

# Assessing the link between neurophysiological and psycho-affective responses to acoustic roughness

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June 9, 2023



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## Abstract

Acoustic roughness refers to a particular type of sound that makes us react faster and uses broader brain networks than classical auditory perception. Evolution has selected this trait because of the survival advantage it gives by processing environmental information more efficiently through the sound modality. Electroencephalography can probe the integrity of our neural pathways thanks to this characteristic of auditory roughness perception. We know that neurodegenerative diseases such as Alzheimer's, which affect these networks, show different patterns of responses to roughness, with a modification of the corresponding ERPs components. In order to propose more early diagnostic tools, this feature is currently being studied. Autism is not a neurodegenerative disorder but a neurodevelopmental syndrome characterised by a different brain connectivity. However, the relationship between autism and auditory roughness perception remains to be explored. Our research proposes to investigate the association between autism and neurophysiological and psycho-affective responses to acoustic roughness. Our experiment consisted in the simultaneous recording of two EEG headsets, to compare between a classical and a wearable one, in order to assess the possibility of a home-based diagnosis with such a tool. We collected both behavioural and electrophysiological responses from 26 participants, assessing their autistic trait to explore the possible specificity of autism to perception of such sounds.

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## Abbreviations

Name	Abbreviations
Electroencephalography	EEG
Auditory steady-state response	ASSR
Event related potentials	ERP
Electrocardiogram	ECG
Electromyography	EMG
Lab Streaming Layer	LSL
Autism Spectrum Disorder	ASD
Obsessive Compulsive Disorder	OCD
Modulation Power Spectrum	MPS
Brain Imaging Data Structure	BIDS
Independant component analysis	ICA

## 1 Acknowledgements

I want to thanks all the people that made possible this experiment and this internship.

Emma Ducos, for all her advices and all the good jokes and happiness.

Luc Arnal, for his advices, tutoring on research in general and for having me in his team.

Tanguy Delmas, Keith Dolling, Nadège Marin and Mathieu Pham Van Cang for their welcome, as well as all the stimulating discussions, scientific or not.

And all the others persons from the hearing institute that helped me during my stay.

For the Ecole Normale Supérieure, I want to thanks Daniel Pressnitzer for his advices and tutoring, Yves Boubenec and Camille Lemarchand for the organization part.

And also, my family for their advices and patience, and all the other Cogmaster students for the discussions that helped the project.

## 2 Preamble note

All this report is available online, at this link. Some links are used in effort to provide more interactivity throughout the document and with external ressources.

If you read this report on PDF, the links will be active. If you read it on paper, you can report to the web section to get all the corresponding links.

**GitHub repository :** <https://github.com/MatthieuFra/roughness-eeg-internship-report>

**OSF Project :** [https://osf.io/5tdes/?view\\_only=afb587f8add24c009fc036f5ec1d8cf](https://osf.io/5tdes/?view_only=afb587f8add24c009fc036f5ec1d8cf)

### 3 Summary

Acoustic roughness refers to a particular type of sound that makes us react faster and uses broader brain networks than classical auditory perception.

Evolution has selected this trait because of the survival advantage it gives by processing environmental information more efficiently through the sound modality.

Electroencephalography can probe the integrity of our neural pathways thanks to this characteristic of auditory roughness perception.

We know that neurodegenerative diseases such as Alzheimer's, which affect these networks, show different patterns of responses to roughness, with a modification of the corresponding ERPs components.

In order to propose more early diagnostic tools, this feature is currently being studied.

Autism is not a neurodegenerative disorder but a neurodevelopmental syndrome characterised by a different brain connectivity.

However, the relationship between autism and auditory roughness perception remains to be explored.

Our research proposes to investigate the association between autism and neurophysiological and psycho-affective responses to acoustic roughness. Our experiment consisted in the simultaneous recording of two EEG headsets, to compare between a classical and a wearable one, in order to assess the possibility of a home-based diagnosis with such a tool.

We collected both behavioural and electrophysiological responses from 26 participants, assessing their autistic trait to explore the possible specificity of autism to perception of such sounds.

## 4 Introduction

Communication is a fundamental aspect of human interaction, enabling the exchange of information, ideas and emotions between individuals. Audition plays a crucial role in our ability to communicate effectively. It involves the perception and interpretation of auditory stimuli such as speech, music and environmental sounds.

But it seems that some sounds make us react differently than others (Arnal et al., 2015). Hearing babies crying, screams, alarms and other sounds have the ability to make us react strongly with aversion. These reactions are an interesting way to probe our brains and gain a better understanding of our auditory perception and, more generally, our cognition (Arnal et al., 2019).

These sounds have one thing in common: roughness. Roughness refers to the perceived quality of a sound (Pressnitzer, 1998), characterised by the sensation of rapid fluctuations in sound intensity or frequency (Terhardt, 1974). It can be described as a sensation of auditory "aggressivity" or "irregularity". Acoustically, roughness is defined by rapid temporal fluctuations and is characterised by frequencies around the boundary between discrete and continuous sounds, lying between the perception of rhythms, sound events and the perception of pitch or other continuous vocalisations (Arnal et al., 2015).

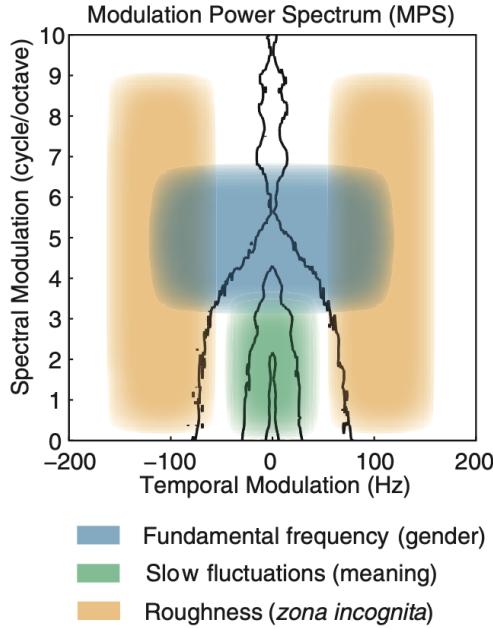


Figure 1: Modulation power spectrum (MPS) of a sentence represented in black. Roughness is contained in the orange zone (From Arnal et al., 2015)

Studies have shown that our perception of roughness is a very interesting phenomenon. We respond faster than to other sounds, and by recruiting broader neural circuits across the brain (for example, the amygdala), in a much more general way than just the classical auditory related areas (Arnal et al., 2019). These stereotyped responses make us more efficient at recognising these particular sounds. From an evolutionary point of view, it makes sense that this trait has been selected by natural selection, since being better at detecting rough sounds can help us escape from a predator or help our relatives.

Since roughness perception recruits larger neural circuits, it has been postulated that using electroencephalography (EEG) to study brain responses to roughness may be a good proxy for the integrity of these large networks. Using EEG measures of the perceiving brain to roughness, we can assess the dynamic properties of the underlying networks (Schneefeld et al., 2022).

Neurodegenerative diseases are known to alter neural circuits and therefore brain responses. Using event-related potentials, we can observe a change in the evoked components, with a reduced response in people affected by such diseases. For example, Alzheimer's disease has been associated with a different brain response in event related potentials (Hedges et al., 2016), and also to roughness perception (van Deursen et al., 2011)(Ducos, *in preparation*). Knowing that these diseases are associated with such responses allows this technique to be used as a future diagnostic tool, able to probe the integrity of large neuronal pathways affected by neurodegenerative processes at an early stage (Schneefeld et al., 2022).

Autism spectrum disorder (ASD) is known to be a neurodevelopmental disorder that shows altered neuronal activity with increased local connectivity but reduced connectivity between wider brain areas. The relationship between ASD and auditory perception has been explored, and we know that it affect brain responses (Wilson et al., 2007). However, research investigating ASD's responses to roughness is lacking. Does autism, like other conditions involving changes or alterations in neural pathways, show a different pattern of response to roughness? This is the main question we're trying to answer in this internship.

In addition, patients with such diseases are often restricted from going to hospital, and carrying out studies or diagnoses can quickly become a challenge. To avoid such difficulties, it's tempting to use recent technological advances such as wearable EEG to perform such recordings at home in a more comfortable way for patients.

However, these new devices are still under development and their ability to provide clinical-grade recordings is still under debate (Radüntz, 2018) despite promising results (Spinelli et al., 2020). To address this, we decided to conduct a benchmark within our experiment, comparing a traditional EEG headset with a wearable one, and assessing its ability to perform such recordings. A previous internship in the team had used the same wearable headset, but the results were mixed.

So we decided to conduct another experiment to assess the relationship between autism and neurophysiological and psycho-affective responses to acoustic roughness. This time with more participants to increase statistical power, and also to record alongside a classical clinical EEG to compare the two more accurately.

As this experiment is a replication of related research in the team, it will be necessary to confirm that we obtain the same pattern of response to roughness as previously found.

## 5 Material and method

### 5.1 Participants

We conducted this experiment with a group of participants ( $n = 26$ ) recruited via the Expescience mailing list of the RISC. The group of participants consisted of 15 females and 11 males, with an age range of 20-66 years ( $SD = 13.0$ ). All participants were normal hearing and neurotypical.

However, due to time constraints it wasn't possible to do a tonal audiogram before each session, so we are not completely sure of each participant's audiogram. Neurotypicality wasn't assessed either, but an autistic traits questionnaire was given.

This experiment was ethically approved (CPP approval 28/06/2022, [https://matthieufr.github.io/roughness-eeg-internship-report/online\\_interactive\\_content/pdfs/1.pdf](https://matthieufr.github.io/roughness-eeg-internship-report/online_interactive_content/pdfs/1.pdf)) and participants were paid 20 euros per hour for their participation. The experiment lasted one hour.

Descriptives	
	<b>Age</b>
N	26
Mean	35.5
Median	31.5
Standard deviation	13.0
Minimum	20
Maximum	66

Figure 2: Descriptive statistics of participants age

Frequencies of Gender			
<b>Gender</b>	<b>Counts</b>	<b>% of Total</b>	<b>Cumulative %</b>
F	15	57.7 %	57.7 %
M	11	42.3 %	100.0 %

Figure 3: Descriptive statistics of gender

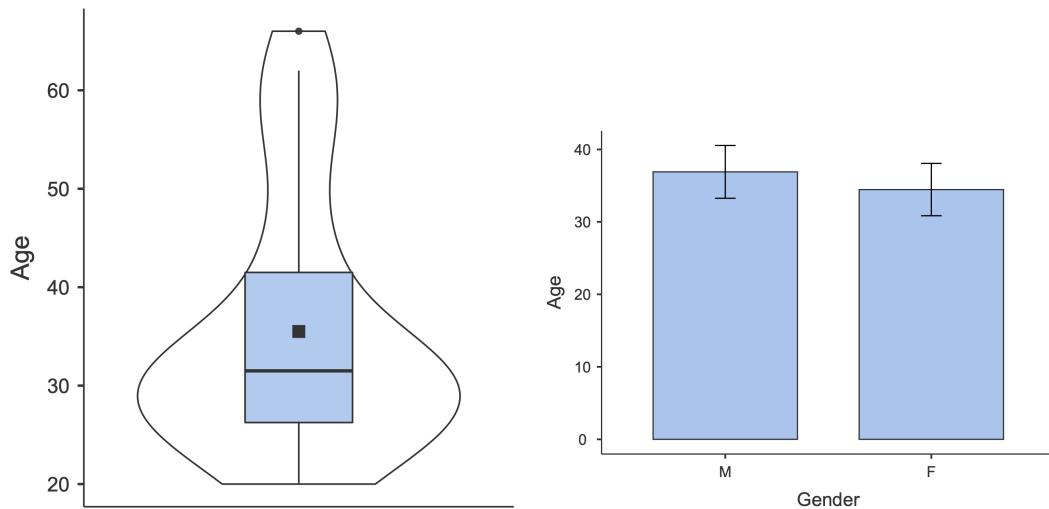


Figure 4: Box plot and violin of age distribution on the left, Bar plot of age by gender repartition on the right

Frequencies of Handedness			
Handedness	Counts	% of Total	Cumulative %
L	1	3.8 %	3.8 %
R	25	96.2 %	100.0 %

Figure 5: Descriptive statistics of handedness

## 5.2 Stimuli

The audio stimuli presented were clicktrains of different frequencies. Two click trains were presented one after the other.

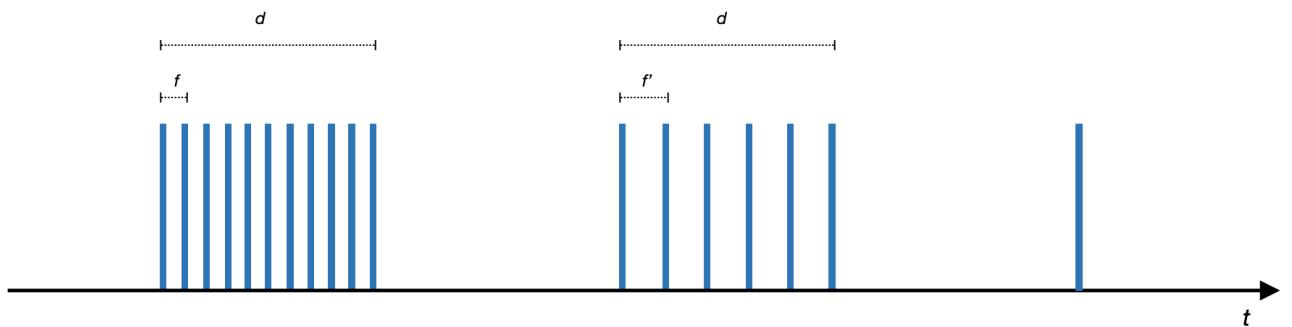


Figure 6: Schematic of two click trains of frequencies  $f$  and  $f'$ , a single click is represented on the right

A click is an audio impulse with a vertical rise and a vertical fall. Click trains are made up of several clicks that occur periodically at a given frequency. It's this frequency that we refer to when we talk about the click train frequencies. The duration of each click train is one second, and the inter-stimulus interval (ISI) between the different trains remains constant (also one second).

For this experiment we used click trains of 10Hz, 20Hz, 30Hz, 40Hz, 60Hz, 80Hz and 90Hz. We didn't go any higher due to our bandwidth limitations for EEG recordings on the Q+, in fact its high-end internal bandwidth is 100Hz. The different sounds are available in the supplementary material and can be listened to by clicking [here](#). All stimuli were displayed using a PsychoPy script (Peirce et al., 2019).

The loudness was controlled and the sound chain was calibrated using an artificial ear. Each participant could set the volume at the beginning of the experiment, but could only go higher. The instructions were "*set the volume to a tolerable level*". Then we could get an estimate of the loudness of the sounds for each participant, knowing the calibrated point and the exact increase in PsychoPy.

To generate the different click trains we used a MatLab code.

### 5.3 EEG Headsets

#### 5.3.1 *Brain product R-Net*

The BrainProduct R-net is a classic clinical EEG with 32 wet passive electrodes using a solution of water and potassium chloride (KCl). The chosen sampling rate of the R-net was 1000Hz. The reference was a common reference averaged over all electrodes.



Figure 7: R-Net on a participant's head

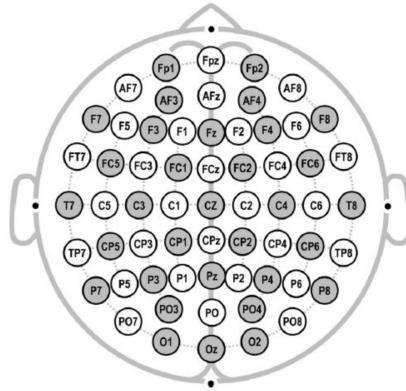


Figure 8: Placement of the 32 electrodes (gray dots) according to the extended 10-20 system

### 5.3.2 MBT Q+

The Q+ from MyBrainTechnology is a wearable EEG headset that attaches to a pair of headphones and uses 6 dry active electrodes. The sampling rate of the Q+ is 250Hz.

Four electrodes are placed on the head at  $P3$ ,  $P4$ ,  $AF3$  and  $AF4$  of the 10-20 location system. Two reference electrodes ( $A1$ ,  $A2$ ) are located on the side of the headphones, behind the ear, on the mastoid bone.  $A1$  was used as the ground electrode and  $A2$  as the reference electrode.

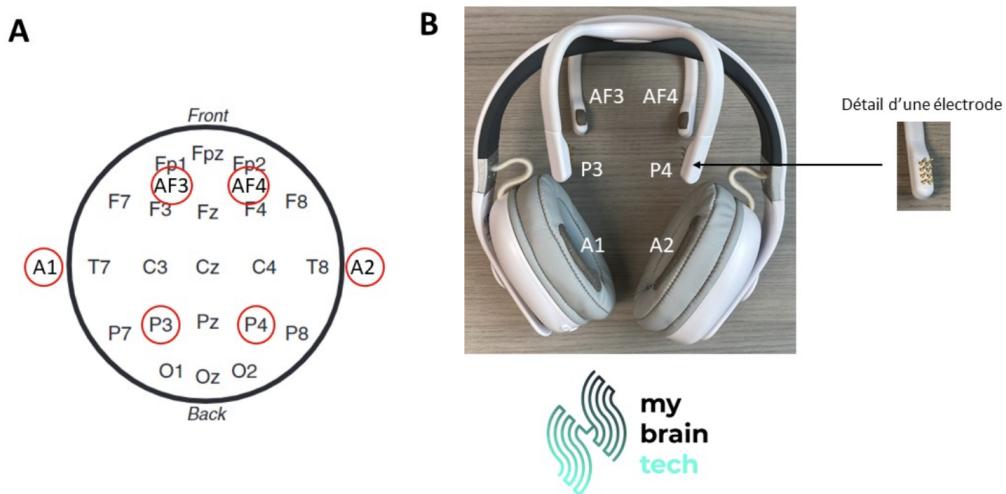


Figure 9: A: Schematic of electrode placement according to the international 10-20 system, (adapted from J. Luck, 2014). The black circle represents a top view of the skull, front and back as indicated. The electrodes circled in red are those on the Q+ helmet. B: Q+ helmet and name of electrodes in white (top), start-up logo (bottom). (Adapted from Lafargue-Hauret, 2022)

## 5.4 Experimental design

Several sensors are attached to the participant. First, facial electromyography (EMG) is installed to record the activity of the orbicularis oculi (Boxtel, 2010). Two electrodes were placed under the participant's left eye and the reference electrode was placed on the right cheek to avoid muscle activity.

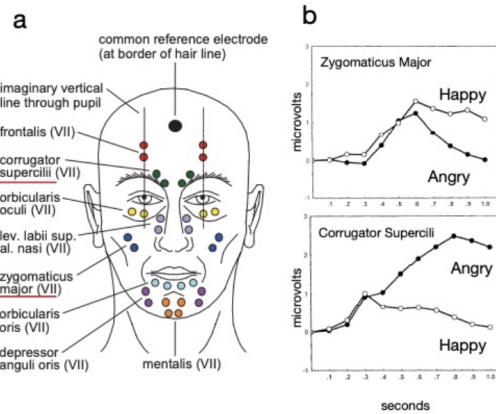


Figure 10: Facial reactions measured with facial EMG (adapted from Boxtel, 2010)

The electrocardiogram (ECG) consisted of three electrodes placed on the sites RL, LA and LL (right leg, left arm and left leg, respectively) as shown in the figure below.

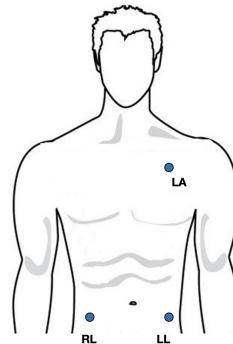


Figure 11: Placement of standard ECG using 3 electrodes (adapted from Hakimi and Setarehdan, 2018)

After installing these electrophysiological sensors, we placed the R-net on the participant, using the correct size cap and adjusting the placement of the electrodes so that Cz was in the centre of the nasion-nion distance and the headset was symmetrical on both sides.

Finally, we were able to place the Q+, adjusting the A1 and A2 electrodes so that they were in contact with the back of the ear, and the other electrodes so that they did not touch any of the R-net electrodes.

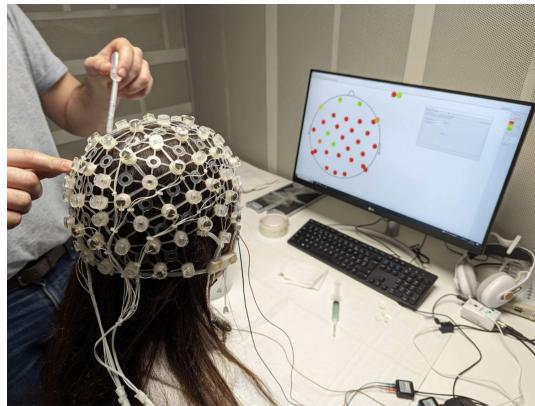


Figure 12: Adjustment of impedance

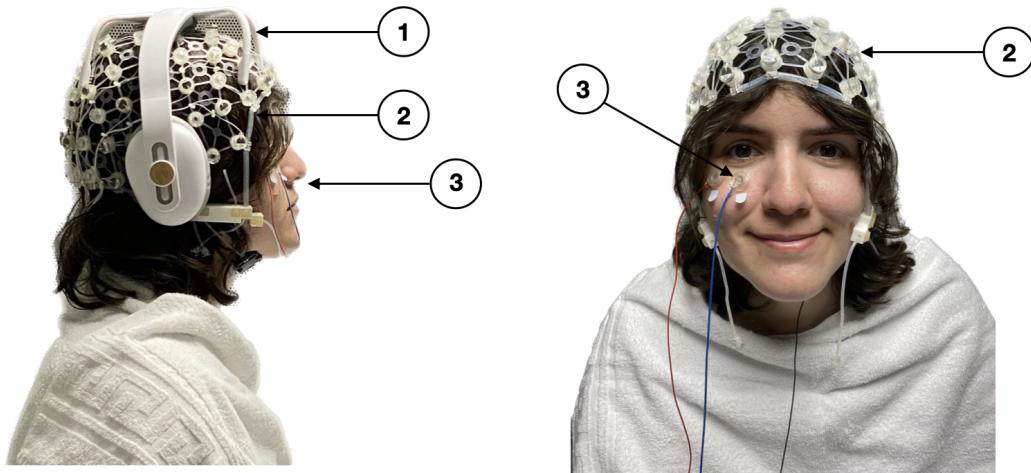


Figure 13: Diagram of the experimental design. 1: Q+ Headset, 2: R-Net Headset, 3: EMG Electrodes

## 5.5 Experimental procedure

The experiment consisted of an oddball paradigm, in line with previous experiments conducted by the team. The instructions were as follows:

Vous allez entendre des sons.

Lorsqu'une échelle apparaît, veuillez noter les sons que vous avez entendus parmi :

“neutre”, “acceptable”, “gênant”, “insupportable”, “horrible”

Lorsque vous êtes prêts, faites un clic droit avec la souris.

We remind participants to avoid blinking during the recording (especially during the sound presentation) and to clench their jaws to avoid muscular artefacts.

The participant was asked to sit in an anechoic chamber to ensure sound isolation from the outside. They completed a questionnaire investigating autistic traits, the QA questionnaire (Baron-Cohen et al., 2001); and two anxiety scales: the STAI-T (for the anxiety trait) and the STAI-S (for present state anxiety) (Spielberger et al., 1999)(Skapinakis, 2014) for the *before* condition.

First, they are asked to close their eyes for about two minutes in order to perform a resting state with closed eyes. After this short period, the trials begin.

We present them with two click trains, one after the other. The first click train presented is randomly selected from the 7 possible frequencies. Then, after an ISI of 1 s, the second clicktrain is presented. 80% of the time the second clicktrain is the same frequency as the first. In 20% of the cases it's a different frequency, chosen between the left possibilities. 150 pairs of click trains are presented, for a total of 300 click trains. After the presentation of the second stimuli, the participant has to indicate his aversion using a continuous scale with a slider. The participant can choose between 5 levels with the mouse, from "neutral" to "horrible".

They then complete the STAI-S a second time, for the *after* condition.

The more detailed operational version we used can be found here: IDA Experiment Protocol

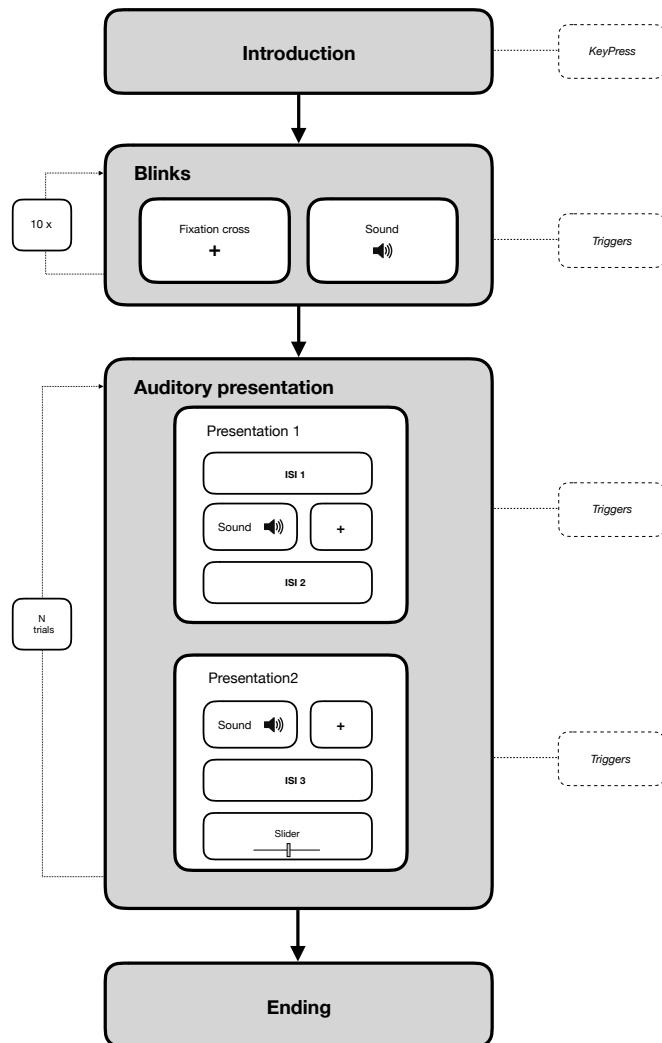


Figure 14: Diagram of the experiment

The entire experimental procedure takes 30 minutes, with a further 30 minutes for the questionnaires and the installation of the EEG, ECG and EMG equipment.

**Fig:**



Figure 15: Participant doing the experiment

## 5.6 Data acquisition

Data were collected using two computers, a tablet for the Q+ and the ActiChamp for the R-Net. The stimulation computer was the host of the PsychoPy experiment, displaying the stimuli but also recording the behavioural data (slider responses). The recording computer was responsible of acquiring the EEG data for the two headsets.

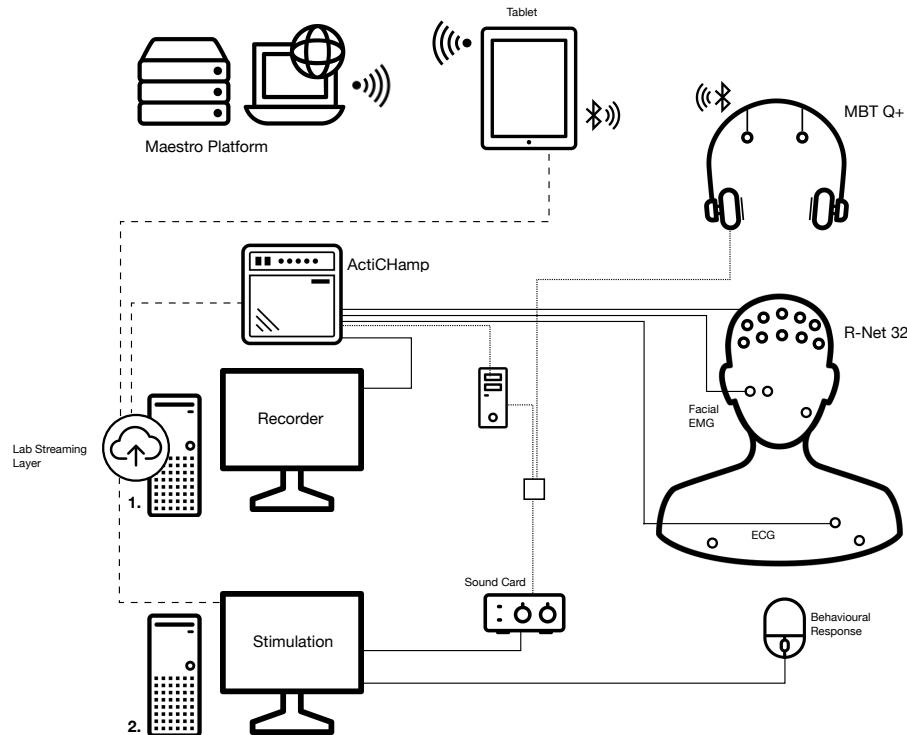


Figure 16: Diagram of the experimental design

To carefully control the synchronisation between all the devices, we used LabStreamingLayer (LSL).

LSL is a software used to stream and synchronise data streams from different sensor hardware. It allows to unify the acquisition of different streams (such as Q+ and R-net) and, more importantly, to ensure time synchronisation between the streams through the network.

The acquisition computer was designed to host the LSL network. The ActiChamp was connected to it using the specially designed BrainProduct LSL software connector, and the tablet used for the Q+ was used to generate an LSL stream using a special application developed by MyBrainTechnology for our experiment.

We then used LSL's LabRecorder to record on the dedicated computer. To collect triggers to synchronise the different streams, the audio stimuli went into an auxiliary channel of the ActiChamp amplifier, passing through a StimTracker that sent triggers at the onset of each presented click.

Data were recorded in BIDS format, with a sampling rate of 1000 Hz for the R-net and 250 Hz for the Q+, in the .xdf format provided by LSL.

## 5.7 Behavioural analysis

The behavioural analysis concerns both the autistic trait and anxiety questionnaires, in addition to the aversion response of the slider.

In addition to simple descriptive statistics of the individual scores for each questionnaire, we decided to perform a regression analysis between aversion and the autistic score obtained.

In a more exploratory way, we also investigated the possible correlation between QA and STAI-T scores. As these are published scales, we simply had to use the scoring tools provided.

For PsychoPy, we collected the slider responses for each participant, knowing which stimuli they corresponded to.

## 5.8 EEG analysis

Data analysis was performed on the data after conversion to FIFF format.

We used MNE-Python for the analysis of the EEG data (Gramfort et al., 2014)(Gramfort et al., 2013), with Jupyter NoteBooks in Visual Studio Code. The code is available [here](#).

The analysis of the EEG data consisted of several operations, including some preprocessing and the main analysis. The preprocessing consisted of the following operations:

1. Filtering (bandwidth and notch filters of the line noise),
2. Independent Component Analysis (ICA),
3. Signal epoching.

### 5.8.1 Filtering

Filtering consists of removing the unwanted frequencies to eliminate noise. We filtered the bandwidth, between 0.1Hz and 500Hz for the R-net and between 0.1Hz and 100Hz for the Q+.

Then a notch filter is applied at 50Hz (including filtering for each harmonic of the AC power, up to the limit of the bandwidth) to remove power line noise.

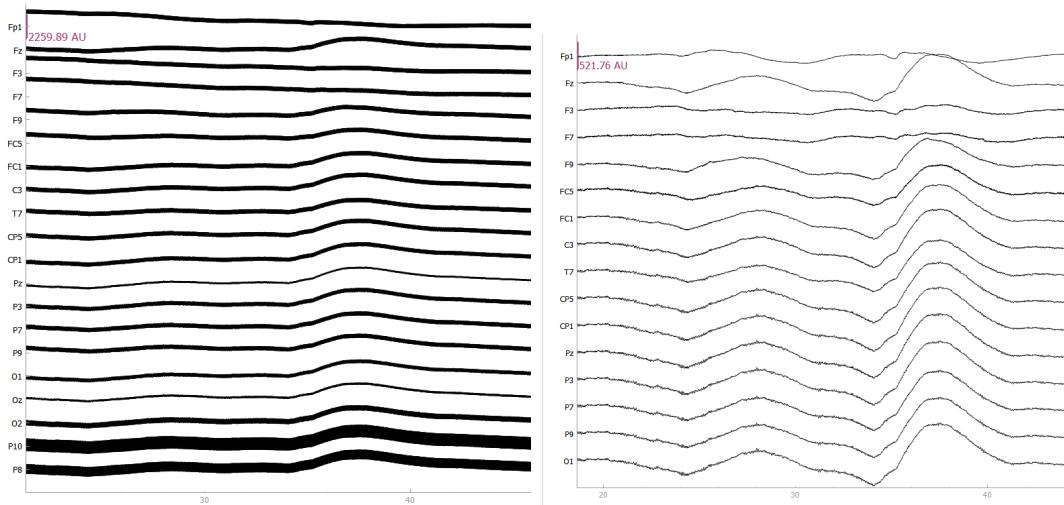


Figure 17: Raw plot of EEG signal of the R-Net, **A:** without any preprocessing, **B:** with notch filter of the line noise and band-with limitation

### 5.8.2 Independant component analysis

The Independent Component Analysis (ICA) of the signal, is a signal processing method to perform a linear decomposition of the signal to separate independent sources linearly mixed in several sensors.

In our case, we used it to remove blinking artefacts and other eye movements. We plotted the ICA components resulting from the analysis, looking for those that contained the blinks and eye artefacts. We then used a topographical plot of the components to check whether they were close to the eyes.

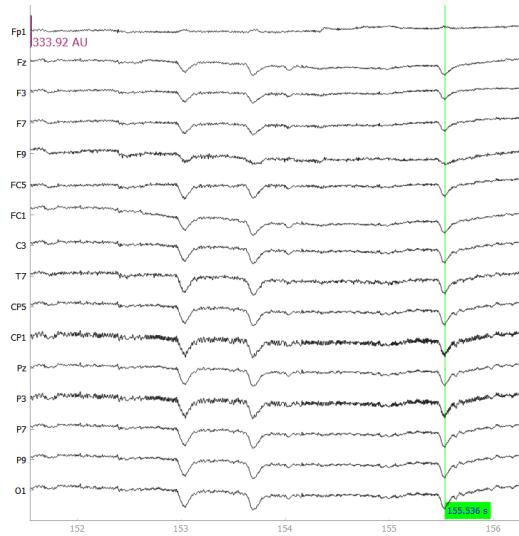


Figure 18: Example of an eye-blink artefact, at 155s, on almost all channels.

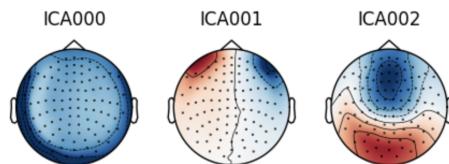


Figure 19: Example of ICA components: ICA0001 contains eye information

Electrodes Fp1 and Fp2 were used to fit the ICA model to the raw data. The model was fitted to the raw data with a high pass at 1 Hz because ICA is very sensitive to low frequencies (J. Luck, 2014). We first wanted to use the facial EMG to remove eye movements, but due to time constraints it wasn't possible to test this beforehand.

This pre-processing step was only performed on the R-net, as the Q+, with only 4 channels of interest, lacks the sources to perform a meaningful ICA.

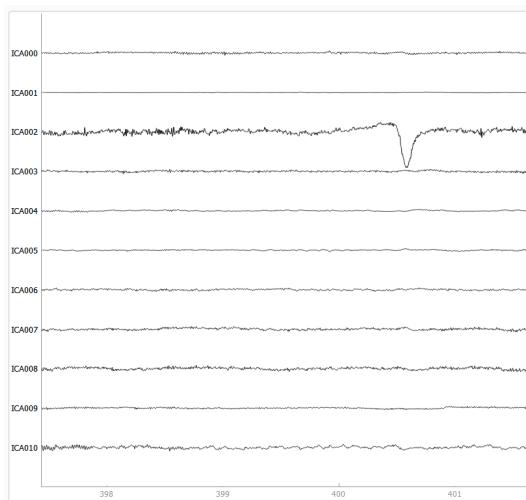


Figure 20: ICA components, showing the third component containing the blinks

### 5.8.3 Epochs

The epoching of the data is the fact of going from a continuous signal to an event segmented one.

Indeed, in the experiment we carried out many trials that need to be grouped together.

In order to segment the signal correctly to correspond to the trials, we use the triggers we used in the experiment.

Since we couldn't get PsychoPy to send triggers directly to LSL on the recording computer, we had to use a StimTracker to create onset events for each click, as described above. From this STIM channel we've got a lot of events corresponding to each click. Since we're only interested in the onset of each clicktrain, we used a code to take only those events into account.

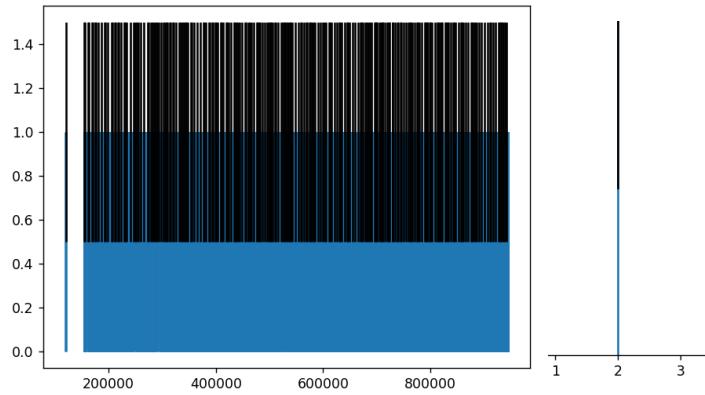


Figure 21: On the left in blue, the actual events recorded for each clicks, in black, the result of parsing onsets with our code. On the right, verification of the correspondance between the obtained onset event of interest, and the actual event

After extracting the events, we epoched the signal using an interval of -0.5ms to 1.5ms around the event and applied a baseline of -0.3 to 0.1 around the event.

Once the signal is segmented, we check the epochs, both visually and automatically, to remove the bad ones from the analysis. A bad epoch is one that contains a residual blink or some other kind of artefact. We used an MNE function to automatically remove bad epochs, resulting in a loss of about 5% for the R-net. A visual check is then performed to remove epochs that pass the filter but are still unusable.

For the Q+, due to an extremely bad signal, we lost more than 10% of the epochs, with a lower threshold to avoid losing too much statistical power.

#### 5.8.4 Main analysis

The main analysis was to get the evoked responses from the two headsets. To do this we had to combine all the epochs and average them to get an ERP. We wanted to do both grand average ERPs for both headsets and then go into more precise evoked potentials, separating in terms of order of presentation and by frequency.

Also, to look more closely at the links with autism, we created ERPs by dividing the participants into a low autism group and a high autism group.

For the electrophysiological data, we originally planned to use the Python toolbox for neurophysiological signal processing NeuroKit2. to perform analysis on ECG and EMG data.

However, due to time constraints, we weren't able to use the electrophysiological data. This dataset will be used later for another experiment in the team.

## 6 Results

### 6.1 The responses to the questionnaires are standard and consistent with a neurotypical population

#### 6.1.1 Autistic trait questionnaire (QA)

For the Autistic Trait Questionnaire (QA) we found that our group had a mean score of 14.0 ( $SD = 5.56$ ).

Nevertheless, the distribution seems to be compatible with a bimodal distribution, which allows the group to be split into high and low autistic participants in order to further evaluate the responses to roughness. The normative data for the questionnaire indicate a significant deviation from the norm above 35. None of the participants fell into this category.

Descriptives	
	QA
N	26
Mean	14.0
Median	15.0
Standard deviation	5.56
Minimum	4
Maximum	22

Figure 22: Descriptive statistics of autism questionnaire

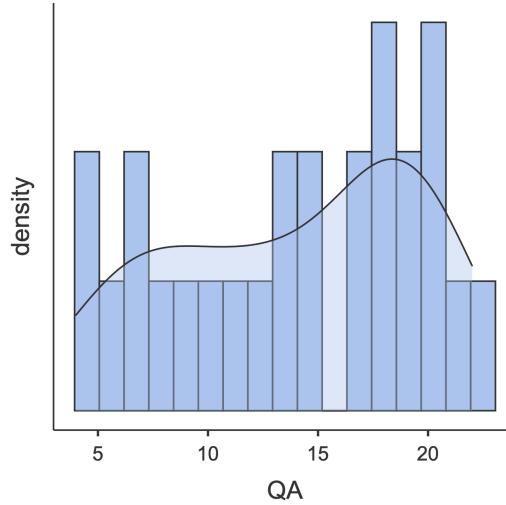


Figure 23: Density plot of QA scores

#### 6.1.2 STAI-T

The anxiety scale for the general condition (the participant had to respond about their state in general) which was administered to the whole group of participants, has a mean score of 40.5 ( $SD = 9.25$ ).

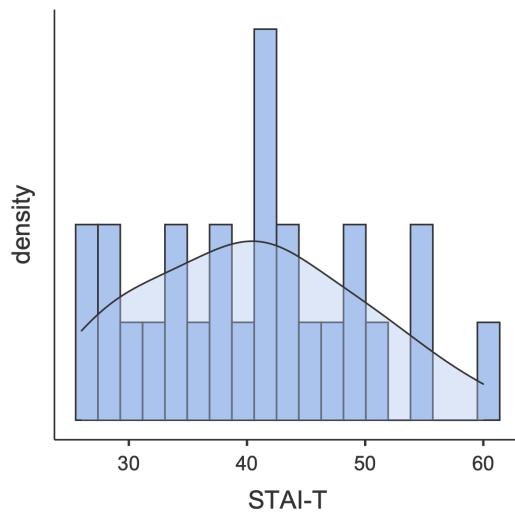


Figure 24: Density plot of STAI-T scores

The density of STAI-T scores compared to QA is not bimodal and doesn't allow differentiation into two subsets.

#### 6.1.3 *STAI-S Pre and Post experiment*

The anxiety scale for the state condition (the participant had to answer about his state in the present moment), administered to the whole group of participants, has a mean score of 29.7 ( $SD = 7.89$ ) pre-experiment and 32.1 ( $SD = 9.81$ ) post-experiment.

Descriptives			
	STAI-T	STAI-S B	STAI-S A
Mean	40.5	29.7	32.1
Median	41.0	29.0	30.5
Standard deviation	9.25	7.89	9.81
Minimum	26	20	20
Maximum	60	54	61

Figure 25: Descriptive statistics of the Anxiety scale

<b>Means, Standard Deviations, and Alpha Coefficients for Working Adults in Three Age Groups</b>						
	<b>Ages 19-39</b>		<b>Ages 40-49</b>		<b>Ages 50-69</b>	
	M (446)	F (210)	M (559)	F (135)	M (382)	F (382)
<b>S-Anxiety</b>						
<b>Mean</b>	36.54	36.17	35.88	36.03	34.51	32.20
<b>SD</b>	10.22	10.96	10.52	11.07	10.34	8.67
<b>Alpha</b>	.92	.93	.93	.94	.92	.90
<b>T-Anxiety</b>						
<b>Mean</b>	35.55	36.15	35.06	35.03	33.86	31.79
<b>SD</b>	9.76	9.53	8.88	9.31	8.86	7.78
<b>Alpha</b>	.92	.92	.91	.92	.96	.89

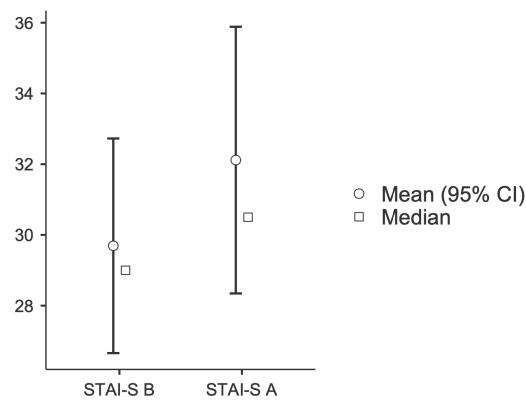
Figure 26: Normative data for STAI-S and STAI-T (adapted from Spielberger, 1983)

The standard mean for normative use of the STAI-S is approximately 35.22 ( $SD = 10.30$ ) and for the STAI-T approximately 34.57 ( $SD = 9.02$ ), averaged over all age groups and both sexes. Our group doesn't differ statistically from this value, neither for the STAI-S nor for the STAI-T.

A t-test between before and after shows that there's no significant difference between the two ( $s = -1.09$   $p < 0.142$ ).

Paired Samples T-Test					
			<b>statistic</b>	<b>df</b>	<b>p</b>
STAI-S B	STAI-S A	Student's t	-1.09	25.0	0.284

*Note.*  $H_0: \mu_{\text{Measure 1} - \text{Measure 2}} \neq 0$

Figure 27: Plot of t-test of difference between *before* and *after*Figure 28: Plot of difference between *before* and *after* condition

We were also interested to see if there was a relationship between QA and STAI-T scores, as studies suggest that although anxiety isn't considered a core feature of ASD, 40% of young people with ASD have clinically elevated levels of anxiety or at least one anxiety disorder, including OCD.

Unfortunately, our results don't show this kind of relationship overall ( $r = 0.313$ ,  $p = 0.119$ ).

Correlation Matrix		
	QA	STAI-T
QA	Pearson's r df p-value	— — —
STAI-T	Pearson's r df p-value	0.313 24 0.119

Figure 29: Correlation matrix of STAI-T and QA

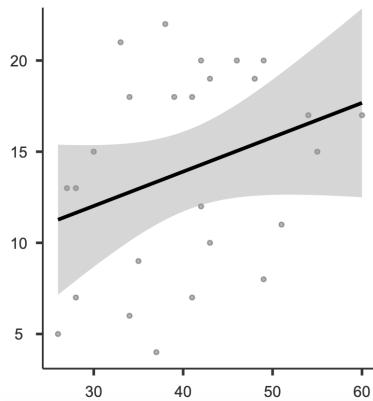


Figure 30: Regression plot between STAI-T (x-axis) and QA (y-axis)

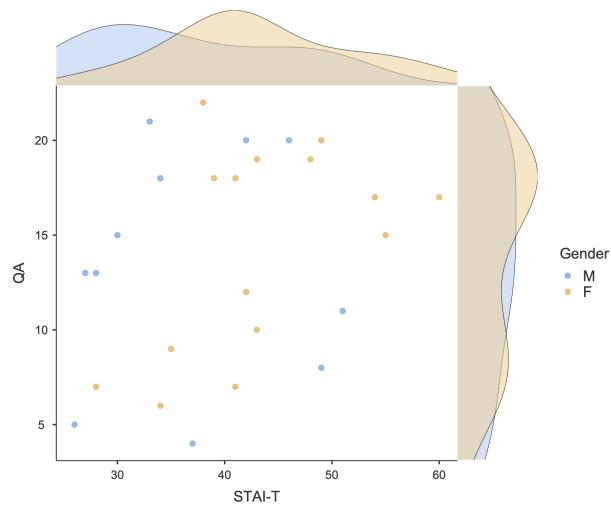


Figure 31: egression plot between STAI-T (x-axis) and QA (y-axis) with gender distinction.

Distinguishing between the sexes doesn't provide any further insight, except for a tendency for females to have higher anxiety scores than males.

## 6.2 Behavioural data doesn't fit the expected pattern regarding autistic trait

As the participants had to rate their subjective aversion using a slider, we could use the PsychoPy output. Unfortunately, a software problem prevented us from collecting all the CSV files from PsychoPy, and we had to write scrapping code to extract information from log files and PSYDAT files.

This created one file per participant showing the sounds played and the corresponding slider response of the participant.

This allowed us to plot the evolution of aversion in relation to the frequency of the stimulation, as shown in the figure below. We decided to baseline each curve to remove the personal criterion of the participants.

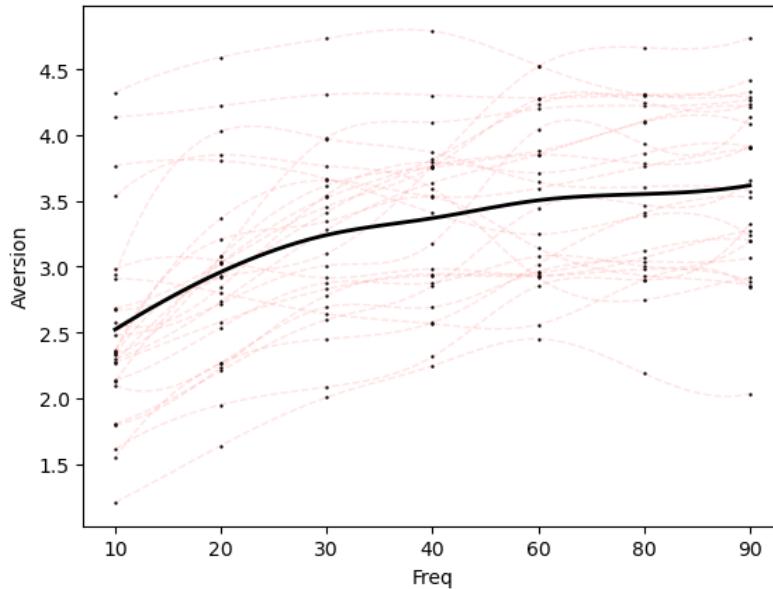


Figure 32: Relationship between aversion (y-axis) and frequencies (x-axis). Each red curve is a participant, the thick black curve is the overall mean of each participant.

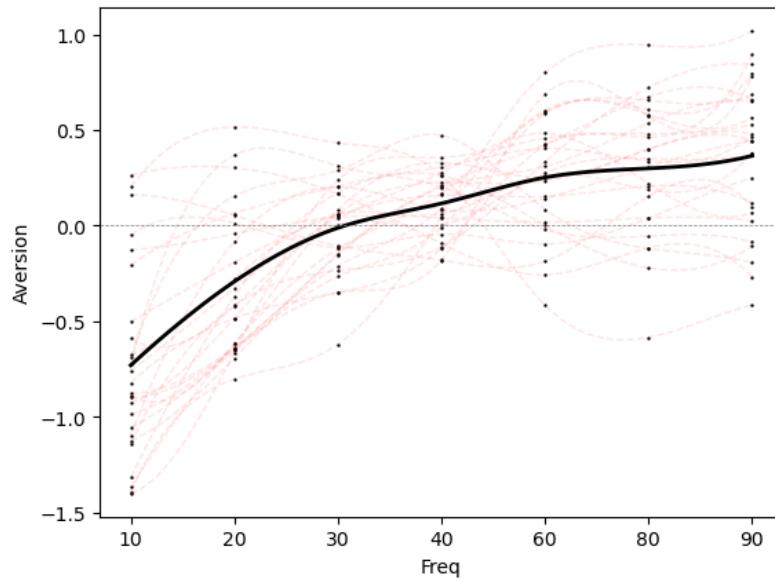


Figure 33: Relationship between aversion (y-axis) and frequencies (x-axis). Each red curve is a participant, the thick black curve is the overall mean of each participant. Each curve is normalised

Then, we decided to split the curves between the two groups described earlier.

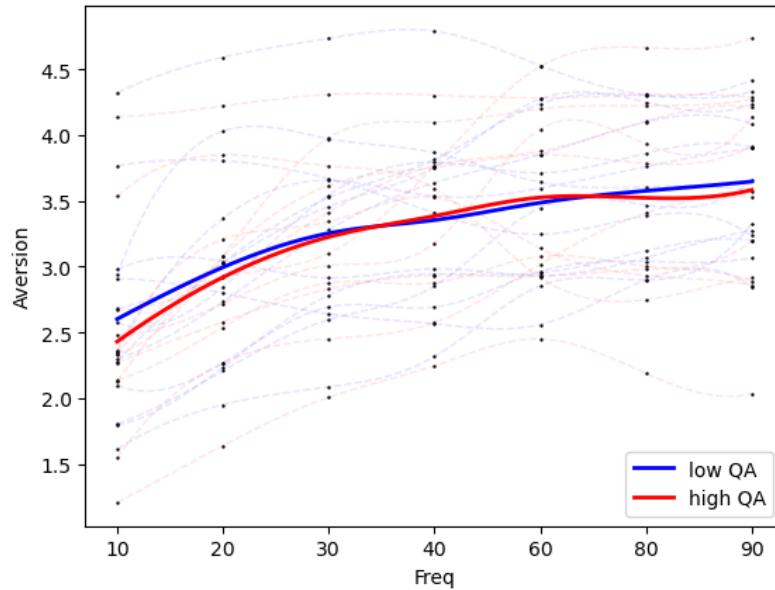


Figure 34: Relationship between aversion (y-axis) and frequencies (x-axis). Each red curve is a participant in the high QA group, the thick red curve is the general mean of each participant in this group. Each blue curve is a participant in the low QA group, the thick blue curve is the general mean of each participant in this group.

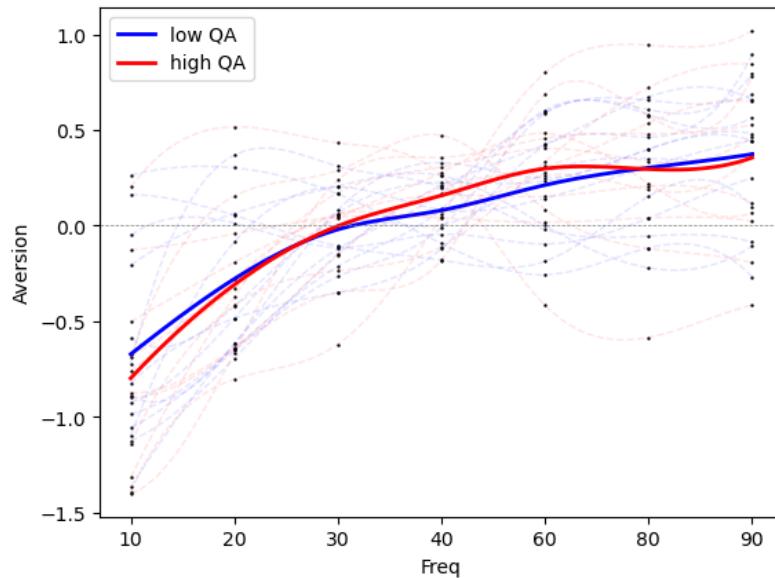


Figure 35: Relationship between aversion (y-axis) and frequencies (x-axis). Each red curve is a participant in the high QA group, the thick red curve is the general mean of each participant in this group. Each blue curve is a participant in the low QA group, the thick blue curve is the general mean of each participant in this group. All curves are normalised

This distinction doesn't seem to make any noticeable difference.

This may be due to the artificial grouping we have done, based on a median split. To investigate this further, we decided to see if there was a correlation between QA scores and aversion, for each frequency, as shown in the figure below.

We ended up with 14 sub-plots showing Pearson's  $r$  regression coefficient and a regression line for each frequency, with and without normalisation. The figures are shown on the following pages. And to get a complete view of these relationships, we decide to do the same for the STAI-T results.

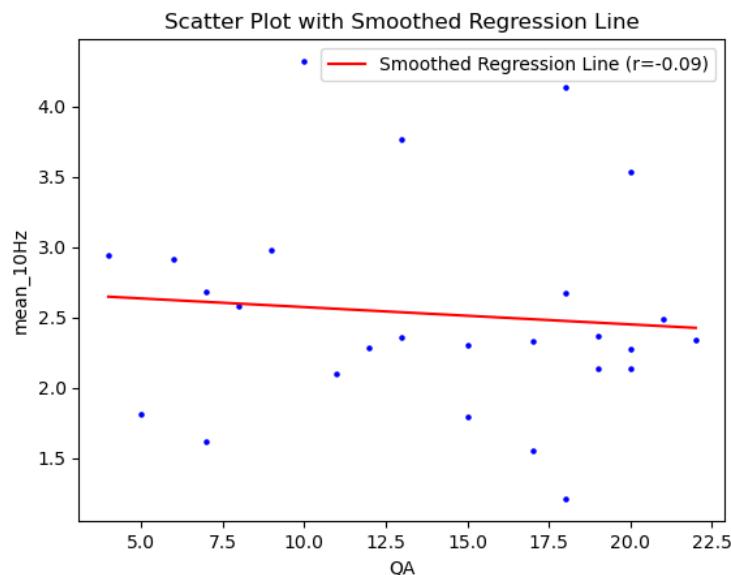


Figure 36: Regression plot between STAI-T (x-axis) and QA (y-axis)

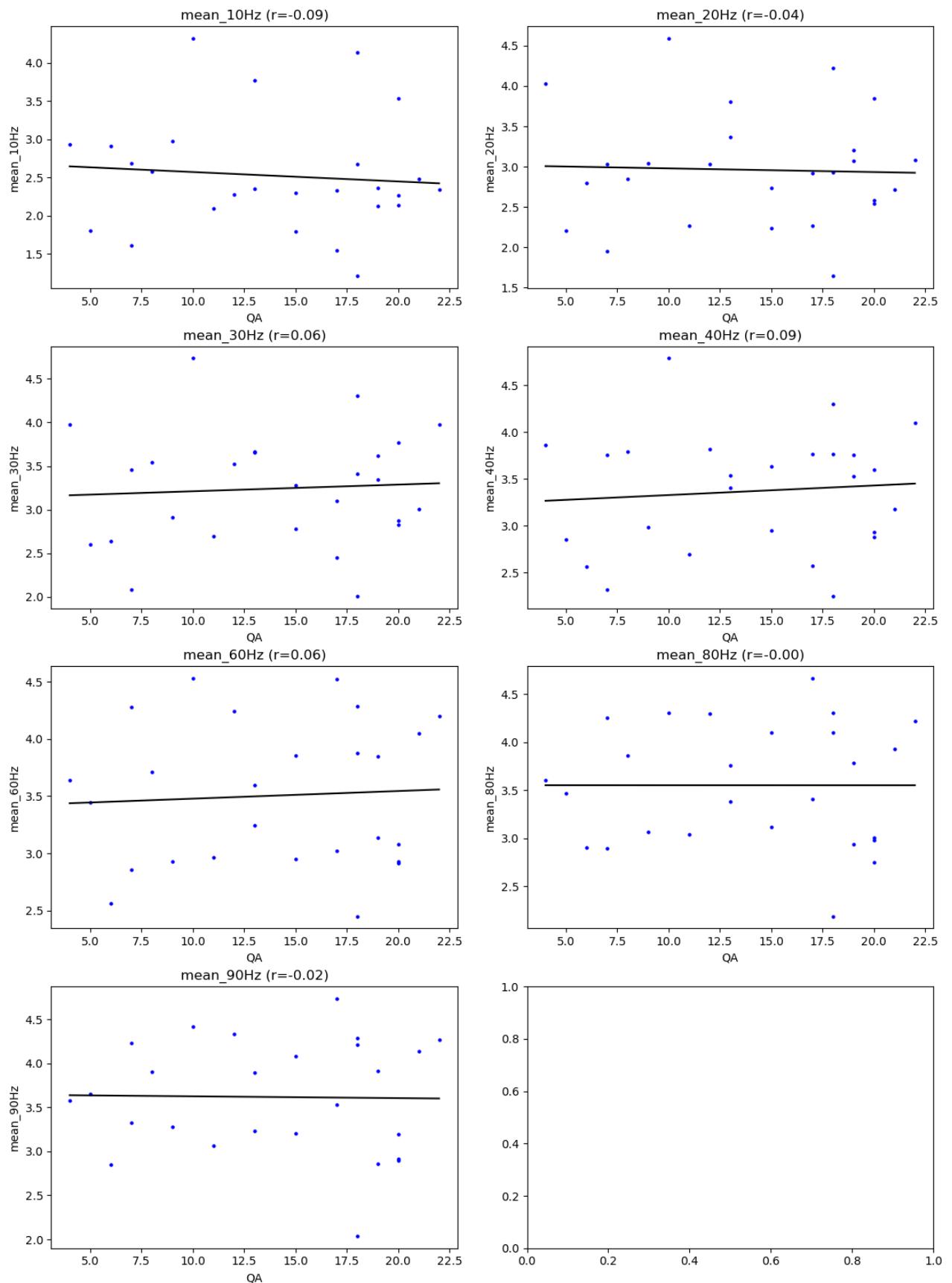


Figure 37: Regression plot between QA (x-axis) and aversion (y-axis) for each stimulus frequency

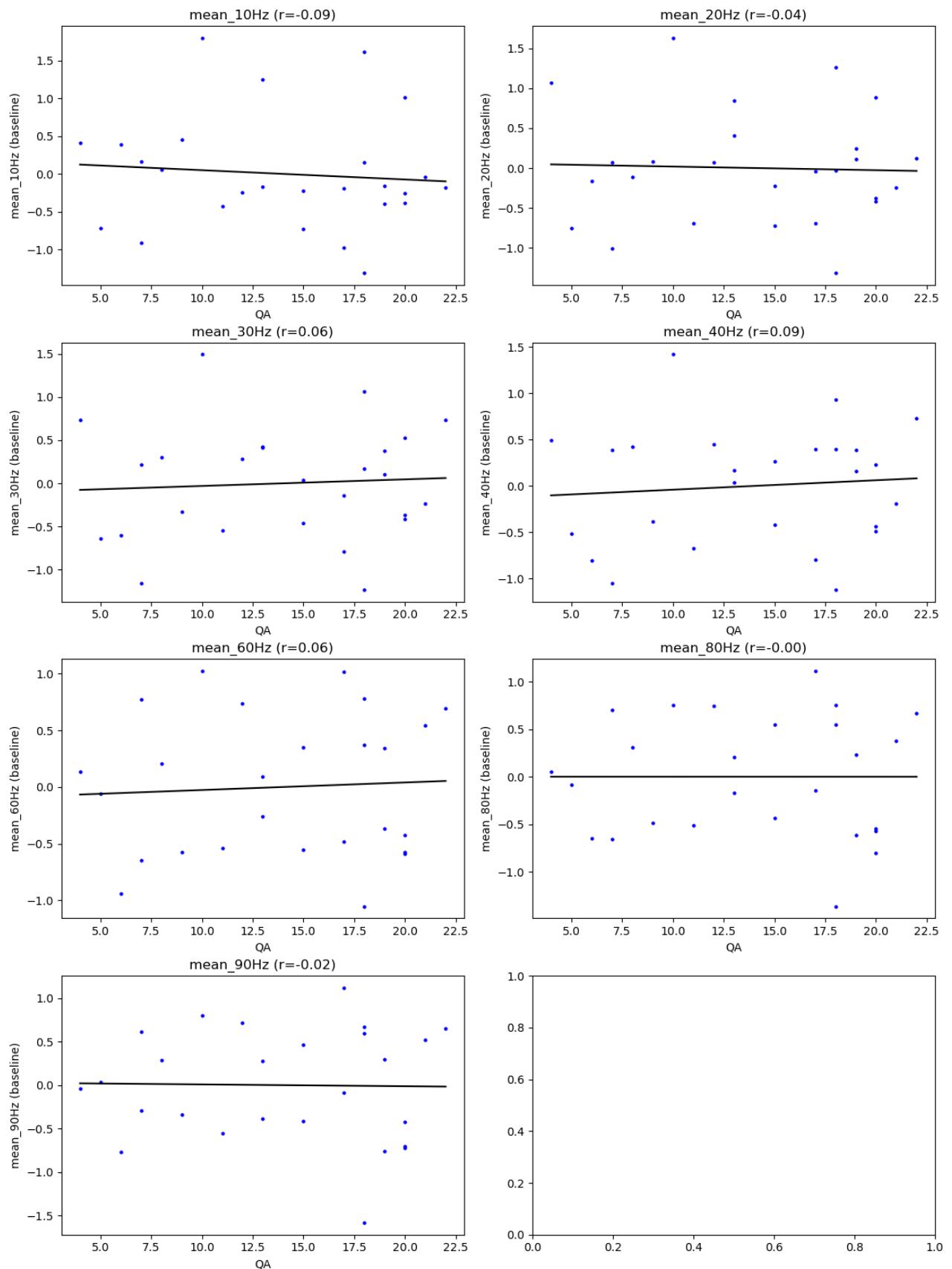


Figure 38: Regression plot between QA (x-axis) and aversion (y-axis) for each stimulus frequency. With a normalisation for each participant

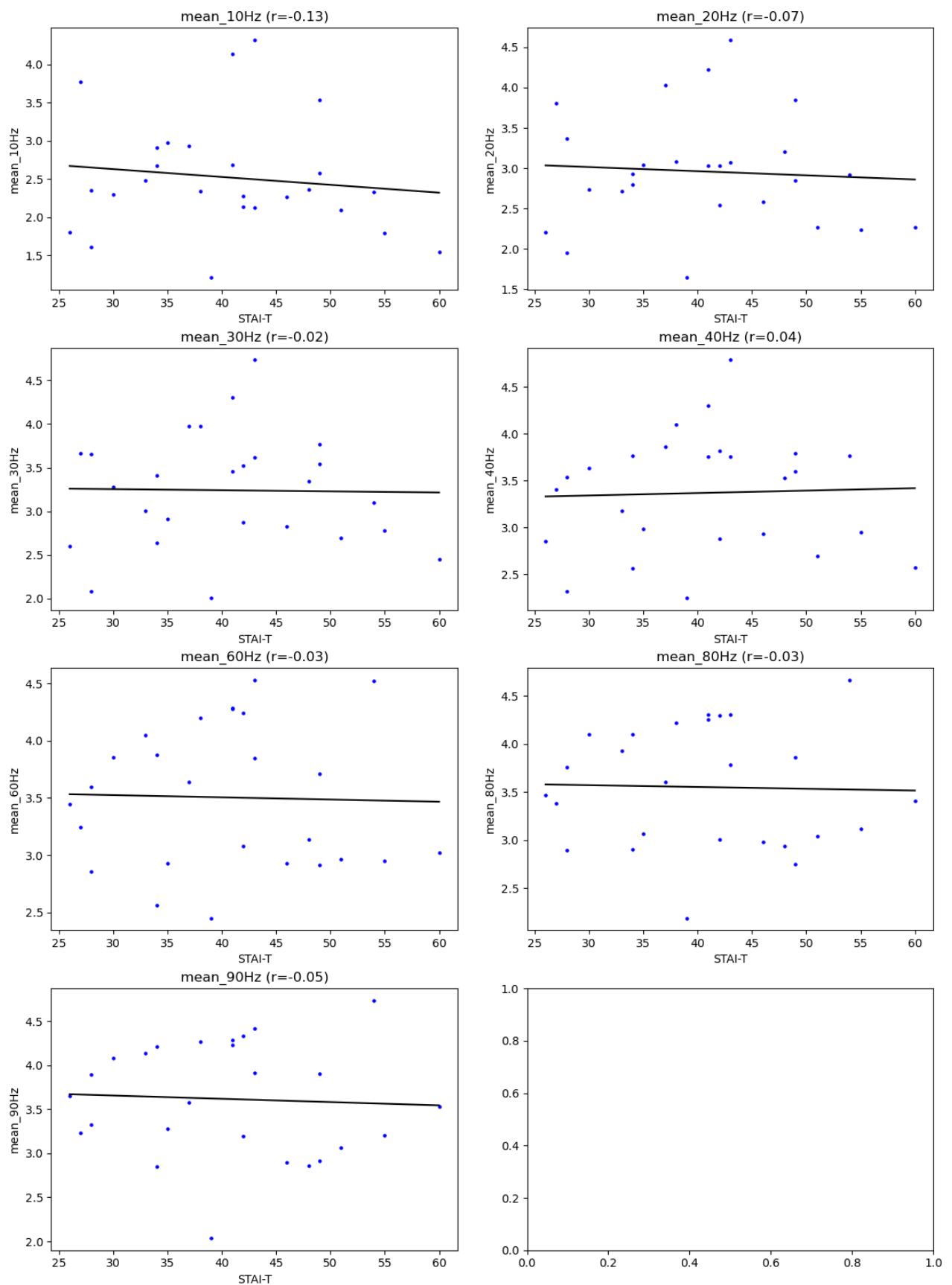


Figure 39: Regression plot between STAI-T (x-axis) and aversion (y-axis) for each stimulus frequency

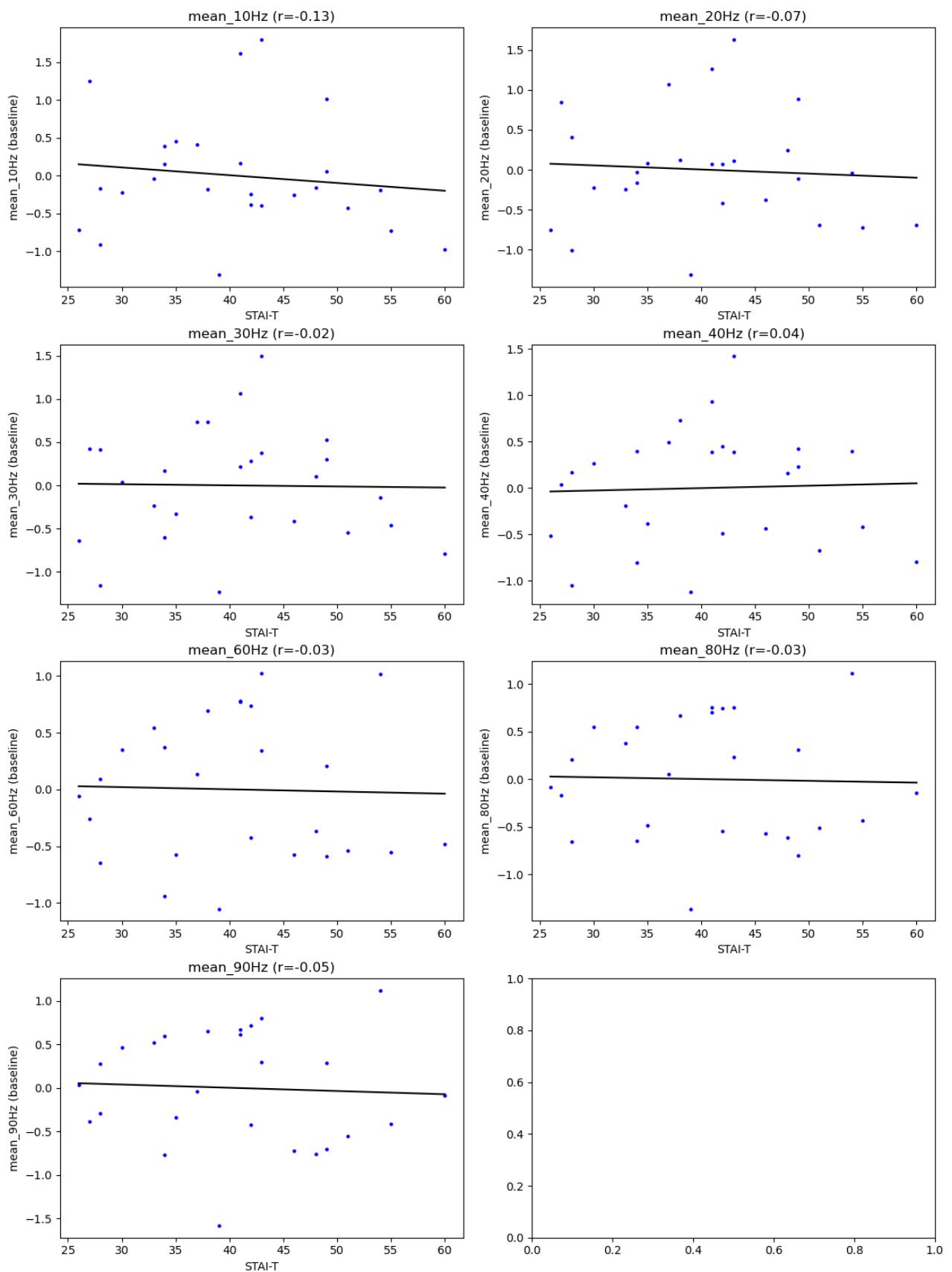


Figure 40: Regression plot between STAI-T (x-axis) and aversion (y-axis) for each stimuli frequencies. With normalisation for each participant

We can see that we have not found an interesting correlation coefficient, our maximum being  $r = 0.13$ . With these results we cannot replicate the previous results of XXXX regarding the STAI questionnaire.

### 6.3 Mixed results for electroencephalography data

For the EEG signal, after all the pre-processing described in the Methods section, it was possible to average the epochs across all participants and visualise the event-related potentials.

Due to the difficulty in extracting the event ID from the recorded signals, we couldn't group the epochs according to frequency or order of presentation. We'll discuss this in more detail later.

We also decided to limit our analysis to the electrodes of interest: C3, Cz, C4, P3, Pz, P4. We've limited our analysis to these electrodes because they are able to probe the activity of the brain networks we're interested in.

#### 6.3.1 R-Net produces the expected global ERP shape

Despite the noisy signals, which resulted in a loss of about 10% of the epochs, we were able to plot the ERP for the R-network, averaging over all epochs. This means that we combine the epochs of both the first and the second presented clicktrain.

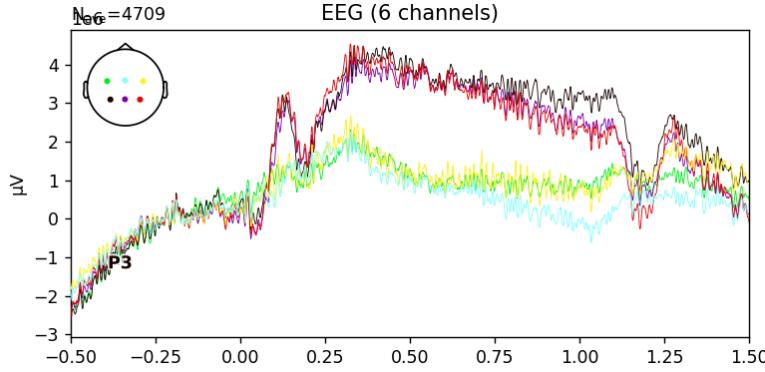


Figure 41: ERP of the R-Net Headset for electrodes of interest, from 0.1Hz to 500Hz

As we can see, the signal has a lot of noise. However, despite the poor signal-to-noise ratio, we can distinguish classic ERP components. To get a clearer view, we filtered this evoked response with a low pass at  $f=30\text{Hz}$  to smooth the result.

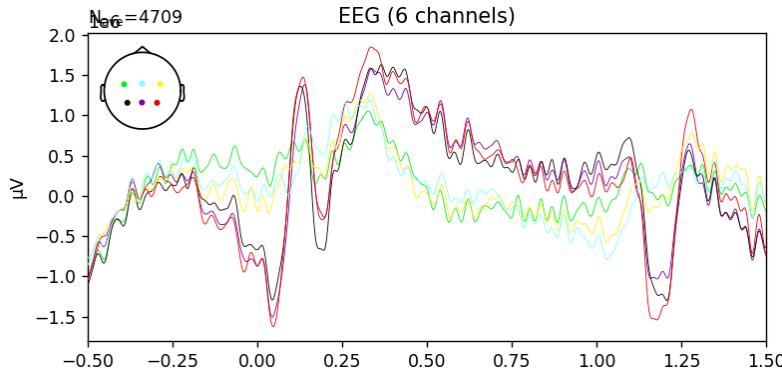


Figure 42: ERP of the R-Net Headset for electrodes of interest, from 0.1Hz to 30Hz

We can see the components more clearly: the N200 in particular. The last negative component at about 1.20 seconds corresponds to the end of the stimuli, which leads to the end of the corresponding neural activity.

### 6.3.2 Q+ fail to display any classical ERP components

We have followed the same procedure for the Q+. The corresponding electrodes on the Q+ are P3, P4, AF3 and AF4.

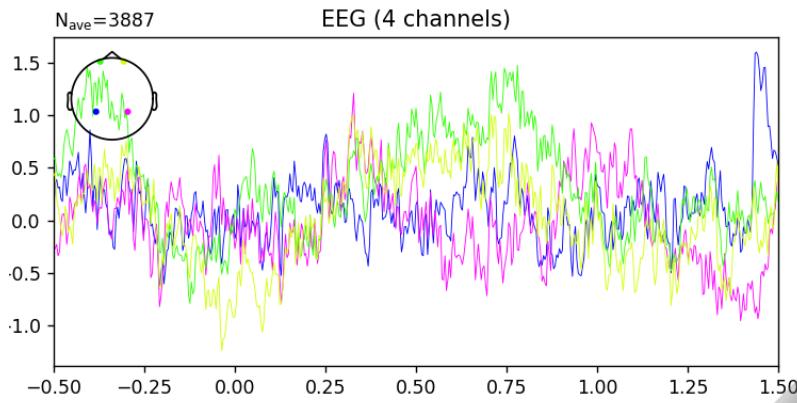


Figure 43: Averaged epochs of the R-Net headset for electrodes of interest, from 1Hz to 250Hz

As you can see, the result doesn't look like an ERP. Even a filter at 30Hz, as for the R-net, doesn't reveal any clear components. If we compare this plot with those obtained in the previous internship focusing on the Q+, we do not notice any improvement, even with 26 participants.

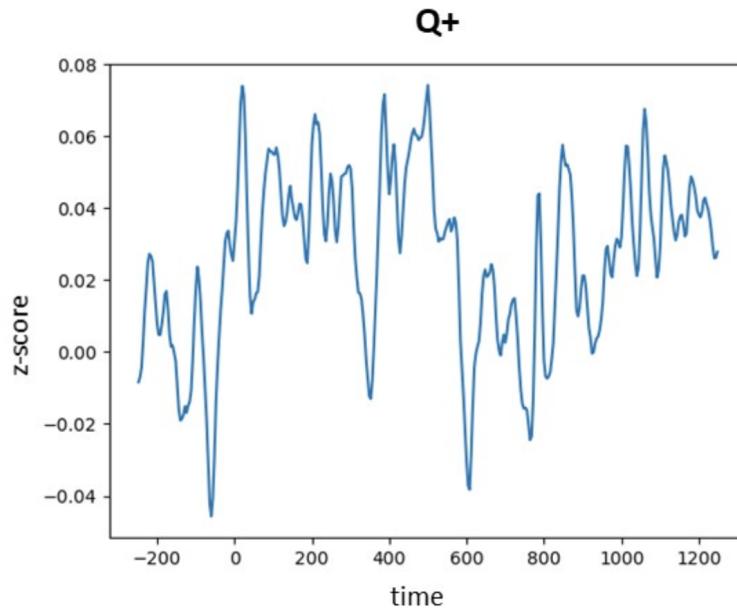


Figure 44: "ERP" obtained during the last internship using the Q+ (From Lafargue-Hauret, 2022)

### 6.3.3 ERPs and autistic trait

To continue our exploration of the responses to acoustic roughness in relation to autism, we decided to compare the ERPs of the low and high autistic trait groups.

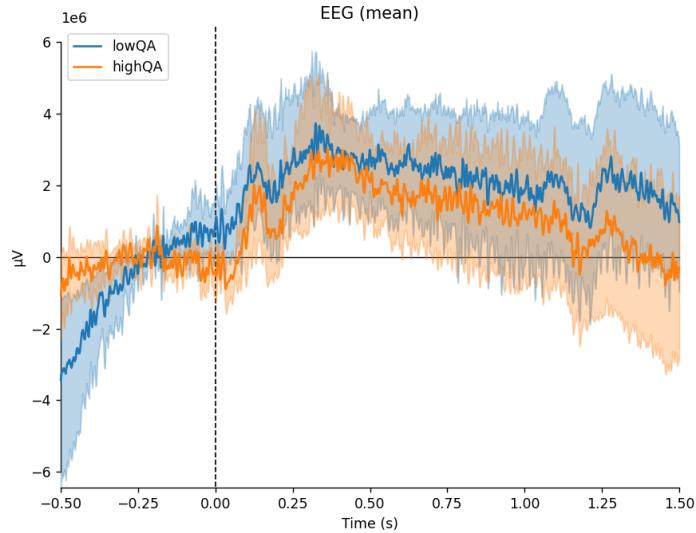


Figure 45: ERPs of the R-Net headset, averaged over the electrodes of interest, from 0.1Hz to 500Hz. In blue the low QA group and in orange the high QA group

We can see once again that a lot of high frequency noise is interfering with our visualisation. As before, we filter both ERPs with a low pass of 30Hz.

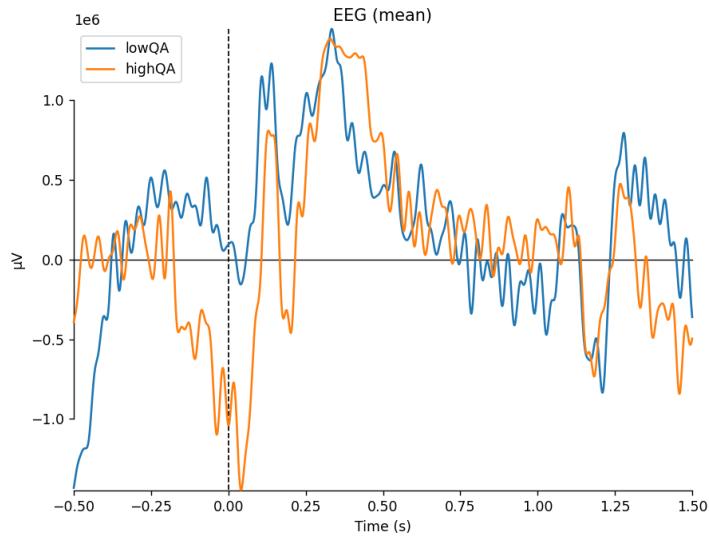


Figure 46: ERPs of the R-Net headset, averaged over the electrodes of interest, from 0.1Hz to 30Hz. In blue the low QA group and in orange the high QA group

It appears that the high QA group has a lower response than the low QA group. This could be consistent with the fact that autism is known to be associated with higher local connectivity but weaker neural connectivity across areas. However, the ERPs presented here are too noisy to be confident.

## 6.4 Electrophysiology data

The EMG data were to be used for principal component analysis for EEG preprocessing.

The EMG could also be used as a proxy for aversion through facial reactions.

However, we didn't have time to investigate this part in the present project, and it will be something useful for further experiments using the dataset.

## 7 Discussion

### 7.1 Mixed results

The results presented are mixed. In fact, we are not able to show a clear difference in both behavioural and EEG responses. There may be several reasons for this.

First, as already mentioned, we chose to present stimuli from 10Hz to 90Hz for a technical reason: the limitation imposed by the Q+ bandwidth, which prevented us from going higher than approximately 125Hz (maximum frequency is the sampling rate divided by two). After 90Hz, the other stimuli were at 130Hz, above our limit. Therefore, in order to find a compromise between usable data and keeping the experimental procedure to one hour, we didn't present higher stimuli (130Hz, 180Hz, 240Hz). Also, our original goal was to use auditory steady-state responses, which would have been unusable above the bandwidth limit. However due to time constraints and code issues, we had to drop it from the project.

But it's above 90Hz that we leave the acoustic roughness to go to a more tonal perception of the stimuli. And it's with this new range of perception that different response profiles emerge. By limiting the range of stimuli, we have certainly smoothed the results, making them negative or difficult to interpret. Despite the impossibility of using stimuli above 125 Hz for the Q+, we should have presented stimuli of higher frequencies for the R-net and for the behavioural responses.

Secondly, we were interested in assessing the relationship between the response to acoustic roughness and autism. However, our population was neurotypical. The autistic trait questionnaire scores aren't outside the normative data of the instrument. We performed a median split according to the suggested shape of the score distribution, but it is doubtful that this can be meaningful for the responses. In fact, the median was  $m = 15$ , a fairly intermediate value with no normative significance.

Thirdly, our inability to extract the events' IDs from the recordings prevented us from distinguishing between the different frequencies of the click trains and their presentation, thus confounding our result. In fact, we kept the experiment used in previous studies to be consistent: an oddball paradigm. But the instructions didn't make it clear which sounds the participants had to pay more attention to. We think that their response is mainly linked to the second stimuli presented (due to the recency effect) and we would compare the ERPs of the first and second stimuli. At the moment we don't have this information, so we can't disentangle the mixed results. Also, without the events, we can't get the ERPs corresponding to the average response by frequency. This prevents us from getting a clearer picture of the participants' perceptions.

Finally, there are several reasons for the lack of results for the Q+ ERPs. Firstly, it's the second time that an experiment with the Q+ has failed to produce ERPs. However, as stated in the preprint of the constructor (Spinelli et al., 2020), the headset should be able to produce such recordings. Their experimental design is similar to ours, with simultaneous recording with two EEG headsets. In addition, we are recruiting more participants than in the previous internship, which increases the statistical power of our results. So why don't we find ERPs? Either the headset isn't able to record such signals under laboratory conditions, or some noise is added along the way.

One possible explanation for the extra noise is the Bluetooth connection between the headset and the tablet that is streaming the data. In fact, Bluetooth is not a reliable synchronous connection. Any variability in the data packets sent would have a massive impact on the ERPs we were able to obtain, as we can't reduce random noise by summing up all the epochs (Iwama et al., 2022). And since the triggers are received from the STIM channel of the BrainProduct, the accuracy of the synchronisation between the Q+ and the tablet is still unknown.

MyBrainTechnology has also recently added the ability to play audio directly through the headphones. Previously, earplugs were required. However, by visualising some epochs for some participants, it seems that some stimulus information *leaked* into the electrode circuit. This part should be isolated,

but we see a strange correspondence between these artefacts, shown in the figure below, and the stimuli we used. More analysis needs to be done to assess the similarity between them in order to draw conclusions, but this may be a major flaw in the device.

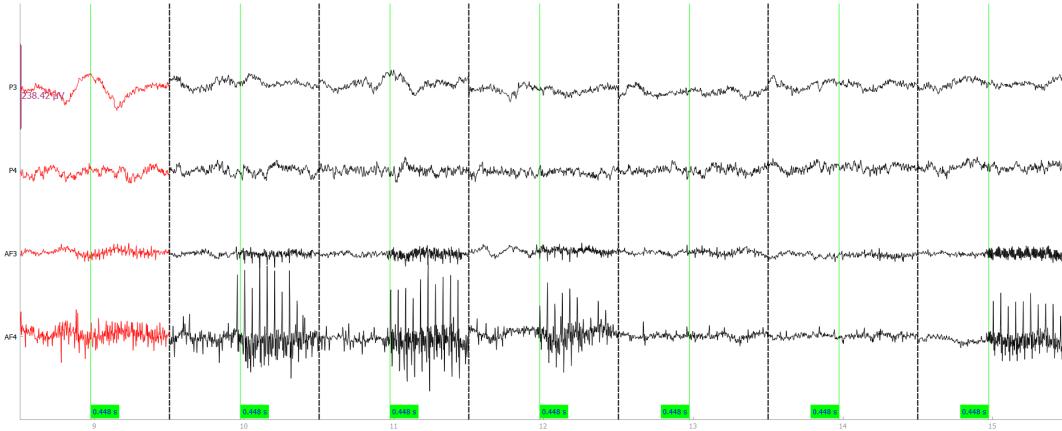


Figure 47: Visualisation of Q+ epochs, with a stimulus *leak* visible in the AF4 electrode

## 7.2 General difficulties

There are many difficulties in this experiment and opportunities to learn a lot.

First of all, this project is the result of a collaboration between a public research institute, the Pasteur Hearing Institute, and a private company, MyBrainTechnology. Certainly, this kind of synergy is an interesting opportunity to benefit from each other's experience, but it can also be the place for misalignment of interests and temporality. Some problems have arisen as a result, and it has been difficult to get support from the company for some synchronisation issues with the Q+, but also for the accessibility of the data. In fact, the recordings were originally sent to the company's private servers and it was impossible to access the raw content. This was resolved in the second half of the internship with the help of an engineer from the team, which limited the time available for the experiment.

Synchronisation was one of the main challenges of the project. Putting together different hardware that doesn't use the same software background was a tricky task, but we were able to develop an implementation of LabStreamingLayer that allowed precise real-time synchronisation of the different data streams. However, as this implementation was the first time we had used this framework, we couldn't benefit from previous knowledge as much as we could from maintaining the BrainProducts infrastructure.

## 8 Conclusion

In conclusion, despite our hypothesis of a different pattern of responses to acoustic roughness in people with a high autistic trait, we weren't able to say this with certainty, either at the behavioural level with the aversion score, or with the EEG signals.

This may be due to the fact that the population we studied didn't show enough variability in their autistic trait scores, which would be expected if they were neurotypical.

It could also be due to an inappropriate range of stimuli, lacking more contrast between the acoustic roughness domain and the tonal-like domain.

Finally, technical difficulties prevented us from carrying out a more detailed analysis of the EEG data, by order of presentation and for frequencies, in the time available. The results may be lurking in these analyses.

Nevertheless, this project was a great opportunity to learn about a new subject, a new technique and new data for studying cognition, and I enjoyed being part of it.

Thank you for reading this report.

## 9 Web references

The links to access supplementary material, the data, the code and to some interactive content.

**GitHub repository :**

<https://github.com/MatthieuFra/roughness-eeg-internship-report>

**OSF Project :**

[https://osf.io/5tdes/?view\\_only=afb587f8add24c009cf036f5ec1d8cf](https://osf.io/5tdes/?view_only=afb587f8add24c009cf036f5ec1d8cf)

**Precise protocol of the experiment :**

<https://www.notion.so/emmaducos/roughxpmbt-protocol-V3-9826d796c9ce43cc98610fe106cc6566>

**Listen to the click trains :**

[https://matthieufra.github.io/roughness-eeg-internship-report/online\\_interactive\\_content/online\\_interactive\\_content.html](https://matthieufra.github.io/roughness-eeg-internship-report/online_interactive_content/online_interactive_content.html)

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