Master thesis

Evaluating the reliability of relative frontal alpha asymmetry as a state-dependent correlate of the stress response in a mixed-sex sample: A replication study

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Abstract

Relative frontal asymmetry (RFA) has previously been outlined as an index of emotional regulation and valence and was recently linked to the human stress response. Zhang et al. (2018) found RFA at rest to be predictive of the cortisol response after being subjected to a bilateral feet Cold Pressor Test (CPT) and observed functional changes in RFA during the CPT. The current study tried to replicate these results following the same methodology in both a larger sample based on the same inclusion criteria as the original study and a second sample including female subjects. Although the stress induction was successful in both samples shown by increases of cortisol, heart rate, blood pressure and ratings of stress and arousal absent in the control condition, no state-dependent shift of RFA during stress induction was observed in either sample. The current study confirmed the relation between RFA at rest and cortisol, however the observed response pattern differed from the original study as RFA both pre-, and post-stress was significantly correlated to cortisol. However, the correlation with cortisol was only significant for the exclusively male sample. In general, sex only presented a significant factor in regard to the stress parameters and not in relation to RFA, yet this might also be attributable to the overall absence of state-dependent changes in RFA in the present study. For future studies the present paper recommends differentiating the stress and particularly cortisol response into two phases of reactivity and regulation as proposed by prior studies.

1. Introduction

Stress has been outlined as a risk factor for adverse physical and mental health conditions and described as a catalyser of psychopathology (Vanhollebeke et al., 2022; Zhang et al., 2018). As such, stress has been shown to affect memory, cognition and behaviour as well as the development and exacerbation of mood-related disorders, anxiety and even post-traumatic-stress disorders and schizophrenia (Glier et al., 2022; Zhang et al., 2018). As a research field, stress has gained importance recently due to global crises let alone the COVID-19 pandemic which has produced a lot of stress-related studies in the past four years. The American Institute of Stress defined stress broadly as physical, mental, or emotional strain (Minguillon, Lopez-Gordo, & Pelayo, 2016). Important for the extent of the stress response is the subjective appraisal of stressors. Stress responses have been shown to increase if an individual perceives something as a threat to the social self, uncontrollable, unpredictable or exceeding the direct mitigating capability of the body (Vanhollebeke et al., 2022; Zhang et al., 2018). However, individual differences in trait-resilience or situational coping strategies are difficult to assess, leaving us in the dark about what individuals are more susceptible to stress and why so. In this context, studies suggested relative frontal asymmetry (RFA) as a potentially valuable index of the cognitive processes involved in the human stress response.

Research on RFA has brought forth a wealth of different theories on the structural and functional role of hemispheric asymmetry in our experience and processing of emotions. Davidson et al. (1990) first proposed RFA as an index of trait tendencies of both affective style and emotional responding. In their model they argued that stronger right-sided activity corresponds to tendencies of withdrawal from challenging stimuli and emotions of negative valence and stronger left-sided activity to indicate positive emotions and approach behaviour (Davidson et al., 1990). Technically speaking, RFA scores indicate the lateralization of alpha band for a given time interval by computing the difference in alpha band power between electrodes over the right and left frontal areas[1] (Sharpley et al., 2023). Negative RFA scores indicate less alpha band power in the right hemisphere while positive RFA scores represent less alpha activity in the left hemisphere (Berretz et al., 2022; Smith et al., 2017). As alpha power is commonly believed to be the inverse of cortical activity this translates into negative RFA scores corresponding to relative higher cortical activity in the right hemisphere whereas positive scores reflect stronger left hemispheric activity. Generally, studies focus on whether RFA presents a valuable predictor for individual trait-components of the psychological or physiological response to emotional processing. Within this line of research, Zhang et al. (2018) examined whether physically induced stress can be observed in RFA scores and if these changes are predictive of the stress response. Their results supported the general notion that RFA represents foremost trait components of affective processing involved in moderating the stress response and additionally reflects state-like emotional variations seen in temporal changes of frontal asymmetry during stress (Berretz et al., 2022; Coan & Allen, 2004; Quaedflieg et al.,

[1] ln[R]-ln[L]

2015). The present study is foremost a direct replication of Zhang et al. (2018) to investigate the reliability of their results. Additionally, the study assessed the generalizability of the results in a larger and more diverse sample including female subjects. In the following the theoretical framework underlying RFA and subsequent research focuses will be explained first. Next, contemporary results on the correlation between RFA and stress will be elaborated whereafter the benefits and research questions regarding the replication of the study from Zhang et al. (2018) are presented.

1.1 Theoretical background

Numerous studies have researched RFA as a predictor of affective processing and emotional regulation (Coan & Allen, 2004; Berretz et al., 2022; Smith, Reznik, Stewart, & Allen, 2017; Quaedflieg et al., 2015). Coan and Allen (2004) summarized the research goals of these studies into four categories (Fig. 1). Accordingly, studies examined RFA as either (1) a marker of individual differences in trait-like measures; (2) a predictor of people's tendency of state-related emotional responding; (3) an indicator of risk of psychopathology; or (4) a mediator of and neurological reaction to changes in emotion. The first three categories conceptualize RFA as structural corresponding to the theoretical model of Davidson et al. (1990) and subsequently examined RFA as a trait-component of emotional processing. Corresponding studies have linked RFA to trait-like concepts such as emotional flexibility or trait optimism in the first category, tendencies to respond either aversively or approaching to emotionally salient stimuli in the second, and lastly pathologies like depression, anxiety, and other mood-related disorders in the third type. There is an emerging consensus in these studies that stronger right-sided activity is correlated with avoidant responses and negative emotions while more left-sided activity is related to approach-behaviour and emotions of positive valence (Quaedflieg et al., 2015; Smith et al., 2017). The fourth category as presented by Coan and Allen (2004) summarizes a newer direction of RFA research focusing on the functional changes in RFA in response to certain stimuli. Coan et al. (2006) argued in their capability model of individual differences that asymmetries during the processing of emotions are even more pronounced than at rest and proposing RFA as a situational and state-dependent measure of emotional regulation in addition to a dispositional marker (Berretz et al., 2022; Coan et al., 2006). To this date, short-lived and state-dependent RFA changes were observed by various studies, yet their role in the processing of emotions remains elusive as studies reported either opposing or irreplicable changes in RFA during emotional challenges (Berretz et al., 2022; Coan & Allen, 2004; Zhang et al., 2018).

The value of RFA as a potential predictor of emotional processing lies in the context of emerging research on the risks of stress on both physical and mental health (Vanhollebeke et al., 2022). Consequently, many RFA studies shifted their research focus towards the correlation between both structural and functional RFA and stress to explore if RFA can be utilised as a parameter to better understand the human stress response and its determinants (Berretz et al., 2022; Glier et al., 2022; Tops et al., 2005; Quaedflieg et al., 2015; Zhang et al., 2018). As such, these particular studies mainly pursue

the question whether RFA holds predictive power over components of the psychological or physiological response to stress (classification (1), (2) and (4) of Coan and Allen (2004)).

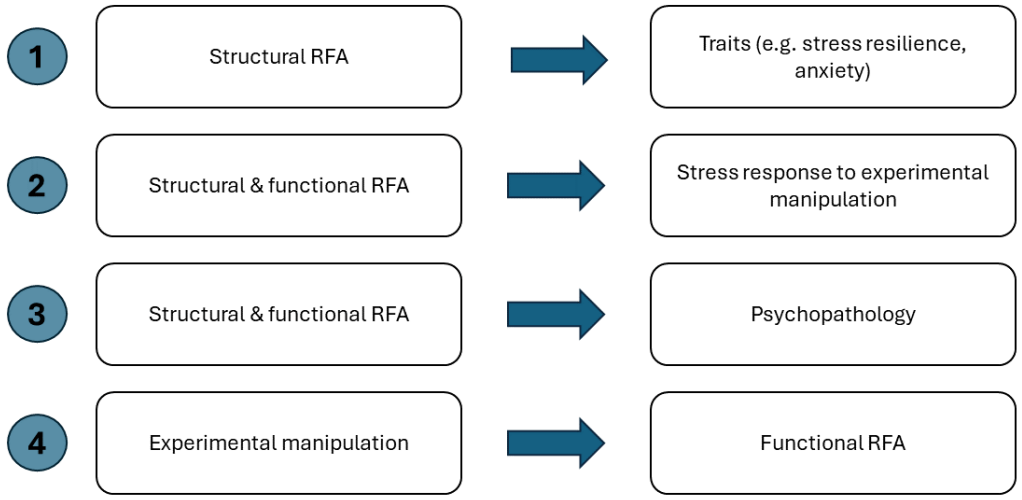

Fig. 1 Illustration of the model of Coan and Allen (2004)

To accurately quantify the different manifestations of the stress response it is important to understand the underlying processes. Physiologically, the response to stress involves a complex interaction of various effector systems, mainly subdivided into two systems (Vanhollebeke et al., 2022). The immediate fight-flight reaction to a stressor characterized by increased heart rate and blood pressure results from a release of epinephrine and norepinephrine into the blood upon activation of the sympatho-andreno-medullar (SAM) system (Bachmann et al., 2018; Berretz et al., 2022). In contrast, the hypothalamus-pituitary-adrenal (HPA) axis initiates the production of cortisol based on the appraisal of stress by the frontal cortex (Glier et al., 2022). This reaction is slower with cortisol blood levels peaking 20-30 minutes after the stressor as well as longer subsequent effects on the body and brain (Berretz et al., 2022; Zhang et al., 2018). Therefore, to assess mentally appraised as well as unmediated aspects of the stress response it is best to collect measurements of both cortisol and cardiovascular responses. In addition, studies commonly employ stress ratings to gain insight into the subjective experience of stress.

So far, contemporary research linked negative structural RFA to both prolonged as well as acute stress supporting Davidson et al.'s (1990) model (Lewis et al., 2007; Quaedflieg et al., 2015; Zhang et al., 2018). However, studies differ considerably from one another in their research goals, experimental designs and lastly results (Table 1). Firstly, studies investigated not only structural (trait) RFA but also functional (state-dependent) shifts in RFA and the relation of trait- and state-dependent RFA to the stress response. The first two research branches correspond to the first and fourth category of Coan and Allen's (2004) classification respectively whereas the relation to the stress response is summarized in the second category (see section 1.1). Trait-related research has repeatedly found baseline RFA to correlate negatively with the strength of the cortisol response after experiencing stress whereas functional RFA studies were mostly unsuccessful in correlating RFA with stress response parameters (Table 1). Studies on functional RFA did in contrast find affective shifts in reaction to the stress induction, however the

observed frontal asymmetries changed inconsistently towards greater left- or right-sided activity as well as being unrelated to other stress parameters wherefore their functional role remains yet unclear (Zhang et al., 2018; see Table 1).

Table 1. Overview of comparable studies on RFA and stress and respective results. Stress induction shows whether cold pressor tests (bfCPT), Maastricht Acute Stress Test (MAST), Trier Social Stress Test (TSST) have been employed. Aim indicates the study type based on the classification of Coan and Allen (2004); (1) structural RFA in relation to traits, (2) RFA in relation to the stress response and (4) effect of stress induction on functional RFA. Symbols indicate the direction of correlations.

Study	Stress induction	RFA measurement (relative to stress induction)	Aim	Results
Zhang et al. (2018)	bfCPT	pre, during, post	(1), (2), (4)	(1), (2) RFA – Cortisol, HR & BP at F4-F3 (4) Stress – RFA at F8-F7
Quaedflieg et al. (2015)	MAST	pre, post	(1), (2), (4)	(1), (2) RFA – Cortisol at F4-F3 (4) No RFA activation in response to the stress induction
Glier et al. (2022)	TSST	pre, post	(2)	(2) RFA – Cortisol reactivity at F8-F7 (2) RFA + Cortisol recovery at F8-F7
Düsing et al. (2016)	TSST	pre, post	(2), (4)	(2) RFA + Cortisol (4) Stress – RFA at F4-F3
Berretz et al. (2022)	TSST	during, post	(4)	(4) Stress + RFA at F4-F3
Tops et al. (2005)	Cortisol administration	post	(4)	(4) Stress – RFA at F4-F3 and F8-F7
Tops et al. (2006)	Cortisol administration	post	(4)	(4) Stress + RFA at F4-F3 and F8-F7
Lewis et al. (2007)	Natural exam stress	During	(2), (4)	(2) No association between RFA and stress responses (2) RFA – negative health ratings (4) Stress – RFA

Secondly, experimental designs differ with respect to the employed stress induction procedures and subsequently suitable experimental phases for RFA computation. Consideration of the stress induction method is important due to its impact on the stress response (Berretz et al., 2022; Finke et al., 2021). Just like the human stress response, stressors have physiological and psychological qualities. While some experiments rely on physical stimulation like cold pressor tests to simulate the stress response, others employ social or cognitive stressors in the form of peer evaluation, mock job interviews and mental arithmetic tasks as seen in the Trier-Social-Stress-Test (TSST) or Maastricht Acute Stress Task (MAST) (Minguillon et al., 2016; Quaedflieg et al., 2015; Zhang et al., 2018. Berretz et al. (2022) highlighted that psychosocial stressors might be more affected by coping processes than physical stimulation which is immediately processed by the hypothalamus and thus not mediated by subjective

evaluation. Additionally, a significant limitation of psychosocial stressors is that EEG recording during the stress induction will be heavily contaminated by the cognitive processing of the stressor. Consequently, study designs with psychosocial stress induction procedures have to compute state-dependent changes in RFA based on the difference between pre- and post-stress RFA phases. Discrepant results are subsequently often attributed to the diversity of RFA phases and stress induction procedures throughout studies wherefore cross-interpretation is heavily limited.

1.2 Replication study

This leads to the study of Zhang et al. (2018) which stands out for its methodology. Most importantly, the use of an automated physical stress induction allowed not only to measure the effect of stress on RFA during stress induction but also without interference from movement artifacts, lateralization effects due to the cold pressor, nor psychological processing of the stressor or potential coping mechanisms present in studies with psychosocial stress induction procedures. However, being the only study employing a physical stressor, it stands in isolation without the possibility to directly compare its results.

The study addresses the first, second and last classification of Coan and Allen (2004) (Fig. 1). As such, it investigated RFA as an index of trait-resilience against stress and additionally, as a state-dependent measure during acute stress. Two main results were reported. First, a negative correlation between trait-RFA at F4-F3 and all measured stress parameters including cortisol, cardiovascular measurements, and lastly subjective ratings of stress and arousal was observed. Secondly, Zhang et al. (2018) found a short-lived change towards right-sided RFA during the stress induction that returned to baseline immediately after the stress induction and had not been recorded in previous studies examining state-dependent changes as the difference between RFA pre- and post-stress induction (Quaedflieg et al., 2015; Zhang et al., 2018).

Especially the latter finding stands out in comparison to studies with psychosocial stressors. Whereas studies relying on psychosocial stressors commonly compute state-dependent RFA based on the difference between pre- and post-stress induction the study of Zhang et al. (2018) conceptualizes functional RFA as changes present during the stress induction. The importance of this differentiation is reflected in the results of Zhang et al. (2018) who reported no difference in RFA pre- compared to post-stress indicating that observed state-dependent changes in RFA are restricted to the time interval of the stress induction and thus not captured by experimental designs dependent on pre- to post-stress differences on RFA. Consequently, the results of Zhang et al. (2018) could explain the inconsistent results of prior studies by differentiating what experimental phases are relevant for measuring functional RFA. As such it is important to verify the reliability of the result of Zhang et al. (2018) to confirm whether the difference stems from discrepant study designs and can be replicated using the same methodology. This is especially true given that there is yet no comparable study using physical stimulation while the only study measuring RFA during the stress induction observed a contradictory shift towards left-sided activity and was criticized by the authors themselves due to possible EEG interference by the psychosocial stressor (Berretz et al., 2022).

Besides the main findings, the study of Zhang et al. (2018) proposed interesting interpretations concerning trait-RFA that are worth validating. Regarding the first main result, cortisol was predicted best by the average baseline RFA of both measurement days while cardiovascular measurements correlated more strongly with same-day baseline RFA. Based on this, Zhang et al. (2018) concluded that cortisol might be a more stable trait-like component of RFA whereas cardiovascular measurements seemed more prone to fluctuations of mood. Furthermore, while the trait-related correlation between RFA and stress parameters was restricted to F4-F3, the state-dependent shift in RFA during the stress induction was observed only at F8-F7. This let them to postulate that the electrode pairs have distinct functions in the stress response as RFA at F4-F3 remained constant throughout the experiment and F8-F7 shifted towards higher right-sided activity during the stress induction. At last, the study was also successful in linking baseline-corrected RFA at F4-F3 and subjective ratings of the stressor.

However, the reliability of the results is in question. The threat of false positives in frequentist statistics and the overall issue of replicability in psychological studies were exemplified by two RFA studies examining the effect of cortisol administration on RFA. Tops et al. (2005, 2006) conducted two consecutive studies with identical methodology that yielded the exact mirror image of the observed response patterns. In their first study they found an increase in right-sided activity after stress induction via cortisol administration while the follow-up study showed an increase in left-sided activity (Tops et al., 2005; Tops et al., 2006). Furthermore, many studies found inconsistent results in comparison to Zhang et al. (2018). For example, Lewis et al (2007) were unable to correlate the stress response with RFA and while Düsing et al. (2016) found a correlation between RFA and cortisol it was positive in contrast to the negative correlation observed by Zhang et al. (2018) and Quaedflieg et al. (2015). Additionally, Berretz et al. (2022) and Düsing et al (2016) found shifts towards greater left- instead of right-sided activity in reaction to the stress induction as reported by Zhang et al. (2018). These inconsistencies justify a direct replication of the study of Zhang et al. (2018) as a foundation for further interpretation and future research. Generally, a direct replication would bolster the interpretative value and reliability of the various and compelling results from Zhang et al. (2018) as well as highlight the potential benefit of an automated physiological stress induction procedure to measure RFA during stress in future studies.

Another advantage of a direct replication study is the possibility to compare different samples directly. Zhang et al. (2018) called out that to this date no study examined the relation between physical stress and RFA in a mixed-sex sample. Replicating the design of a former study allows to investigate the generalizability for female participants through direct comparison with the original study. Previous studies with psychosocial stressors have found sex-differences to be only relevant in regard to cortisol responsivity but not RFA or the correlation between RFA and the stress response (Berretz et al., 2022; Glier et al., 2022; Quaedflieg et al., 2015). Ocklenburg et al. (2019) observed sex-differences in RFA only after experimental manipulation thus arguing that these differences are only state-dependent and not present in structural RFA (Sharpley et al., 2023; Stewart et al., 2010). Consequently, a study design

as Zhang et al.'s (2018) with both baseline and state-dependent measures will allow to fully investigate the influence of sex differences in this context.

In conclusion, RFA has been outlined as a correlate of individuals' neuroendocrine reaction and resilience to stress. However, interpretation across studies is limited by different experimental designs wherefore inconsistent results cannot be explained. As a consequence, this study will replicate the design of Zhang et al. (2018) instead of using a new one to test the reliability of their results and furthermore examine the generalizability for a mixed-sex sample. As such, the success of the stress induction will be evaluated first as a prerequisite for investigating the first, second, and last overarching research goals summarized by Coan and Allen (2006). This implies researching RFA as a marker of trait resilience in relation to stress and further, whether functional changes in RFA can be observed during the stress induction. Additionally, the most important implications are considered including the potentially distinct role of the electrode pairs F4-F3 and F8-F7 as trait- and state-dependent components respectively as well as the susceptibility of cardiovascular and cortisol measurements to mood-fluctuations based on stronger correlations to same-day baseline or the average baseline RFA of both measurement days. Lastly, the complete analysis will be extended to examine the effect of sex on the observed correlations. The research goals are summarized in Table 2 below.

Table 2. Predictions based on Zhang et al. (2018). Symbols indicate the direction of the correlation.

Predictions
CPT induces increases in Cortisol, HR, BP, and stress and arousal ratings
Both day RFA average (F4-F3) at baseline correlates with Cortisol values (-)
CPT induces a shift towards negative RFA (right-sided activity) at F8-F7 (-)
Same-day RFA (F4-F3) at baseline and during the CPT correlates with cardiovascular responses (-)
Only state-dependent sex differences are expected

2. Methods

2.1. Participants

The study tested 83 participants (mean age: 24.8 years, range: 18-35 years, std dev.: 4.32, 42 male) at the Leibniz Institute for working environment and human factors (IFaDo) in Dortmund, Germany. Participants were recruited from the Technical University of Dortmund (TU Dortmund) and through the website of the IFaDo. The sample was selected based on the following criteria from Zhang et al. (2018). They sampled only right-handed participants with normal weight (BMI between 19 and 25), aged between 18 and 35 years and no history of acute or chronic diseases of the circulatory system, psychiatric disease or family history of arterial hypertension, and cerebral or aortic aneurism. Furthermore, smoking more than 5 cigarettes per day or use of drugs or medication, except for occasional use of pain killers such as paracetamol, acetylsalicylic acid, NSAIDs, led to exclusion from the study. Lastly, sensitivity to cold and dermatologic lesions, burns or infections of the feet led to exclusion from the study. Upon selection, subjects were briefed that drinking alcohol and caffeine had to be omitted for 24 and 12 hours prior to the study respectively. Additionally, vigorous exercise in the morning had to be avoided. The only difference in sample criteria between the current and original study concerned subject's sex, while the original study sampled exclusively male participants the current study included male as well as female subjects.

Sixteen participants had to be excluded due to premature termination of the study (problems with the CPT or failure to attend to both measurement days) or malfunctioning of the measuring equipment (n = 4) resulting in a final number of 68 participants (Table. 3). Before the experiment participants received the written informed consent and were reminded of their right to withdraw from the experiment at any point. In face of the physical and psychological stress and potential pain each participant was compensated with either 85€ or 7 subject hours relevant for their respective studies. The experimental design was reviewed and approved by the ethical board of the IFaDo.

Table 3. Final sample sizes and demographics of the original and the current replication study

	Zhang et al. (2018)	Direct replication	Mixed-sex sample
N	21	32	68
Mean age (SD) in years	26.5 (NA)	23.7 (3.97)	25.12 (4.38)
Gender (M/F)	21/0	32/0	32/36

2.2. Procedure

The procedure resembled the original study as close as possible with only one major change made to the number of stress inductions (Fig. 2, 3). Participants were tested at the IfaDo in Dortmund, Germany. To compare stress responses within each participant, data were collected on two separate days exactly one week apart. As in the original study, all experiments were conducted from 1-5 p.m. given the sensitivity of cortisol to the diurnal cycle. To assure homogeneity in the sample each participant had to confirm the

above-mentioned exclusion criteria in person prior to the first session. Afterwards participants were informed about the procedure including the different physiological recordings and the bilateral feet Cold Pressor Test (bfCPT) as well as warm water control. Participants were not told about the experimental conditions and the alternation between the sessions. To control for potential effects of the sequence of experimental conditions the order was counterbalanced between participants. Experimental conditions differed only in regard to the water temperature while the rest of the procedure was identical. The experiment was conducted in a stimulation chamber with dimly lit light and sound-isolation to avoid artifacts in the EEG which also contained the fully automated bfCPT (Fig. 4). Participants had to put their bare feet into the empty water tanks which were fixed right in front of their chair. After preparing the electrodes an initial saliva sample was taken and baseline resting-state EEG was measured over the course of ten minutes. This was followed by three blocks of bfCPT which lasted 3 minutes each and were separated by 20 minute-breaks in which participants had to complete a working memory task. Prior to each bfCPT participants were asked to rate their current level of stress and arousal and to give a saliva sample after which a sound announced the start of the CPT. Stress and arousal ratings were additionally taken right after the end of the CPT. Heart rate and blood pressure were measured at the beginning and end of the intervention. Alpha asymmetry was computed during two one-minute blocks between the cardiovascular measurements in which participants were asked to keep their eyes open and closed with alternating order. The intervention was repeated three times in the current experiment in comparison to one intervention in the original study. During the three interventions exposure to cold or warm water was limited to only the right or left foot in the first two intervals whereas both feet were exposed in the last intervention. In the end, another 10-minute resting phase was administered to measure resting state EEG. After participants completed the experimtal procedure of both measurement days they were thanked at the end of the second day and compensated monetarily or through participant hours for their respective studies.

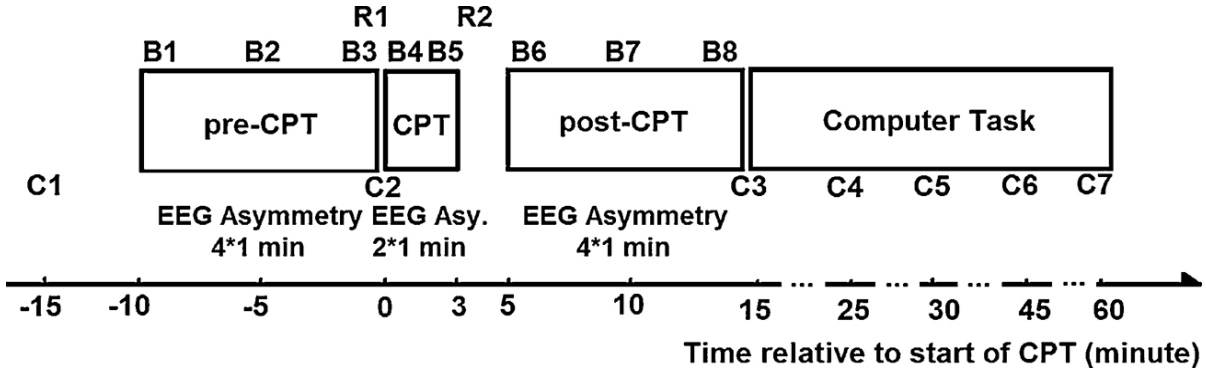

Fig. 2 Procedure of the original experiment by Zhang et al. (2018) (C = cortisol, B = blood pressure, R = rating)

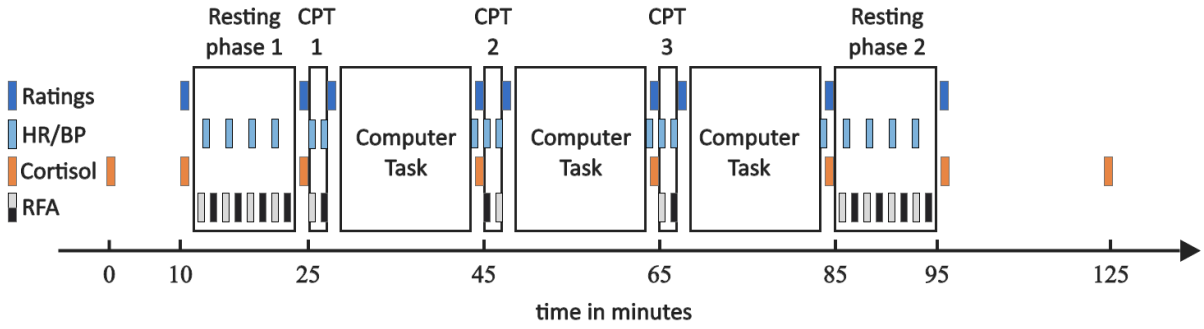

Fig. 3 Timeline of the replication study (grey and black fills at asymmetry indicates eyes open and eyes closed). CPT 1 and 2 were unilateral whereas the third CPT was bilateral.

2.3. Stressor

The stress induction was done using a standardized version of CPT as in Zhang et al. (2018). This bfCPT was validated to significantly correlate with the hemodynamic, subjective, and endocrine characteristics of the human stress response (Bachmann et al., 2018; Zhang et al., 2018). For the bfCPT and control condition the two separate tanks were filled with either cold (4 °C) or warm water (36–37 °C) respectively. Water temperature was controlled through a cooling and flow-type heater system respectively. Exposure lasted for three minutes at a time, however, participants could remove their feet at any time. While the CPT was running, participants were not informed about the remaining time. The water was moved using hydrostatic pressure allowing the tubs to be both filled as well as drained within 20 seconds and to keep the water circulating during the intervention to prevent temperature layers along the skin. LabVIEW (National Instruments™, Munich, Germany) was used to automate the timing and execution of the bfCPT.

The aforementioned briefing informed participants verbally that the cold temperature applied would not damage any tissue. Participants were reassured despite being painful, most of the participants had been able to stand the procedure completely and that they would be permanently monitored for safety reasons. Finally, subjects were informed that, in case of emergency, communication with the experimenter would be possible via an interphone system at any time. At the end, participants were offered a towel to dry their feet. A schematic draft of the construction and its functional principle is shown in Fig. 4. Additional information related to the design of the bfCPT can be found in Bachmann et al. (2018).

2.4. Data acquisition

2.4.1. Cortisol

Cortisol was measured with saliva samples using Saliviettes (Saarstedt; Nümbrecht, Germany). Eight samples were taken (after 0, 10, 23, 43, 63, 85, 95, 125 min. relative to the start of the experiment) with three samples prior to the CPT and two samples 30 and 60 minutes after the last CPT (Fig. 3). After the experiments the samples were first stored at room temperature before they were transferred into a cooler with a temperature of -20 °C. Salivary cortisol was analysed using a time-resolved immunoassay with

fluorometric detection (see: Dressendorfer et al., 1992). Cortisol values were quantified based on the area under the curve (AUC) as done in other studies on the topic of stress (Bachmann et al., 2018; Quaedflieg et al., 2015; Zhang et al., 2018).

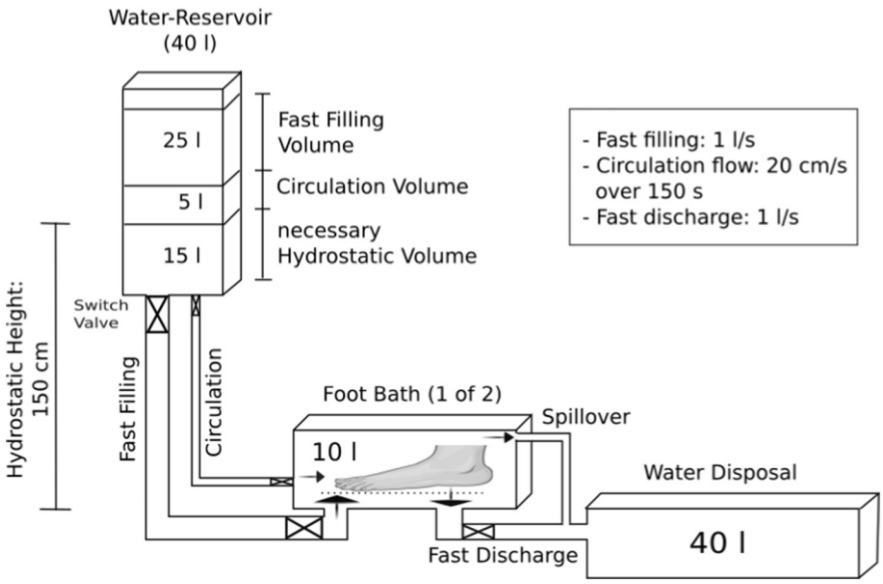

Fig. 4. Schematic draft of the automated bfCPT construction from Bachmann et al. (2018)

2.4.2. Cardiovascular measurements

Besides cortisol, heart rate as well as blood pressure were measured with the Dinamap system (Critikon; Tampa, Florida, USA). Measurements were taken four times during the resting phases with three-minutes between measurements and twice during the interventions once 30 seconds after start and again 30 seconds before the end. Importantly, blood pressure was not measured during intervals designated for the EEG analysis to avoid possible artifacts in the EEG recording.

2.4.3. Subjective ratings

As a third measure, subjective ratings of participants' arousal and perceived stress level were gathered. Participants had to indicate these before and after each resting phase or intervention using a visual analogue scale which was presented on the monitor in front of them. The scales ranged from 0-100 representing "not stressed/aroused at all" or "extremely stressed/aroused" respectively and participants could interact with the scale using a mouse.

2.4.4. EEG

For the EEG measurement a 64-channel actiCap System was used (Brain Products GmbH; Gilching, Germany). The actiCap was positioned based on the international 10-20 system. AFz and FCz were used as ground and reference electrode respectively. To account for ocular artifacts, the horizontal and vertical electrooculogram (EOG) were measured as well. For the entire duration of the experiment impedance of the electrodes was kept below 20 kΩ. Processing of the EEG data was done using Brain

Vision Analyzer V2.0.4 in addition to the EEGLAB toolbox for MATLAB (Brain Products GmbH; Gilching, Germany; Delorme & Makeig, 2004). Prior to the analysis the data was compressed to a sample-rate of 256 Hz.

2.4.5. Relative frontal asymmetry

To compute the relative frontal alpha asymmetry (RFA) the EEG data was pre-processed as in Zhang et al. (2018). First the data was re-referenced to the common average and then band-pass filtered (1-30Hz) with a Butterworth filter. Bad channels were automatically removed using the legacy function of EEGLAB for rejecting artifacts (Delorme & Makeig, 2004). Channels were deemed improbable or abnormal and subsequently removed when their probability of occurrence exceeded 5 standard deviations or the kurtosis measure exceeded 10 standard deviations from the probability distribution. Similarly, bad epochs were rejected when they exceeded the probability distribution by 5 standard deviation or potentials were higher than 500 uV. Epoch length was set to 2 seconds and a maximum of 10 epochs were rejected per channel.

Afterwards, an independent component analysis (ICA) was run retaining only 62 channels for improved effectiveness. ICA weights were used to remove components with a brain probability below 30% and an eye movement probability above 70%. Empty channels were accommodated for using spherical interpolation. To determine alpha band power a Fast Fourier Transformation (FFT) was performed with an epoch length of 2 seconds and a total of 20 non-overlapping segments and a sampling rate of 1000Hz. The power spectral density (PSD) plots were computed separately for each segment using the Welch's method. Only the PSD values of the first 100 frequency bins (0-50Hz) were stored for further analysis. Average alpha power was then computed by summarizing the frequency bins corresponding to 8-13Hz during the following time intervals. The resting phases consisted of eight blocks and the interventions of two. Each block was one-minute long and blocks alternated between 'eyes open' and 'eyes closed'. Participants were verbally instructed throughout the experiment about when to keep their eyes open or closed and the order of blocks was counterbalanced between participants.

RFA was calculated as common practice by computing the logarithm of alpha power and subtracting activity in the left hemisphere from corresponding electrodes of the right hemisphere (ln[R]-ln[L]) for each block (Berretz et al., 2022; Zhang et al., 2018). Finally, RFA of all blocks of the resting phase prior to the intervention, the last block of the intervention and again all blocks of the resting period after the intervention were averaged into the three experimental phases pre, during, and post. Thus, as in Zhang et al. (2018) RFA was summarized between blocks of eyes open and eyes closed to obtain a more robust index as with either condition alone.

2.5 Data analysis

The data was analysed in Rstudio version 4.2.2. Cardiovascular, cortisol and subjective stress and arousal data were summarized into separate datasets and transformed into long format to accommodate

the repeated measures within-subject ANOVA using the afex package in R. Furthermore, a separate dataset was created from the total sample with only male subjects whereafter the following analysis was conducted first on the exclusively male sample (Table 3). An extended analysis was run on the total sample where each of the following ANOVAs was run with the addition of sex as a predictor in the model to examine potential effects of sex on RFA or stress parameters.

To test the success of the stress induction, each stress parameter was analysed with a repeated measures ANOVA comprising the experimental condition and time as independent variables and the respective stress parameter as dependent variable. Time represented in case of the cortisol dataset the time point of each cortisol measurement (0, 10, 22, 43, 65, 84, 95, 125 min. in relation to the start of the experiment) whereas the cardiovascular measurements and stress ratings were averaged into three time phases (pre, during and post) in relation to the intervention. Furthermore, an additional error term was defined to account for all between-participants variation. Besides the ANOVA, t-tests for each time phase of the respective stress parameters were computed to examine the effect sizes of the differences.

Another dataset was created with the frontal asymmetry values at F4-F3 and F8-F7 for pre-, during-, and post-intervention. Importantly, only RFA during the bilateral feet CPT (the last intervention block) was taken for the analysis. The dataset was used to examine the effects of stress on RFA using another repeated measures ANOVA with RFA as dependent variable and experimental condition, time, and electrode as independent variables.

Lastly, the RFA dataset was used to compute a final dataset containing both RFA values and stress parameters to examine the relation between the stress response and RFA using bivariate Pearson correlation coefficients. For this five RFA values were computed, one each at baseline, during- and post-CPT, as well as two more representing the average baseline RFA of both measurement days and a baseline correction which reflected the difference between same-day baseline RFA and RFA during the CPT. Similarly, all stress response measures were summarized in a single value representing the difference between pre- and during-CPT. A correlation matrix was computed with the correlations of each RFA phase at F4-F3 and F8-F7 respectively and the baseline-corrected stress parameters. The table used for representing the correlation matrix was taken from Zhang et al. (2018) to allow for a direct comparison of the results (Appendix A).

3. Results

3.1 Direct replication

3.1.1 Stress responses

3.1.1.1 Cortisol

First, a repeated measures ANOVA was run with the experimental condition (CPT and control condition) and time (0, 10, 22, 43, 65, 84, 95, 125 min.) as independent variables and cortisol as dependent variable. The results showed a significant main effect for experimental condition on cortisol (F [1, 31] = 20.3 p < .001), time (F [7, 217] = 5.44, p < .001) and an interaction between time and experimental condition (F [7, 217] = 5.49, p < .001. Additionally, t-tests were carried out to confirm the differences in cortisol across each measurement. Contrary to the expectation average cortisol was already higher in the CPT-group at the start of the experiment (0 min. t[62] = -2.39, p = .019). For the remaining experiment cortisol was consistently higher in the CPT-group than in the control group (t[62] < -2.21, p < .031) except for the measurement immediately prior to the stress induction or control procedure (22 min. t[62] = -1.84, p = .654).

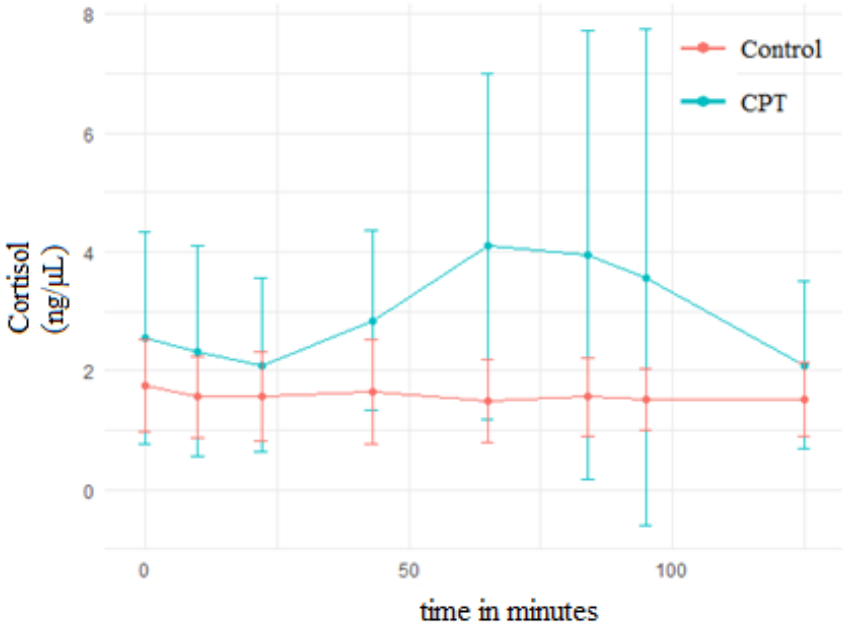

Fig. 4 Cortisol over time by experimental condition for male subjects (error bars show standard deviation)

3.1.1.2 Heart rate and blood pressure

Regarding the cardiovascular parameters which were separately analysed with an ANOVA predicted by experimental condition * time (pre, during, post), systolic (SYS), diastolic (DIA) and mean arterial blood pressure (MAP) showed significant effects of experimental condition (SYS: F [1, 31] = 6.54, p = .016; DIA: F [1, 31] = 18.1, p < .001; MAP: F [1, 31] = 4.61, p = .039) whereas heart rate (HR) was not significant (F [1, 31] = 2.3, p = .139). Additionally, significant effects of time was observed for all four response measures (SYS: F [2, 62] = 3.15, p = .049; DIA: F [2, 62] = 18, p < .001; MAP: F [2, 62] =

8.57, $p < .001$; HR: F [2, 62] = 16, $p < .001$) as well as the interaction between time * experimental condition (SYS: F [2, 62] = 10.4, $p < .001$; DIA: F [2, 62] = 11.2, $p < .001$; MAP: F [2, 62] = 9.05, $p < .001$; HR: F [2, 62] = 12.8, $p < .001$). No significant difference in heart rate nor blood pressure between experimental groups was seen at the start of the experiment (Table 4). During the CPT all cardiovascular parameters except the heart rate showed a significant difference depending on experimental group and after the CPT both experimental groups stopped differing significantly (Table 4).

Table 4. Summary of t-tests for cardiovascular responses and subjective ratings with experimental condition for each time phase in the exclusively male sample. Significant p-values (<.05) are bold.

Parameter	CPT		Control condition		t(62)	p
	M	*SD*	*M*	*SD*		
SYS:pre	119.8	7.96	119.3	7.09	-0.23	.817
SYS:during	**125.0**	**10.5**	**118.6**	**7.19**	**-2.84**	**.006**
SYS:post	122.1	10.5	119.7	9.02	-0.97	.335
DIA:pre	72.5	5.78	71.6	5.88	-0.62	.534
DIA:during	**76.9**	**6.85**	**72.1**	**6.25**	**-2.95**	**.004**
DIA:post	75.2	5.93	73.8	6.46	-0.9	.371
MAP:pre	88.0	5.83	88.9	3.92	0.71	.482
MAP:during	**92.9**	**5.36**	**89.1**	**4.91**	**-2.93**	**.004**
MAP:post	90.8	6.19	90.4	4.77	-0.27	.783
HR:pre	69.6	12.8	70.0	12.3	0.12	.904
HR:during	74.3	12.6	68.7	11.3	-1.88	.064
HR:post	67.8	11.1	66.9	10.4	-0.31	.757
Arousal:pre	13.5	16.5	13.8	17.9	0.07	.941
Arousal:during	**42.1**	**26.4**	**9.56**	**12.2**	**-6.32**	**.001**
Arousal:post	**32.1**	**30.1**	**14.6**	**19.7**	**-2.75**	**.007**
Stress:pre	12.9	16.8	13.7	16.9	0.19	.846
Stress:during	**36.6**	**23.3**	**11.5**	**13.1**	**-5.31**	**.001**
Stress:post	**28.9**	**30.1**	**13.8**	**19.7**	**-2.61**	**.011**

3.1.1.3 Subjective ratings of stress and arousal

For the subjective ratings the same ANOVA as above reported a significant effect of the experimental condition for both stress ratings (Arousal: F [1, 31] = 24.1, $p < .001$; Stress: F [1, 31] = 20.5, $p < .001$) as well as for time (Arousal: F [2, 62] = 13, $p < .001$; Stress: F [2, 62] = 9.26, $p < .001$) and the interaction of time * experimental condition (Arousal: F [2, 62] = 20.4, $p < .001$; Stress: F [2, 62] = 12.7, $p < .001$). Consistently, the t-tests showed no difference between groups at start, however differences emerged between experimental groups during the CPT. After the intervention arousal and stress ratings were higher in the CPT group than in the control group.

3.1.2. Effects of stress on frontal alpha asymmetry

To investigate the effect of stress on RFA a repeated measures ANOVA was run with experimental condition * time (pre, during, post) * electrode (F4-F3, F8-F7) as independent and RFA as dependent variable. However, only time showed a significant effect (F [4, 124] = 6.92, $p < .001$) and neither the experimental condition nor the interaction experimental condition and time were significant.

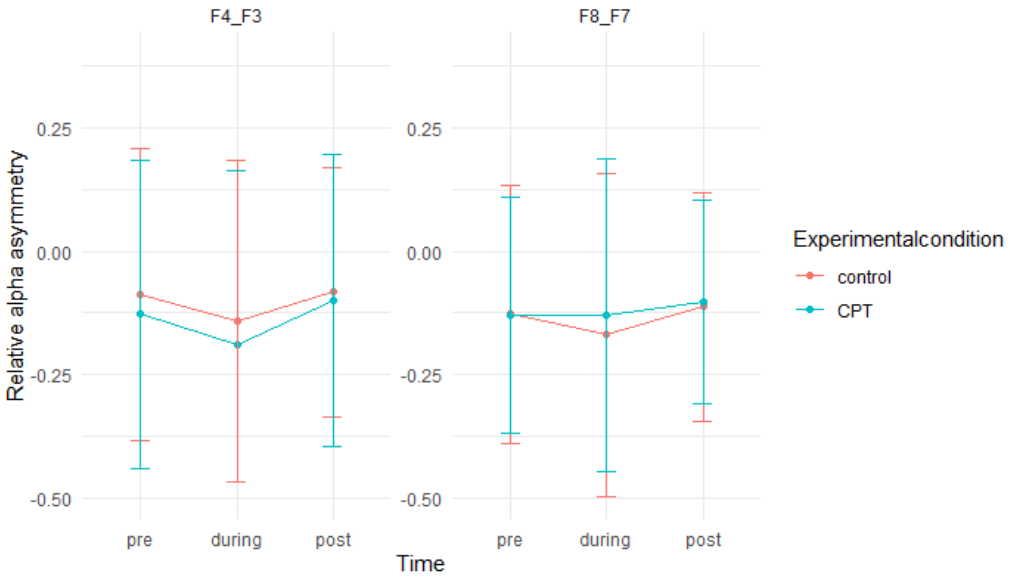

Fig. 5 RFA values before, during, and after CPT and control condition for male subjects (error bars show standard deviation)

3.1.3. RFA and stress responses

To evaluate the correlation of RFA with the stress parameters, bivariate Pearson correlations were computed (Table 5). The same format as in Zhang et al. (2018) was used for the correlation table to facilitate cross-comparison between the studies. For each stress parameter a baseline-correction was computed by subtracting the values during baseline (pre-CPT) from those of the CPT phase Cortisol AUCi thus represents the difference in cortisol between baseline and CPT, whereas Cortisol AUCg corresponds to the total cortisol measured during the experiment. In addition to the three experimental phases (pre, during, post) RFA values were averaged across the pre-phase of both measurement days and baseline corrected for the measurement day of the CPT.

None of the expected correlations between trait-RFA and cortisol were observed. Instead, contradictory to the hypothesis RFA at F8-F7 was positively correlated to Cortisol AUCi in the resting phases pre- and post-CPT (pre-CPT: r = .37, p = .037; post-CPT: r = .401, p = .022). Similarly, the response pattern between RFA and cardiovascular responses could not be replicated. The only expected results are negative correlations between RFA at F4-F3 and HR pre-, during- and post-CPT (pre-CPT: r = -.537, p = .001; during-CPT: r = -.486, p = .004; post-CPT: r = -.481, p = .005). Additionally, however only marginally significant was the correlation between DIA and pre-CPT RFA at F4-F3 (r = -.339, p = 0.58). In contrast to the original study, both-day RFA at F4-F3 was negatively correlated with DIA (r = -.542, p = .001) and was marginally significant for SYS, MAP and HR (SYS: r = -.323, p = .071; DIA: r = -.345, p = .053; HR: r = -.323, p = .071). Two aberrant and unexpected findings are the correlations of RFA at F8-F7 with MAP pre-CPT (r = -.366, p = .039) and baseline-corrected RFA and SBP (r = .41, p = .019). Lastly, the expected correlation with subjective stress and arousal ratings were insignificant and instead stress ratings correlated positively with average pre-CPT RFA at F4-F3 (r = .382, p =031).

Table 5. Pearson correlation coefficients with *p*-values in brackets between RFA conditions and baseline corrected stress parameters of the exclusively male sample. Significant *p*-values (<.05) of the current study are bold and significant *p*-values of the replicated study are underscored.

	Average	Pre	Pre		During		Post		Δ (During- Pre)	
	F4-F3	F8-F7	F4-F3	F8-F7	F4-F3	F8-F7	F4-F3	F8-F7	F4-F3	F8-F7
Cortisol										
AUCg	.117	.173	.265	.211	.315	.115	.262	.185	.173	−.081
	(.523)	(.344)	(.142)	(.245)	(.079)	(.528)	(.147)	(.311)	(.341)	(.66)
AUCi	.074	.182	.273	**.37**	.278	.233	.275	**.401**	.079	−.085
	(.686)	(.318)	(.13)	**(.037)**	(.124)	(.198)	(.127)	**(.022)**	(.668)	(.643)
Cardiovascular responses										
Δ SBP	−.323	−.156	−.066	−.134	−.007	.121	.004	.012	.111	**.41**
	(.071)	(.392)	(.717)	(.465)	(.968)	(.51)	(.982)	(.949)	(.546)	**(.019)**
Δ DIA	**−.542**	−.29	-.339	−.27	−.301	−.209	−.145	−.000	−.006	−.009
	(.001)	(.107)	(.058)	(.134)	(.093)	(.251)	(.428)	(.999)	(.975)	(.958)
Δ MAP	−.345	−.331	−.214	**−.366**	−.149	−.155	−.132	−.266	.086	.223
	(.053)	(.064)	(.238)	**(.039)**	(.414)	(.395)	(.471)	(.14)	(.639)	(.219)
Δ HR	−.323	.029	**−.537**	.013	**−.486**	.072	**−.481**	.05	−.026	.114
	(.071)	(.873)	**(.001)**	(.944)	**(.004)**	(.697)	**(.005)**	(.784)	(.887)	(.533)
Subjective ratings										
Δ arousal	−.222	.196	−.043	.224	−.09	.138	−.006	.282	−.113	−.056
	(.222)	(.282)	(.816)	(.218)	(.623)	(.449)	(.972)	(.118)	(.538)	(.762)
Δ stress	.037	**.382**	.033	.260	−.01	.175	−.039	.070	−.084	−.038
	(.841)	**(.031)**	(.858)	(.150)	(.956)	(.337)	(.831)	(.702)	(.647)	(.832)

3.2 Mixed-sex sample results

In the replicated analysis the repeated measures ANOVAs included sex as a predictor variable to evaluate the effect of sex on the analysed correlations.

3.2.1 Stress responses

3.2.1.1 Cortisol

The analysis between cortisol as dependent variable and experimental condition (CPT, control), time (0, 10, 22, 43, 65, 84, 95, 125 min.) and sex (male, female) as independent variables showed again a significant effect of experimental condition (F [1, 66] = 21.2, p < .001), time (F [7, 462] = 10.3, p < .001) and the interaction between time * experimental condition (F [7, 462] = 10.3, p < .001) confirming the success of the stress induction in the mixed-sex sample. Sex itself was not significant (F [1, 66] = 0.052, p < .82) however the interaction between sex and experimental condition was significant (F [1, 66] = 8.15, p < .005). In the total sample, experimental groups did not differ from another prior to the intervention this time (0-22 min. t[134] < -0.473, p > .108). Similar to the male sample, the intervention induced a significant difference between experimental groups (43-95 min. t[134] < -2.231, p < .027).

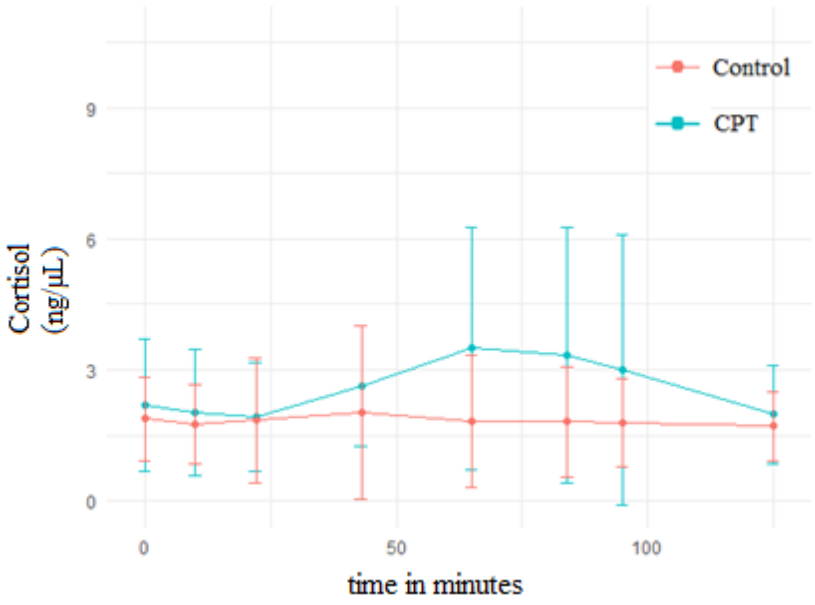

Fig. 6 Cortisol values over time by experimental condition for the mixed-sex sample (error bars show standard deviation)

3.2.1.2 Heart rate and blood pressure

The ANOVA revealed significant effects of the experimental condition on all cardiovascular parameters including HR in the mixed-sex sample (SYS: F [1, 66] = 10.3, p = .002; DIA: F [1, 66] = 39.8, p < .001; MAP: F [1, 66] = 18.9, p < .001; HR: F [1, 66] = 4.19, p = .044). As in the exclusively male sample all cardiovascular measurements showed significant effects of time (pre, during, post) and the interaction of experimental condition and time. The addition of sex as a predictor revealed a significant effect of sex on systolic blood pressure (F [1, 66] = 15.9, p < .001) and a marginally significant effect on mean arterial blood pressure (F [1, 66] = 3.9, p = .052). The interaction of sex with other parameters was insignificant.

3.2.1.3 Subjective ratings of stress and arousal

The results of the ANOVA on subjective ratings of stress and arousal are the same in the mixed-sex sample with significant effects of experimental condition, time and the interaction of time * experimental condition for both parameters. Also, the t-tests showed no difference between samples with no differences between experimental groups at start, significant differences during the intervention and higher arousal and stress ratings in the CPT group after the intervention. In both ANOVAs sex was not a significant predictor (Arousal: F [1, 66] = 0.77, p = .383; Stress: F [1, 66] = 1.74, p = .191).

3.2.2. Effects of stress on frontal alpha asymmetry

In the replicated ANOVA on experimental condition * time * electrode with RFA as dependent variable sex was added as a fourth independent variable. However, as before only time showed a significant main effect (F [4, 264] = 5.01, p < .001) and neither experimental condition, electrode, sex, nor the interactions were significant.

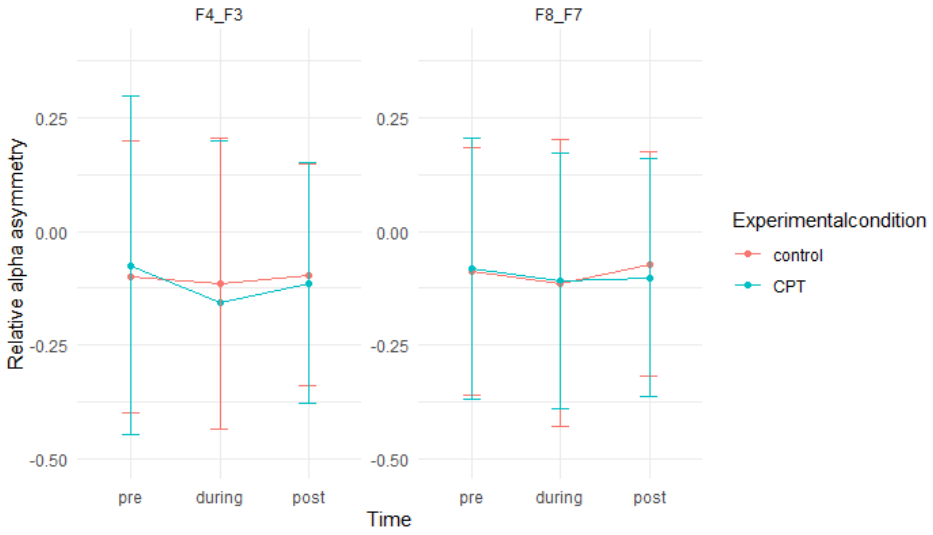

Fig. 7 RFA values before, during, and after CPT and control condition for the mixed-sex sample (error bars show standard deviation)

Table 6. Pearson correlation coefficients with *p*-values in brackets between RFA conditions and baseline corrected stress parameters of the mixed-sex sample. Significant *p*-values (<.05) of the current study are bold and significant *p*-values of the replicated study are underscored.

	Average	Pre	Pre		During		Post		Δ (During- Pre)	
	F4-F3	F8-F7	F4-F3	F8-F7	F4-F3	F8-F7	F4-F3	F8-F7	F4-F3	F8-F7
Cortisol										
AUCg	−.045	.047	.032	.068	.088	.088	.162	.124	.077	.024
	(.715)	(.706)	(.795)	(.585)	(.479)	(.478)	(.187)	(.315)	(.536)	(.851)
AUCi	.006	.117	.088	.169	.114	.159	.184	.204	.029	−.017
	(.960)	(.344)	(.478)	(.172)	(.358)	(.198)	(.135)	(.096)	(.811)	(.889)
Cardiovascular responses										
Δ SBP	−.145	.158	−.129	.077	−.139	−.152	.096	.124	−.005	.091
	(.237)	(.197)	(.291)	(.533)	(.256)	(.216)	(.437)	(.310)	(.966)	(.461)
Δ DIA	−.151	−.006	−181	.000	−.233	−.036	−.099	.095	−.063	−.045
	(.217)	(.961)	(.140)	(.998)	(.055)	(.771)	(.419)	(.437)	(.611)	(.714)
Δ MAP	−.157	−.062	−.166	−.099	−.182	−.052	−.115	−.041	−.011	.062
	(.202)	(.616)	(.175)	(.419)	(.138)	(.673)	(.352)	(.739)	(.931)	(.613)
Δ HR	−.198	.075	**−.343**	.014	**−.406**	.043	**−.369**	−.039	−.067	.036
	(.105)	(.545)	**(.004)**	(.908)	**(.000)**	(.726)	**(.002)**	(.746)	(.587)	(.772)
Subjective ratings										
Δ arousal	−.065	.109	.056	.136	−.012	.023	−.065	.114	−.100	−.145
	(.596)	(.377)	(.646)	(.268)	(.924)	(.85)	(.599)	(.355)	(.415)	(.237)
Δ stress	.018	.132	.052	.103	−.028	.004	.012	.008	−.116	−.127
	(.884)	(.283)	(.673)	(.404)	(.822)	(.973)	(.919)	(.949)	(.344)	(.303)

3.2.3. RFA and stress responses

In the replicated correlation table using bivariate Pearson correlation no clear relation between RFA and any of the stress parameters was found (Table 6). The only significant correlations were found for heart rate with RFA at F4-F3 pre-, during-, and post CPT (pre-CPT: r = -.343, p = .004; during-CPT: r = -.406, p < .001; post-CPT: r = -.369, p = -.002). The effect sizes indicate that more right-sided activity

corresponded to higher increases in heart rate. Cortisol and subjective ratings were not correlated with RFA at any condition.

4. Discussion

Establishing RFA as a reliable correlate of the stress response holds value for both basic as well as clinical research. Therefore, the current study aimed at replicating a recent influential paper on RFA by Zhang et al. (2018) to confirm the reliability of structural RFA as a predictor of the neuroendocrine stress response and functional changes in RFA during the stress induction. First, the original study was replicated with identical sample criteria including only male subjects. Secondly the sample was extended with female participants to examine the generalizability of the results for a mixed-sex sample.

The current study successfully replicated the stress induction of Zhang et al. (2018) shown by increases in cardiovascular measures and cortisol levels. However, RFA was contrary to the predictions not significantly affected by the experimental condition. Similarly, the expected response patterns between baseline RFA and cortisol and cardiovascular responses each was not observed. HR was the only exception showing the same correlations as reported by Zhang et al. (2018) with RFA at F4-F3 pre, during and post stress. Furthermore, no stress induced shift in RFA was recorded as RFA only changed significantly over the course of the experiment irrespective of experimental condition.

Inconsistent correlations between RFA and cortisol have already been found in previous studies. Thus, for example Tops et al. (2005, 2006) first observed a shift to right-sided activity after cortisol injection however in a replication study the asymmetry shifted towards higher left-sided activity. Similarly, the current study found a contradictory correlation between cortisol and stronger left-sided RFA compared to Zhang et al. (2018) who observed a correlation with stronger right-sided activity. Furthermore, the correlation was only observed with same day pre- and post-RFA scores and at the electrode pair F8-F7 which was expected to be unrelated to stress parameters.

Several studies proposed potential explanations to these divergent findings in relation to cortisol. Firstly, Glier et al. (2022) argued the relation between RFA and the stress response differs in respect to the reactivity to and recovery from stress. They found that right-sided RFA throughout their experiment corresponded to blunted cortisol increases in response to stress while left-sided RFA was correlated with prolonged cortisol recovery phases (Glier et al., 2022). As the current study quantified the cortisol response based on the area under the curve which summarizes both the increase and decrease of cortisol in relation to the time between each measurement this might potentially explain the inconsistent results of this study in comparison to Zhang et al. (2018). Thus, for more insight, it may be useful to separate the cortisol response in two distinct phases of reactivity and recovery. Similarly, Quaedflieg et al. (2015) argued that the stress response might itself involve a lateralized process respective to the phases of reactivity to and regulation of stress. Generally, research suggests that the stress response is initiated by right-sided activity whereas the regulation and return to homeostasis is driven by left-sided activity (Quaedflieg et al., 2015). Consequently, the current research might have inadequately conceptualized the stress response as well as functional changes in RFA as a single distinct phase and not as two phases corresponding to the reaction to and regulation of stress.

A different explanation was brought forth by two studies which considered potential confounding effects of co-morbidity or heterogeneity within their samples as for example anxiety or depression play a role in emotional regulation. Consequently, they controlled for trait tendencies of anxiety and action orientation highlighting that this differentiation was integral to observing significant correlations between RFA and cortisol in their samples (Düsing et al., 2016; Glier et al., 2022). Action orientation describes the ability to efficiently switch from contemplation of potential actions to their implementation and is therefore closely related to the concept of approach-oriented behaviour as described by Davidson et al. (1990) in their approach-withdrawal model (Düsing et al., 2016). Similarly, anxiety is frequently considered to be closely related to an individual's stress responsivity (Glier et al., 2022). Specifically, these studies found subjects with high trait anxiety and low action orientation showed stronger correlations of RFA and cortisol (Düsing et al., 2016; Glier et al., 2022). As such controlling for trait tendencies of emotional responding might be an important addition to the capability model of individual differences by Coan et al. (2006) as the functional changes in RFA expected during emotional processing might only reach statistical significance when considering stress-related trait differences.

Besides cortisol, Zhang et al. (2018) observed a particular response pattern between RFA and cardiovascular measurements. However, in the current study, all cardiovascular measurements were correlated to both-day baseline RFA and only with marginal significance. Therefore, the present study does not reflect the results of Zhang et al. (2018) showing cardiovascular measurements to be primarily correlated with same-day baseline RFA and subsequently contradicts their claim that cardiovascular measurements seem susceptible to mood-fluctuations. This furthermore implies more generally that the differentiation between cortisol as a more robust trait-component of RFA as compared to cardiovascular responses as a more mood-dependent reaction is also not supported. The only consistent result throughout both replication and original study was HR. It thus seems as if HR is a fairly robust correlate of RFA at F4-F3 pre-, during- and post-stress induction, however further inference is limited by the fact that no other RFA studies measured cardiovascular activity.

The second main research goal investigated the functional shift towards right-sided RFA measured by Zhang et al. (2018) during the stress induction. However, the current study was unable to replicate this state-dependent change in RFA raising doubt on the reliability of RFA as an index of situational emotional processing. While Zhang et al. (2018) argued other studies failed to measure this change in activity due to it being short-lived and not observable in pre- to post-stress comparisons of RFA the current replication has shown that even during stress induction the functional shift is not reliably measurable. Instead, a significant effect of time on RFA irrespective of experimental condition was found. As the success of the stress induction procedure was reflected in cortisol and cardiovascular measurements as well as subjective stress and arousal ratings it seems unlikely that both bfCPT and control condition evoked the same changes in RFA over time. Rather, this effect might be due to the

increased number of stress inductions and control procedures as compared to the original study which could have introduced effects due to tiredness or exhaustion throughout the experiment.

A supplementary finding is presented by the positive correlation between subjective stress ratings and the average resting RFA of both measurement days observed in the exclusively male sample. Zhang et al. (2018) observed baseline-corrected RFA to be negatively correlated with subjective ratings of stress and arousal. Finding yet another correlation of opposite direction provides another argument for yet unaccounted periods of the stress response This is highlighted by the fact that the current study observed the correlation in relation to baseline RFA representing trait-like characteristics whereas Zhang et al. (2018) observed the correlation in regards to baseline-corrected RFA, reflecting state-dependent activation present during the stressor. Thus, conceptualizing the reactivity to and recovery from stress as two distinct phases of the stress response might clear up these inconsistencies. Lastly, besides the inconsistent correlations between RFA and stress ratings, establishing a link between the subjective experience of stressful events and RFA is an important advancement with the potential to measure individual differences in emotional responding and processing.

Regarding the mixed-sex sample, sex differences were found for cortisol, systolic and mean arterial blood pressure. Regarding cortisol, sex differences were only significant for the interaction of sex and experimental condition revealing that sex did not affect baseline cortisol levels but cortisol responsivity after stress induction. Previous studies support this result showing that laboratory stressors have repeatedly been observed to evoke stronger cortisol responsivity in male compared to female subjects (Quaedflieg et al., 2015). Furthermore, it might explain why the correlation between RFA and the increase in cortisol represented by cortisol AUCi lost significance in the mixed-sex sample. In contrast systolic and mean arterial blood pressure were significantly and marginally significantly correlated with sex as single predictor suggesting overall sex differences in these parameters that are not specific to the stress induction. As such sex might have confounded with the correlations analysed in the correlation table between RFA and cardiovascular parameters. Due to the different responsivity in stress response parameters due to subjects' sex it is important to include sex as a predictor in the statistical models on mixed-sex samples and continue to investigate significant effects of sex in future studies. While the correlation table for the mixed-sex sample showed overall less significant correlation it is important to consider that this might be also a byproduct of the increased sample size in the mixed-sex sample. Lastly, as this study was unable to observe state-dependent changes in RFA as seen in Zhang et al. (2018) in both the male and mixed-sex sample, finding no sex-related differences in this analysis might also be attributed to the overall insignificance of the present results instead of evidence for the absence of sex-differences in functional RFA.

Looking back on the research questions the current study presents some crucial implications. It falls in line with a lot of other comparable studies yielding unexpected and inconsistent results. The lack of replicability despite the identical methodology limits the reliability of previously made interpretations of Zhang et al. (2018) and puts into question the contemporary conceptualization and theoretical model

underlying RFA. As such the following claims made by Zhang et al. (2018) cannot be confirmed by the present results. Firstly, the predictive power of RFA at F4-F3 on cardiovascular and cortisol responses, secondly, the reliability of RFA at F8-F7 as a marker of state-dependent affective processing and thirdly, the proclaimed distinct roles of the two examined electrode pairs in the stress response. Additionally, as mentioned before, the present results do not confirm that cortisol is a more robust and trait-like component of RFA whereas cardiovascular measurements are more susceptible to mood-fluctuations. Because this is currently the only study besides Zhang et al. (2018) with physical stress induction it is important to evaluate the reliability of the stress induction. Unfortunately, as the current study did not replicate the state-dependent changes in RFA reported by Zhang et al. (2018) it could not establish the bfCPT or physical stress induction as methodologically superior for investigating functional changes in RFA in comparison to psychosocial stressors. While physical stress induction nonetheless provides the possibility to measure RFA during stress, it did not lead to more informative results on functional RFA changes than comparable studies with psychosocial stressors.

4.1 Limitations

Some limitations of the current study have to be considered. Firstly, a major limitation in respect to the replication lies in the repeated CPTs which might have caused habituation or desensitisation effects not present in the original study. This change was made for a separate research question unrelated to the current study, however it significantly limits the validity of the replication. While Berretz et al. (2018) as well as Coan and Allen (2004) argued that RFA presents good reliability especially within same sessions, it is nonetheless possible that the repeated exposure to the bfCPT affected the neuroendocrine reaction to the separate stress inductions over time. Thus, the lack of a significant state-dependent change in RFA during stress induction in the present study might also be attributable to the discrepancy in stress induction procedures between the replication and original study.

Furthermore, the significantly higher levels of cortisol observed in the CPT group of the exclusively male sample at the start of the experiment indicate issues with the randomization. As this baseline difference was not observed in the mixed-sex sample and the order of experimental conditions was counterbalanced between subjects it seems unlikely that a systematic issue in the experimental procedure caused it.

Lastly, the used statistical model might be inadequate to reveal the interaction of RFA and the stress responses. As argued by Coan and Allen (2004), three possible models could describe the relation between stress and RFA including linear, non-linear, and lastly step-function models. A Bayesian approach would allow to fit non-linear models, compute repeated measure analyses with continuous variables such as time and relaxes assumptions of normality and equal variance. Furthermore, it would rule out the risk of false positives produced by frequentist approaches. Consequently, a more exploratory approach comparing the model fit of different statistical models might be the best choice to advance the contemporary theoretical understanding and move past inconsistent results.

4.2 Conclusion

In conclusion, the current study could not confirm RFA as the state-dependent marker of emotional processing as presented by Zhang et al. (2018). While RFA was again correlated to cortisol responses as well as cardiovascular measures and subjective stress ratings indicating predictive power as a trait index, the observed response pattern contradicted commonly accepted conceptualizations of RFA as correlations were positive and not negative as predicted. Similarly, the previously reported state-dependent changes in RFA could not be replicated in the current study. As such the current study demonstrated the lack of replicability of studies supporting contemporary conceptualizations of RFA even despite almost identical methodology. To overcome these inconsistent results, it is suggested to differentiate the stress response in two distinct phases corresponding to the reactivity and regulation of stress respectively. Lastly, in extension of Coan and Allen (2004) it is recommended to explore non-linear statistical models to describe the interaction between RFA and stress response parameters to account for potentially disregarded types of interaction for both trait- and state-dependent RFA.

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Appendix A

Correlation table Zhang et al. (2018)

Pearson correlation coefficients and *p*-values (in brackets) of correlations between RFA before ("pre"), during and after ("post") the bfCPT, as well as the average pre- intervention RFA ("average pre") of both days and different stress responses. Bold values indicate $p < .05$.

	Average Pre		Pre		During		Post		Δ (During-Pre)	
	F4-F3	F8-F7	F4-F3	F8-F7	F4-F3	F8-F7	F4-F3	F8-F7	F4-F3	F8-F7
Cortisol										
AUCg	**−.546**	−.157	**−.512**	−.324	−.364	−.203	−.385	−.342	−.248	−.099
	(.010)	(.496)	**(.018)**	(.152)	(.104)	(.377)	(.085)	(.129)	(.278)	(.670)
AUCi	**−.448**	−.029	−.429	−.214	−.290	−.140	−.410	−.270	−.230	−.019
	(.042)	(.496)	(.052)	(.352)	(.202)	(.546)	(.065)	(.237)	(.316)	(.935)
Cardiovascular responses										
Δ SBP	−.447	−.119	**−.494**	−.169	**−.567**	−.256	−.376	−.043	.082	−.032
	(.055)	(.628)	**(.032)**	(.489)	**(.011)**	(.291)	(.113)	(.860)	(.740)	(.896)
Δ DIA	−.341	−.181	**−.498**	−.422	**−.587**	−.214	−.270	−.186	−.139	.031
	(.153)	(.458)	**(.030)**	(.072)	**(.008)**	(.380)	(.263)	(.446)	(.571)	(.901)
Δ MAP	−.390	−.210	**−.540**	−.388	**−.655**	−.310	−.339	−.191	.062	.202
	(.099)	(.388)	**(.017)**	(.101)	**(.002)**	(.156)	(.104)	(.433)	(.800)	(.407)
Δ HR	−.401	−.275	**−.563**	−.367	**−.472**	−.232	**−.621**	**−.556**	.110	.114
	(.089)	(.254)	**(.012)**	(.122)	**(.041)**	(.338)	**(.005)**	**(.013)**	(.653)	(.643)
Subjective ratings										
Δ arousal	−.368	.089	−.307	−.001	.059	.213	−.289	−.060	**−.548**	−.296
	(.101)	(.700)	(.176)	(.997)	(.800)	(.353)	(.203)	(.795)	**(.010)**	(.193)
Δ stress	−.292	.218	−.204	.146	.115	.303	−.255	.030	**−.473**	−.275
	(.198)	(.342)	(.375)	(.527)	(.620)	(.181)	(.265)	(.899)	**(.030)**	(-228)

Appendix B

Replicating “The role of relative frontal alpha asymmetry in shaping the stress response” in a mixed sex sample

Milan

2023-09-25

#Packages

```
library(tidyverse)
library(openxlsx)
library(readxl)
library(writexl)
library(dplyr)
library(rstanarm)
#library(bayr)
library(brms)
library(stringr)
library(ggplot2)
library(zoo)
library(ggpubr)
library(psych)
library(afex)
library(rstatix)
library(lme4)
```

#Data

```
VP_Data <- read_csv("VP Data Exp102-103.csv")
Cortisol_102 <- read_csv("Cortisol Exp102.csv")
Cortisol_103 <- read_excel("Cortisol_Exp103.xlsx")
FAA <- read_excel("FAA DATA.xlsx")
Rating_102 <- read_csv("rating_102.csv")
Rating_103 <- read_csv("rating_103.csv")

#Exclude participants with insufficient data
exclude_participant_numbers <- c(8, 9, 10, 15, 16, 30, 32, 34, 36, 39, 50, 58, 65, 73, 74)

filter_participant_numbers <- function(df) {df %>%  filter(!vp_overall %in% exclude_participant_numbers
)}
```

##joining VP_Data from 102 and 103

```
VP_Data <- VP_Data %>%
  mutate(vp_overall = ifelse(vp_overall >= 101 & vp_overall <= 143, vp_overall - 60, vp_overall))

VP_Data <- VP_Data %>%
  select(-exp, -vp_exp, -both_sessions)

VP_Data <- VP_Data %>%
  mutate(across(-c(vp_overall, sex, group), as.double))

#filter excluded participants
VP_Data <- filter_participant_numbers(VP_Data)
```

#changing wide format into long format

```
VP_Data_long <- VP_Data %>%
  pivot_longer(
    cols = -c(vp_overall, age, group, sex),
    names_to = "measurement",
    values_to = "dinamap")
```

```r
VP_Data_long <- VP_Data_long %>%
  separate(measurement, into = c("type", "session"), sep = "_", remove = FALSE)

VP_Data_long <- VP_Data_long %>%
  mutate(measurement = str_extract(measurement, "\\d+"))

# Keep only the letter in 'type'
VP_Data_long <- VP_Data_long %>%
  mutate(type = str_extract(type, "[A-Za-z]")) %>%
  mutate(session = as.double(session))

#adding experimental condition, order and CPT_order
VP_Data_long <- VP_Data_long %>%
  mutate(
    Experimentalcondition = ifelse(group %in% c(1, 2), ifelse(session == 1, 'CPT', 'control'), ifelse(s
ession == 1, 'control', 'CPT')),
    Order = ifelse(group %in% c(1, 2), 'Stress first', 'Control first'),
    CPT_order = ifelse(group %in% c(1, 3), 'left first', 'right first'))

#average among pre, during, and post
VP_Data_average <- VP_Data_long %>%
  mutate(time = case_when(
    between(as.numeric(measurement), 1, 4) ~ "pre",
    between(as.numeric(measurement), 5, 13) ~ "during",
    between(as.numeric(measurement), 14, 17) ~ "post",
    TRUE ~ "Other"))

VP_Data_average <- VP_Data_average %>%
  group_by(vp_overall, session, type, time, group, Experimentalcondition, Order, CPT_order, age, sex) %
>%
  summarize(dinamap_average = mean(as.numeric(dinamap), na.rm = TRUE))

#spreading dinamap measurements
VP_Data_average <- VP_Data_average %>%
  pivot_wider(names_from = type, values_from = dinamap_average)

#filling in missing values
values_to_copy <- VP_Data_average[2, c('d', 'm', 'p', 's')]
VP_Data_average[c(123, 223, 224, 225), c('d', 'm', 'p', 's')] <- values_to_copy

#Perform baseline correction
VP_baseline <- VP_Data_average %>%
  group_by(vp_overall, Experimentalcondition) %>%
  filter(time == "pre") %>%
  summarise(baseline_value_d = (d),
            baseline_value_m = (m),
            baseline_value_p = (p),
            baseline_value_s = (s))

VP_Data_baseline_corr <- VP_Data_average %>%
  left_join(VP_baseline, by = c("vp_overall", "Experimentalcondition")) %>%
  mutate(d_corrected = d - baseline_value_d,
         m_corrected = m - baseline_value_m,
         p_corrected = p - baseline_value_p,
         s_corrected = s - baseline_value_s) %>%
  filter(time == "during")

VP_Data_baseline_corr = subset(VP_Data_baseline_corr, select = c(vp_overall, Experimentalcondition, d_c
orrected, m_corrected, p_corrected, s_corrected, sex))

#population level mean and sd
VP_Data_summary <- VP_Data_average %>%
  group_by(time, Experimentalcondition) %>%
  summarise(
    avg_d = mean(d),
    avg_m = mean(m),
    avg_p = mean(p),
    avg_s = mean(s),
    sd_d = sd(d),
    sd_m = sd(m),
    sd_p = sd(p),
    sd_s = sd(s))
```

##adding VP_Data key variable to Cortisol Data from 102 and 103

```r
#creating participant, session, and measurement number
Cortisol_103 <- Cortisol_103 %>%
  mutate(vp_overall = as.numeric(sub("^VP(\\d+); EXP: 103; M(\\d+)-(\\d+)$", "\\1", ProbenID)),
         Session = as.numeric(sub("^VP(\\d+); EXP: 103; M(\\d+)-(\\d+)$", "\\2", ProbenID)),
         Measurement = as.numeric(sub("^VP(\\d+); EXP: 103; M(\\d+)-(\\d+)$", "\\3", ProbenID)))

Cortisol_103 <- Cortisol_103 %>%
  mutate(vp_overall = vp_overall + 40,
        Measurement_1 = as.double(Measurement_1),
        Measurement_2 = as.double(Measurement_2))

#adding group variable
Cortisol_103 <- left_join(Cortisol_103, VP_Data %>% select(vp_overall, group, sex), by = 'vp_overall')
%>%
  rename(measurement = Measurement,
         session = Session)

Cortisol_102 <- Cortisol_102 %>%
  mutate(sex = as.double(sex)) %>%
  rename(vp_overall = Subject,
         Measurement_1 = X1..Messung,
         Measurement_2 = X2..Messung,
         `Cortisol [ng/µL]` = Mittelwert,
         group = Group,
         session = Session,
         measurement = Measurement)
```

##merging Cortisol data

```r
Cortisol_Complete <- bind_rows(Cortisol_102, Cortisol_103)

#filtering exluded participants
Cortisol_Complete <- filter_participant_numbers(Cortisol_Complete)

Cortisol_Complete <- Cortisol_Complete %>%
  select(-ordered, -`Nr.`, -Measurement_min, -Measurement_fac, -ProbenID, -`CV [%]`, -cort_nmolL, -cort
, -Anmerkungen, -sex) %>%
  rename(Cortisol = `Cortisol [ng/µL]`)

Cortisol_Complete <- Cortisol_Complete %>%
  mutate(
    Experimentalcondition = ifelse(group %in% c(1, 2), ifelse(session == 1, 'CPT', 'control'), ifelse(s
ession == 1, 'control', 'CPT')),
    Order = ifelse(group %in% c(1, 2), 'Stress first', 'Control first'),
    CPT_order = ifelse(group %in% c(1, 3), 'left first', 'right first'))

#filling in and correcting measurement_t
Cortisol_Complete <- Cortisol_Complete %>%
  mutate(Measurement_t = ifelse(Measurement_t >= 17, Measurement_t + 5, Measurement_t))

Cortisol_Complete <- Cortisol_Complete %>%
  mutate(Measurement_t = ifelse(vp_overall > 40, Measurement_t[vp_overall <= 40], Measurement_t))

Cortisol_Complete <- Cortisol_Complete %>%
  mutate(Measurement_t = ifelse(row_number() %in% c(1153:1160), c(0, 10, 22, 43, 65, 84, 95, 125), Meas
urement_t))

#approximate missing values for AUCg computation
Cortisol_Complete <- Cortisol_Complete %>%
  arrange(vp_overall, Measurement_t) %>%
  group_by(vp_overall) %>%
  mutate(Cortisol = zoo::na.approx(Cortisol, na.rm = FALSE))

Cortisol_Complete <- Cortisol_Complete %>%
  group_by(vp_overall, session) %>%
  mutate(Cortisol = ifelse(
      measurement == 8 &
      ((vp_overall == 8 & session == 1) |
       (vp_overall %in% c(19, 35, 40, 50, 65) & session == 2)),
      first(Cortisol),
      Cortisol))

#deleting empty rows
Cortisol_Complete <- Cortisol_Complete[complete.cases(Cortisol_Complete$vp_overall), ]
```

```r
#computing AUCg for measurement
Cortisol_AUC <- Cortisol_Complete %>%
  group_by(vp_overall, Experimentalcondition, Order, CPT_order) %>%
  summarize(
    Cortisol_AUCg = (((Cortisol[-1] + Cortisol[-n()]) * diff(Measurement_t)) / 2),
    Cortisol_AUCg_Cum = cumsum(Cortisol_AUCg),
    Cortisol_AUCi = Cortisol_AUCg_Cum - first(Cortisol) * 125)

#adding timestamps to Cortisol_AUCg
measurement_t_values <- c(10, 22, 43, 65, 84, 95, 125)
time_values <- c('pre', 'pre', 'during', 'during', 'during', 'post', 'post')

Cortisol_AUC <- Cortisol_AUC %>%
  group_by(vp_overall, Experimentalcondition) %>%
  mutate(measurement_t = rep(measurement_t_values, length.out = n()),
    time = rep(time_values, length.out = n())) %>%
  ungroup()

#adding timestamps to cortisol_complete
measurement_t_values_2 <- c(0, 10, 22, 43, 65, 84, 95, 125)
time_values_2 <- c('pre', 'pre', 'pre', 'during', 'during', 'during', 'post', 'post')

Cortisol_Complete <- Cortisol_Complete %>%
  group_by(vp_overall, Experimentalcondition) %>%
  mutate(measurement_t = rep(measurement_t_values_2, length.out = n()),
    time = rep(time_values_2, length.out = n())) %>%
  ungroup()

Cortisol_Complete <- Cortisol_Complete %>%
  group_by(vp_overall, Experimentalcondition, time) %>%
  mutate(Cortisol_mean_time = mean(Cortisol))

Cortisol_Complete_time <- Cortisol_Complete %>%
  group_by(vp_overall, Experimentalcondition, time) %>%
  slice(1)

Cortisol_Complete_pre <- Cortisol_Complete_time %>%
  filter(time == "pre") %>%
  slice(1)

Cortisol_Complete_during <- Cortisol_Complete_time %>%
  filter(time == "during") %>%
  slice(1)

Cortisol_Complete_post <- Cortisol_Complete_time %>%
  filter(time == "post") %>%
  slice(1)

#sum Cort_AUCg by time and create pre, during, and post dataset
Cortisol_AUC <- Cortisol_AUC %>%
  group_by(vp_overall, Experimentalcondition, time) %>%
  mutate(Cortisol_AUCg_Sum_cond = sum(Cortisol_AUCg))

Cortisol_AUC_pre <- Cortisol_AUC %>%
  filter(time == "pre") %>%
  slice(1)

Cortisol_AUC_during <- Cortisol_AUC %>%
  filter(time == "during") %>%
  slice(1)

Cortisol_AUC_post <- Cortisol_AUC %>%
  filter(time == "post") %>%
  slice(1)

Cortisol_AUC_total <- Cortisol_AUC %>%
  filter(measurement_t == "125")
Cortisol_AUC_total = subset(Cortisol_AUC_total, select = c(vp_overall, Experimentalcondition, Cortisol_
AUCg_Cum, Cortisol_AUCi))

Cortisol_AUC_time <- Cortisol_AUC %>%
  group_by(vp_overall, Experimentalcondition, time) %>%
  slice(1)
```

##adding VP_Data key variable to Rating Data from 102 and 103

```
Rating_102 <- Rating_102 %>%
  mutate(vp_overall = Subject)

Rating_103 <- Rating_103 %>%
  mutate(vp_overall = Subject + 40)
```

##merging Rating Data

```
#merging
Rating_Complete <- bind_rows(Rating_102, Rating_103)

#filter excluded participants
Rating_Complete <- filter_participant_numbers(Rating_Complete)

#adapting variables
Rating_Complete <- Rating_Complete %>%
  select(-Subject) %>%
  rename(group = Group,
         session = Session)

Rating_average <- Rating_Complete %>%
  mutate(time = case_when(
    between(as.numeric(measurement), 1, 2) ~ "pre",
    between(as.numeric(measurement), 3, 7) ~ "during",
    between(as.numeric(measurement), 8, 9) ~ "post",
    TRUE ~ "Other"))

Rating_average <- Rating_average %>%
  group_by(vp_overall, session, time, group) %>%
  summarize(stress = mean(as.numeric(stress), na.rm = TRUE),
            erregung = mean(as.numeric(erregung), na.rm = TRUE),
            schmerz = mean(as.numeric(schmerz), na.rm = TRUE))

Rating_average <- Rating_average %>%
  mutate(
    Experimentalcondition = ifelse(group %in% c(1, 2), ifelse(session == 1, 'CPT', 'control'), ifelse(s
ession == 1, 'control', 'CPT')),
    Order = ifelse(group %in% c(1, 2), 'Stress first', 'Control first'),
    CPT_order = ifelse(group %in% c(1, 3), 'left first', 'right first'))

#Perform baseline correction
Rating_baseline <- Rating_average %>%
  group_by(vp_overall, Experimentalcondition) %>%
  filter(time == "pre") %>%
  summarise(baseline_value_subj_stress = (stress),
            baseline_value_arousal = (erregung))

Rating_baseline_corr <- Rating_average %>%
  left_join(Rating_baseline, by = c("vp_overall", "Experimentalcondition")) %>%
  mutate(subj_stress_corr = stress - baseline_value_subj_stress) %>%
  mutate(arousal_corr = erregung - baseline_value_arousal) %>%
  filter(time == "during")

Rating_baseline_corr = subset(Rating_baseline_corr, select = c(vp_overall, Experimentalcondition, subj_
stress_corr, arousal_corr))

#population level mean and sd
Rating_summary <- Rating_average %>%
  group_by(time, Experimentalcondition) %>%
  summarise(
    avg_arousal = mean(erregung),
    avg_subj_stress = mean(stress),
    sd_arousal = sd(erregung),
    sd_subj_stress = sd(stress))
```

##adding VP_Data key variable to FAA Data from 102 and 103

```
FAA <- FAA %>%
  mutate(
    vp_overall = as.numeric(
      ifelse(
        grepl("^ExpExp103_", Datei),
        sub("^ExpExp103_(\\d+)_(\\d+)_(\\d+)_specs.mat$", "\\1", Datei),
        sub("^ExpSimHR2_(\\d+)_(\\d+)_(\\d+)_specs.mat$", "\\1", Datei))),
    vp_overall = ifelse(grepl("^ExpExp103_", Datei), vp_overall + 40, vp_overall),
```

```
    group = as.numeric(
      ifelse(
        grepl("^ExpExp103_", Datei),
        sub("^ExpExp103_(\\d+)_(\\d+)_(\\d+)_specs.mat$", "\\2", Datei),
        sub("^ExpSimHR2_(\\d+)_(\\d+)_(\\d+)_specs.mat$", "\\2", Datei))),
    session = as.numeric(
      ifelse(
        grepl("^ExpExp103_", Datei),
        sub("^ExpExp103_(\\d+)_(\\d+)_(\\d+)_specs.mat$", "\\3", Datei),
        sub("^ExpSimHR2_(\\d+)_(\\d+)_(\\d+)_specs.mat$", "\\3", Datei))))

#filter excluded participants
FAA <- filter_participant_numbers(FAA)
```

##finalizing FAA data

```
# Separate the 'variable' column into three new columns: event, eye, and electrode
FAA_long <- FAA %>%
  gather(key = "variable", value = "value", -vp_overall, -group, -session, -Datei)

FAA_long <- FAA_long %>%
  separate(variable, into = c("event", "eye", "electrode"), sep = "_", extra = "merge", fill = "right")

# Create a new variable 'RFA' to store the combined information
FAA_long <- FAA_long %>%
  mutate(RFA = paste(event, eye, electrode, sep = "_"))

FAA_long <- FAA_long%>%
  select(-Datei, -RFA) %>%
  rename(RFA = value)

#average different eye conditions and seperate into pre, during, and post
FAA_long <- FAA_long %>%
  mutate(time = case_when(
    event %in% c("R1") ~ "pre",
    event %in% c("S1", "S2", "S3") ~ "during",
    event %in% c("R2") ~ "post",
    TRUE ~ event))

#EYES TEST
#FAA_long <- FAA_long %>%
#  mutate(eye = case_when(
#    eye %in% c("AA", "AA1", "AA2", "AA3", "AA4") ~ "AA",
#    eye %in% c("AZ", "AZ1", "AZ2", "AZ3", "AZ4") ~ "AZ",
#    TRUE ~ eye))

#CPT ORDER TEST
FAA_long <- FAA_long %>%
  mutate(time = case_when(
    event %in% c("R1") ~ "pre",
    event %in% c("S3") ~ "during",
    event %in% c("R2") ~ "post",
    event %in% c("S1", "S2") ~ "del",
    TRUE ~ event))

FAA_long <- FAA_long %>%
  filter(time %in% c("pre", "during", "post"))

#ADD EYE FOR TEST eye,
RFA_average <- FAA_long %>%
  group_by(vp_overall, session, electrode, group, time) %>%
  summarize(RFA_averaged = mean(as.numeric(RFA), na.rm = TRUE))

#adding experimental condition, order and CPT_order
RFA_average <- RFA_average %>%
  mutate(Experimentalcondition = ifelse(group %in% c(1, 2), ifelse(session == 1, 'CPT', 'control'), ife
lse(session == 1, 'control', 'CPT')),
    Order = ifelse(group %in% c(1, 2), 'Stress first', 'Control first'),
    CPT_order = ifelse(group %in% c(1, 3), 'left first', 'right first'))

RFA_average$time <- factor(RFA_average$time, levels = c("pre", "during", "post"))

#Calculate avg and sd
RFA_summary <- RFA_average %>%
  group_by(time, electrode, Experimentalcondition) %>%
```

```
  mutate(
    avg = mean(RFA_averaged),
    sd = sd(RFA_averaged))

RFA_wide <- RFA_summary %>%
  subset(select = -c(avg, sd, CPT_order, Order, session, group)) %>%
  pivot_wider(names_from = c(time, Experimentalcondition, electrode),
              values_from = RFA_averaged)
RFA_wide <- RFA_wide %>%
  select(-vp_overall)

#Perform baseline correction
RFA_average_pre <- RFA_average %>%
  group_by(vp_overall, electrode) %>%
  filter(time == "pre") %>%
  mutate(time = "average_pre") %>%
  mutate(RFA_averaged = mean(RFA_averaged))

RFA_baseline <- RFA_average %>%
  group_by(vp_overall, electrode, Experimentalcondition) %>%
  filter(time == "pre") %>%
  summarise(baseline_value = (RFA_averaged))

RFA_baseline_corr <- RFA_average %>%
  left_join(RFA_baseline, by = c("vp_overall", "electrode", "Experimentalcondition")) %>%
  mutate(RFA_averaged = RFA_averaged - baseline_value) %>%
  filter(time == "during") %>%
  mutate(time = "during_pre")

RFA_average <- bind_rows(RFA_average, RFA_average_pre, RFA_baseline_corr) %>%
  select(-baseline_value)
```

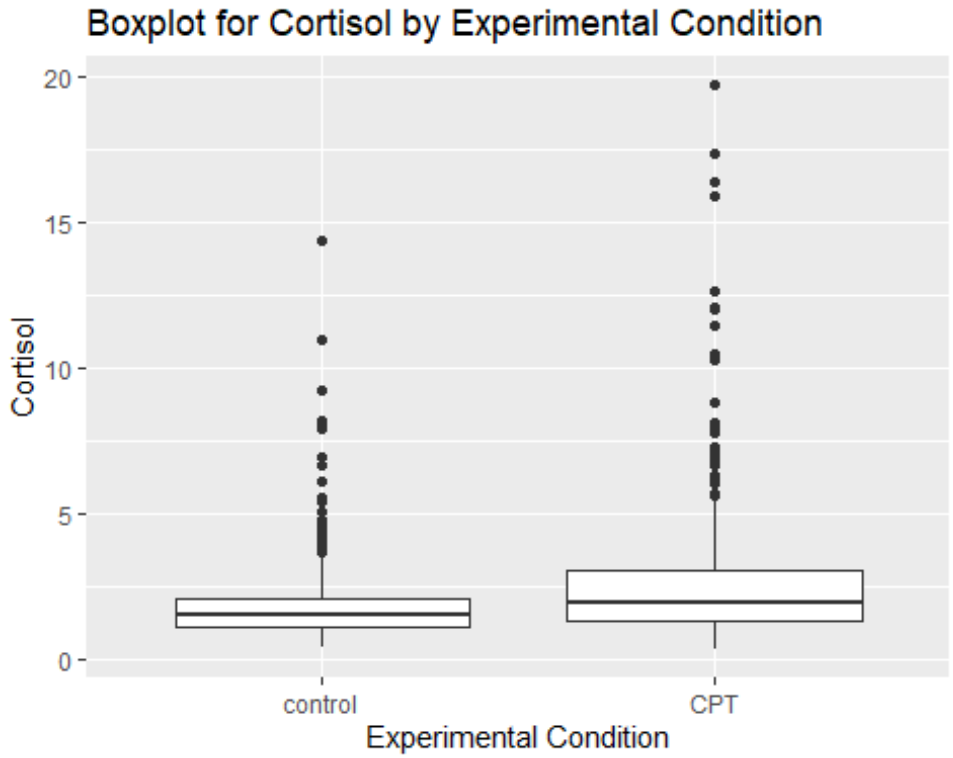
##joining RFA_average and Cortisol_AUC

```
#creating dataset with only CPT condition and both RFA and all stress measurements
CPT_total <- RFA_average %>%
  left_join(Cortisol_AUC_total, by = c("vp_overall", "Experimentalcondition")) %>%
  left_join(VP_Data_baseline_corr, by = c("vp_overall", "Experimentalcondition")) %>%
  left_join(Rating_baseline_corr, by = c("vp_overall", "Experimentalcondition")) %>%
  filter(Experimentalcondition == "CPT")

control_total <- RFA_average %>%
  left_join(Cortisol_AUC_total, by = c("vp_overall", "Experimentalcondition")) %>%
  left_join(VP_Data_baseline_corr, by = c("vp_overall", "Experimentalcondition")) %>%
  left_join(Rating_baseline_corr, by = c("vp_overall", "Experimentalcondition")) %>%
  filter(Experimentalcondition == "control")

#dataset with cardiovascular and subjective stress measurements
Data_Rating_Summary <- left_join(Rating_summary, VP_Data_summary,
                         by = c("time", "Experimentalcondition"))

#add sex variable into all datasets
VP_sex <- subset(VP_Data_baseline_corr, select = c(vp_overall, sex))
VP_sex <- distinct(VP_sex)
Cortisol_Complete <- left_join(Cortisol_Complete, VP_sex, by = "vp_overall")
Rating_average <- left_join(Rating_average, VP_sex, by = "vp_overall")
RFA_average <- left_join(RFA_average, VP_sex, by = "vp_overall")
RFA_summary <- left_join(RFA_summary, VP_sex, by = "vp_overall")

#filter by sex
Cortisol_Complete_m <- subset(Cortisol_Complete, sex == 2)
Cortisol_Complete_f <- subset(Cortisol_Complete, sex == 1)
VP_Data_average_m <- subset(VP_Data_average, sex == 2)
VP_Data_average_f <- subset(VP_Data_average, sex == 1)
Rating_average_m <- subset(Rating_average, sex == 2)
Rating_average_f <- subset(Rating_average, sex == 1)
RFA_average_m <- subset(RFA_average, sex == 2)
RFA_average_f <- subset(RFA_average, sex == 1)
RFA_summary_m <- subset(RFA_summary, sex == 2)
RFA_summary_f <- subset(RFA_summary, sex == 1)
CPT_total_m <- subset(CPT_total, sex == 2)
CPT_total_f <- subset(CPT_total, sex == 1)
control_total_m <- subset(control_total, sex == 2)
control_total_f <- subset(control_total, sex == 1)
```

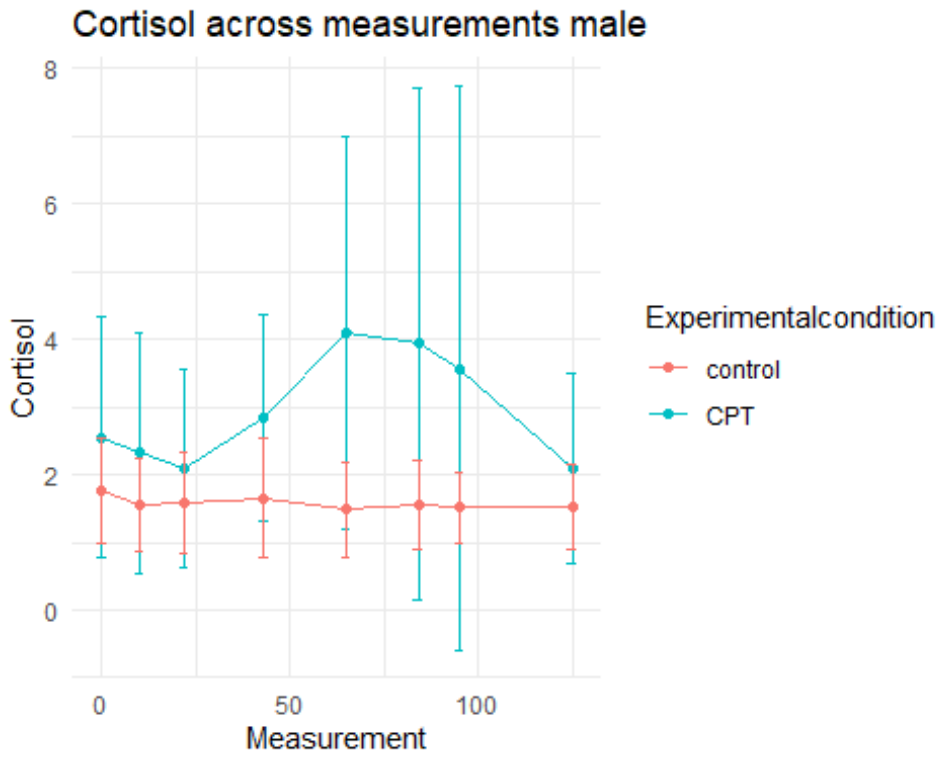
```r
Rating_summary <- Rating_average_m %>%
  group_by(time, Experimentalcondition) %>%
  summarise(
    avg_arousal = mean(erregung),
    avg_subj_stress = mean(stress),
    sd_arousal = sd(erregung),
    sd_subj_stress = sd(stress))

Cardio_summary <- VP_Data_average_m %>%
  group_by(time, Experimentalcondition) %>%
  summarise(
    avg_d = mean(d),
    avg_m = mean(m),
    avg_p = mean(p),
    avg_s = mean(s),
    sd_d = sd(d),
    sd_m = sd(m),
    sd_p = sd(p),
    sd_s = sd(s))

##descriptive statistics of final sample
gender_counts <- VP_Data %>%
  count(sex)

total_participants <- sum(gender_counts$n)

gender_counts <- gender_counts %>%
  mutate(percentage = (n / total_participants) * 100)

mean_age <- mean(VP_Data$age)
sd_age <- sd(VP_Data$age)
min_age <- min(VP_Data$age)
max_age <- max(VP_Data$age)

cat("Mean Age:", mean_age, "\n")

## Mean Age: 25.01471

cat("Standard Deviation Age:", sd_age, "\n")

## Standard Deviation Age: 4.396378

cat("Minimum Age:", min_age, "\n")

## Minimum Age: 18

cat("Maximum Age:", max_age, "\n")

## Maximum Age: 35

mean_age <- mean(VP_Data_average_m$age)
sd_age <- sd(VP_Data_average_m$age)
min_age <- min(VP_Data_average_m$age)
max_age <- max(VP_Data_average_m$age)

cat("Mean Age:", mean_age, "\n")

## Mean Age: 26.40625

cat("Standard Deviation Age:", sd_age, "\n")

## Standard Deviation Age: 4.38364

cat("Minimum Age:", min_age, "\n")

## Minimum Age: 19

cat("Maximum Age:", max_age, "\n")

## Maximum Age: 35
```

##visualization

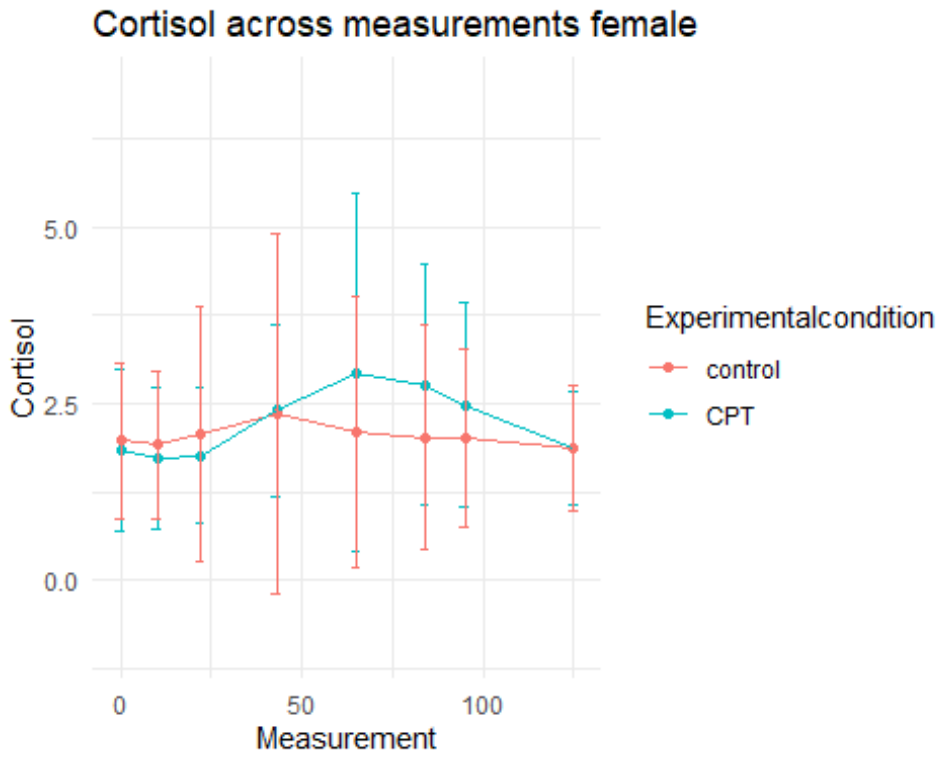
```r
# Create a boxplot for 'Experimentalcondition' vs 'Cortisol'
boxplot_graph <- ggplot(Cortisol_Complete, aes(x = Experimentalcondition, y = Cortisol)) +
  geom_boxplot() +
  labs(title = "Boxplot for Cortisol by Experimental Condition",
       x = "Experimental Condition",
       y = "Cortisol")
print(boxplot_graph)
```



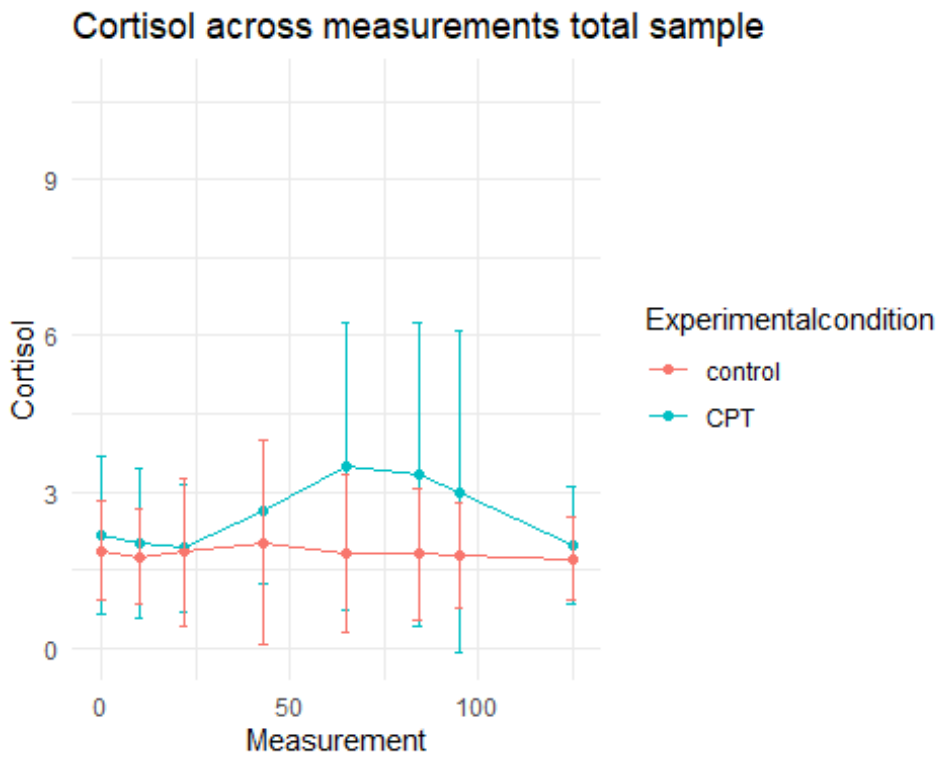

```r
#visualize cortisol across measurements for both experimental conditions
male_graph <- Cortisol_Complete_m %>%
  group_by(Experimentalcondition, Measurement_t) %>%
  summarise(avg_Cortisol = mean(Cortisol),
            sd_Cortisol = sd(Cortisol))

graph_1 <- ggplot(male_graph, aes(x = Measurement_t, y = avg_Cortisol, color = Experimentalcondition))
+
  geom_point() +
  geom_line() +
  geom_errorbar(aes(ymin = avg_Cortisol - sd_Cortisol, ymax = avg_Cortisol + sd_Cortisol), width = 2.5)
+
  labs(title = "Cortisol across measurements male",
       x = "Measurement",
       y = "Cortisol") +
  theme_minimal()
print(graph_1)
```



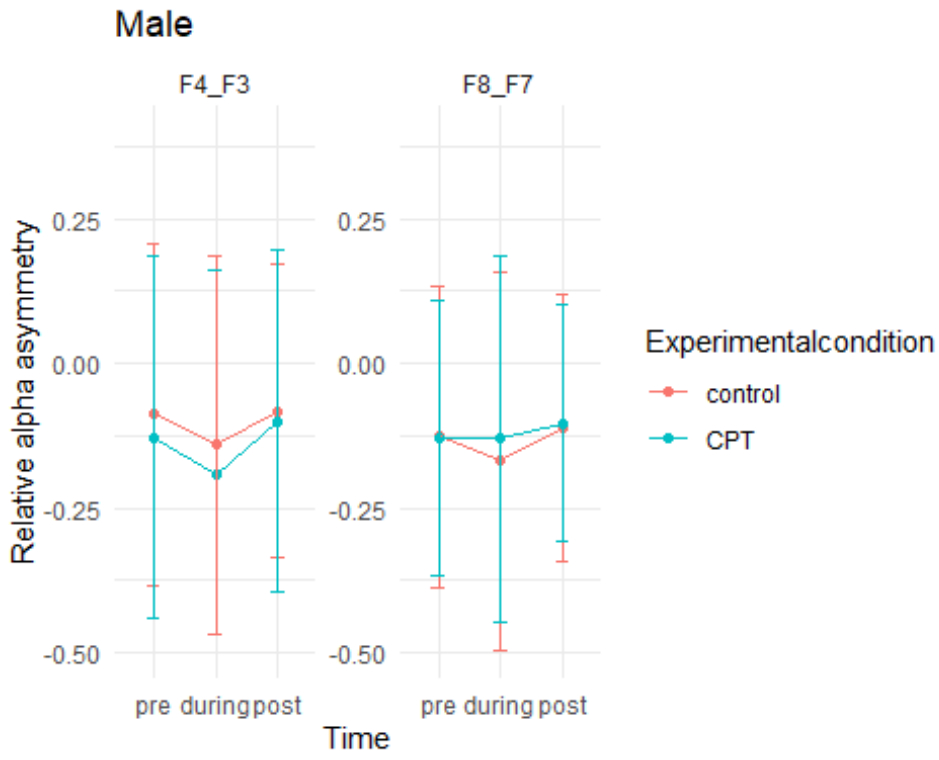

```r
female_graph <- Cortisol_Complete_f %>%
  group_by(Experimentalcondition, Measurement_t) %>%
  summarise(avg_Cortisol = mean(Cortisol),
            sd_Cortisol = sd(Cortisol))

graph_2 <- ggplot(female_graph, aes(x = Measurement_t, y = avg_Cortisol, color = Experimentalcondition)
) +
  geom_point() +
  geom_line() +
  geom_errorbar(aes(ymin = avg_Cortisol - sd_Cortisol, ymax = avg_Cortisol + sd_Cortisol), width = 2.5)
+
  labs(title = "Cortisol across measurements female",
       x = "Measurement",
       y = "Cortisol") +
  theme_minimal() +
  ylim(-1, 7)
print(graph_2)
```



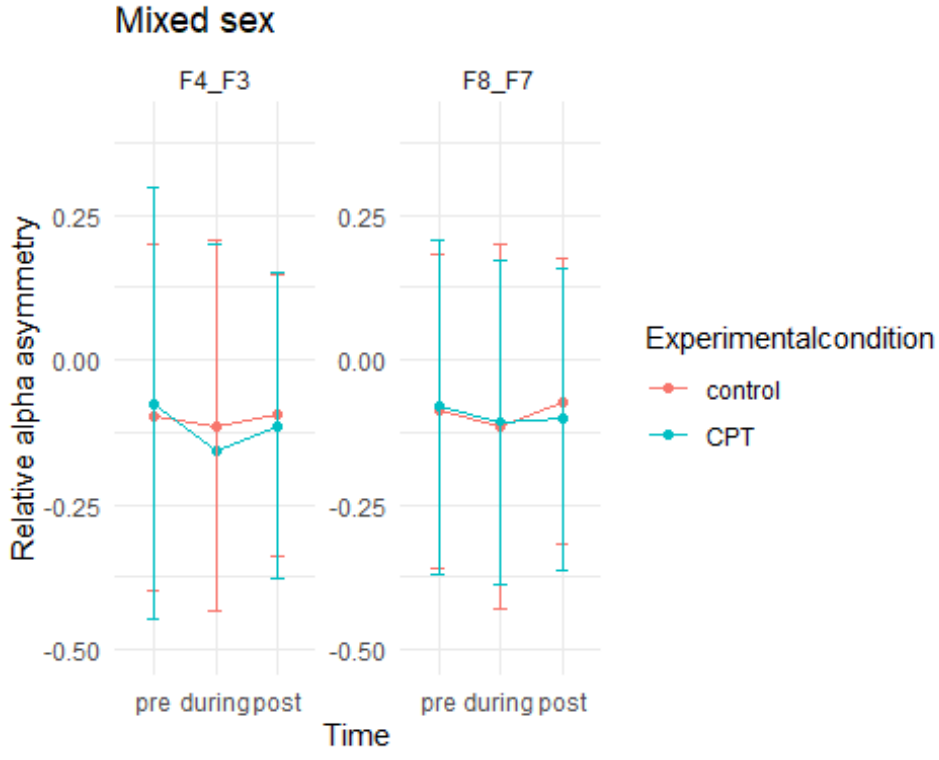

```r
total_graph <- Cortisol_Complete %>%
  group_by(Experimentalcondition, Measurement_t) %>%
  summarise(avg_Cortisol = mean(Cortisol),
            sd_Cortisol = sd(Cortisol))

graph_3 <- ggplot(total_graph, aes(x = Measurement_t, y = avg_Cortisol, color = Experimentalcondition))
+
  geom_point() +
  geom_line() +
  geom_errorbar(aes(ymin = avg_Cortisol - sd_Cortisol, ymax = avg_Cortisol + sd_Cortisol), width = 2.5)
+
  labs(title = "Cortisol across measurements total sample",
       x = "Measurement",
       y = "Cortisol") +
  theme_minimal()
print(graph_3)
```




```
#Compare FAA activity at electrodes throughout time
RFA_summary_m <- RFA_summary_m %>%
  select (-avg, -sd) %>%
  group_by(time, electrode, Experimentalcondition) %>%
  mutate(
    avg = mean(RFA_averaged),
    sd = sd(RFA_averaged))

graph_4 <- ggplot(RFA_summary_m, aes(x = time, y = avg, color = Experimentalcondition, group = Experime
ntalcondition)) +
  geom_point() +
  geom_line() +
  geom_errorbar(aes(ymin = avg - sd, ymax = avg + sd), width = 0.2) +
  facet_wrap(~ electrode, scales = "free") +
  labs(x = "Time", y = "Relative alpha asymmetry", title = "Male") +
  theme_minimal() +
  ylim(-0.5, 0.4)
print(graph_4)
```




```
graph_5 <- ggplot(RFA_summary, aes(x = time, y = avg, color = Experimentalcondition, group = Experiment
alcondition)) +
  geom_point() +
  geom_line() +
  geom_errorbar(aes(ymin = avg - sd, ymax = avg + sd), width = 0.2) +
  facet_wrap(~ electrode, scales = "free") +
  labs(x = "Time", y = "Relative alpha asymmetry", title = "Mixed sex") +
  theme_minimal() +
  ylim(-0.5, 0.4)
print(graph_5)
```



##Analysis 1 precise replication

```
#anova cortisol within subjects
aov_Cortisol <- aov_car(Cortisol ~ Experimentalcondition + measurement_t + Experimentalcondition*measur
ement_t + Error(vp_overall/(Experimentalcondition + measurement_t + Experimentalcondition * measurement
_t)), data = Cortisol_Complete_m)
summary(aov_Cortisol)

##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                                    Sum Sq num Df Error SS den Df  F value
## (Intercept)                       2609.00      1   539.04     31 150.0431
## Experimentalcondition              238.10      1   363.33     31  20.3154
## measurement_t                       74.39      7   423.50    217   5.4452
## Experimentalcondition:measurement_t   77.04      7   435.00    217   5.4902
##                                      Pr(>F)
## (Intercept)                       2.048e-13 ***
## Experimentalcondition             8.769e-05 ***
## measurement_t                     8.954e-06 ***
## Experimentalcondition:measurement_t 7.962e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                                   Test statistic    p-value
## measurement_t                         3.2837e-05 4.7287e-46
## Experimentalcondition:measurement_t     1.3841e-05 1.0000e-50
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                                    GG eps Pr(>F[GG])
## measurement_t                     0.24555   0.009746 **
## Experimentalcondition:measurement_t 0.22490   0.011526 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                                      HF eps  Pr(>F[HF])
## measurement_t                     0.2585972 0.008596748
## Experimentalcondition:measurement_t 0.2348711 0.010457436

# t-test on cortisol over time
perform_t_test <- function(data, timepoints, response_var, group_var) {
  results <- list()
  for (timepoint in timepoints) {
    subset_data <- subset(data, measurement_t == timepoint)
    result <- t.test(subset_data[[response_var]] ~ subset_data[[group_var]], var.equal = TRUE, alternat
ive = "two.sided")
    results[[timepoint]] <- result
  }
  return(results)
}

t <- c("0", "10", "22", "43", "65", "84", "95", "125")
t_cortisol <- perform_t_test(Cortisol_Complete_m, t, "Cortisol", "Experimentalcondition")
print(t_cortisol)

## $`0`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -2.3973, df = 62, p-value = 0.01954
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -1.5102827 -0.1368423
## sample estimates:
## mean in group control     mean in group CPT
##              1.726609              2.550172
##
```

```
##
## $`10`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -2.3562, df = 62, p-value = 0.02164
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -1.4677201 -0.1203737
## sample estimates:
## mean in group control     mean in group CPT
##              1.535375              2.329422
##
##
## $`22`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -1.8466, df = 62, p-value = 0.06958
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -1.12014253  0.04439253
## sample estimates:
## mean in group control     mean in group CPT
##              1.554172              2.092047
##
##
## $`43`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -3.8554, df = 62, p-value = 0.0002771
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -1.8069014 -0.5729736
## sample estimates:
## mean in group control     mean in group CPT
##              1.655484              2.845422
##
##
## $`65`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -4.8756, df = 62, p-value = 7.886e-06
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -3.632956 -1.520200
## sample estimates:
## mean in group control     mean in group CPT
##              1.515937              4.092516
##
##
## $`84`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -3.48, df = 62, p-value = 0.0009238
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -3.710051 -1.002856
## sample estimates:
## mean in group control     mean in group CPT
##              1.580969              3.937422
##
```

```
##
## $`95`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -2.7357, df = 62, p-value = 0.008109
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -3.5174506 -0.5472994
## sample estimates:
## mean in group control     mean in group CPT
##              1.539969              3.572344
##
##
## $`125`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -2.2121, df = 62, p-value = 0.03066
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -1.14273534 -0.05782716
## sample estimates:
## mean in group control     mean in group CPT
##              1.494875              2.095156
```

```
#anova cardiovascular measurements
aov_s <- aov_car(s ~ Experimentalcondition + time + Experimentalcondition*time + Error(vp_overall/(Expe
rimentalcondition + time + Experimentalcondition * time)), data = VP_Data_average_m)
aov_d <- aov_car(d ~ Experimentalcondition + time + Experimentalcondition*time + Error(vp_overall/(Expe
rimentalcondition + time + Experimentalcondition * time)), data = VP_Data_average_m)
aov_m <- aov_car(m ~ Experimentalcondition + time + Experimentalcondition*time + Error(vp_overall/(Expe
rimentalcondition + time + Experimentalcondition * time)), data = VP_Data_average_m)
aov_p <- aov_car(p ~ Experimentalcondition + time + Experimentalcondition*time + Error(vp_overall/(Expe
rimentalcondition + time + Experimentalcondition * time)), data = VP_Data_average_m)

summary(aov_s)
```

```
##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                              Sum Sq num Df Error SS den Df   F value    Pr(>F)
## (Intercept)                2800048      1   9881.9     31 8783.8913 < 2.2e-16
## Experimentalcondition          450      1   2132.4     31    6.5451 0.0156234
## time                           163      2   1601.4     62    3.1495 0.0498075
## Experimentalcondition:time     292      2    870.5     62   10.4132 0.0001262
##
## (Intercept)                ***
## Experimentalcondition      *
## time                       *
## Experimentalcondition:time ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                              Test statistic p-value
## time                                 0.95327 0.48779
## Experimentalcondition:time           0.97521 0.68626
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                               GG eps Pr(>F[GG])
## time                         0.95536  0.0523365 .
## Experimentalcondition:time 0.97581  0.0001467 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
##                              HF eps  Pr(>F[HF])
## time                        1.016572 0.049807464
## Experimentalcondition:time 1.040540 0.000126159
```

```
summary(aov_d)
```

```
##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                              Sum Sq num Df Error SS den Df  F value    Pr(>F)
## (Intercept)                1042632      1   5843.4     31 5531.288 < 2.2e-16
## Experimentalcondition          273      1    468.6     31   18.064 0.0001814
## time                           261      2    449.8     62   18.001 6.853e-07
## Experimentalcondition:time     147      2    407.7     62   11.188 7.099e-05
##
## (Intercept)                ***
## Experimentalcondition      ***
## time                       ***
## Experimentalcondition:time ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                            Test statistic  p-value
## time                              0.83381 0.065469
## Experimentalcondition:time        0.88601 0.162784
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                              GG eps Pr(>F[GG])
## time                        0.85750   3.35e-06 ***
## Experimentalcondition:time 0.89768  0.0001421 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                               HF eps   Pr(>F[HF])
## time                        0.9028466 2.020453e-06
## Experimentalcondition:time 0.9493588 1.000651e-04
```

```
summary(aov_m)
```

```
##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                              Sum Sq num Df Error SS den Df    F value    Pr(>F)
## (Intercept)                1556467      1   3183.1     31 15158.2748 < 2.2e-16
## Experimentalcondition           57      1    386.0     31     4.6056 0.0398061
## time                           238      2    861.8     62     8.5674 0.0005185
## Experimentalcondition:time     185      2    634.4     62     9.0487 0.0003564
##
## (Intercept)                ***
## Experimentalcondition      *
## time                       ***
## Experimentalcondition:time ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                            Test statistic  p-value
## time                              0.70921 0.005776
## Experimentalcondition:time        0.91622 0.269135
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                              GG eps Pr(>F[GG])
## time                        0.77472  0.0015944 **
## Experimentalcondition:time 0.92269  0.0005373 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                               HF eps   Pr(>F[HF])
## time                         0.8078276 0.0013508781
## Experimentalcondition:time 0.9784451 0.0003995883
```

```
summary(aov_p)
```

```
##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                             Sum Sq num Df Error SS den Df   F value    Pr(>F)
## (Intercept)                 929311      1  21338.0     31 1350.1107 < 2.2e-16
## Experimentalcondition         198      1   2667.9     31    2.3036    0.1392
## time                          553      2   1069.5     62   16.0274 2.451e-06
## Experimentalcondition:time    324      2    784.8     62   12.8137 2.199e-05
##
## (Intercept)                 ***
## Experimentalcondition
## time                        ***
## Experimentalcondition:time ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                             Test statistic p-value
## time                               0.94565 0.43246
## Experimentalcondition:time         0.96386 0.57571
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                              GG eps Pr(>F[GG])
## time                         0.94845  4.087e-06 ***
## Experimentalcondition:time 0.96512  2.893e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                               HF eps   Pr(>F[HF])
## time                         1.008497 2.450947e-06
## Experimentalcondition:time 1.028005 2.199356e-05
```

```
#t-test cardiovascular measurements
perform_t_test <- function(data, timepoints, response_var, group_var) {
  results <- list()
  for (response in response_var) {
    for (timepoint in timepoints) {
      subset_data <- subset(data, time == timepoint)
      result <- t.test(subset_data[[response]] ~ subset_data[[group_var]], var.equal = TRUE, alternativ
e = "two.sided")
      results[[paste(response, "_", timepoint, sep = "")]] <- result
    }
  }
  return(results)
}

cardiovascular <- c("s", "d", "m", "p")
time <- c("pre", "during", "post")
t_cardio <- perform_t_test(VP_Data_average_m, time, cardiovascular, "Experimentalcondition")
print(t_cardio)
```

```
## $s_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -0.23214, df = 62, p-value = 0.8172
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -4.204892  3.329892
```

```
## sample estimates:
## mean in group control     mean in group CPT
##              119.3594              119.7969
##
##
## $s_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -2.835, df = 62, p-value = 0.00618
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -10.857418  -1.877701
## sample estimates:
## mean in group control     mean in group CPT
##              118.6389              125.0064
##
##
## $s_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -0.97228, df = 62, p-value = 0.3347
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -7.281800  2.516175
## sample estimates:
## mean in group control     mean in group CPT
##              119.6953              122.0781
##
##
## $d_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -0.62513, df = 62, p-value = 0.5342
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -3.826039  2.003123
## sample estimates:
## mean in group control     mean in group CPT
##              71.58594              72.49740
##
##
## $d_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -2.954, df = 62, p-value = 0.004428
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -8.124034 -1.566442
## sample estimates:
## mean in group control     mean in group CPT
##              72.09722              76.94246
##
##
## $d_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -0.90062, df = 62, p-value = 0.3713
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -4.502353  1.705478
```

```
## sample estimates:
## mean in group control     mean in group CPT
##              73.81250              75.21094
##
##
## $m_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = 0.70653, df = 62, p-value = 0.4825
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -1.605380  3.360588
## sample estimates:
## mean in group control     mean in group CPT
##              88.92448              88.04688
##
##
## $m_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -2.9341, df = 62, p-value = 0.004685
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -6.344881 -1.202738
## sample estimates:
## mean in group control     mean in group CPT
##              89.16319              92.93700
##
##
## $m_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -0.27707, df = 62, p-value = 0.7827
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -3.144732  2.379107
## sample estimates:
## mean in group control     mean in group CPT
##              90.38281              90.76562
##
##
## $p_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = 0.12112, df = 62, p-value = 0.904
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -5.894704  6.655121
## sample estimates:
## mean in group control     mean in group CPT
##              70.03125              69.65104
##
##
## $p_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -1.8839, df = 62, p-value = 0.06428
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -11.6270887   0.3447226
```

```
## sample estimates:
## mean in group control     mean in group CPT
##              68.68099              74.32217
##
##
## $p_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -0.3105, df = 62, p-value = 0.7572
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -6.217610  4.545735
## sample estimates:
## mean in group control     mean in group CPT
##              66.95312              67.78906

#anova stress & arousal ratings
aov_subj_stress <- aov_car(stress ~ Experimentalcondition + time + Experimentalcondition*time + Error(v
p_overall/(Experimentalcondition + time + Experimentalcondition * time)), data = Rating_average_m)
aov_arousal <- aov_car(erregung ~ Experimentalcondition + time + Experimentalcondition*time + Error(vp_
overall/(Experimentalcondition + time + Experimentalcondition * time)), data = Rating_average_m)
summary(aov_subj_stress)

##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                            Sum Sq num Df Error SS den Df F value    Pr(>F)
## (Intercept)                 73456      1    33723     31 67.5252 2.787e-09 ***
## Experimentalcondition        8269      1    12497     31 20.5115 8.245e-05 ***
## time                         4004      2    13401     62  9.2614 0.0003024 ***
## Experimentalcondition:time   5469      2    13349     62 12.6997 2.384e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                            Test statistic  p-value
## time                              0.80229 0.036722
## Experimentalcondition:time        0.73248 0.009374
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                             GG eps Pr(>F[GG])
## time                       0.83492  0.0007457 ***
## Experimentalcondition:time 0.78894  0.0001239 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                               HF eps   Pr(>F[HF])
## time                       0.8768295 5.927227e-04
## Experimentalcondition:time 0.8240768 9.408736e-05

summary(aov_arousal)

##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                            Sum Sq num Df Error SS den Df F value    Pr(>F)
## (Intercept)                 84330      1    42205     31  61.942 6.972e-09 ***
## Experimentalcondition       13194      1    16998     31  24.063 2.816e-05 ***
## time                         5281      2    12543     62  13.053 1.857e-05 ***
## Experimentalcondition:time   8661      2    13160     62  20.403 1.555e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                            Test statistic  p-value
```

```
## time                              0.75498 0.014757
## Experimentalcondition:time        0.80409 0.037984
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                              GG eps Pr(>F[GG])
## time                        0.80320  9.034e-05 ***
## Experimentalcondition:time 0.83619  1.215e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                                HF eps   Pr(>F[HF])
## time                        0.8403985 6.694176e-05
## Experimentalcondition:time 0.8782833 7.158764e-07

#t-test ratings
ratings <- c("stress", "erregung")
t_ratings <- perform_t_test(Rating_average_m, time, ratings, "Experimentalcondition")
print(t_ratings)

## $stress_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = 0.19502, df = 62, p-value = 0.846
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -7.606835  9.251572
## sample estimates:
## mean in group control     mean in group CPT
##              13.70066              12.87829
##
##
## $stress_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -5.3148, df = 62, p-value = 1.542e-06
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -34.53863 -15.65874
## sample estimates:
## mean in group control     mean in group CPT
##              11.48355              36.58224
##
##
## $stress_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -2.6096, df = 62, p-value = 0.01135
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -26.664398  -3.532971
## sample estimates:
## mean in group control     mean in group CPT
##              13.80757              28.90625
##
##
## $erregung_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = 0.074287, df = 62, p-value = 0.941
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
```

```
## 95 percent confidence interval:
##  -8.309502  8.950950
## sample estimates:
## mean in group control     mean in group CPT
##              13.84046              13.51974
##
##
## $erregung_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -6.325, df = 62, p-value = 3.119e-08
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -42.82763 -22.25790
## sample estimates:
## mean in group control     mean in group CPT
##              9.565789             42.108553
##
##
## $erregung_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -2.7532, df = 62, p-value = 0.007733
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -30.234441  -4.798453
## sample estimates:
## mean in group control     mean in group CPT
##              14.59704              32.11349

#cronbachs alpha of RFA values
RFA_wide_m <- RFA_average_m %>%
  subset(select = -c(CPT_order, Order, session, group)) %>%
  pivot_wider(names_from = c(time, Experimentalcondition, electrode),
              values_from = RFA_averaged)
RFA_wide_m <- subset(RFA_wide_m, select = -c(vp_overall, sex))
RFA_alpha_m <- alpha(RFA_wide_m)

RFA_average_m_F8_F7 <- subset(RFA_average_m, electrode == "F8_F7")
RFA_average_m_F4_F3 <- subset(RFA_average_m, electrode == "F4_F3")

#anova RFA
aov_RFA_m <- aov_car(RFA_averaged ~ Experimentalcondition + time + electrode + Experimentalcondition*ti
me + Experimentalcondition *electrode + time*electrode + Experimentalcondition*time*electrode + Error(v
p_overall/(Experimentalcondition + time + electrode + Experimentalcondition*time + Experimentalconditio
n *electrode + time*electrode + Experimentalcondition*time*electrode)), data = RFA_average_m)
summary(aov_RFA_m)

##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                                     Sum Sq num Df Error SS den Df F value
## (Intercept)                         7.2526      1  15.1447     31 14.8455
## Experimentalcondition               0.0018      1   5.3361     31  0.0106
## time                                0.9448      4   4.2298    124  6.9240
## electrode                           0.0002      1   3.1893     31  0.0016
## Experimentalcondition:time          0.0208      4   4.5736    124  0.1410
## Experimentalcondition:electrode     0.0659      1   2.4401     31  0.8377
## time:electrode                      0.0850      4   1.4746    124  1.7880
## Experimentalcondition:time:electrode 0.0332     4   2.0537    124  0.5009
##                                        Pr(>F)
## (Intercept)                         0.0005487 ***
## Experimentalcondition               0.9185133
## time                                4.596e-05 ***
## electrode                           0.9682735
## Experimentalcondition:time          0.9666316
## Experimentalcondition:electrode     0.3671129
## time:electrode                      0.1354252
## Experimentalcondition:time:electrode 0.7351042
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

aov_RFA_F8_F7 <- aov_car(RFA_averaged ~ Experimentalcondition + time + Experimentalcondition*time + Err
or(vp_overall/(Experimentalcondition + time + Experimentalcondition*time)), data = RFA_average_m_F8_F7)
summary(aov_RFA_F8_F7)

##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                            Sum Sq num Df Error SS den Df F value    Pr(>F)
## (Intercept)                3.6610      1   8.9672     31 12.6564  0.001228 **
## Experimentalcondition      0.0229      1   3.0002     31  0.2366  0.630108
## time                       0.6399      4   2.7015    124  7.3425 2.432e-05 ***
## Experimentalcondition:time 0.0265      4   2.4399    124  0.3363  0.853031
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

aov_RFA_F4_F3 <- aov_car(RFA_averaged ~ Experimentalcondition + time + Experimentalcondition*time + Err
or(vp_overall/(Experimentalcondition + time + Experimentalcondition*time)), data = RFA_average_m_F4_F3)
summary(aov_RFA_F4_F3)

##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                            Sum Sq num Df Error SS den Df F value   Pr(>F)
## (Intercept)                3.5918      1   9.3668     31 11.8871 0.001648 **
## Experimentalcondition      0.0449      1   4.7760     31  0.2913 0.593264
## time                       0.3899      4   3.0030    124  4.0255 0.004193 **
## Experimentalcondition:time 0.0275      4   4.1874    124  0.2037 0.935930
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

#correlation table CPT
CPT_total_F4_F3 <- subset(CPT_total_m, electrode == "F4_F3")
CPT_total_F8_F7 <- subset(CPT_total_m, electrode == "F8_F7")

total_correlation <- function(data, timepoints, x_list, RFA_averaged) {
  results <- list()

  for (response in x_list) {
    temp_result <- list()
    for (timepoint in timepoints) {
      subset_data <- data[data$time == timepoint, ]
      result <- cor.test(subset_data[[response]], subset_data[[RFA_averaged]], method = "pearson")
      temp_result[[timepoint]] <- result
    }
    results[[response]] <- temp_result
  }

  return(results)
}

time <- c("pre", "during", "post", "average_pre", "during_pre")
x_list <- c("Cortisol_AUCg_Cum", "Cortisol_AUCi", "d_corrected", "m_corrected", "p_corrected", "s_corre
cted", "subj_stress_corr", "arousal_corr")
result_F4_F3 <- total_correlation(CPT_total_F4_F3, time, x_list, "RFA_averaged")
result_F8_F7 <- total_correlation(CPT_total_F8_F7, time, x_list, "RFA_averaged")
```

##Analysis 2

```
#anova cortisol within subjects
aov_Cortisol_2 <- aov_car(Cortisol ~ Experimentalcondition + measurement_t + sex + Experimentalconditio
n*measurement_t + Experimentalcondition*sex + measurement_t*sex + Experimentalcondition*measurement_t*s
ex + Error(vp_overall/(Experimentalcondition + measurement_t + Experimentalcondition*measurement_t)), d
ata = Cortisol_Complete)
summary(aov_Cortisol_2)

##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                                      Sum Sq num Df Error SS den Df  F value
## (Intercept)                          5378.6      1  1243.97     66 285.3678
## sex                                     1.0      1  1243.97     66   0.0521
## Experimentalcondition                 192.4      1   596.60     66  21.2812
```

```
## sex:Experimentalcondition                 73.7      1   596.60     66   8.1537
## measurement_t                            121.0      7   776.73    462  10.2819
## sex:measurement_t                          7.7      7   776.73    462   0.6576
## Experimentalcondition:measurement_t      108.2      7   695.33    462  10.2708
## sex:Experimentalcondition:measurement_t    6.4      7   695.33    462   0.6096
##                                             Pr(>F)
## (Intercept)                              < 2.2e-16 ***
## sex                                       0.820154
## Experimentalcondition                    1.877e-05 ***
## sex:Experimentalcondition                 0.005739 **
## measurement_t                            5.313e-12 ***
## sex:measurement_t                         0.708008
## Experimentalcondition:measurement_t      5.482e-12 ***
## sex:Experimentalcondition:measurement_t   0.748130
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                                         Test statistic    p-value
## measurement_t                                0.00058126 1.5400e-82
## sex:measurement_t                            0.00058126 1.5400e-82
## Experimentalcondition:measurement_t          0.00074985 3.0965e-79
## sex:Experimentalcondition:measurement_t      0.00074985 3.0965e-79
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                                          GG eps Pr(>F[GG])
## measurement_t                           0.32443  2.863e-05 ***
## sex:measurement_t                       0.32443     0.5382
## Experimentalcondition:measurement_t     0.30022  5.093e-05 ***
## sex:Experimentalcondition:measurement_t 0.30022     0.5529
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                                             HF eps   Pr(>F[HF])
## measurement_t                           0.3365967 2.154910e-05
## sex:measurement_t                       0.3365967 5.436043e-01
## Experimentalcondition:measurement_t     0.3103168 4.022125e-05
## sex:Experimentalcondition:measurement_t 0.3103168 5.581005e-01
```

```r
# t-test on cortisol over time
perform_t_test <- function(data, timepoints, response_var, group_var) {
  results <- list()
  for (timepoint in timepoints) {
    subset_data <- subset(data, measurement_t == timepoint)
    result <- t.test(subset_data[[response_var]] ~ subset_data[[group_var]], var.equal = TRUE, alternat
ive = "two.sided")
    results[[timepoint]] <- result
  }
  return(results)
}

t <- c("0", "10", "22", "43", "65", "84", "95", "125")
t_cortisol <- perform_t_test(Cortisol_Complete, t, "Cortisol", "Experimentalcondition")
print(t_cortisol)
```

```
## $`0`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -1.6199, df = 134, p-value = 0.1076
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -0.78915169  0.07850463
## sample estimates:
## mean in group control     mean in group CPT
##              1.855382              2.210706
##
##
```

```
## $`10`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -1.4796, df = 134, p-value = 0.1413
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -0.7259446  0.1046211
## sample estimates:
## mean in group control     mean in group CPT
##              1.735662              2.046324
##
##
## $`22`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -0.47308, df = 134, p-value = 0.6369
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -0.5578795  0.3425118
## sample estimates:
## mean in group control     mean in group CPT
##              1.826206              1.933890
##
##
## $`43`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -2.2318, df = 134, p-value = 0.02729
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -1.28149700 -0.07732653
## sample estimates:
## mean in group control     mean in group CPT
##              2.026640              2.706051
##
##
## $`65`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -4.4885, df = 134, p-value = 1.53e-05
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -2.601338 -1.010029
## sample estimates:
## mean in group control     mean in group CPT
##              1.820801              3.626485
##
##
## $`84`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -4.07, df = 134, p-value = 7.989e-05
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -2.424470 -0.838721
## sample estimates:
## mean in group control     mean in group CPT
##              1.812912              3.444507
##
##
```

```
## $`95`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -3.2369, df = 134, p-value = 0.001523
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -2.0787145 -0.5018885
## sample estimates:
## mean in group control     mean in group CPT
##              1.784684              3.074985
##
##
## $`125`
##
##  Two Sample t-test
##
## data:  subset_data[[response_var]] by subset_data[[group_var]]
## t = -1.8576, df = 134, p-value = 0.06542
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -0.64715128  0.02028363
## sample estimates:
## mean in group control     mean in group CPT
##              1.694691              2.008125
```

```
#anova cardiovascular measurements
aov_s <- aov_car(s ~ Experimentalcondition + time + sex + Experimentalcondition*time + Experimentalcond
ition*sex + time*sex + Experimentalcondition*time*sex + Error(vp_overall/(Experimentalcondition + time
+ Experimentalcondition * time)), data = VP_Data_average)
aov_d <- aov_car(d ~ Experimentalcondition + time + sex + Experimentalcondition*time + Experimentalcond
ition*sex + time*sex + Experimentalcondition*time*sex + Error(vp_overall/(Experimentalcondition + time
+ Experimentalcondition * time)), data = VP_Data_average)
aov_m <- aov_car(m ~ Experimentalcondition + time + sex + Experimentalcondition*time + Experimentalcond
ition*sex + time*sex + Experimentalcondition*time*sex + Error(vp_overall/(Experimentalcondition + time
+ Experimentalcondition * time)), data = VP_Data_average)
aov_p <- aov_car(p ~ Experimentalcondition + time + sex + Experimentalcondition*time + Experimentalcond
ition*sex + time*sex + Experimentalcondition*time*sex + Error(vp_overall/(Experimentalcondition + time
+ Experimentalcondition * time)), data = VP_Data_average)

summary(aov_s)
```

```
##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                                Sum Sq num Df Error SS den Df    F value
## (Intercept)                   5555442      1  25199.1     66 14550.4574
## sex                              6093      1  25199.1     66    15.9596
## Experimentalcondition             706      1   4503.6     66    10.3536
## sex:Experimentalcondition          18      1   4503.6     66     0.2706
## time                              756      2   3083.5    132    16.1719
## sex:time                           84      2   3083.5    132     1.7993
## Experimentalcondition:time        875      2   2681.1    132    21.5459
## sex:Experimentalcondition:time     28      2   2681.1    132     0.6849
##                                  Pr(>F)
## (Intercept)                   < 2.2e-16 ***
## sex                           0.0001654 ***
## Experimentalcondition         0.0020040 **
## sex:Experimentalcondition     0.6046420
## time                          5.226e-07 ***
## sex:time                      0.1694554
## Experimentalcondition:time    7.986e-09 ***
## sex:Experimentalcondition:time 0.5059464
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                               Test statistic p-value
## time                                 0.93418 0.10938
## sex:time                             0.93418 0.10938
```

```
## Experimentalcondition:time            0.97205 0.39806
## sex:Experimentalcondition:time        0.97205 0.39806
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                                GG eps Pr(>F[GG])
## time                          0.93824  1.048e-06 ***
## sex:time                      0.93824     0.1720
## Experimentalcondition:time    0.97281  1.208e-08 ***
## sex:Experimentalcondition:time 0.97281     0.5021
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                                   HF eps   Pr(>F[HF])
## time                          0.9647357 7.773932e-07
## sex:time                      0.9647357 1.708915e-01
## Experimentalcondition:time    1.0019388 7.986144e-09
## sex:Experimentalcondition:time 1.0019388 5.059464e-01
```

```
summary(aov_d)
```

```
##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                                Sum Sq num Df Error SS den Df   F value
## (Intercept)                   2153392      1  17063.7     66 8329.0184
## sex                               341      1  17063.7     66    1.3188
## Experimentalcondition             706      1   1172.0     66   39.7663
## sex:Experimentalcondition           6      1   1172.0     66    0.3596
## time                              515      2    858.8    132   39.6029
## sex:time                            8      2    858.8    132    0.6029
## Experimentalcondition:time        407      2    723.3    132   37.1036
## sex:Experimentalcondition:time      9      2    723.3    132    0.8599
##                                   Pr(>F)
## (Intercept)                   < 2.2e-16 ***
## sex                              0.2550
## Experimentalcondition         2.719e-08 ***
## sex:Experimentalcondition        0.5508
## time                          3.367e-14 ***
## sex:time                         0.5487
## Experimentalcondition:time    1.636e-13 ***
## sex:Experimentalcondition:time   0.4255
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                               Test statistic  p-value
## time                                 0.88272 0.017350
## sex:time                             0.88272 0.017350
## Experimentalcondition:time           0.92608 0.082433
## sex:Experimentalcondition:time       0.92608 0.082433
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                                GG eps Pr(>F[GG])
## time                          0.89503  5.864e-13 ***
## sex:time                      0.89503     0.5312
## Experimentalcondition:time    0.93117  9.578e-13 ***
## sex:Experimentalcondition:time 0.93117     0.4188
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                                   HF eps   Pr(>F[HF])
## time                          0.9183502 3.107579e-13
## sex:time                      0.9183502 5.352295e-01
## Experimentalcondition:time    0.9571344 4.916864e-13
## sex:Experimentalcondition:time 0.9571344 4.214046e-01
```

```
summary(aov_m)
```

```
##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                                 Sum Sq num Df Error SS den Df    F value
## (Intercept)                    3203502      1  11147.6     66 18966.5199
## sex                                659      1  11147.6     66     3.9011
## Experimentalcondition              266      1    926.8     66    18.9628
## sex:Experimentalcondition           28      1    926.8     66     1.9992
## time                               450      2   1146.6    132    25.9300
## sex:time                            23      2   1146.6    132     1.3249
## Experimentalcondition:time         444      2    943.7    132    31.0181
## sex:Experimentalcondition:time       3      2    943.7    132     0.2135
##                                   Pr(>F)
## (Intercept)                    < 2.2e-16 ***
## sex                              0.05244 .
## Experimentalcondition          4.749e-05 ***
## sex:Experimentalcondition        0.16209
## time                           3.175e-10 ***
## sex:time                         0.26935
## Experimentalcondition:time     9.070e-12 ***
## sex:Experimentalcondition:time   0.80800
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                                 Test statistic p-value
## time                                   0.87975 0.01555
## sex:time                               0.87975 0.01555
## Experimentalcondition:time             0.97871 0.49693
## sex:Experimentalcondition:time         0.97871 0.49693
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                                  GG eps Pr(>F[GG])
## time                           0.89266  2.274e-09 ***
## sex:time                       0.89266     0.2684
## Experimentalcondition:time     0.97916  1.428e-11 ***
## sex:Experimentalcondition:time 0.97916     0.8035
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                                    HF eps   Pr(>F[HF])
## time                           0.9158065 1.486785e-09
## sex:time                       0.9158065 2.686615e-01
## Experimentalcondition:time     1.0087721 9.070492e-12
## sex:Experimentalcondition:time 1.0087721 8.079999e-01
```

```
summary(aov_p)
```

```
##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                                 Sum Sq num Df Error SS den Df   F value
## (Intercept)                    2019022      1    45535     66 2926.4314
## sex                                327      1    45535     66    0.4741
## Experimentalcondition              271      1     4271     66    4.1933
## sex:Experimentalcondition           16      1     4271     66    0.2494
## time                              1224      2     1774    132   45.5232
## sex:time                            26      2     1774    132    0.9724
## Experimentalcondition:time         589      2     1436    132   27.0593
## sex:Experimentalcondition:time       6      2     1436    132    0.2655
##                                   Pr(>F)
## (Intercept)                    < 2.2e-16 ***
## sex                              0.49353
## Experimentalcondition            0.04457 *
## sex:Experimentalcondition        0.61913
## time                           9.200e-16 ***
## sex:time                         0.38085
## Experimentalcondition:time     1.418e-10 ***
## sex:Experimentalcondition:time   0.76725
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                                Test statistic  p-value
## time                                  0.91910 0.064469
## sex:time                              0.91910 0.064469
## Experimentalcondition:time            0.96144 0.278556
## sex:Experimentalcondition:time        0.96144 0.278556
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                                 GG eps Pr(>F[GG])
## time                           0.92516  9.179e-15 ***
## sex:time                       0.92516     0.3754
## Experimentalcondition:time     0.96287  2.883e-10 ***
## sex:Experimentalcondition:time 0.96287     0.7589
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                                    HF eps   Pr(>F[HF])
## time                           0.9506769 4.188584e-15
## sex:time                       0.9506769 3.773515e-01
## Experimentalcondition:time     0.9912272 1.677041e-10
## sex:Experimentalcondition:time 0.9912272 7.653213e-01
```

```
#t-test cardiovascular measurements
perform_t_test <- function(data, timepoints, response_var, group_var) {
  results <- list()
  for (response in response_var) {
    for (timepoint in timepoints) {
      subset_data <- subset(data, time == timepoint)
      result <- t.test(subset_data[[response]] ~ subset_data[[group_var]], var.equal = TRUE, alternativ
e = "two.sided")
      results[[paste(response, "_", timepoint, sep = "")]] <- result
    }
  }
  return(results)
}

cardiovascular <- c("s", "d", "m", "p")
time <- c("pre", "during", "post")
t_cardio <- perform_t_test(VP_Data_average, time, cardiovascular, "Experimentalcondition")
print(t_cardio)
```

```
## $s_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = 0.16172, df = 134, p-value = 0.8718
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -3.041439  3.583106
## sample estimates:
## mean in group control     mean in group CPT
##              115.0980              114.8272
##
##
## $s_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -3.9852, df = 134, p-value = 0.0001102
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -10.003681  -3.367585
## sample estimates:
## mean in group control     mean in group CPT
```

```
##              115.0233              121.7089
##
##
## $s_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -0.75513, df = 134, p-value = 0.4515
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -5.136058  2.297823
## sample estimates:
## mean in group control     mean in group CPT
##              115.9522              117.3713
##
##
## $d_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -0.62047, df = 134, p-value = 0.536
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -3.089398  1.613908
## sample estimates:
## mean in group control     mean in group CPT
##              70.77574              71.51348
##
##
## $d_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -4.288, df = 134, p-value = 3.424e-05
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -7.944157 -2.928976
## sample estimates:
## mean in group control     mean in group CPT
##              70.96446              76.40103
##
##
## $d_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -1.4972, df = 134, p-value = 0.1367
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -4.1243813  0.5704598
## sample estimates:
## mean in group control     mean in group CPT
##              72.44853              74.22549
##
##
## $m_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = 0.31936, df = 134, p-value = 0.75
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -1.654689  2.291944
## sample estimates:
## mean in group control     mean in group CPT
```

```
##              87.48039              87.16176
##
##
## $m_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -4.2103, df = 134, p-value = 4.648e-05
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -6.692881 -2.414554
## sample estimates:
## mean in group control     mean in group CPT
##              87.59824              92.15196
##
##
## $m_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -0.67996, df = 134, p-value = 0.4977
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -2.78785  1.36138
## sample estimates:
## mean in group control     mean in group CPT
##              88.51348              89.22672
##
##
## $p_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = 0.37491, df = 134, p-value = 0.7083
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -3.248485  4.768092
## sample estimates:
## mean in group control     mean in group CPT
##              70.79779              70.03799
##
##
## $p_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -2.3947, df = 134, p-value = 0.01802
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -8.9309354 -0.8514525
## sample estimates:
## mean in group control     mean in group CPT
##              70.25388              75.14507
##
##
## $p_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -0.3773, df = 134, p-value = 0.7065
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -4.367922  2.968412
## sample estimates:
```

```
## mean in group control     mean in group CPT
##              68.09559              68.79534

#anova stress & arousal ratings
aov_subj_stress <- aov_car(stress ~ Experimentalcondition + time + sex + Experimentalcondition*time + E
xperimentalcondition*sex + time*sex + Experimentalcondition*time*sex + Error(vp_overall/(Experimentalco
ndition + time + Experimentalcondition * time)), data = Rating_average)
aov_arousal <- aov_car(erregung ~ Experimentalcondition + time + sex + Experimentalcondition*time + Exp
erimentalcondition*sex + time*sex + Experimentalcondition*time*sex + Error(vp_overall/(Experimentalcond
ition + time + Experimentalcondition * time)), data = Rating_average)
summary(aov_subj_stress)

##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                               Sum Sq num Df Error SS den Df  F value    Pr(>F)
## (Intercept)                   198970      1   101076     66 129.9227 < 2.2e-16
## sex                             2668      1   101076     66   1.7425    0.1914
## Experimentalcondition          17363      1    25302     66  45.2906 4.883e-09
## sex:Experimentalcondition          0      1    25302     66   0.0008    0.9773
## time                            8046      2    23904    132  22.2146 4.833e-09
## sex:time                         204      2    23904    132   0.5640    0.5703
## Experimentalcondition:time     12119      2    24746    132  32.3227 3.756e-12
## sex:Experimentalcondition:time   147      2    24746    132   0.3926    0.6761
##
## (Intercept)                   ***
## sex
## Experimentalcondition         ***
## sex:Experimentalcondition
## time                          ***
## sex:time
## Experimentalcondition:time    ***
## sex:Experimentalcondition:time
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                               Test statistic  p-value
## time                                 0.91174 0.049640
## sex:time                             0.91174 0.049640
## Experimentalcondition:time           0.92761 0.086978
## sex:Experimentalcondition:time       0.92761 0.086978
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                               GG eps Pr(>F[GG])
## time                          0.9189   1.73e-08 ***
## sex:time                      0.9189     0.5561
## Experimentalcondition:time    0.9325   1.73e-11 ***
## sex:Experimentalcondition:time 0.9325    0.6616
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                                  HF eps   Pr(>F[HF])
## time                          0.9439555 1.166247e-08
## sex:time                      0.9439555 5.605930e-01
## Experimentalcondition:time    0.9585623 9.590965e-12
## sex:Experimentalcondition:time 0.9585623 6.673128e-01

summary(aov_arousal)

##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                               Sum Sq num Df Error SS den Df  F value    Pr(>F)
## (Intercept)                   211646      1   119896     66 116.5060 3.215e-16
## sex                             1403      1   119896     66   0.7725    0.3826
## Experimentalcondition          18825      1    31179     66  39.8488 2.648e-08
## sex:Experimentalcondition        897      1    31179     66   1.8990    0.1728
## time                            9677      2    23562    132  27.1073 1.371e-10
## sex:time                         271      2    23562    132   0.7597    0.4698
```

```
## Experimentalcondition:time      18112      2    23073    132  51.8082 < 2.2e-16
## sex:Experimentalcondition:time     62      2    23073    132   0.1778    0.8373
##
## (Intercept)                    ***
## sex
## Experimentalcondition          ***
## sex:Experimentalcondition
## time                           ***
## sex:time
## Experimentalcondition:time     ***
## sex:Experimentalcondition:time
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Mauchly Tests for Sphericity
##
##                                Test statistic  p-value
## time                                  0.90595 0.040355
## sex:time                              0.90595 0.040355
## Experimentalcondition:time            0.89921 0.031661
## sex:Experimentalcondition:time        0.89921 0.031661
##
##
## Greenhouse-Geisser and Huynh-Feldt Corrections
##  for Departure from Sphericity
##
##                                 GG eps Pr(>F[GG])
## time                           0.91404  7.110e-10 ***
## sex:time                       0.91404     0.4591
## Experimentalcondition:time     0.90844  5.696e-16 ***
## sex:Experimentalcondition:time 0.90844     0.8169
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                                    HF eps   Pr(>F[HF])
## time                           0.9387342 4.429488e-10
## sex:time                       0.9387342 4.623207e-01
## Experimentalcondition:time     0.9327297 2.476325e-16
## sex:Experimentalcondition:time 0.9327297 8.225733e-01
```

```
#t-test ratings
ratings <- c("stress", "erregung")
t_ratings <- perform_t_test(Rating_average, time, ratings, "Experimentalcondition")
print(t_ratings)
```

```
## $stress_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = 0.13856, df = 134, p-value = 0.89
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -5.959208  6.857041
## sample estimates:
## mean in group control     mean in group CPT
##              16.72214              16.27322
##
##
## $stress_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -7.3334, df = 134, p-value = 1.919e-11
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -33.44265 -19.23537
## sample estimates:
## mean in group control     mean in group CPT
##              14.14087              40.47988
##
```

```
##
## $stress_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -3.3607, df = 134, p-value = 0.001013
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -21.141230  -5.476417
## sample estimates:
## mean in group control     mean in group CPT
##              16.35449              29.66331
##
##
## $erregung_pre
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = 0.82893, df = 134, p-value = 0.4086
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -3.872634  9.460869
## sample estimates:
## mean in group control     mean in group CPT
##              17.85991              15.06579
##
##
## $erregung_during
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -8.0165, df = 134, p-value = 4.747e-13
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -37.26646 -22.51682
## sample estimates:
## mean in group control     mean in group CPT
##              13.23994              43.13158
##
##
## $erregung_post
##
##  Two Sample t-test
##
## data:  subset_data[[response]] by subset_data[[group_var]]
## t = -3.0528, df = 134, p-value = 0.002735
## alternative hypothesis: true difference in means between group control and group CPT is not equal to
0
## 95 percent confidence interval:
##  -21.759011  -4.649657
## sample estimates:
## mean in group control     mean in group CPT
##              17.52322              30.72755

#cronbachs alpha of RFA values
RFA_wide <- RFA_average %>%
  subset(select = -c(CPT_order, Order, session, group)) %>%
  pivot_wider(names_from = c(time, Experimentalcondition, electrode),
              values_from = RFA_averaged)
RFA_wide <- subset(RFA_wide, select = -c(vp_overall, sex))
RFA_alpha <- alpha(RFA_wide)

## Some items ( during_pre_CPT_F4_F3 during_pre_CPT_F8_F7 ) were negatively correlated with the first p
rincipal component and
## probably should be reversed.
## To do this, run the function again with the 'check.keys=TRUE' option

RFA_average_F8_F7 <- subset(RFA_average, electrode == "F8_F7")
RFA_average_F4_F3 <- subset(RFA_average, electrode == "F4_F3")
```

```r
#anova RFA
aov_RFA <- aov_car(RFA_averaged ~ Experimentalcondition + sex + time + electrode + Experimentalconditio
n* sex + sex*time + sex*electrode + sex*Experimentalcondition*time + Experimentalcondition *electrode*s
ex + time*electrode*sex + Experimentalcondition*time*electrode*sex + Experimentalcondition*time + Exper
imentalcondition *electrode + time*electrode + Experimentalcondition*time*electrode + Error(vp_overall/
(Experimentalcondition + time + electrode + Experimentalcondition*time + Experimentalcondition *electro
de + time*electrode + Experimentalcondition*time*electrode)), data = RFA_average)
summary(aov_RFA)

##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##                                          Sum Sq num Df Error SS den Df F value
## (Intercept)                             10.2207      1  27.4510     66 24.5734
## sex                                      0.5213      1  27.4510     66  1.2534
## Experimentalcondition                    0.0466      1  10.3198     66  0.2981
## sex:Experimentalcondition                0.0236      1  10.3198     66  0.1509
## time                                     1.0809      4  14.2395    264  5.0099
## sex:time                                 0.2580      4  14.2395    264  1.1960
## electrode                                0.0576      1  10.2233     66  0.3718
## sex:electrode                            0.0669      1  10.2233     66  0.4320
## Experimentalcondition:time               0.0860      4  13.8589    264  0.4096
## sex:Experimentalcondition:time           0.2251      4  13.8589    264  1.0722
## Experimentalcondition:electrode          0.0279      1   6.5713     66  0.2799
## sex:Experimentalcondition:electrode      0.0427      1   6.5713     66  0.4293
## time:electrode                           0.0362      4   4.0128    264  0.5953
## sex:time:electrode                       0.0813      4   4.0128    264  1.3377
## Experimentalcondition:time:electrode     0.0877      4   5.2793    264  1.0965
## sex:Experimentalcondition:time:electrode 0.0522      4   5.2793    264  0.6521
##                                            Pr(>F)
## (Intercept)                             5.272e-06 ***
## sex                                     0.2669670
## Experimentalcondition                   0.5869462
## sex:Experimentalcondition               0.6989273
## time                                    0.0006593 ***
## sex:time                                0.3129386
## electrode                               0.5441303
## sex:electrode                           0.5132810
## Experimentalcondition:time              0.8017094
## sex:Experimentalcondition:time          0.3706589
## Experimentalcondition:electrode         0.5985601
## sex:Experimentalcondition:electrode     0.5146016
## time:electrode                          0.6663625
## sex:time:electrode                      0.2562770
## Experimentalcondition:time:electrode    0.3586752
## sex:Experimentalcondition:time:electrode 0.6258541
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

#correlation table CPT
CPT_total_F4_F3 <- subset(CPT_total, electrode == "F4_F3")
CPT_total_F8_F7 <- subset(CPT_total, electrode == "F8_F7")

total_correlation <- function(data, timepoints, x_list, RFA_averaged) {
  results <- list()

  for (response in x_list) {
    temp_result <- list()
    for (timepoint in timepoints) {
      subset_data <- data[data$time == timepoint, ]
      result <- cor.test(subset_data[[response]], subset_data[[RFA_averaged]], method = "pearson")
      temp_result[[timepoint]] <- result
    }
    results[[response]] <- temp_result
  }

  return(results)
}

time <- c("pre", "during", "post", "average_pre", "during_pre")
x_list <- c("Cortisol_AUCg_Cum", "Cortisol_AUCi", "d_corrected", "m_corrected", "p_corrected", "s_corre
cted", "subj_stress_corr", "arousal_corr")
result_F4_F3 <- total_correlation(CPT_total_F4_F3, time, x_list, "RFA_averaged")
```

```r
result_F8_F7 <- total_correlation(CPT_total_F8_F7, time, x_list, "RFA_averaged")
print(result_F4_F3)
```

```
## $Cortisol_AUCg_Cum
## $Cortisol_AUCg_Cum$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.2598, df = 65, p-value = 0.7958
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2096224  0.2703252
## sample estimates:
##        cor
## 0.03220795
##
##
## $Cortisol_AUCg_Cum$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.71232, df = 65, p-value = 0.4788
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1554866  0.3214226
## sample estimates:
##        cor
## 0.08800905
##
##
## $Cortisol_AUCg_Cum$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.331, df = 65, p-value = 0.1878
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.08047352  0.38791476
## sample estimates:
##       cor
## 0.1628837
##
##
## $Cortisol_AUCg_Cum$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.36663, df = 65, p-value = 0.7151
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2825532  0.1969297
## sample estimates:
##        cor
## -0.0454278
##
##
## $Cortisol_AUCg_Cum$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.62175, df = 65, p-value = 0.5363
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1663915  0.3113485
## sample estimates:
##        cor
## 0.07689036
##
##
##
```

```
## $Cortisol_AUCi
## $Cortisol_AUCi$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.71226, df = 65, p-value = 0.4789
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1554929  0.3214169
## sample estimates:
##        cor
## 0.08800269
##
##
## $Cortisol_AUCi$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.92481, df = 65, p-value = 0.3585
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1298008  0.3447328
## sample estimates:
##      cor
## 0.113961
##
##
## $Cortisol_AUCi$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.5138, df = 65, p-value = 0.1349
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.05824591  0.40672359
## sample estimates:
##       cor
## 0.1845447
##
##
## $Cortisol_AUCi$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.050167, df = 65, p-value = 0.9601
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2343366  0.2460632
## sample estimates:
##         cor
## 0.006222313
##
##
## $Cortisol_AUCi$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.23922, df = 65, p-value = 0.8117
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2120608  0.2679582
## sample estimates:
##        cor
## 0.02965861
##
##
##
## $d_corrected
## $d_corrected$pre
##
```

```
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.493, df = 66, p-value = 0.1402
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.40185103  0.06027957
## sample estimates:
##        cor
## -0.1807432
##
##
## $d_corrected$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.9518, df = 66, p-value = 0.05521
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.447124040  0.005107294
## sample estimates:
##        cor
## -0.2336023
##
##
## $d_corrected$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.81374, df = 66, p-value = 0.4187
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3302429  0.1421374
## sample estimates:
##         cor
## -0.09966526
##
##
## $d_corrected$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.2442, df = 66, p-value = 0.2178
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.37622990  0.09029997
## sample estimates:
##        cor
## -0.1513844
##
##
## $d_corrected$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.51011, df = 66, p-value = 0.6117
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2966594  0.1784242
## sample estimates:
##         cor
## -0.06266683
##
##
##
## $m_corrected
## $m_corrected$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
```

```
## t = -1.3708, df = 66, p-value = 0.1751
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.38936581  0.07501375
## sample estimates:
##        cor
## -0.1663872
##
##
## $m_corrected$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.5019, df = 66, p-value = 0.1379
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.40275763  0.05920176
## sample estimates:
##        cor
## -0.1817893
##
##
## $m_corrected$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.93818, df = 66, p-value = 0.3516
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3437424  0.1271845
## sample estimates:
##        cor
## -0.1147194
##
##
## $m_corrected$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.2889, df = 66, p-value = 0.2019
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.38088691  0.08490566
## sample estimates:
##        cor
## -0.1566914
##
##
## $m_corrected$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.086691, df = 66, p-value = 0.9312
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2484634  0.2283356
## sample estimates:
##         cor
## -0.01067037
##
##
##
## $p_corrected
## $p_corrected$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -2.9642, df = 66, p-value = 0.004218
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
```

```
##  -0.5372837 -0.1136290
## sample estimates:
##        cor
## -0.3427678
##
##
## $p_corrected$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -3.6131, df = 66, p-value = 0.0005849
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.5878363 -0.1859572
## sample estimates:
##        cor
## -0.4063654
##
##
## $p_corrected$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -3.2313, df = 66, p-value = 0.001924
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.5587704 -0.1438320
## sample estimates:
##        cor
## -0.3695829
##
##
## $p_corrected$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.6428, df = 66, p-value = 0.1052
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.41692402  0.04221905
## sample estimates:
##        cor
## -0.1982011
##
##
## $p_corrected$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.54582, df = 66, p-value = 0.587
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3006549  0.1741737
## sample estimates:
##         cor
## -0.06703515
##
##
##
## $s_corrected
## $s_corrected$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.0632, df = 66, p-value = 0.2915
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3571438  0.1121255
## sample estimates:
##        cor
```

```
## -0.1297687
##
##
## $s_corrected$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.1453, df = 66, p-value = 0.2562
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3658399  0.1022371
## sample estimates:
##        cor
## -0.1395906
##
##
## $s_corrected$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.72532, df = 66, p-value = 0.4708
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3205559  0.1527361
## sample estimates:
##         cor
## -0.08892737
##
##
## $s_corrected$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.1912, df = 66, p-value = 0.2379
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.37067443  0.09669938
## sample estimates:
##        cor
## -0.1450704
##
##
## $s_corrected$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.04245, df = 66, p-value = 0.9663
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2433471  0.2334908
## sample estimates:
##         cor
## -0.00522518
##
##
##
## $subj_stress_corr
## $subj_stress_corr$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.42363, df = 66, p-value = 0.6732
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1886935  0.2869369
## sample estimates:
##        cor
## 0.05207441
##
##
```

```
## $subj_stress_corr$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.22644, df = 66, p-value = 0.8216
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2645295  0.2119715
## sample estimates:
##         cor
## -0.02786167
##
##
## $subj_stress_corr$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.10118, df = 66, p-value = 0.9197
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2266447  0.2501358
## sample estimates:
##        cor
## 0.01245338
##
##
## $subj_stress_corr$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.14642, df = 66, p-value = 0.884
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2553486  0.2213555
## sample estimates:
##         cor
## -0.01802065
##
##
## $subj_stress_corr$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.95281, df = 66, p-value = 0.3442
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3453191  0.1254240
## sample estimates:
##        cor
## -0.1164845
##
##
##
## $arousal_corr
## $arousal_corr$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.46071, df = 66, p-value = 0.6465
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1842945  0.2911137
## sample estimates:
##        cor
## 0.05661838
##
##
## $arousal_corr$during
##
##  Pearson's product-moment correlation
```

```
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.09489, df = 66, p-value = 0.9247
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2494099  0.2273789
## sample estimates:
##         cor
## -0.01167937
##
##
## $arousal_corr$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.52729, df = 66, p-value = 0.5998
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1763802  0.2985829
## sample estimates:
##        cor
## 0.06476865
##
##
## $arousal_corr$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.53178, df = 66, p-value = 0.5967
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2990856  0.1758453
## sample estimates:
##         cor
## -0.06531833
##
##
## $arousal_corr$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.81925, df = 66, p-value = 0.4156
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3308447  0.1414754
## sample estimates:
##        cor
## -0.1003341
```

```
print(result_F8_F7)
```

```
## $Cortisol_AUCg_Cum
## $Cortisol_AUCg_Cum$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.54939, df = 65, p-value = 0.5846
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1750815  0.3032428
## sample estimates:
##        cor
## 0.06798639
##
##
## $Cortisol_AUCg_Cum$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.71437, df = 65, p-value = 0.4776
```

```
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1552393  0.3216498
## sample estimates:
##        cor
## 0.08826049
##
##
## $Cortisol_AUCg_Cum$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.0118, df = 65, p-value = 0.3154
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1192500  0.3541411
## sample estimates:
##       cor
## 0.1245256
##
##
## $Cortisol_AUCg_Cum$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.37861, df = 65, p-value = 0.7062
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1955027  0.2839183
## sample estimates:
##        cor
## 0.04690887
##
##
## $Cortisol_AUCg_Cum$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.18865, df = 65, p-value = 0.851
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2180413  0.2621282
## sample estimates:
##        cor
## 0.02339254
##
##
##
## $Cortisol_AUCi
## $Cortisol_AUCi$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.382, df = 65, p-value = 0.1717
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.07426692  0.39320628
## sample estimates:
##       cor
## 0.1689558
##
##
## $Cortisol_AUCi$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.3004, df = 65, p-value = 0.1981
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.08419348  0.38472838
```

```
## sample estimates:
##       cor
## 0.1592355
##
##
## $Cortisol_AUCi$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.6883, df = 65, p-value = 0.09614
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.0370689  0.4242841
## sample estimates:
##       cor
## 0.2049648
##
##
## $Cortisol_AUCi$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.95413, df = 65, p-value = 0.3436
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1262472  0.3479123
## sample estimates:
##       cor
## 0.1175255
##
##
## $Cortisol_AUCi$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.14029, df = 65, p-value = 0.8889
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2565348  0.2237454
## sample estimates:
##         cor
## -0.01739826
##
##
##
## $d_corrected
## $d_corrected$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.0021461, df = 66, p-value = 0.9983
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2381759  0.2386742
## sample estimates:
##          cor
## 0.0002641652
##
##
## $d_corrected$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.29203, df = 66, p-value = 0.7712
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2720184  0.2042514
## sample estimates:
##         cor
## -0.03592311
```

```
##
##
## $d_corrected$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.78101, df = 66, p-value = 0.4376
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1460634  0.3266662
## sample estimates:
##       cor
## 0.0956943
##
##
## $d_corrected$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.048741, df = 66, p-value = 0.9613
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2440755  0.2327585
## sample estimates:
##          cor
## -0.005999497
##
##
## $d_corrected$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.36762, df = 66, p-value = 0.7143
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2806054  0.1953257
## sample estimates:
##         cor
## -0.04520462
##
##
##
## $m_corrected
## $m_corrected$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.81187, df = 66, p-value = 0.4198
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3300392  0.1423614
## sample estimates:
##         cor
## -0.09943891
##
##
## $m_corrected$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.4241, df = 66, p-value = 0.6729
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2869902  0.1886375
## sample estimates:
##         cor
## -0.05213226
##
##
## $m_corrected$post
```

```
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.33363, df = 66, p-value = 0.7397
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2767501  0.1993428
## sample estimates:
##         cor
## -0.04103253
##
##
## $m_corrected$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.50396, df = 66, p-value = 0.616
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2959702  0.1791556
## sample estimates:
##         cor
## -0.06191421
##
##
## $m_corrected$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.50821, df = 66, p-value = 0.613
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1786498  0.2964468
## sample estimates:
##        cor
## 0.06243465
##
##
##
## $p_corrected
## $p_corrected$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.11597, df = 66, p-value = 0.908
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2249171  0.2518415
## sample estimates:
##        cor
## 0.01427345
##
##
## $p_corrected$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.35197, df = 66, p-value = 0.726
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1971761  0.2788314
## sample estimates:
##        cor
## 0.04328384
##
##
## $p_corrected$post
##
##  Pearson's product-moment correlation
##
```

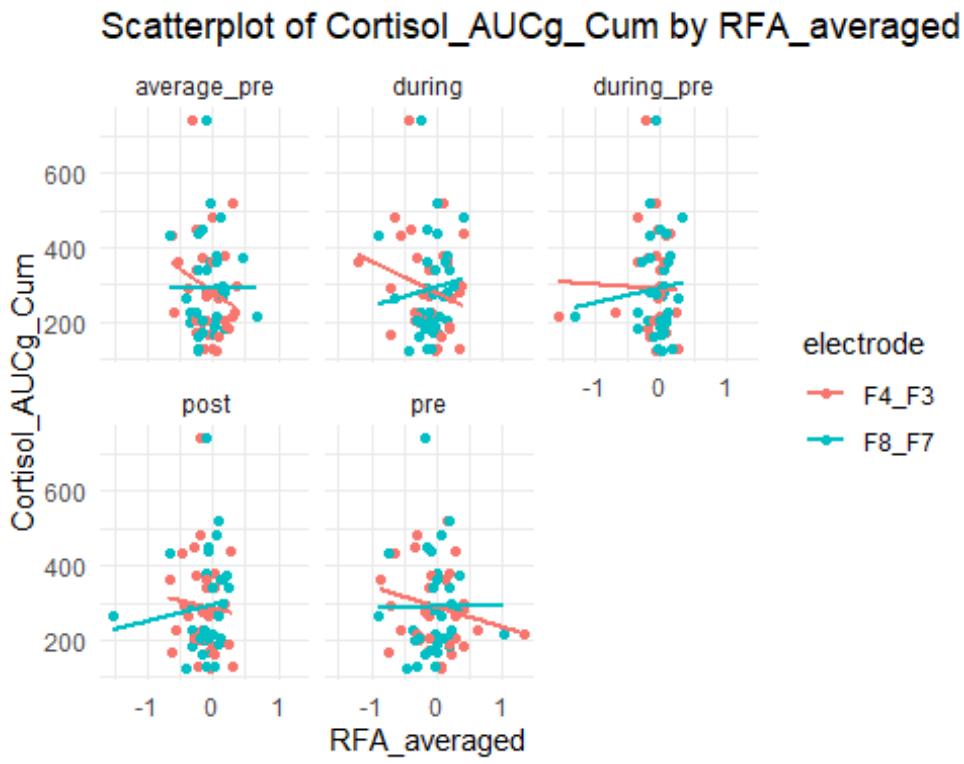
```
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -0.32474, df = 66, p-value = 0.7464
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2757395  0.2003932
## sample estimates:
##         cor
## -0.03994023
##
##
## $p_corrected$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.60839, df = 66, p-value = 0.545
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1667145  0.3076267
## sample estimates:
##        cor
## 0.07467905
##
##
## $p_corrected$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.29063, df = 66, p-value = 0.7722
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2044164  0.2718589
## sample estimates:
##        cor
## 0.03575115
##
##
##
## $s_corrected
## $s_corrected$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.62665, df = 66, p-value = 0.533
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1645350  0.3096542
## sample estimates:
##        cor
## 0.07690711
##
##
## $s_corrected$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.2479, df = 66, p-value = 0.2165
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.08985817  0.37661220
## sample estimates:
##       cor
## 0.1518196
##
##
## $s_corrected$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.0226, df = 66, p-value = 0.3102
## alternative hypothesis: true correlation is not equal to 0
```

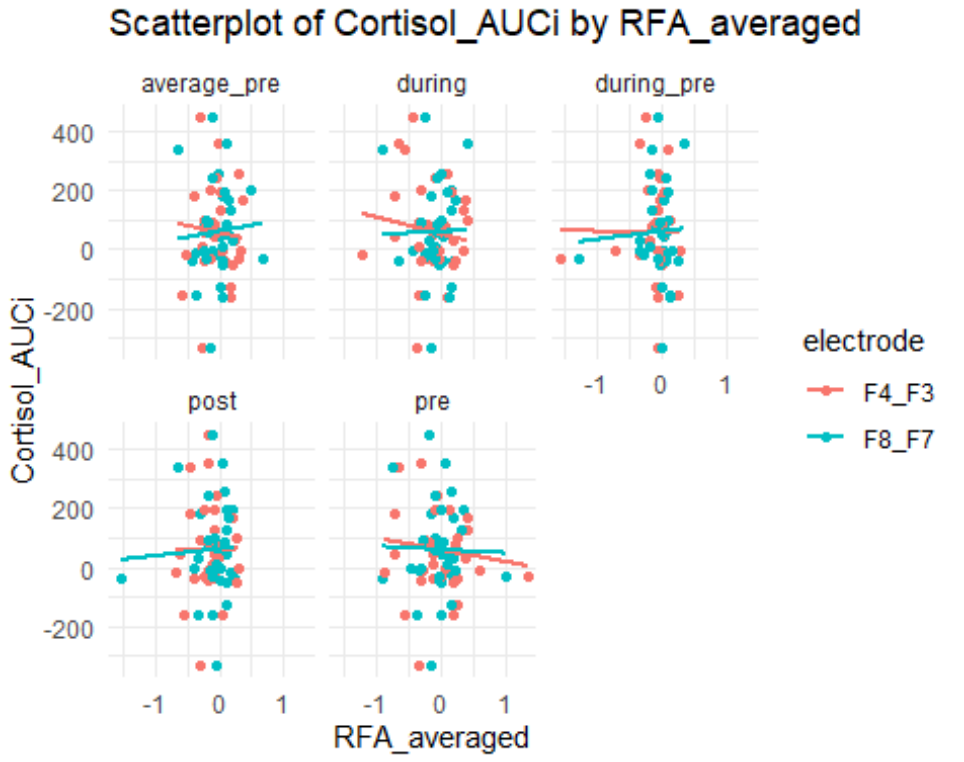
```
## 95 percent confidence interval:
##  -0.1170177  0.3528112
## sample estimates:
##       cor
## 0.1248919
##
##
## $s_corrected$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.3024, df = 66, p-value = 0.1973
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.08328054  0.38228529
## sample estimates:
##       cor
## 0.1582875
##
##
## $s_corrected$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.74211, df = 66, p-value = 0.4607
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1507252  0.3224015
## sample estimates:
##        cor
## 0.09096903
##
##
##
## $subj_stress_corr
## $subj_stress_corr$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.83956, df = 66, p-value = 0.4042
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1390375  0.3330574
## sample estimates:
##       cor
## 0.1027952
##
##
## $subj_stress_corr$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.033549, df = 66, p-value = 0.9733
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2345264  0.2423161
## sample estimates:
##         cor
## 0.004129589
##
##
## $subj_stress_corr$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.063144, df = 66, p-value = 0.9498
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.231081  0.245742
## sample estimates:
```

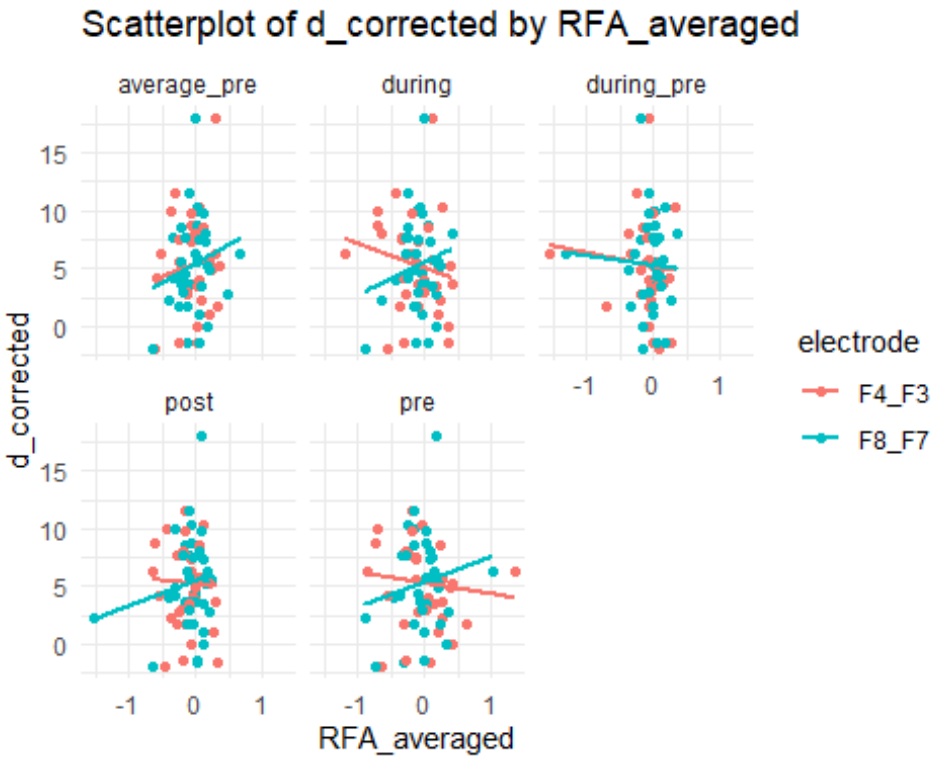
```
##         cor
## 0.007772303
##
##
## $subj_stress_corr$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.0803, df = 66, p-value = 0.2839
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1100686  0.3589594
## sample estimates:
##       cor
## 0.1318158
##
##
## $subj_stress_corr$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.0376, df = 66, p-value = 0.3032
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3544116  0.1152132
## sample estimates:
##        cor
## -0.1266921
##
##
##
## $arousal_corr
## $arousal_corr$pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 1.1162, df = 66, p-value = 0.2684
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1057406  0.3627681
## sample estimates:
##       cor
## 0.1361161
##
##
## $arousal_corr$during
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.18992, df = 66, p-value = 0.85
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2162590  0.2603455
## sample estimates:
##       cor
## 0.0233711
##
##
## $arousal_corr$post
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.9309, df = 66, p-value = 0.3553
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1280606  0.3429568
## sample estimates:
##       cor
## 0.1138404
##
```

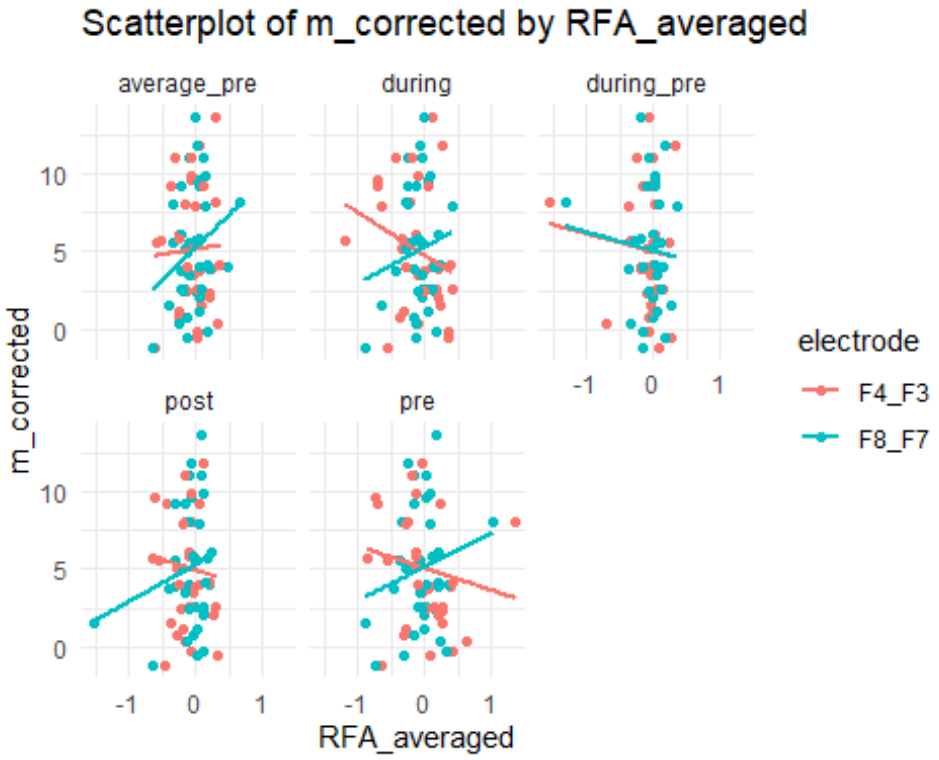
```
##
## $arousal_corr$average_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = 0.88995, df = 66, p-value = 0.3767
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1329842  0.3385294
## sample estimates:
##       cor
## 0.1088935
##
##
## $arousal_corr$during_pre
##
##  Pearson's product-moment correlation
##
## data:  subset_data[[response]] and subset_data[[RFA_averaged]]
## t = -1.1939, df = 66, p-value = 0.2368
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.37096430  0.09636644
## sample estimates:
##        cor
## -0.1453994
```

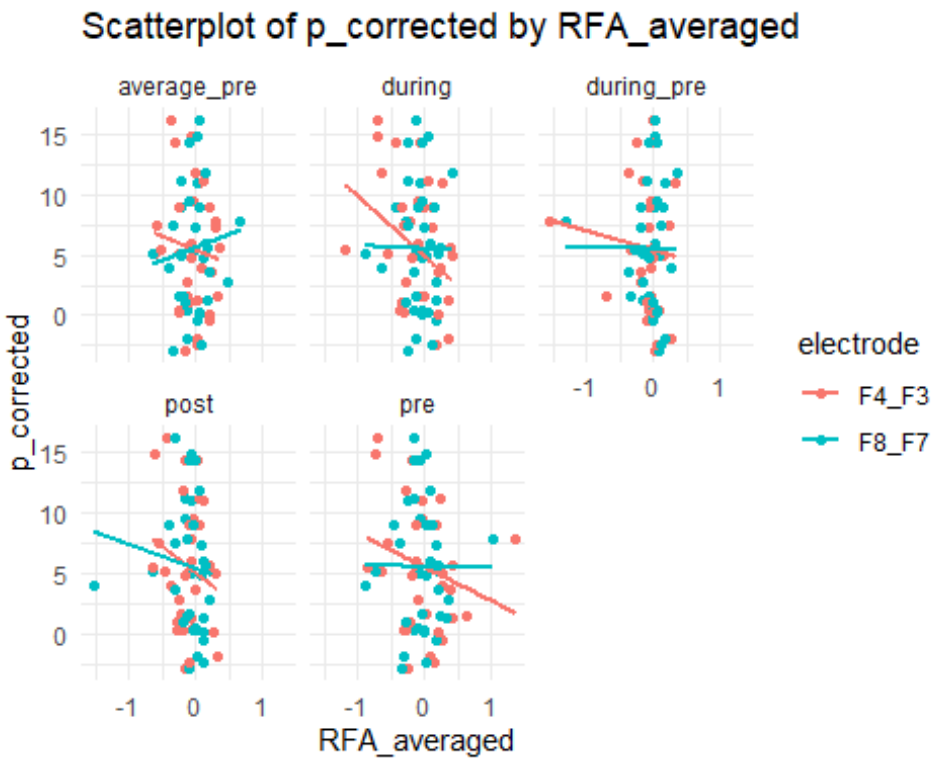
```r
# Define a function to create scatterplots for a given variable and gender
create_scatterplot <- function(data, x_var, y_var) {
  ggplot(data = data, aes_string(x = x_var, y = y_var, color = "electrode")) +
    geom_point() +
    geom_smooth(method = "lm", se = FALSE) +
    facet_wrap(~ time) +
    labs(x = x_var, y = y_var) +
    theme_minimal() +
    ggtitle(paste("Scatterplot of", y_var, "by", x_var))
}

# Define the variables and genders
variables <- c("Cortisol_AUCg_Cum", "Cortisol_AUCi", "d_corrected", "m_corrected", "p_corrected", "s_co
rrected", "subj_stress_corr", "arousal_corr")

# Loop over variables and genders to create scatterplots
for (variable in variables) {
    print(create_scatterplot(CPT_total_f, "RFA_averaged", variable))
  }
```


Scatterplot of Cortisol_AUCg_Cum by RFA_averaged
average_pre
during
during_pre
post
pre
Cortisol_AUCg_Cum
600
400
200
-1
0
1
RFA_averaged
electrode
F4_F3
F8_F7

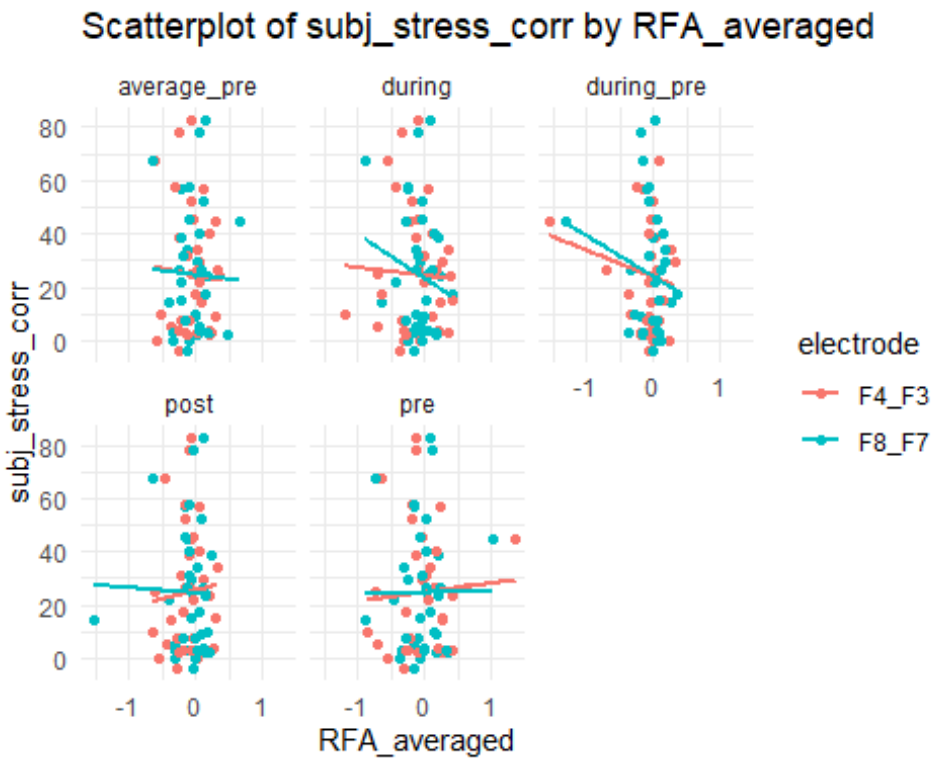

Scatterplot of Cortisol_AUCi by RFA_averaged
average_pre
during
during_pre
post
pre
Cortisol_AUCi
400
200
0
-200
-1
0
1
RFA_averaged
electrode
F4_F3
F8_F7

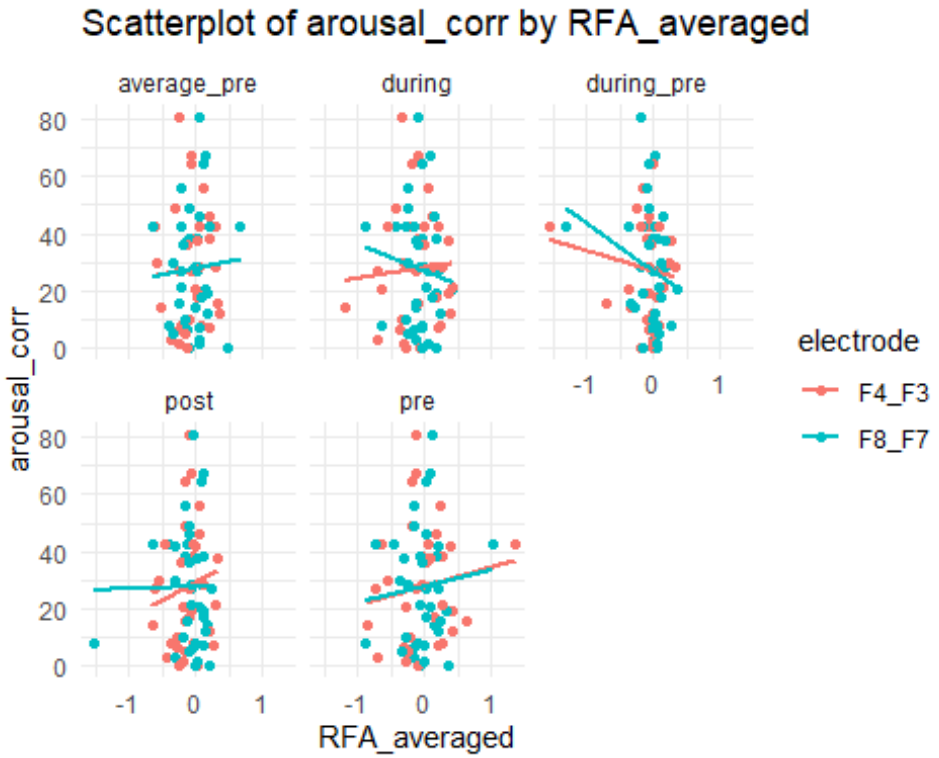

Scatterplot of d_corrected by RFA_averaged
average_pre
during
during_pre
post
pre
d_corrected
RFA_averaged
electrode
F4_F3
F8_F7


Scatterplot of m_corrected by RFA_averaged
average_pre
during
during_pre
post
pre
m_corrected
RFA_averaged
electrode
F4_F3
F8_F7

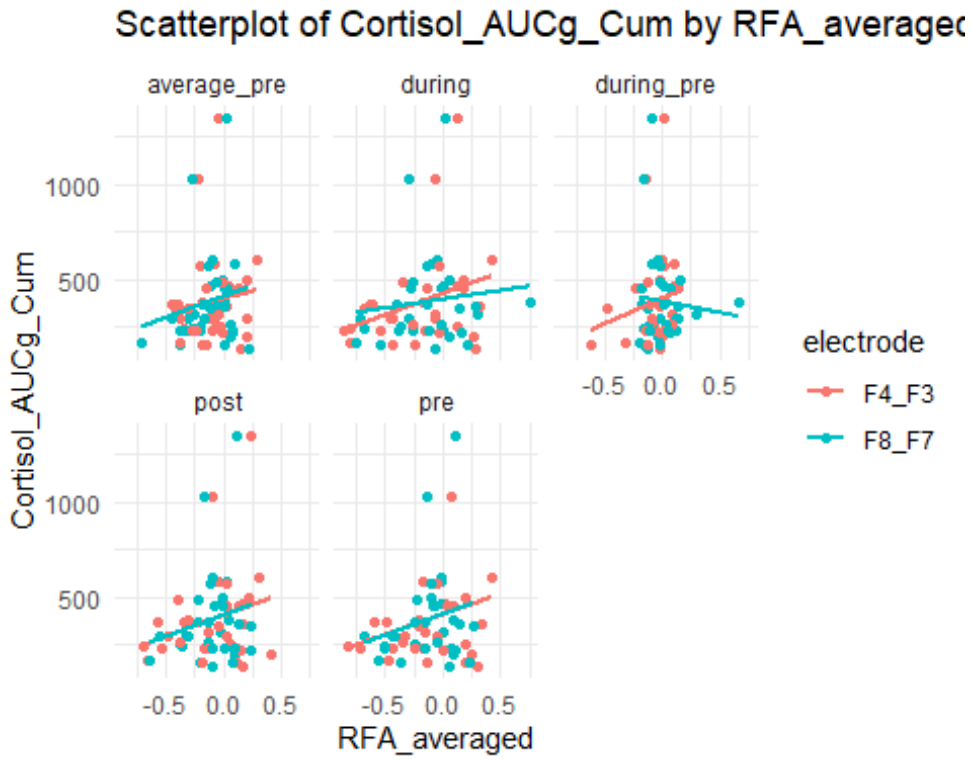

Scatterplot of p_corrected by RFA_averaged
average_pre
during
during_pre
post
pre
p_corrected
RFA_averaged
electrode
F4_F3
F8_F7

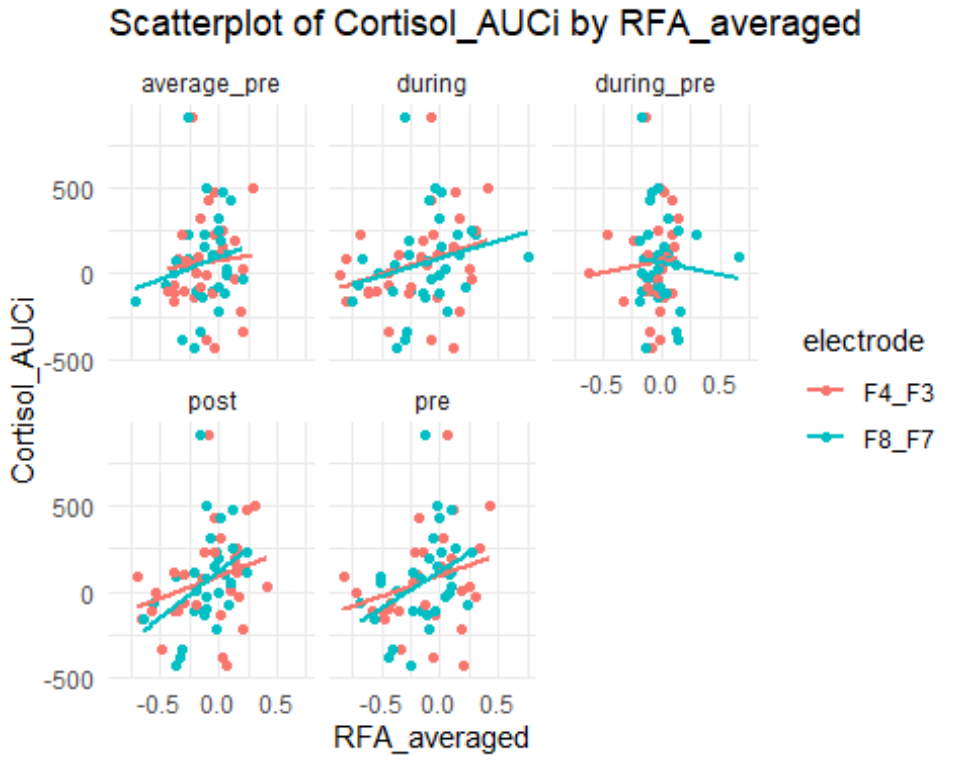

Scatterplot of s_corrected by RFA_averaged
average_pre
during
during_pre
post
pre
s_corrected
RFA_averaged
electrode
F4_F3
F8_F7

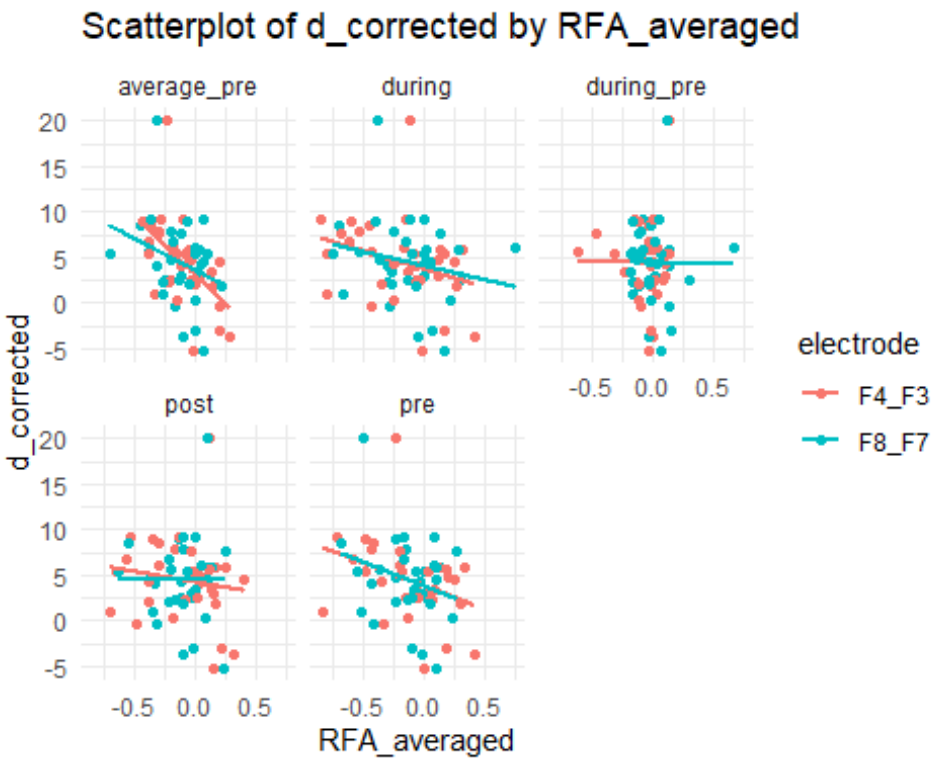


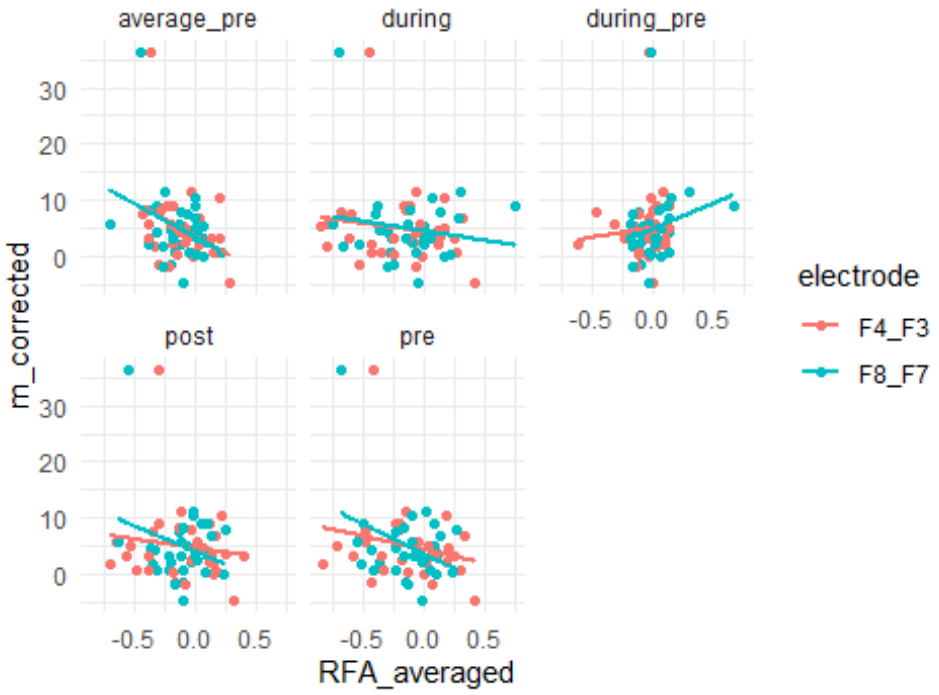


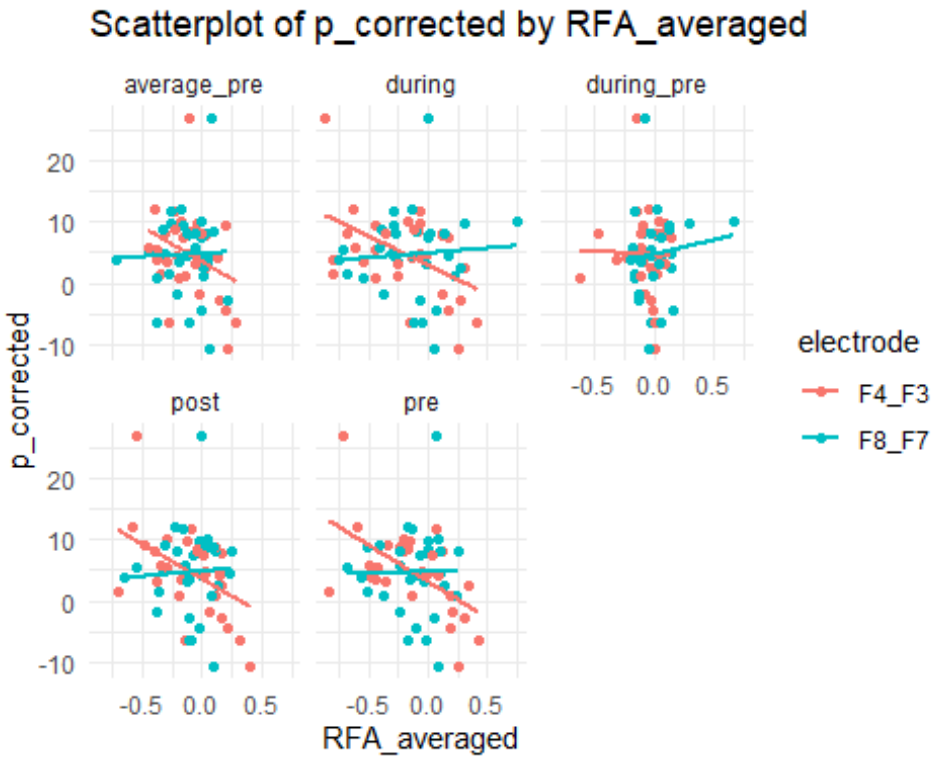

```
# Loop over variables and genders to create scatterplots
for (variable in variables) {
    print(create_scatterplot(CPT_total_m, "RFA_averaged", variable))
}
```

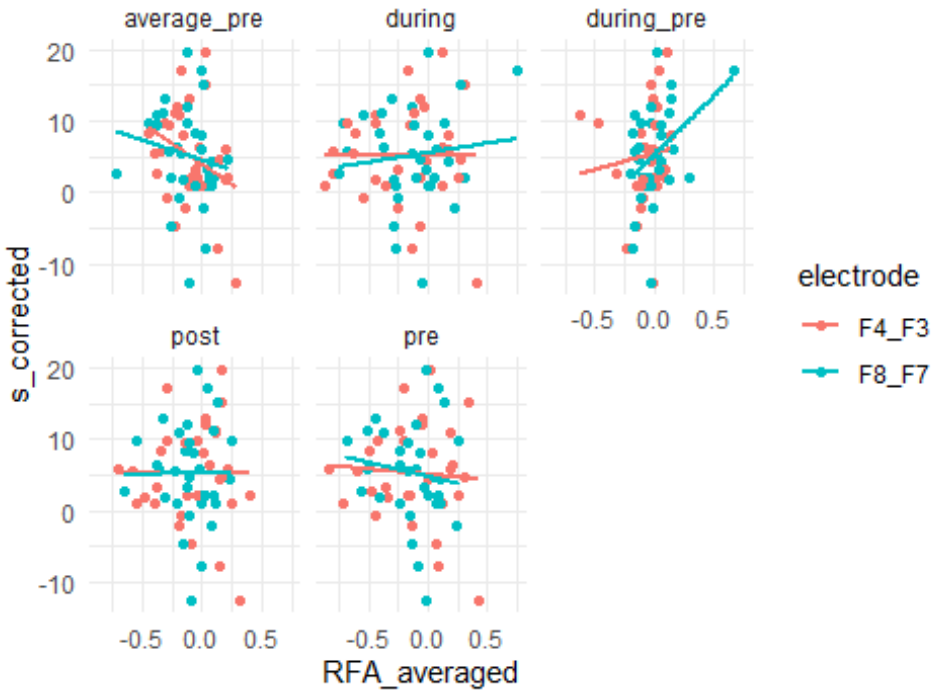

Scatterplot of Cortisol_AUCg_Cum by RFA_averaged
average_pre
during
during_pre
post
pre
Cortisol_AUCg_Cum
1000
500
-0.5
0.0
0.5
RFA_averaged
electrode
F4_F3
F8_F7

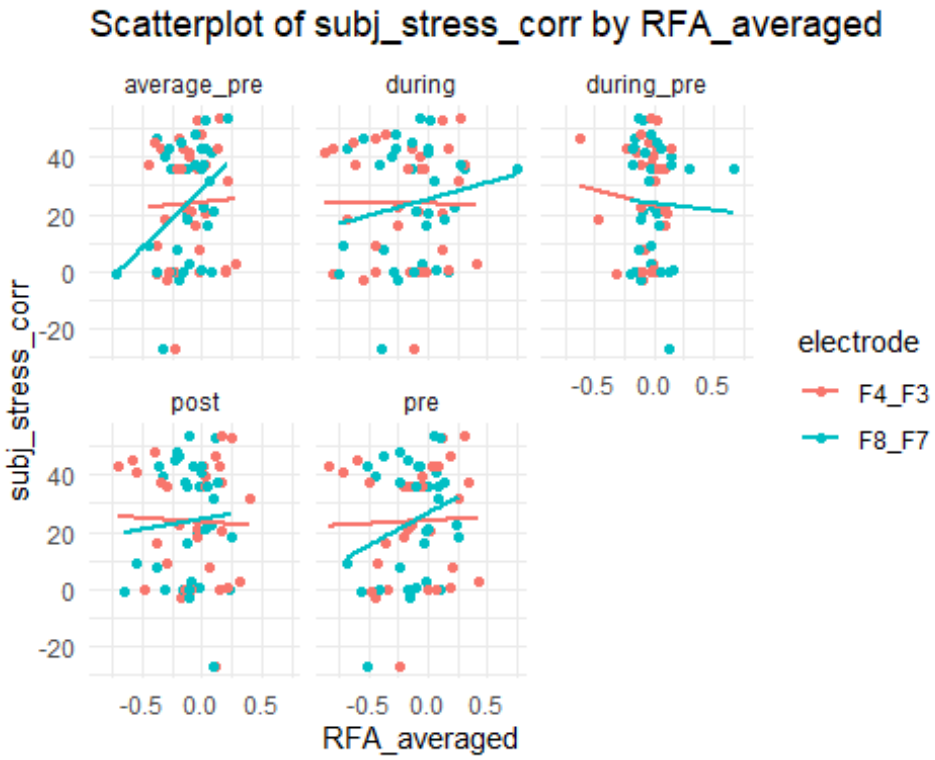

Scatterplot of Cortisol_AUCi by RFA_averaged
average_pre
during
during_pre
post
pre
Cortisol_AUCi
500
0
-500
-0.5
0.0
0.5
RFA_averaged
electrode
F4_F3
F8_F7

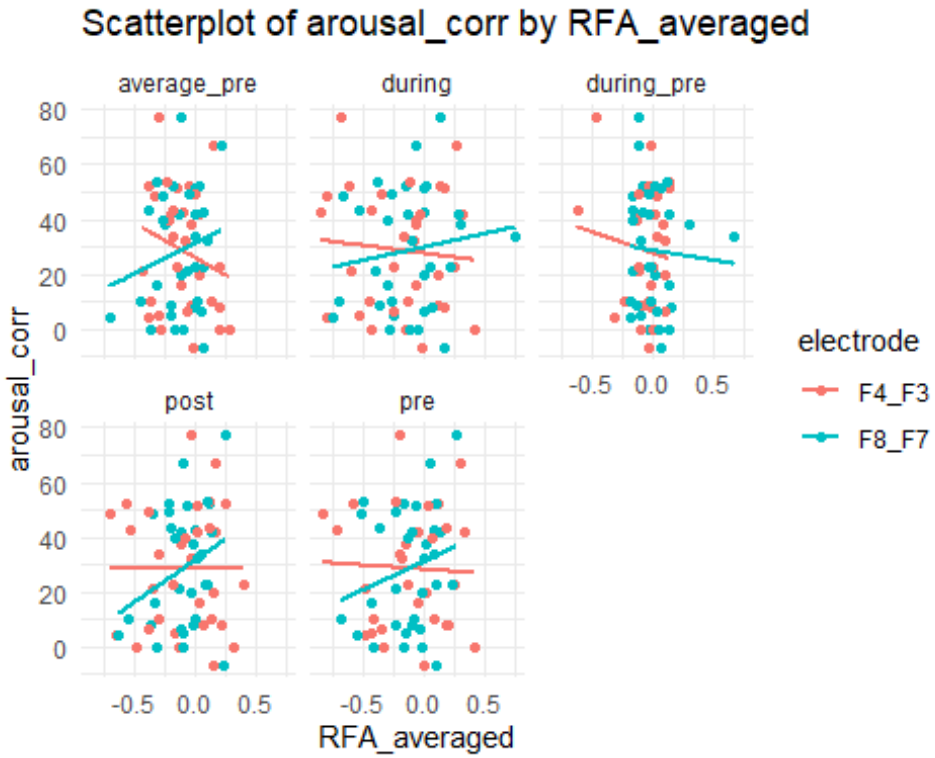

Scatterplot of d_corrected by RFA_averaged
average_pre
during
during_pre
post
pre
d_corrected
RFA_averaged
electrode
F4_F3
F8_F7


Scatterplot of m_corrected by RFA_averaged
average_pre
during
during_pre
post
pre
m_corrected
RFA_averaged
electrode
F4_F3
F8_F7

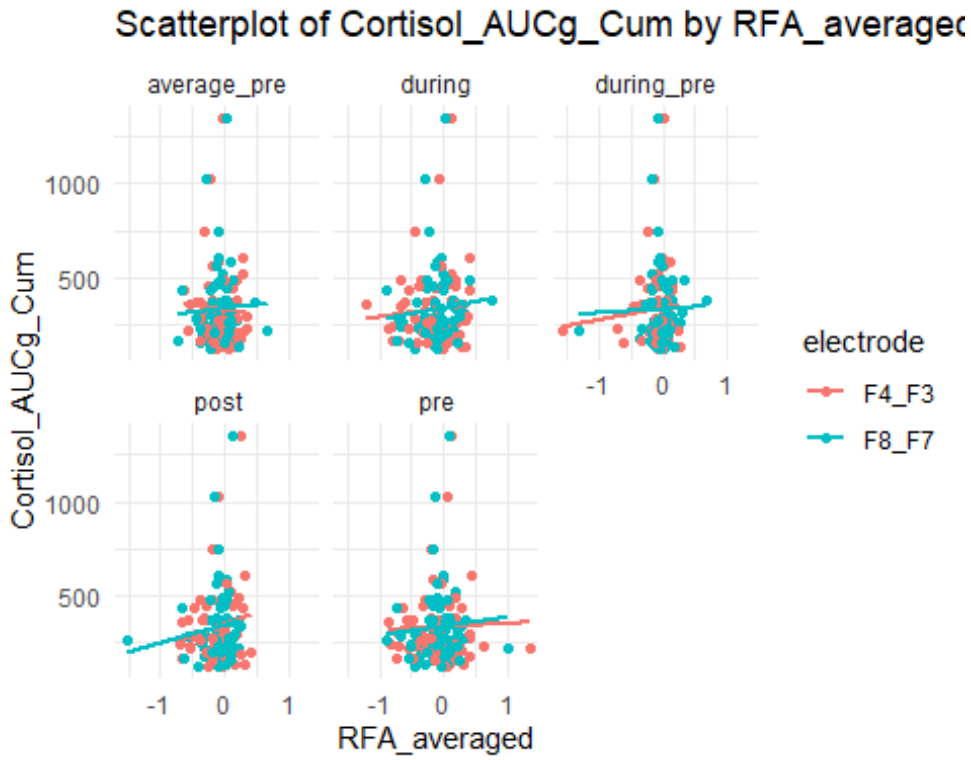

Scatterplot of p_corrected by RFA_averaged
average_pre
during
during_pre
post
pre
p_corrected
RFA_averaged
electrode
F4_F3
F8_F7


Scatterplot of s_corrected by RFA_averaged
average_pre
during
during_pre
post
pre
s_corrected
RFA_averaged
electrode
F4_F3
F8_F7

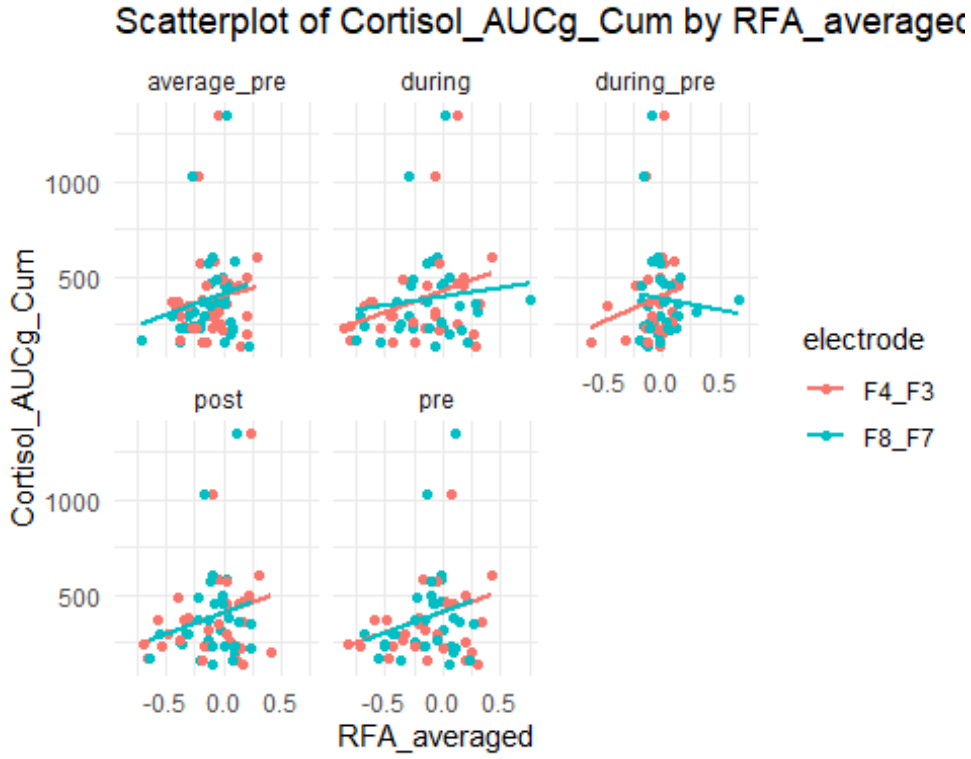




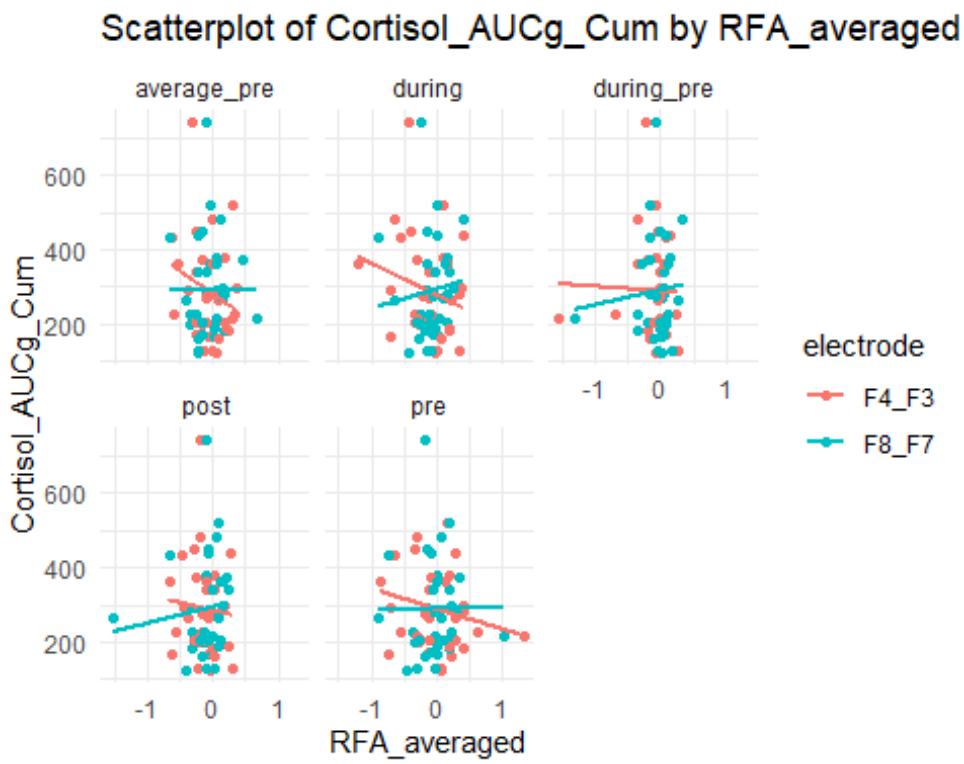

```
print(create_scatterplot(CPT_total, "RFA_averaged", "Cortisol_AUCg_Cum"))
```




```
print(create_scatterplot(CPT_total_m, "RFA_averaged", "Cortisol_AUCg_Cum"))
```




```
print(create_scatterplot(CPT_total_f, "RFA_averaged", "Cortisol_AUCg_Cum"))
```


Scatterplot of Cortisol_AUCg_Cum by RFA_averaged
average_pre
during
during_pre
post
pre
Cortisol_AUCg_Cum
600
400
200
-1
0
1
RFA_averaged
electrode
F4_F3
F8_F7