He et al., 2023). Ultimately, increased mind wandering has been found to decrease task performance (Randall et al., 2014).

Furthermore, increased motivation becomes behaviourally visible in individuals' task performance, such as an increased likelihood of action initiation and response speed (Karsh & Eitam, 2015; Karsh et al., 2020; Penton et al., 2018). Karsh and Eitam (2015), for example, asked participants to press one of four keyboard keys right after a response cue was shown. There were three experimental conditions with different probabilities of an effect (response cue changing its colour) occurring after one of the keys was pressed. There was either a very high probability of an effect, a key-specific probability of an effect, or no effect. The results have shown that with higher control over their environment, participants responded faster, implying higher motivation. Karsh and Eitam (2015) further substantiated these findings with previous research that argues agency in itself can act as a motivator and reward (e.g., Behne et al., 2008; Leotti & Delgado, 2011).

Closely related to outcome controllability is cognitive control, as it influences how individuals perceive the impact of their actions on their environment. Cognitive control can be defined as the ability to control one's thoughts and behaviours according to internally set behavioural goals (Shenhav et al., 2013). Not so well understood is the relationship between cognitive control and motivation (Botvinick et al., 2001), however, cognitive control is more likely applied when the effort is worth the cost (Shenhav et al., 2013). Shenhav et al. (2013) have proposed the expected value of control (EVC) framework, describing how human decision-making can be understood. The framework states that the amount of cognitive control that is invested in a task is regulated by the expected reward and the effort of investing cognitive control. As discussed before, mere perceived control can act as a reward and could, therefore, increase the expected value of control (Ren et al., 2023). A high expected value of control has been found to increase an individual's motivation to reach their goals. As a result from higher motivation, different studies have found higher accuracy and speed in task completion (Mir et al., 2011), increased cognitive control (Locke & Braver, 2008), or improved memory performance (Wittmann et al., 2005).

Cognitive control is proposed to operate in two different modes that are described by the dual mechanisms of control (DMC) framework. The two mechanisms are proactive and reactive control (Braver, 2012). The former is characterized by its anticipatory nature with which relevant, goal-specific information is gathered in advance to cognitively demanding tasks. Therefore, proactive control is primarily used for reaching specific goals. Using proactive control helps to maintain the gathered information to effectively prepare for potentially challenging tasks and minimize potential errors during task completion (Moscarello & Hartley, 2017). However, while maintaining proactive control is well suited for preparing tasks, it also costs a lot of cognitive effort. Thus, proactive control mechanisms are more frequently applied when humans feel like they have some control over a situation and have higher certainty their effort is worth the cost (Moscarello & Hartley, 2017). Proactive control can be allocated in the brain to the lateral prefrontal cortex (PFC), the part of the brain where decision-making and planning are processed. Reactive control, on the other hand, is a response strategy that is triggered by task disruptions, such as errors and unexpected task interferences (Braver, 2012). Therefore, situations in which reactive control mechanisms are more likely applied are the ones offering little control (Moscarello & Hartley, 2017). Next to the lateral PFC, reactive control is reflected on a broader network of brain activity, such as the anterior cingulate cortex (ACC), an area of the brain associated with error detection (Botvinick et al., 2001).

The dual mechanisms system is an efficient way of using cognitive resources since both, proactive and reactive control complement each other and switch around depending on which fits the situation better (Braver, 2012; Burgess & Braver, 2010). It is assumed that even slight changes in similar tasks can alter the preferred use of either proactive or reactive control (Braver, 2012) which can be attributed to trade-offs between costs and benefits in cognitive resource management (Jimura et al., 2010). Research has indicated that motivators such as rewards facilitate the use of proactive control mechanisms (e.g., Small et al., 2005; Etzel et al., 2015; Locke & Braver, 2008). In their study, Locke and Braver (2008) investigated how motivational influences affect the preferred control mechanism. They compared the effects of punishment and reward, and concluded that when expecting a reward, participants more often used a proactive control mode, while facing punishment, the mechanism shifted to reactive control. The shifting between control mechanisms is observable by using an electroencephalogram (EEG), which will be used in the present study.

To properly assess which control mechanism is used, the contingent negative variation (CNV) will be looked at. The CVN is a component of an event-related potential (ERP) and can be observed in the brain with an electroencephalogram (EEG). The CNV is a negative shift in electrical activity that occurs in the frontal-central regions of the brain. The shift is evoked by a cue that indicates the appearance of an upcoming stimulus which requires a response (Kononowicz & Penney, 2016). Walter et al. (1964) first related CNV with expectancy and task anticipation and investigated how individuals prepare for their upcoming tasks. Since the initial introduction of CNV, it has been utilised as a neural marker for studying numerous aspects of, e.g., motor preparation and cognitive expectancy (Mento, 2013), motivation (Schevernels et al., 2014), cognitive control (Chaillou et al., 2017; Chaillou et al., 2018), and attentional processes (Heinrich et al., 2004).

The Present Study

In this study, we anticipated that high outcome controllability increases motivation. We hypothesized that this increase in motivation leads to decreased mind wandering and increased focus during task completion. Furthermore, we expected that the increase in motivation would become behaviourally visible in shorter response times (RT) and higher response accuracy. Lastly, we expected to see that increased outcome controllability resulted in an increase in proactive control as compared to low outcome control.

This study was a 2x2 within-subjects design, where the independent variables were reliability (reliable vs. unreliable) and difficulty (easy vs. difficult). The dependent variable was motivation, which was measured with participants' self-reports of motivation, mind wandering and focus, and recorded RTs and response accuracy. The task was a colour distinction task in which the participants were shown a square with blue and orange pixels and had to decide which of the colours was depicted more dominantly. After each trial, participants received either reliable or unreliable performance feedback in the form of happy or unhappy smiley faces. Importantly, participants were told before each block whether there would be reliable or unreliable feedback, wherefore they knew whether their answers impacted the feedback or not.

As was shown by various studies, a simple manipulation between the expected and actual outcome is enough to influence the sense of agency (Hon et al., 2015; Knoblich & Kirchner, 2004; Oishi et al., 2018). Therefore, when the expected outcome and the actual outcome did not match and participants had low outcome control, SoA is predicted to be low. According to the expected value of control framework (Shenhav et al., 2013), high expected SoA can suffice to increase an individual's effort to reach a goal. Therefore, RT and response accuracy were expected to increase when reliable feedback was provided. Furthermore, it has been found that higher motivation increases the focus on task and ultimately decreases mind wandering during task performance (He et al., 2023), which is why focus was expected to increase and mind wandering is expected to decrease when reliable feedback is given. Additionally, the control mechanism that is used is greatly dependent on expectancy and outcome controllability (Moscarello & Hartley, 2017). Therefore, we predicted that in the reliable feedback conditions, participants use more proactive control which can be observed by an increased CNV amplitude. The increased CNV amplitude shows an increased task preparation, which aligns with the increased use of proactive control. Preparational processes can be best observed in the PFC, which is why we looked at the Fz and FCz electrodes that are located to measure activity in the frontal-central regions of the brain.

Methods

Participants

A total of 39 individuals (18 female) between the ages of 18 to 35 (M = 25.59, SD = 3.8) participated in the study. Further requirements for participation were right-handedness, no diagnosed neurological or psychiatric disorders, normal or corrected to normal vision, normal colour vision, age between 18 and 35, and written consent. The study was approved by the Ethical Committee of the Leibniz Research Centre for Working Environment and Human Factors and was conducted in accordance with the Declaration of Helsinki. All participants received either credit points for participation hours or a monetary payout of 12€ per hour.

Apparatus

The EEG was recorded using electrode caps with 64 passive Ag/AGCl electrodes (Easycap GmbH, Herrsching, Germany) and a NeurOne Tesla AC-amplifier (Bittium Biosignals Ltd, Kuopio, Finland). The AFz position was used for the ground electrode, and the FCz position was used as the reference electrode. A 250 Hz low-pass filter was applied, and impedances were kept below 10kΩ.

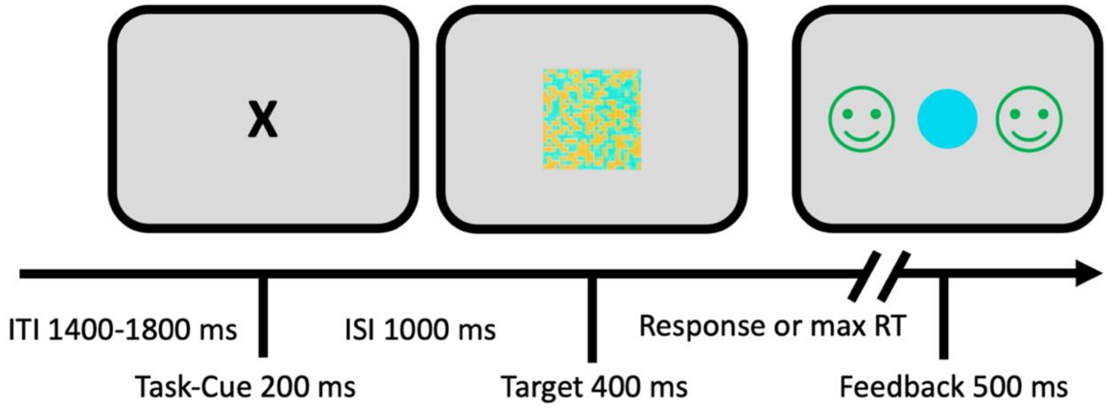
For the experiment, the participants sat alone in an experimental room that was electrically shielded to provide an optimal setting for EEG experiments. In the experimental room, there was a microphone and speakers connected to the outside room to communicate with the participant if necessary. For observation, a camera was placed in the room. The participants sat on a chair with a response key on either side, easily reachable with the participants' index fingers. The chair was placed 1.55 meters in front of a 22-inch monitor with a refresh rate of 100 Hz.

Task

The study examined how feedback reliability influences participants' motivation to perform tasks. During the experiment, participants were first shown a task cue indicating the difficulty of the following trial. The task cue was either an X, indicating a difficult trial, or an O, indicating an easy trial. Afterwards, the target stimulus was shown. The target stimulus was a square consisting of 23 by 23 pixels (light cyan [RGB: #27EDD0] and light orange [RGB: # F9C826]) of which the overall side length was ~ 2° viewing angle. The target stimulus was shown until a response was given or until the response window of a maximum 1000 ms had passed. Lastly, the performance feedback was given in the form of smiley icons with either a happy or unhappy face that were placed around a circle (1.7° viewing angle). In reliable feedback blocks, two happy smiley faces were shown with the correctly chosen colour in between, or unhappy smiley faces with the incorrectly chosen colour. In unreliable feedback blocks, 30% of the response feedback was given independently from the response, i.e., the smiley faces and the colour were given randomly. Figure 1 describes the timely sequence of the task.

Figure 1

Schematic overview of timely sequences per trial



Note. *"ITI" refers to inter-trial interval, "ISI" refers to inter-stimulus interval, and "RT" refers to response time. After an ITI of 1400-1800 ms, the task cue was shown for 200 ms; the task cue was either an O, indicating an easy trial, or an X, indicating a difficult trial. Following the ISI of 1000 ms, the target stimulus was presented until a response was given or until the maximum response time of 1000 ms had passed. Afterwards, performance feedback in the form of smiley icons was shown for 500 ms.*

The experiment consisted of one training block with 20 trials and 6 experimental blocks with 80 trials each. In all blocks, easy and difficult trials were presented randomly but distributed evenly. In easy trials, the proportion of the non-dominant colour was drawn from a uniform distribution ranging from 0.25 to 0.32 while for difficult trials the range was between 0.42 to 0.49. The dominant/non-dominant colours were chosen randomly per trial. Participants had a response key (one light cyan and one light orange) to each of their sides that were pushed with their index fingers. The side to which the coloured response keys were placed, was switched across participants.

Before each experimental block, the participants were informed via text on the monitor whether the following experimental block included reliable or unreliable feedback. Each experiment started with a reliable practice block, followed by a reliable experimental block and an unreliable feedback block. After the second block, the order of reliable/unreliable blocks was counterbalanced across participants; the order of reliable (R) and unreliable (U) was either RURURU or RUURUR. For comparison of the experimental blocks, points could be earned. At the end of each block, participants were shown the total number of points they scored.

Design and Procedure

The experiment was a 2 (reliability: reliable vs. unreliable) x 2 (difficulty: easy vs. difficult) within-subjects design and took place in the Leibniz Research Centre for Working Environment and Human Factors in the Department of Ergonomics. At the beginning of the experiment, participants were introduced, and debriefed about their compensation, and the task was explained. Then, the Ishihara test and the Edinburgh Handedness Inventory were performed, informed consent was signed, and demographics were asked. Afterwards, the EEG cap was applied, and participants were led into the experimental room. Participants were instructed to perform the task as quickly and accurately as possible. The experiment took approximately 37 minutes to complete. At the end of the experiment, participants were asked about their subjective evaluation of motivation, focus, and mind wandering they felt during the experiment. Afterwards, the EEG cap was removed, and participants were led to a bathroom where they could clean their hair and scalp from the gel that was used for the EEG cap. Lastly, participants received a certificate for their obtained credits or were asked about their band details for the monetary reward.

Data Acquisition

Subjective data were obtained after the experiment in the form of self-reports for motivation, focus, and mind wandering. The questions were: 1. How motivated were you during reliable/unreliable blocks? 2. How focused were you during reliable/unreliable blocks? 3. How much did your thoughts wander during reliable/unreliable blocks? Each question was asked for both reliable and unreliable experimental blocks. Participants answered the questions on a 10 cm Likert scale that represented scores from 1-100. The answers were averaged to get the mean score per participant per condition.

Moreover, the behavioural data obtained from this experiment were RT and response accuracy. RT was recorded by the programme and averaged to have a mean RT per participant per condition (reliable-easy, reliable-difficult, unreliable-easy, unreliable-difficult). The response accuracy was calculated from the points that were earned during the experiment. The points were calculated as 1000 ms minus the response time in ms, divided by 80 (to match the average point per trial).

Analyses and Preprocessing

EEG Recording and Preprocessing

The raw EEG data was pre-processed and analysed in MATLAB version R2022B (The Math Works Inc. Natick, Massachusetts), following the custom scripts of the EEGLAB toolbox (Delorme & Makeig, 2004). The data were bandpass filtered at 1 to 30 Hz and based on kurtosis criteria, bad channels were identified and rejected. On average, $M = 3.8$ ($SD = 2.28$) channels per participant were rejected. Afterwards, the remaining data were re-referenced to the average reference and resampled at 250 Hz. The data were then segmented into epochs from -200 to 0 ms intervals relative to the task-cue onset. On average, $M = 126.23$ ($SD = 35.22$) epochs were then rejected after the automatic detection of epochs containing artefacts. Subsequently, an Independent Component Analysis (ICA) was performed where $M = 1.95$ ($SD = 1.26$) channels were further excluded. For ERP calculation, a baseline was set from -200 to 0 ms relative to task-cue onset. To do so, only correctly answered trials were considered for the EEG data, which were then averaged across the experimental condition combinations (reliability x difficulty). The CNV was averaged per participant per condition, and the time window of 600 to 1100 ms relative to task-cue onset was chosen.

Statistical Analysis

The statistical analysis was conducted in RStudio version 4.3.2 (Appendix A). First, the data were prepared, described, and visualized for further analysis. The subjective rating scores (motivation, focus, and mind wandering) were compared for reliable and unreliable blocks. To do so, Wilcoxon signed-rank tests were conducted. For the dependent behavioural variables, response time and response accuracy, a within-subjects repeated measures analysis of variance (ANOVA) was conducted. Lastly, for the EEG data, the dependent variable was the CNV amplitude for which again a within-subjects repeated measures ANOVA was chosen to compare the CNV amplitude for each condition. For all conditions (easy vs. difficult, reliable vs. unreliable) an $\alpha \leq 0.05$ limit was kept.

Results

Subjective Ratings

The subjective ratings gathered from participants were motivation, focus, and mind wandering. It was expected that motivation was higher when participants received reliable feedback than unreliable feedback. Additionally, focus was expected to be higher when reliable feedback was given, and mind wandering was hypothesized to be lower during reliable feedback blocks. Figure 4 visualizes the average scores for motivation, focus, and mind wandering for reliable and unreliable feedback conditions.

Motivation

The Wilcoxon signed-rank test was conducted to determine whether there is an effect of reliability on motivation. The results suggested significantly higher motivation when reliable feedback was given as compared to unreliable feedback, $V = 719.5$, $p = <.001$.

Mind Wandering

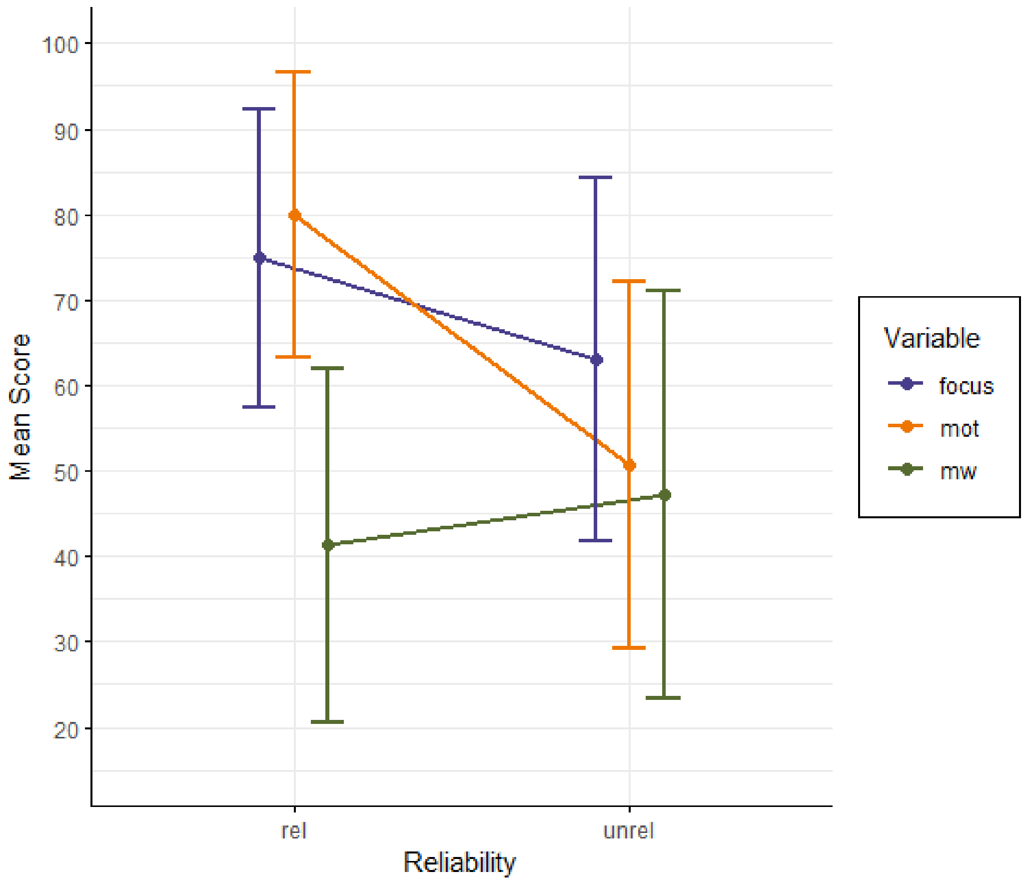
The Wilcoxon signed-rank test was conducted to determine whether there is an effect of reliability on mind wandering. The results suggested a less than significant difference in mind wandering between reliable and unreliable feedback, $V = 275$, $p = 0.11$.

Focus

Lastly, the Wilcoxon signed-rank test was conducted to determine whether there is an effect of reliability on focus. The results suggested a significantly higher focus when reliable feedback was given as compared to unreliable feedback, $V = 579$, $p = <.001$.

Figure 4

Mean Scores of Focus, Motivation, and Mind Wandering per Reliability Condition



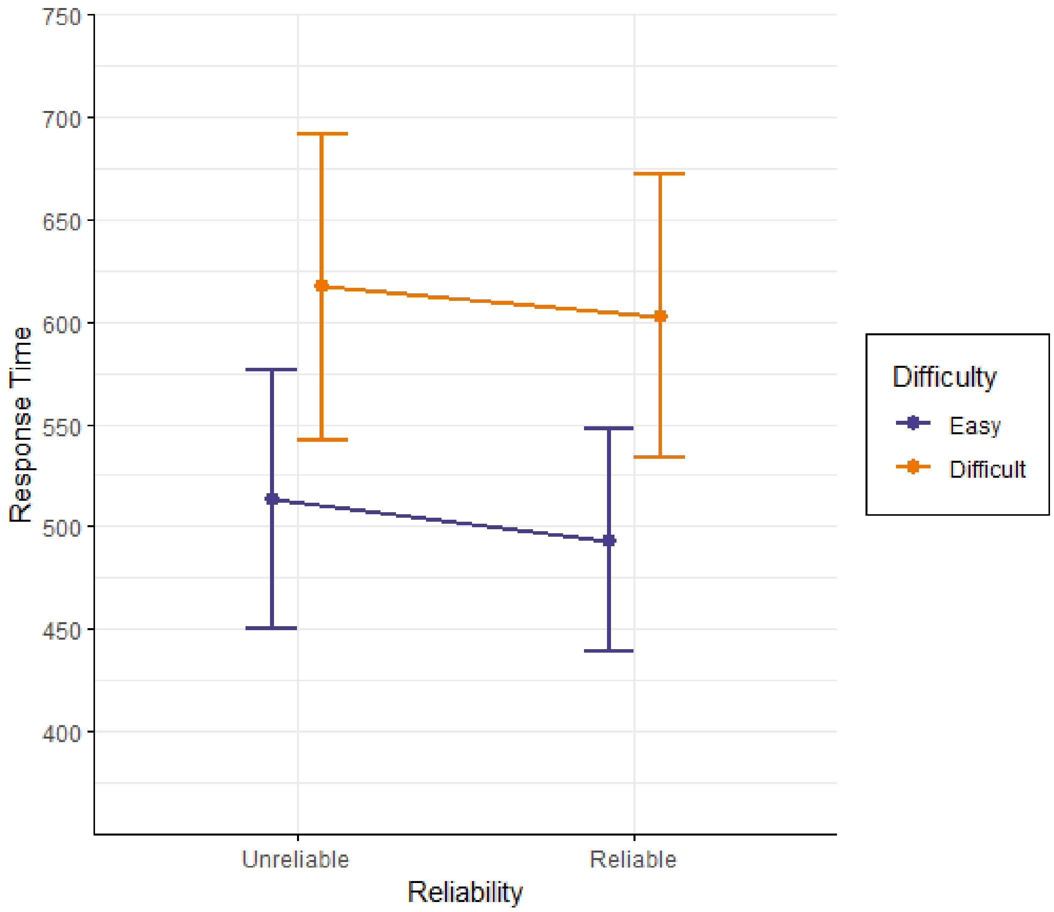
Behavioural Data

Response Time

To test the hypothesis that response time decreases with unreliable performance feedback, a 2x2 within-subjects repeated measures ANOVA was performed. The results showed that RTs were significantly shorter when reliable performance feedback was given $F(1, 37) = 34.61$ $p < .001$, $\eta^2 = 0.03$. Furthermore, during easy trials, RTs were shorter as compared to difficulty trials $F(1, 37) = 330.60$, $p < .001$, $\eta^2 = 0.41$. Nevertheless, no statistically significant interaction between reliability and difficulty was observed, $F(1, 37) = 0.25$, $p = .619$, $\eta^2 = 0.00$, indicating no combined effect of Reliability and Difficulty. The mean scores of RT across the conditions can be seen in Figure 2.

Figure 2

Mean Response Time in Milliseconds Across Experimental Conditions

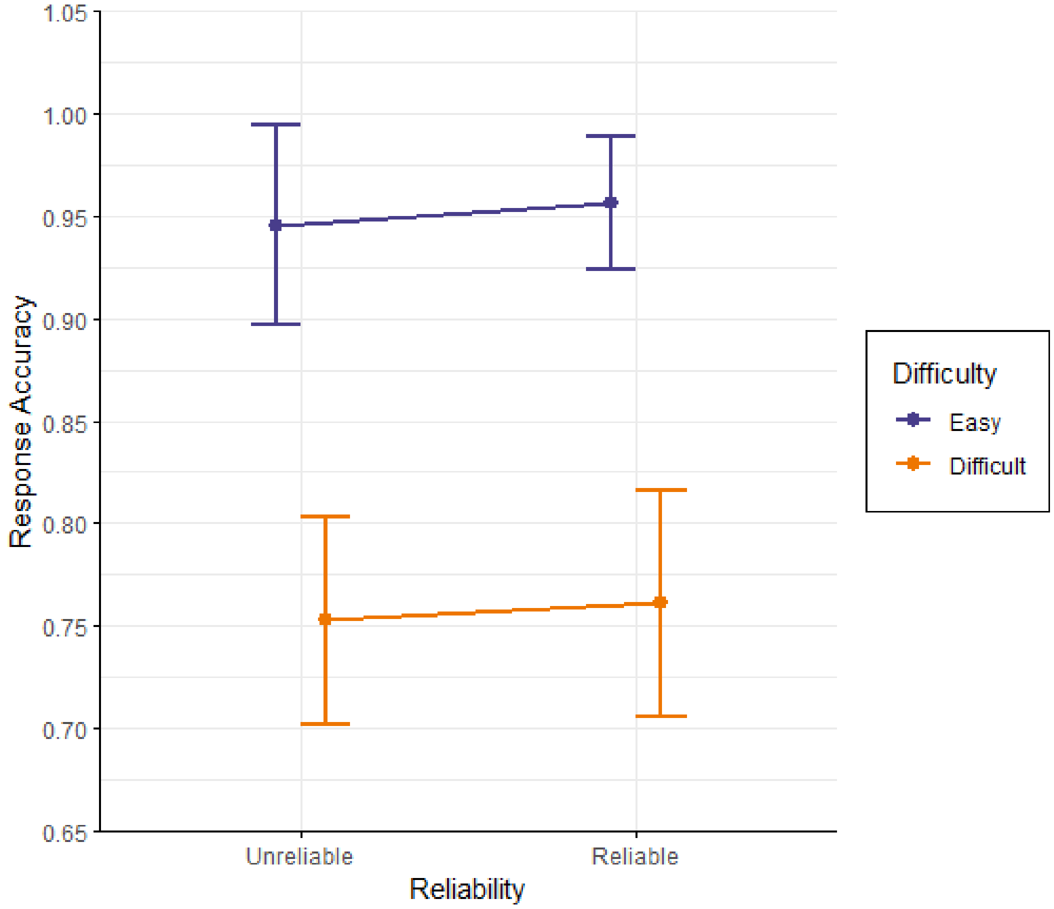


Response Accuracy

For testing the hypothesis that reliable feedback results in increased response accuracy, a 2x2 within-subjects repeated measures ANOVA was performed. The results showed a marginally higher response accuracy for reliable feedback blocks, however, not statistically significant, $F(1, 37) = 3.79$, $p = .059$, $\eta^2 = 0.01$. Response accuracy was significantly higher for easy as compared to difficult trials $F(1, 37) = 913.79$, $p < .001$, $\eta^2 = 0.77$. Further, no statistically significant interaction between reliability and difficulty was found, $F(1, 37) = 0.36$, $p = .554$, $\eta^2 = 0.001$, indicating no combined effect of Reliability and Difficulty. Figure 3 shows the mean response accuracy across the experimental conditions.

Figure 3

Mean Response Accuracy Across Experimental Conditions



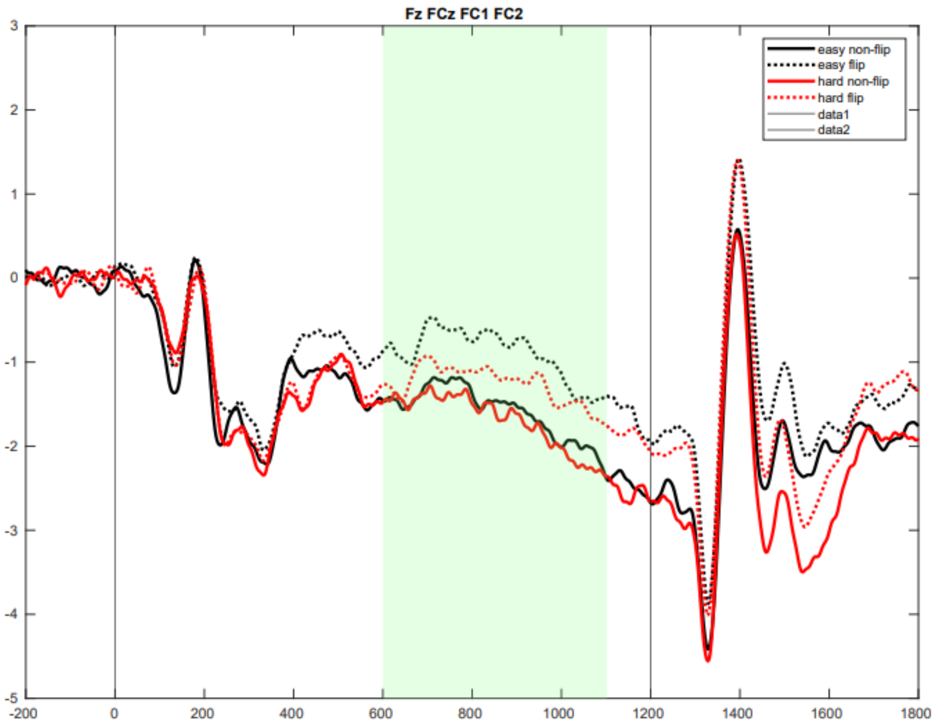
Contingent Negative Variation

Lastly, it was hypothesized that when reliable feedback is given, more proactive control is used, which can be seen in an increased CNV amplitude. Figure 5 shows the time span the CNV can be observed in the ERP between 600 and 1100 ms. On average, there was a higher negativity on easy reliable trials as compared to easy unreliable trials and higher negativity for difficult reliable trials than difficult unreliable trials. For comparing the amplitudes, a 2x2 within-subjects repeated measures ANOVA was conducted. The results showed a higher amplitude when reliable feedback was given, $F(1, 37) = 40.63$, $p < .001$, $\eta^2 = 0.04$. The amplitude was marginally higher for difficult trials as compared to easy trials, $F(1, 37) = 3.83$, $p = .058$, $\eta^2 = 0.007$, suggesting a limited impact of Difficulty on CNV negativity. Furthermore, no interaction between reliability and difficulty was found, $F(1, 37)$

= 1.60, p =.214, η^2 = 0.002, indicating no combined effects of Reliability and Difficulty on the CNV amplitude. Figure 6 portrays the mean CNV amplitudes across the reliability and difficulty conditions. In Figure 7, the topographies of each condition can be seen which show the brain activity during this time period.

Figure 5

Frontal ERP of the frontal electrode cluster including Fz, FCz, FC1, and FC2



Note. *Shown are the ERPs of frontal electrodes for each condition combination. The x-axis shows the time in ms, and the y-axis shows the voltage in µV. At 0 ms, the task cue was shown for 200 ms. In the green window between 600 ms and 1100 ms is the CNV that shows preparational processes right before the target stimulus is shown at 1200 ms. The 'non-flip' conditions are reliable feedback trials, whereas 'flip' conditions present unreliable feedback conditions.*

Figure 6

Mean Amplitude of CNV per Reliability Condition

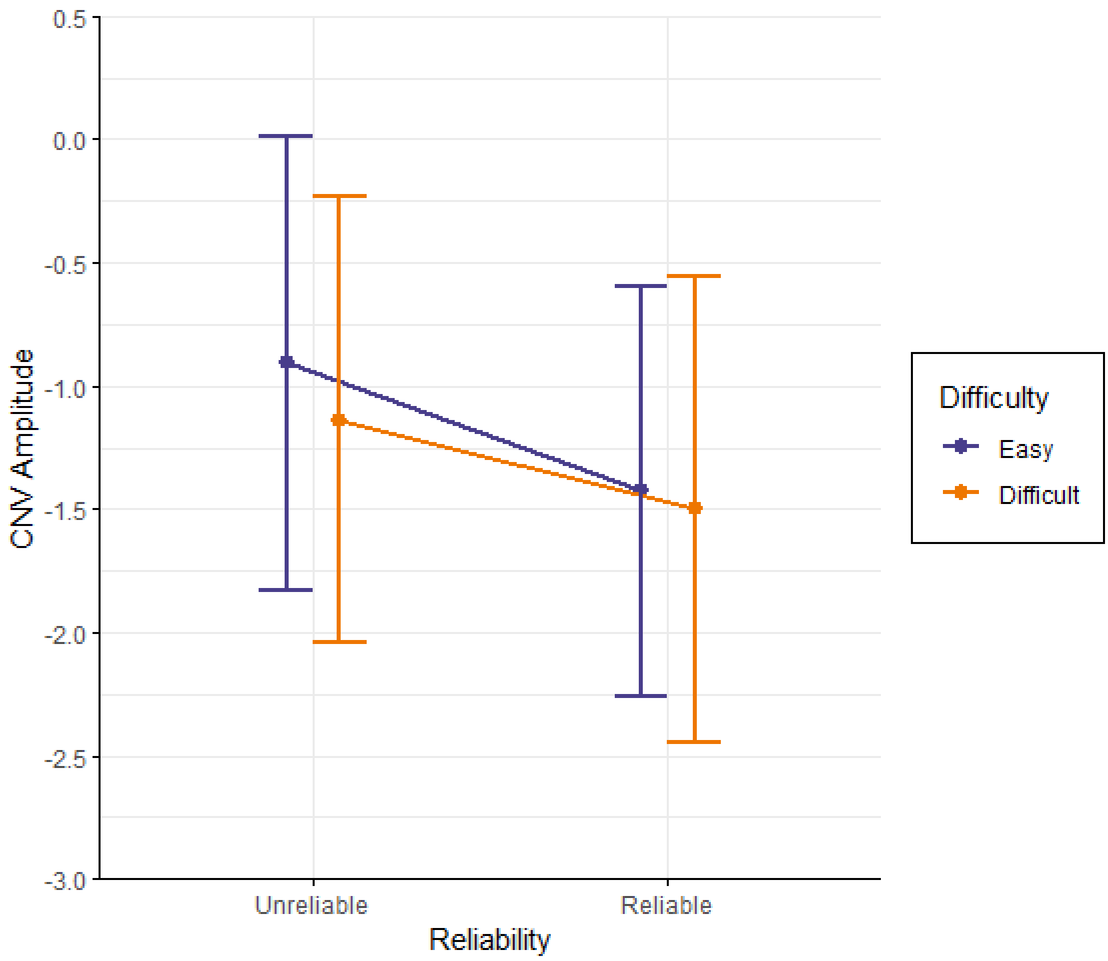
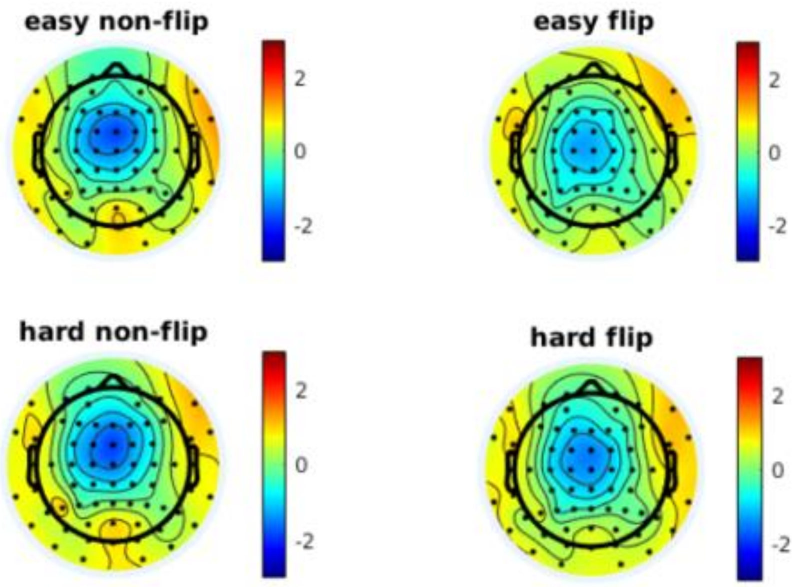
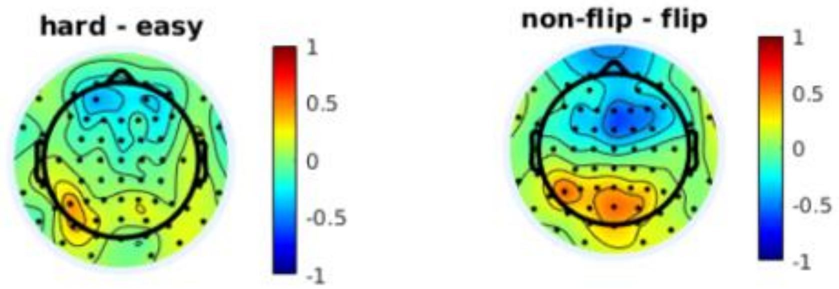


Figure 7

CNV Topographies





Note. The topographies show the brain activity of the CNV per condition during the period between 600 ms and 1100 ms. Non-flip describes the reliable condition and flip describes the unreliable condition.

Discussion

This paper aimed to further investigate the effects of outcome controllability on motivation. Specifically, we examined how different levels of control influence the motivation to perform well on tasks and how that influences the cognitive control mode a person uses. To do so, we let participants perform a colour-distinction task for which they received both reliable and unreliable performance feedback. Importantly, participants were told before each experimental block, whether they received reliable or unreliable performance feedback. Motivation was determined by participants' self-reports and by their task performance. Additionally, we recorded participants' brain activity and examined if a change in motivation could be observed in the use of increased proactive control as described by the dual mechanisms of control (DMC) framework (Braver, 2012). Therefore, we looked at the CNV to see if the amplitude changed, indicating higher or lesser task preparation. With our results, we could confirm our hypothesis that motivation was higher with high outcome controllability. Nonetheless, not all hypotheses could be accepted.

To begin with, the subjective data included motivation, mind wandering and focus. Aligning with our expectations, motivation and focus were self-reportedly higher when reliable response feedback was given. That suggests that higher outcome controllability increases motivation and the focus an individual has, as indicated by previous research (e.g., He et al., 2023; Karsh & Eitam, 2015; Ren et al., 2023). Against our expectations, the manipulation of feedback reliability did not significantly affect self-reported measures of mind wandering. That contradicts the predicted relationship between mind wandering and focus that was found by He et al. (2023). Mind wandering is said to be a default mode that is employed but can be suppressed by increased motivation (Thompson et al., 2015). One reason why mind wandering was not significantly affected in our study might be that the experiment was not long enough. The experiment took approximately 37 minutes to complete, and participants might not have reached the level where mind wandering gets harder to suppress, and their intention of participating in the experiment sufficed to keep their minds on the task.

Moreover, response time and response accuracy were both affected by the reliability and difficulty conditions. As expected, RTs were shorter for reliable feedback across both difficulty conditions. These findings were in line with the literature about the expected value of control (EVC) framework, according to which individuals make cost-benefit calculations for optimal effort investment (Shenhav et al., 2013). While higher SoA acted as an internal reward (Ren et al., 2023), participants invested more cognitive effort and completed the task faster (Shenhav et al., 2013). Against our initial expectation, response accuracy only showed a tendency for higher accuracy when reliable feedback was given. One explanation could be that the task was not complex enough for reliability to have a significant effect on response accuracy. Especially during easy trials, response accuracy was very high and near perfect. These near-perfect scores indicate a lack of complexity which can be a problem, as it does not leave much room for variability in response accuracy. Task complexity was found to be a great influence on the response time accuracy relation (Becker et al., 2016). At the within-participant level, there is often a speed-accuracy trade-off observed, where the participant either answers fast at the cost of inaccuracy or accurately at the cost of response speed. However, for simple tasks, there is a positive correlation, i.e., response time and accuracy are high (Becker et al., 2016). This might explain why response time changes while accuracy stays relatively stable across the reliability conditions. For future research, higher task complexity might result in more significant findings regarding response accuracy. For future research, higher task complexity might result in more significant findings regarding response accuracy.

Lastly, we were interested in how outcome controllability influenced the overall use of proactive control. Using the EEG allowed us to observe changes in the CNV amplitude, which is associated with task preparation and proactive control. In previous research, higher CNV amplitudes have been recorded when more control over the outcome was perceived (Mento, 2013; Walter et al., 1964). Additionally, it has been found that higher CNV amplitudes correlate with shorter response times (van den Berg et al. 2014), which was also observed in this experiment. For both difficulty conditions, higher CNVs were recorded when the participants received reliable feedback as compared to unreliable feedback. That indicates that participants prepared better when they felt more control over their action outcomes and prepared less well when the action outcome was random. We can conclude that in this study our manipulation of Reliability was successful and that the perceived control of action outcomes does have an influence on the control strategies used for task preparation.

Controllability over action outcomes serves as a motivator and was expected to be more rewarding as compared to random action outcomes. While we could confirm the influence of Reliability on the use of proactive control, the difficulty seemed to only have a limited impact. Our results showed a tendency of a higher CNV during difficulty versus easy trials, however, not statistically significant. That is somewhat surprising, as it does not align with previous literature. Schevernels et al. (2014) have shown that more demanding tasks are associated with higher CNV amplitudes as compared to less demanding tasks. Yet again, an explanation could be that the task in general was not complex enough to invoke major differences in brain activity regarding task difficulty. As researched by Schevernels et al. (2014), more demanding tasks induce higher CNV amplitudes, however, if there is no significant difference in cognitive demand while completing easy and difficult tasks, there ultimately will be no major differences in the CNV. Further, no interaction effect between reliability and difficulty regarding the CNV was found, indicating no dependency between both factors in this study context.

Conclusion

Our results confirmed that high outcome controllability influences motivation. Participants reported on overall higher motivation and increased focus when reliable feedback was given and their SoA was assumed to be high. That aligns with shorter response times when reliable feedback is given as RTs can be an indicator of motivation. Further, the EEG data revealed that during reliable feedback trials, participants were better able to prepare the tasks as shown by an increased CNV amplitude. That indicates that participants used more proactive control when the perceived controllability was higher. Furthermore, task difficulty impacted participants' response times, but not response accuracy. The non-significant impact of difficulty across the reliability conditions might suggest a lack of complexity in the task. Overall, we can conclude that higher outcome controllability increases motivation and results in better task preparation, as can be seen in the higher use of proactive control. This study has provided some insights into influences of motivation and task preparation. For example, in educational settings, these findings could help create an environment that increases a student's motivation to set and reach their goals.

Limitations and Future Directions

Lastly, this study has left us with some options for how to further investigate this research domain and get a broader understanding of the topic. As mentioned before, this experiment has some limitations. For one, task complexity seemed to be an issue which was visible when looking at the response accuracy scores. The scores were very homogeneous and near perfect for the easy trials. That can cause problems in concluding the effect of difficulty on participants' response behaviours. Therefore, if a similar study is conducted in the future, an increase in task complexity might give further insight. Furthermore, the measurement of subjective data could have been done differently and potentially more accurately. Generally, subjective measures can be very informative, however, they can be skewed due to biases and incorrect memory (Jahedi & Méndez, 2014). To reduce errors and biases, future research might ask subjective questions directly after each experimental block instead of at the end of the experiment, when participants have to recall the memories of their feelings. For future research, it could also be interesting to see if similar results can be found when participants do not know when reliable or unreliable feedback is given. Going further, it might also be interesting to see if there are differences in the CNV and motivation if participants did not know about the reliability conditions.

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Appendix

Appendix A

R Script of the Statistical Analysis

```
# Statistical Analyses

## Packages and libraries

install.packages("rstatix")


library(tidyverse)

library(readr)

library(ggplot2)

library(rstatix)

library(dplyr)


## Read data

cnv <- read_csv("cnv_values.csv")

performance <- read_csv("behavior.csv")

subjective_ratings <- read_csv("subjective_ratings.csv")


## Rename variables

names(cnv) <- c("id", "difficulty", "reliability", "amplitude")

names(performance) <- c("id", "difficulty", "reliability", "rt", "response_accuracy")

names(subjective_ratings) <- c("id", "age", "female", "focus_easy", "focus_hard",
"focus_rel", "focus_unrel", "mot_rel", "mot_unrel", "mw_rel", "mw_unrel")


## Change data types
```

```
cnv <- cnv %>%
  mutate(
    id = as.character(id),
    difficulty = as.character(difficulty),
    reliability = as.character(reliability)
  )

performance <- performance %>%
  mutate(
    id = as.character(id),
    difficulty = as.character(difficulty),
    reliability = as.character(reliability)
  )

subjective_ratings <- subjective_ratings %>%
  mutate(
    id = as.character(id),
    female = as.character(female)
  )

## Print data sets
cnv
performance
subjective_ratings
```

```
## Check for missing values
missing_values_cnv <- colSums(is.na(cnv))
print(missing_values_cnv)

missing_performance <- colSums(is.na(performance))
print(missing_values_cnv)

missing_subjective <- colSums(is.na(subjective_ratings))
print(missing_subjective)

## Summary statistics
cnv %>%
  group_by(reliability, difficulty) %>%
  get_summary_stats(amplitude, type = "mean_sd")

performance %>%
  group_by(reliability, difficulty) %>%
  get_summary_stats(rt, type = "mean_sd")

performance %>%
  group_by(reliability, difficulty) %>%
  get_summary_stats(response_accuracy, type = "mean_sd")
```

```
subjective_ratings %>%
  get_summary_stats(mot_rel, mot_unrel, type = "mean_sd")


subjective_ratings %>%
  get_summary_stats(focus_rel, focus_unrel, type = "mean_sd")


subjective_ratings %>%
  get_summary_stats(mw_rel, mw_unrel, type = "mean_sd")


# Visualizations
## Response time plot
ggplot(performance, aes(x = reliability, y = rt, color = factor(difficulty))) +
  stat_summary(fun = mean, geom = "point", size = 2.5, position = position_dodge(width =
0.3)) +
  stat_summary(fun = mean, geom = "line", aes(group = factor(difficulty)), position =
position_dodge(width = 0.3), size=1) +
  stat_summary(fun.y = mean, fun.ymin = function(x) mean(x) - sd(x), fun.ymax =
function(x) mean(x) + sd(x),
               geom = "errorbar", width = 0.3, position = position_dodge(width = 0.3), size = 0.9)
+
  labs(x = "Reliability",
       y = "Response Time",
       color = "Difficulty") +
  theme_minimal() +
  theme(axis.line = element_line(colour = "black", size = 0.1),
```

```
        axis.ticks = element_line(colour = "black", size = 0.1),
        axis.ticks.length = unit(0.1, "cm"),
        legend.box.background = element_rect(color = "black", size = 0.1),
        legend.box.margin = margin(5, 5, 5, 5)) +
  scale_y_continuous(limits = c(375, 725), expand = c(0, 0), breaks = seq(400, 725, 50)) +
  scale_x_discrete(labels = c("1" = "Reliable", "0" = "Unreliable")) +
  scale_color_manual(labels = c("0" = "Easy", "1" = "Difficult"),
                     values = c("0" = "darkslateblue", "1" = "darkorange2"))


## Response accuracy plot
ggplot(performance, aes(x = reliability, y = response_accuracy, color = factor(difficulty))) +
  stat_summary(fun = mean, geom = "point", size = 2.5, position = position_dodge(width =
0.3)) +
  stat_summary(fun = mean, geom = "line", aes(group = factor(difficulty)), position =
position_dodge(width = 0.3), size=1) +
  stat_summary(fun.y = mean, fun.ymin = function(x) mean(x) - sd(x), fun.ymax =
function(x) mean(x) + sd(x),
               geom = "errorbar", width = 0.3, position = position_dodge(width = 0.3), size = 0.9)
+
  labs(x = "Reliability",
       y = "Response Accuracy",
       color = "Difficulty") +
  theme_minimal() +
  theme(axis.line = element_line(colour = "black", size = 0.1),
        axis.ticks = element_line(colour = "black", size = 0.1),
```

```
        axis.ticks.length = unit(0.1, "cm"),
        legend.box.background = element_rect(color = "black", size = 0.1),
        legend.box.margin = margin(5, 5, 5, 5)) +
  scale_y_continuous(limits = c(0.65, 1.05), expand = c(0, 0), breaks = seq(0.65, 1.05, 0.05))
+
  scale_x_discrete(labels = c("1" = "Reliable", "0" = "Unreliable")) +
  scale_color_manual(labels = c("0" = "Easy", "1" = "Difficult"),
                     values = c("0" = "darkslateblue", "1" = "darkorange2"))


## CNV amplitude plot
ggplot(cnv, aes(x = reliability, y = amplitude, color = factor(difficulty))) +
  stat_summary(fun = mean, geom = "point", size = 2.5, position = position_dodge(width =
0.3)) +
  stat_summary(fun = mean, geom = "line", aes(group = factor(difficulty)), position =
position_dodge(width = 0.3), size=1) +
  stat_summary(fun.y = mean, fun.ymin = function(x) mean(x) - sd(x), fun.ymax =
function(x) mean(x) + sd(x),
               geom = "errorbar", width = 0.3, position = position_dodge(width = 0.3), size = 0.9)
+
  labs(x = "Reliability",
       y = "CNV Amplitude",
       color = "Difficulty") +
  theme_minimal() +
  theme(axis.line = element_line(colour = "black", size = 0.1),
        axis.ticks = element_line(colour = "black", size = 0.1),
        axis.ticks.length = unit(0.1, "cm"),
```

```
        legend.box.background = element_rect(color = "black", size = 0.1),
        legend.box.margin = margin(5, 5, 5, 5)) +
  scale_y_continuous(limits = c(-3, 0.5), expand = c(0, 0), breaks = seq(-3, 0.5, 0.5)) +
  scale_x_discrete(labels = c("1" = "Reliable", "0" = "Unreliable")) +
  scale_color_manual(labels = c("0" = "Easy", "1" = "Difficult"),
                     values = c("0" = "darkslateblue", "1" = "darkorange2"))


## Subjective ratings plot
### Create suitable data set
subjective_ratings_long <- subjective_ratings %>%
  select(id, focus_rel, focus_unrel, mot_rel, mot_unrel, mw_rel, mw_unrel) %>%
  pivot_longer(cols = c(focus_rel, focus_unrel, mot_rel, mot_unrel, mw_rel, mw_unrel),
               names_to = "variable",
               values_to = "score") %>%
  separate(variable, into = c("variable", "condition"), sep = "_")


### Calculate mean scores for each variable and condition
mean_scores <- subjective_ratings_long %>%
  group_by(variable, condition) %>%
  summarize(
    mean_score = mean(score),
    sd_score = sd(score))


### Plot
```

```
ggplot(mean_scores, aes(x = condition, y = mean_score, color = variable)) +
  geom_point(size = 2, position = position_dodge(width = 0.3)) +
  geom_line(aes(group = variable), size = 1, position = position_dodge(width = 0.3)) +
  geom_errorbar(
    aes(ymin = mean_score - sd_score, ymax = mean_score + sd_score),
    width = 0.3,
    position = position_dodge(width = 0.3),
    size = 0.9
  ) +
  labs(x = "Reliability", y = "Mean Score", color = "Variable") +
  theme_minimal() +
  theme(axis.line = element_line(colour = "black", size = 0.1),
        axis.ticks = element_line(colour = "black", size = 0.1),
        axis.ticks.length = unit(0.1, "cm"),
        legend.box.background = element_rect(color = "black", size = 0.1),
        legend.box.margin = margin(5, 5, 5, 5)) +
  scale_y_continuous(limits = c(15, 100), breaks = seq(0, 100, by = 10)) +
  scale_color_manual(values = c("focus" = "darkslateblue", "mot" = "darkorange2", "mw" =
"darkolivegreen"))


# Assumptions ANOVA
## Outliers
performance %>%
  group_by(reliability, difficulty) %>%
  identify_outliers(rt)
```

```
performance %>%
  group_by(reliability, difficulty) %>%
  identify_outliers(response_accuracy)

cnv %>%
  group_by(reliability, difficulty) %>%
  identify_outliers(amplitude)

## Normality -Shapiro Wilk's Test
performance %>%
  group_by(reliability, difficulty) %>%
  shapiro_test(rt)

performance %>%
  group_by(reliability, difficulty) %>%
  shapiro_test(response_accuracy)

cnv %>%
  group_by(reliability, difficulty) %>%
  shapiro_test(amplitude)

### QQ Plots
ggplot(performance, aes(sample = rt)) +
```

```
  stat_qq(distribution = qnorm, color = "blue") +
  labs(title = "QQ Plot for Response Time",
       x = "Theoretical Quantiles",
       y = "Sample Quantiles") +
  facet_grid(reliability ~ difficulty, scales = "free") +
  theme_minimal()

ggplot(performance, aes(sample = response_accuracy)) +
  stat_qq(distribution = qnorm, color = "blue") +
  labs(title = "QQ Plot for Response Accuracy",
       x = "Theoretical Quantiles",
       y = "Sample Quantiles") +
  facet_grid(reliability ~ difficulty, scales = "free") +
  theme_minimal()

ggplot(cnv, aes(sample = amplitude)) +
  stat_qq(distribution = qnorm, color = "blue") +
  labs(title = "QQ Plot for Amplitude",
       x = "Theoretical Quantiles",
       y = "Sample Quantiles") +
  facet_grid(reliability ~ difficulty, scales = "free") +
  theme_minimal()

# Repeated measures ANOVAs
```

```
D1$reliability <- as.factor(D1$reliability)
D1$difficulty <- as.factor(D1$difficulty)

## Response time
rt.aov <- anova_test(
  data = D1, dv = rt, wid = id,
  within = c(reliability, difficulty))
get_anova_table(rt.aov)

## Response accuracy
accuracy.aov <- anova_test(
  data = D1, dv = response_accuracy, wid = id,
  within = c(reliability, difficulty))
get_anova_table(accuracy.aov)

## Amplitude
amplitude.aov <- anova_test(
  data = D1, dv = amplitude, wid = id,
  within = c(reliability, difficulty))
get_anova_table(amplitude.aov)

# Post-hoc - pairwise comparison
pairwise_tukey <- pairwise.t.test(performance$rt, performance$reliability, p.adjust.method =
"bonferroni")
print(pairwise_tukey)
```

```
pairwise_tukey2 <- pairwise.t.test(performance$response_accuracy,performance$reliability,
p.adjust.method = "bonferroni")

print(pairwise_tukey2)


pairwise_tukey3 <- pairwise.t.test(cnv$amplitude,cnv$reliability, p.adjust.method =
"bonferroni")

print(pairwise_tukey3)


# Unpaired two-samples t-test - subjective ratings

## Create motivation, focus, and mind wandering data sets

motivation_data <- subjective_ratings %>%

  select(id, mot_rel, mot_unrel) %>%

  pivot_longer(cols = starts_with("mot"),

               names_to = "condition",

               values_to = "meanmotivationscore") %>%

  mutate(condition = gsub("mot_", "", condition))

print(motivation_data)


focus_data <- subjective_ratings %>%

  select(id, focus_rel, focus_unrel) %>%

  pivot_longer(cols = starts_with("focus"),

               names_to = "condition",

               values_to = "meanfocusscore") %>%

  mutate(condition = gsub("focus_", "", condition))
```

```
print(focus_data)


mw_data <- subjective_ratings %>%
  select(id, mw_rel, mw_unrel) %>%
  pivot_longer(cols = starts_with("mw"),
               names_to = "condition",
               values_to = "meanmwscore") %>%
  mutate(condition = gsub("mw_", "", condition))
print(mw_data)


## Assumptions
### Normality
shapiro.test(motivation_data$meanmotivationscore)
shapiro.test(focus_data$meanfocusscore)
shapiro.test(mw_data$meanmwscore)


### Homogeneity of variance
library(car)
leveneTest(meanmotivationscore ~ condition, data = motivation_data)
leveneTest(meanfocusscore ~ condition, data = focus_data)
leveneTest(meanmwscore ~ condition, data = mw_data)


## Outliers
motivation_data %>% identify_outliers(meanmotivationscore)
```

```
focus_data %>% identify_outliers(meanfocusscore)

mw_data %>%  identify_outliers(meanmwscore)


## Explore and clean data

summary(motivation_data$meanmotivationscore)

summary(focus_data$meanfocusscore)

summary(mw_data$meanmwscore)


## Paired samples t-test

t_test_mot <- t.test(meanmotivationscore ~ condition, paired = TRUE, data =
motivation_data)

t_test_mot


t_test_focus <- t.test(meanfocusscore ~ condition, paired = TRUE, data = focus_data)

t_test_focus


t_test_mw <- t.test(meanmwscore ~ condition, paired = TRUE, data = mw_data)

t_test_mw


# Libraries

library(dplyr)

library(stats)


# Wilcoxon signed-rank test for motivation data
```

```
wilcox.test(motivation_data$meanmotivationscore ~ motivation_data$condition, paired =
TRUE)


# Wilcoxon signed-rank test for focus data

wilcox.test(focus_data$meanfocusscore ~ focus_data$condition, paired = TRUE)


# Wilcoxon signed-rank test for mind wandering data

wilcox.test(mw_data$meanmwscore ~ mw_data$condition, paired = TRUE)
```