Supplementary Materials Establishing fEMG Measures paper

1 Description of experiments and locations

Table A1 describes the different experimental treatments that were part of one or more data collections. Note that Table 1 specifies which treatments were used at which locations. The table also displays how the characteristics of these designs were coded. The effect of these characteristics on fEMG activity are shown in the main paper in Figure 4.

Table A1. Description of experimental designs

	Description	Video/ Image	Positive/ Negative	Audio	Lab/ Fieldlab
Issues 1	8 videos about inequality, climate, populism or immigration with either left-wing or right-wing rhetoric. Ps exposed to 4 videos, one on each issue.	Video		Yes	Both
Dominance	4 photos of two Danish politicians of which the face was manipulated to look more or less dominant. Ps were randomly exposed to 2 photos, one dominant, one non-dominant	Image		No	Lab
IAPS-threat	4 threatening IAPS pictures, and 2 neutral pictures.	Image	Mix	No	Lab
Issues 2	Same as issues 1. Different videos on immigration and climate, same videos on populism. New videos on EU integration.	Video		Yes	Fieldlab
Party leaders	6 photos of Dutch party leaders, 1 photo of Danish PM.	Image		No	Fieldlab
IAPS-neutral	3 neutral IAPS pictures.	Image	Neutral	No	Fieldlab
Leaders & moral violations	Two photos of inparty leader, two photos of outparty leader. With the second set of photos the leader was accused of a moral violation.	Image		Yes	Both
IAPS-disgust	3 disgusting IAPS pictures, and 5 neutral ones.	Image	Negative	No	Both
Leaders & emotions	6 photos of inparty and outparty leader with neutral, happy or angry expressions.	Image		No	Lab
ADFES	6 photos of males and females with neutral, happy or angry expressions.	Image	Mix	No	Lab
IAPS-positive & negative	4 positive and negative IAPS images.	Image	Mix	No	Lab
IAPS-various	28 threatening, disgusting and positive IAPS images.	Image	Mix	No	Lab
Spoken words	11 political and nonpolitical words visualized and read aloud.	Words	Mix	Yes	Lab

Note: If not mentioned otherwise Ps are exposed to all treatments.

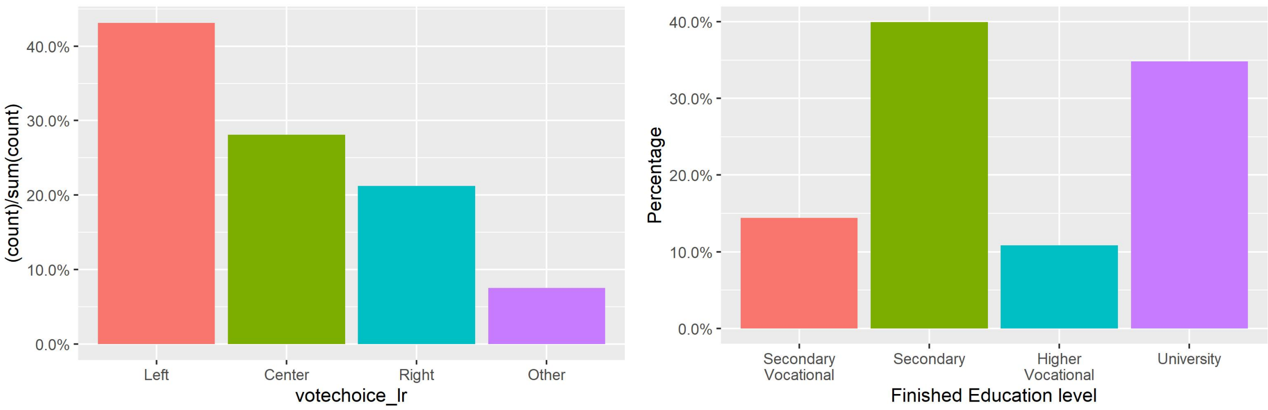
2 Descriptive statistics

In this section we describe the descriptive statistics of the participant characteristics.

Table A2. Descriptive statistics moderators

Statistic	N	Mean	St. Dev.	Min	Max
Gender (3 cats)	584	0.635	0.485	0.000	2.000
Political knowledge (scaled)	584	−0.009	1.000	−2.372	2.417
Age	584	31.255	14.184	16.000	83.000
Alcohol promillage	429	0.041	0.172	0.000	1.500
Student	387	0.000	0.000	0.000	0.000
Left-right ideology	387	4.460	1.885	0.000	10.000
Political cynicism	387	4.207	1.372	1.000	8.000
Political interest	387	4.202	1.646	1.000	7.000
Partisanship strength (scaled)	95	−0.023	0.947	−2.254	2.450

Figure A1. Descriptives of education level and voting behaviour



(a) Vote choice, aggregated

(b) Education level

3 Validation preprocessing

To validate our preprocessing scheme, we analyzed corrugator and zygomatic responses to the IAPS pictures from studies 2 and 5 (see Table 1). In these two studies, positively valenced images (different images of babies, baby polar bears, and beautiful scenery), negatively valenced images (different images of spiders, snakes, guns, hunting and animal testing), and neutral images (e.g. basket, book case or fruit) were shown (for details see, Supplementary Materials table A1). Lang (2005) have rated the IAPS pictures for arousal and valence (from negative to positive). The correlation between these IAPS valence scores and corrugator activity is high and in the expected direction (r=-0.774), the correlation with zygomaticus activity is somewhat lower and in the expected direction (r=0.501)[13]. These correlations are lower if we take the non-preprocessed means of fEMG activity: the correlation between corrugator activity and IAPS valence drops to r=-0.463, which is only 60% of the preprocessed measure. The correlation between non-preprocessed zygomaticus activity and IAPS valence is r=0.451, which is somewhat lower than the correlation with the preprocessed zygomaticus activity (r=0.501). Figure A2 plots the mean zygomaticus activity and the mean corrugator activity per IAPS image. The correlation between the two measures is as expected (r=-0.464). Regarding corrugator activity, animal testing and hunting produce very high scores followed by snakes and spiders. Guns produce relatively little activity. Babies and baby polar bears produce the most zygomaticus activity and images with beautiful scenery less so. As expected, the neutral pictures (in orange) cluster around the middle. All negative images (in black) produce increase in corrugator activity; and all positive images (in blue) produce increases in zygomaticus activity. But the latter measure is also more noisy: while positive images produce a relaxation of corrugator activity, negative images still produce some increased zygomaticus activity. Snakes and spiders in fact produce substantial levels of zygomaticus and corrugator activity. van Berkum, Struiksma, and 't Hart (2023) indeed note that very negative images may also produce some zygomaticus activity. To summarize, these results validate our preprocessing script. At the same time, we emphasize that other preprocessing scripts may produce equally valid results.

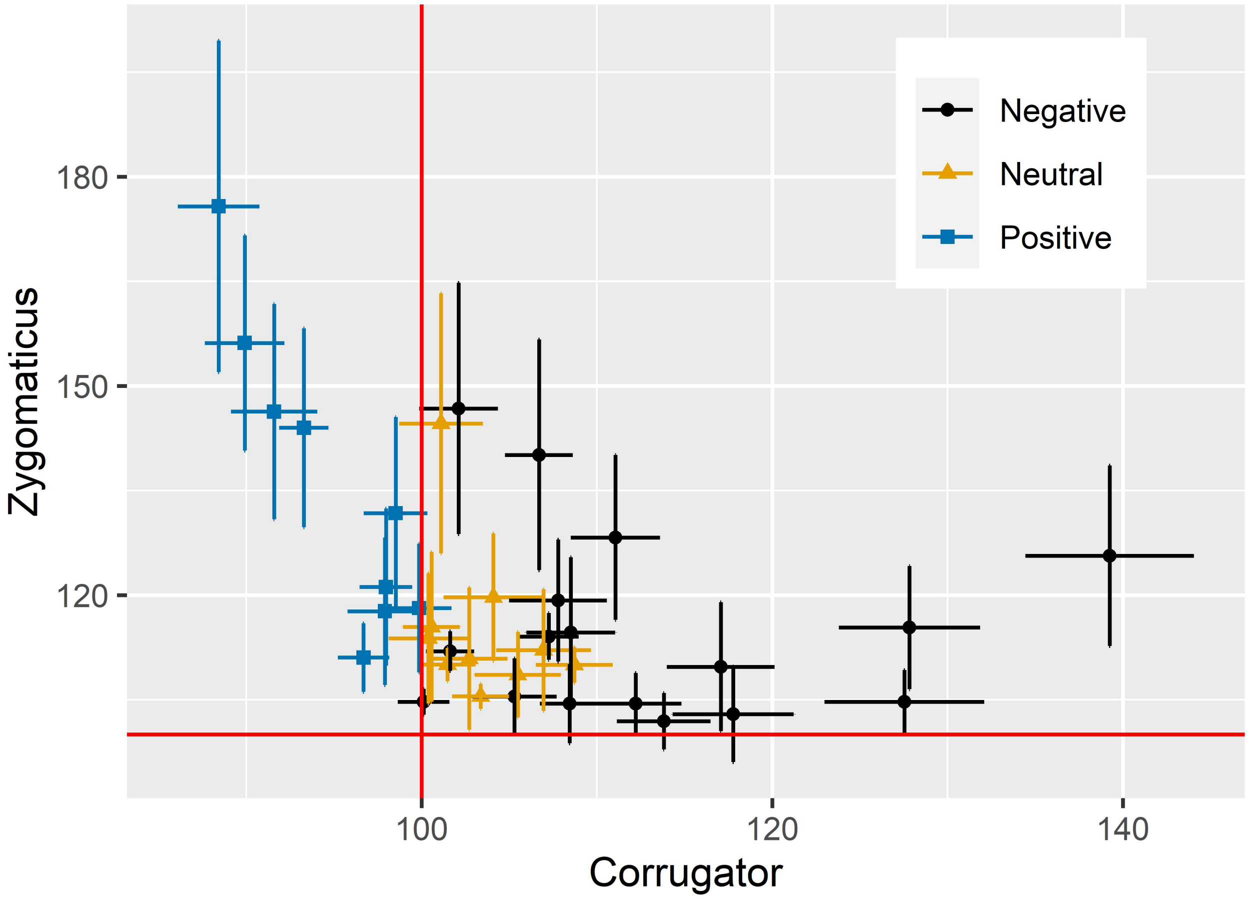
4 Preprocessing protocol

Two authors of this paper independently coded each individual response throughout the dataset. The coders were blind to the treatments participants were shown and the specific independent variables correlated with fEMG responses. The aim was to identify two types of known errors in the signal of the physiological activity. First, the signal is extremely low (below 1 microvolt) and barely changes. We call this flat lines. There is always some tension on a muscle, so these lines are indications of errors, most likely due to a broken electrode or a poorly attached electrode. Signals should always be tested prior to starting the experiment, yet sometimes mistakes are made. Also signals can be lost during an experiment. Second, a signal drops (or increases) dramatically and continues at that lower (or higher) level - without dipping to the extremely low level of a flat line. We call these cliffs. Cliffs may occur due to minor shifts in the placement or adhesiveness of the electrode. We coded the data to identify these errors and we cross-referenced these errors with the logbook we kept during data collection[14].

13. Note that the correlation between arousal, as measured with skin conductance and the IAPS arousal scores, is r=0.324, and thus considerably lower than the correlation with the fEMG measures

14. We were able to identify why signal errors occurred in a number of cases. There are certainly also a number of cases that the logbook could not explain. We consider this inevitable in a data collection process that lasts weeks, and in which each participant spends minimally an hour in the lab

Figure A2. Corrugator and zygomaticus activity for differently valenced IAPS images



Note: Dots represent the mean corrugator activity and mean zygomaticus activity during exposure to different IAPS pictures. Standard errors of the means of both measures are plotted on top of these plots. Images are coded as negative if they have scored below 4 on the 1-9 IAPS human judgment scale. They are coded as positive if they have scored above 6, and neutral when in-between.

We calculated Krippendorff's alphas to measure the agreement between the two coders. For corrugator activity the estimated α is 0.864 (n=585). The agreement for zygomaticus activity is somewhat lower at 0.778 (n=363). These are fairly reasonable levels of agreement. Following this procedure, we identify a total of 13.4% of the corrugator observations to be problematic (seen as problematic by one or two coders) and 16.5% for zygomaticus activity. In most cases, this means a part of the signal we retrieved is not usable. We did not remove this data at first but rather coded the errors into the dataset, as described before. For each error, we coded whether both coders identified it or just one. This is done at the level of the participant. A more detailed coding can be done by coding at the level of the treatment (or even the seconds within the treatment). We did not do this because in most cases errors persist over a large period of the treatment, which is consistent with an electrode malfunctioning or improperly placed. After coding the physiological data, a few very high values remained in the data. To account for this, we also coded a dummy variable indicating whether a value is a statistical outlier or not. The benchmark for this is a value higher than 4 standard deviations above the mean.

5 How to analyze baseline activity?

Researchers agree that baseline activity should reflect a stable, artefact-free signal that captures the participants' fEMG activity when no particular information is send. Baselines therefore are typically blank screens with a plus sign in the middle. The problem, however, is that fEMG signals are rarely stable: they can decline a bit over-time, and artefacts may arise due to participants scratching, moving or suddenly realizing that they forgot the keys to their house. Such artefacts may produce strong fEMG signals, that may subsequently affect our estimate of the baseline signal. But how much? To evaluate this we pursued two inquiries: (1) does it matter how we calculate baseline activity and (2) how do different calculations of baseline activity correlate with gold-standard human coder annotations of baselines?

To address the first question: we took all the thirty seconds baselines used in Designs 1, 2 and 3. We used 5 different statistical operations: mean, median, geometric mean, harmonic mean and the Tukey biweighted-mean. And we subset the baseline data in 9 different ways: all data, last two seconds, last three seconds, last five seconds, last ten seconds, random selection of 10 seconds, random selection of 5 seconds, all data minus minimum and maximum values, all data minus all values two standard deviations above the mean. In total we calculate 45 (5 operations x 9 selections) different measures of baseline activity. We did this both for zygomaticus activity and corrugator activity. The correlations between the different measures and time selections are extremely high (r=.99).

To address the second question: two human coders analyzed baseline activity independently for 100 participants. They were asked to identify the seconds within the baseline that best identified the general tendency of fEMG activity in the baseline. The correlation between the activity in the general tendencies identified by the human coders was r=.99. We subsequently correlated the human-coded baseline activity with the different measures discussed in the previous paragraph. These correlations range between r=.93 and r=.98 with both zygomaticus and corrugator activity. Correlations are relatively low (r=.93) if we compare the two, three or five second baselines to the human coders. Correlations are higher the more data we take in. The logic here is simply that if there is an artefact in the data (e.g. a single large peak) this is much more likely to influence a small set of observations than a larger set.

Given the similarity in baseline measures, we give only a weak recommendation. We suggest to take the median of the baseline (all observations). This measure produced among the highest correlations with the human-coded data and medians are generally more effective in reducing noise in signals than means. Also, by taking all observations in the baseline you prevent engaging in setting rather arbitrary cut-off lines of two, three or five seconds. That said, other choices here are unlikely to produce very different results.

6 Comparison preregistered baseline model and adopted baseline model

Because some of the preregistered models had difficulties converging we simplified the multilevel model by only using random intercepts for respondents. In table A3 we contrast this adopted model to the original preregistered model which also included random intercept for the seconds in the treatment. In most cases the direction and significance of the covariates are similar in the adopted and preregistered models.

Table A3. Preregistered and adopted multilevel models

	Corrugator		Zygomaticus	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	80.719*	75.605*	130.553*	135.048*
	(8.165)	(9.470)	(18.224)	(17.847)
Seconds in experiment	0.089*	0.117*	0.287	0.061*
	(0.022)	(0.006)	(0.168)	(0.026)
Seconds in treatment	0.052*	0.053*	0.008	−0.001
	(0.003)	(0.003)	(0.010)	(0.010)
EO	−1.306	−1.901		
	(3.103)	(3.666)		
Lab	1.342	0.143		
	(2.321)	(2.738)		
Lowlands	−10.465*	−14.999*	−25.878*	−28.875*
	(2.460)	(2.887)	(5.017)	(4.927)
Nijmegen	−2.246	−7.198*		
	(3.051)	(3.601)		
Tilburg	2.724	−2.418		
	(3.157)	(3.697)		
TT Assen	1.572	−2.948		
	(4.326)	(5.048)		
Temperature	0.931*	1.258*	−0.798	−0.908
	(0.348)	(0.403)	(0.869)	(0.851)
AIC	1574100.482	1577821.290	1116714.951	1118457.967
BIC	1574240.304	1577941.137	1116799.955	1118524.081
Log Likelihood	−787036.241	−788898.645	−558348.476	−559221.983
Num. obs.	160704	160704	93418	93418
Num. groups: respondent	514	514	293	293
Var: respondent	160.687	230.101	671.999	643.431
Var: respondent seconds	0.211		7.834	
Cov: respondent seconds	−0.320		−25.021	
Var: Residual	1029.689	1060.880	8912.960	9180.566

*$p < 0.05$

7 Analysis strategy

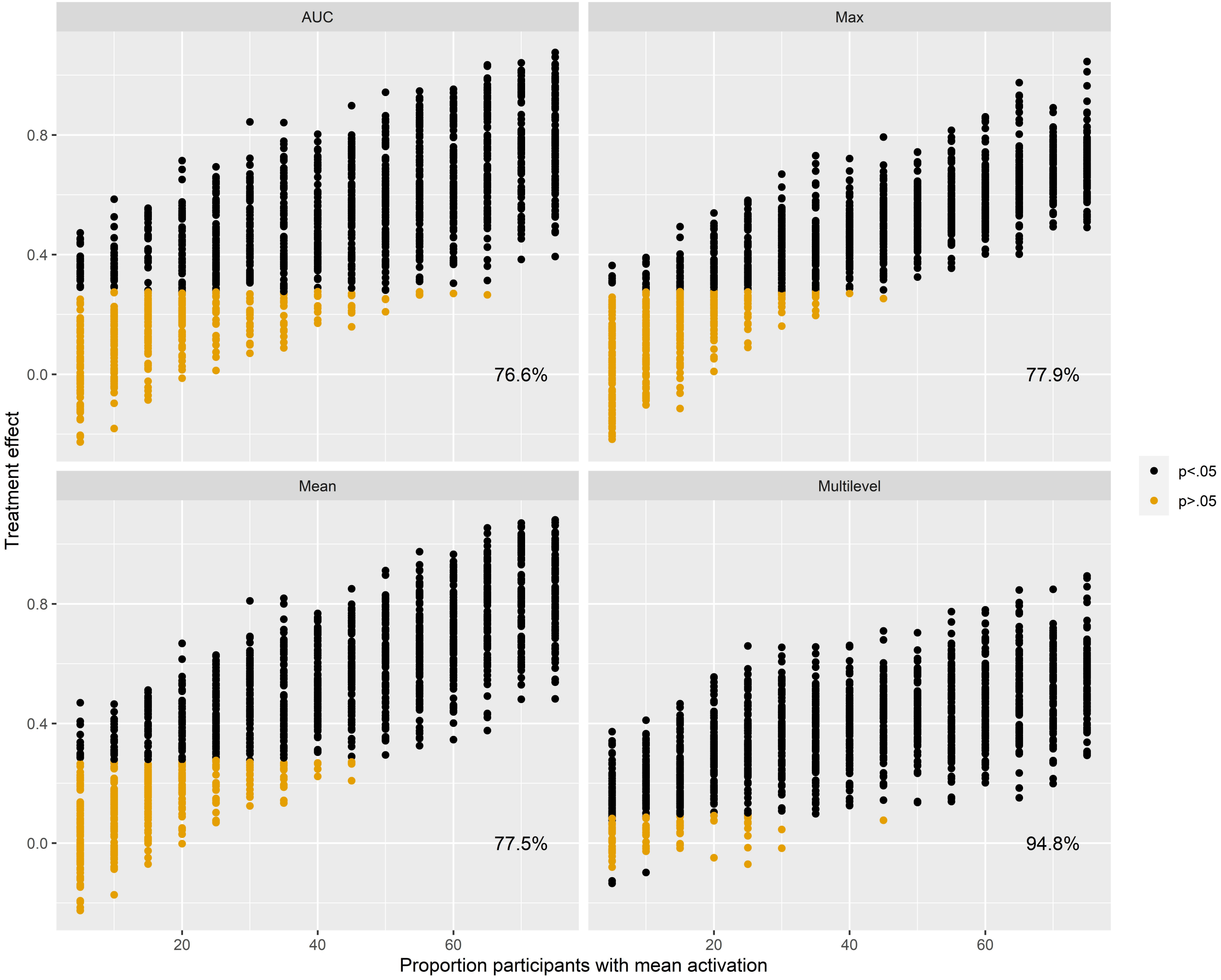
Figure A3 demonstrates this issue further. Here we estimated the difference in corrugator activity between the negative tumor picture and the positive baby picture, drawing different random samples of N=200 from the original data. The x-axis represents the proportion of participants that showed increased corrugator activity during the tumor treatment. We contrast this with the response to the baby treatment during which 87% of the participants showed relaxed corrugator activity. This is kept constant. By consequence, there should always be more corrugator activity during the tumor treatment. The question is whether different transformations of the dependent variable (mean, max, or area under the curve, or activity per second) are capable of finding this positive effect of more corrugator activity to the tumor treatment compared to the baby treatment. Figure A3 describes the output of this simulation. Each dot in the plot is a treatment effect from one simulation. The top left (using the Area Under the Curve approach), bottom left (using the mean activity), and the top right (using the maximum activity) figures are very alike: in each we find approximately 25% of the simulations has an insignificant treatment effect (represented as blue dots). On the bottom right, we ran a multilevel model with participants as a higher-level class and participant-seconds as unit of analysis. In this simulation only about 5% of the treatment effects we retrieved were insignificant.

In all four simulations (panels) of Figure A3, there is clearly a positive effect, meaning that compared to the baby picture, people have much more corrugator activity to the tumor picture. Therefore most simulations retrieve the treatment effect. However, the smaller the treatment effect becomes - moving to the left on the x-axis of Figure A3) - the higher the risk of rejecting a treatment effect. This risk is much lower with the multilevel approach. For that reason, we recommend using a multilevel model to analyze the data. This also allows for investigating specific moments in a treatment, which is particularly helpful when treatments are longer videos.

Regarding effect size, the multilevel models also return slightly lower standardized effects. This is because they also include values after an EMG response peak. This can be specifically dealt with in a multilevel analysis by adding time dynamics. In this stylized example, the correlations between the different outcome measures are still very high[15]. It is likely that for political science applications the results are much less clear-cut and that therefore multi-level models are more powerful in extracting treatment effects.

15. The Pearson correlation coefficients are around .95

Figure A3. Simulated treatment effects with different analysis strategies



Note: The figure shows individual estimates of the treatment effect (tumor vs baby treatment) of random draws of our participant set. The y-axis shows the treatment effect and the x-axis shows the proportion of participants in the random draw with corrugator activation (defined as values above 100). The black dots indicate that the treatment effect is statistically significant, the orange dots indicate the treatment effect is insignificant.

To evaluate our research questions, we use multilevel analyses. Prior to these analyses, we considered different multilevel model specifications excluding the variables of interest (the treatment characteristics). We considered these different models to reduce the heterogeneity between individuals that may stem from differences in location of data collection, differences in computer that performed the data collection, and the timing of the treatment within the larger data collection participants were involved in. Location was assessed with dummies, but also with the recorded temperature at these locations. We compared different model specifications using an ANOVA test that examines whether model improvement is significant considering the increase in model parameters. The best performing model is a multilevel model with random intercepts for each participant, a random effect for time within-treatment, and time within-experiment, location and temperature as independent variables (chi-square dif=7.7, p<.01, compared to a model without temperature which was the best performing model up to this point).[16] For zygomaticus activity, the two models were equally good. Therefore, we run the analysis with computer as independent variable as an additional robustness check. Note that the specific best-fitting multilevel specification may depend on the specifics of a study. Therefore we recommend comparing different multilevel models and preregister the analysis that produces the best fit to the data according to an ANOVA test.

16. Models with both the computer and location variable (as random or fixed effect) had difficulties converging due to the high multicollinearity between these variables (some locations just had one computer). For corrugator activity, the model with locations was better than the model with computers (chi-square dif=15.637, p<.001), and therefore we prefer the former.

8 Direct effect participant characteristics on fEMG activity

We only find a positive, small, significant difference in winsorized corrugator activity (b=5.695, z=0.226, se=2.635, t=2.162) between participants who finished secondary vocational training and participants who only finished secondary education (in our case these are almost all university students). This effect is even smaller and statistically insignificant in the alternative analysis with corrugator activity (b=4.863, z=0.151, se=2.514, t=1.958).

Table A4. Multilevel regression models measuring impact participant characteristics on fEMG

	Corrugator	Cor(winsorized)	Zygomaticus	Zyg(winsorized)
Intercept	−0.090	−0.071	−0.020*	0.288*
	(0.055)	(0.097)	(0.006)	(0.057)
Female	0.027	0.050	−0.006	−0.027
	(0.027)	(0.048)	(0.006)	(0.057)
Age	0.025	0.033	0.003	0.039
	(0.016)	(0.028)	(0.003)	(0.031)
Alcohol	0.054	0.224	−0.003	−0.115
	(0.094)	(0.166)	(0.022)	(0.207)
leftright	0.001	−0.017	−0.003	0.002
	(0.013)	(0.024)	(0.003)	(0.027)
Sec voc vs sec	0.075	0.199*	−0.006	−0.033
	(0.046)	(0.082)	(0.013)	(0.124)
High voc vs sec	−0.012	−0.011	−0.004	−0.002
	(0.043)	(0.077)	(0.011)	(0.103)
University vs sec	−0.011	−0.028	−0.006	−0.069
	(0.030)	(0.054)	(0.007)	(0.065)
EO	−0.030	−0.074		
	(0.067)	(0.119)		
Lab	0.011	0.007		
	(0.055)	(0.098)		
Lowlands	−0.177*	−0.379*	−0.059*	−0.796*
	(0.055)	(0.097)	(0.006)	(0.060)
Nijmegen	−0.133	−0.257		
	(0.280)	(0.497)		
Tilburg	−0.058	−0.104		
	(0.067)	(0.119)		
TT Assen	−0.148	−0.291		
	(0.088)	(0.156)		
seconds in exp	0.002*	0.004*	0.000*	−0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
seconds in treatment	0.001*	0.001*	−0.000	−0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
AIC	229951.484	401689.560	−64065.192	236184.197
BIC	230130.185	401868.375	−63942.594	236306.834
Log Likelihood	−114957.742	−200826.780	32045.596	−118079.098
Num. obs.	151421	152383	92096	92378
Num. groups: study_respondent	476	477	290	290
Var: study_respondent (Intercept)	0.074	0.234	0.002	0.197
Var: Residual	0.263	0.805	0.029	0.744

*$p < 0.05$

9 Statistical Power of multilevel fEMG analysis

It is difficult to assess the statistical power of our proposed statistical tests due to the complexity of the data structure, the various treatment components and the noise inherent in our data. To provide an intuition for the power of our tests, we simulated a random dataset that approximates our real analyses. To this end we generated 8-second response patterns for 1250 participants who saw two fictional treatments. For one treatment, response patterns were calculated by summing a treatment, plus 100 (baseline level) and a time decay. The time decay parameter is randomly generated per individual with a mean of -0.45 and a standard deviation of 0.05. The values are taken from the time effect within the analyses of the tumor versus baby comparison. For the other treatment the calculation is identical except we did not add a treatment effect. We subsequently analyze the data in a similar way as described in the preregistration plan and extract the beta and p coefficients and calculate a cohen's d. We ran 100 simulations with this setup using different treatment effects (0.05 and 0.1). With an assumed treatment effect of 0.05, only 65% of the coefficients were statistically significant ($p<.05$) and positive. With a treatment effect of 0.1, 90% of the coefficients were significant and positive. The treatment effect of 0.1 translates to a cohen's d of on average 0.08. This is the treatment effect we can detect with 90% power.

10 Overview of political science studies tapping into unconscious processes

Political scientists increasingly use techniques that tap into unconscious or preconscious processes, such as the Implicit Association Task (IAT) (Ryan 2017; Ryan and Krupnikov 2021; Pérez 2016), list experiments (Corstange 2009; Glynn 2013; Moseson *et al.* 2017), automated emotion recognition algorithms based upon computer vision techniques (Boussalis and Coan 2021; Masch, Gassner, and Rosar 2021; Joo, Bucy, and Seidel 2019; Boussalis *et al.* 2021), electroencelography (EEG) (Jost *et al.* 2014; Galli *et al.* 2021; Morris *et al.* 2003), functional magnetic resonance imaging (fMRI) (Schreiber *et al.* 2013; Dawes *et al.* 2012) and psychophysiological measures such as skin conductance (Soroka and McAdams 2015; Aarøe, Petersen, and Arceneaux 2017; Mutz 2007; Smith *et al.* 2011; Renshon, Lee, and Tingley 2015; Tursky, Lodge, and Reeder 1979; Bakker, Schumacher, and Homan 2020), heart rate (Soroka, Fournier, and Nir 2019; Wahlke and Lodge 1972), and, recently, facial electromyography (fEMG) (Bakker, Schumacher, and Rooduijn 2021; Bakker *et al.* 2020; Homan, Schumacher, and Bakker 2022).

Table A5 provides an overview of political science studies that specifically use fEMG. On Google Scholar we queried politics, political science together with fEMG, EMG, corrugator and zygomaticus. We subsequently read the titles of each study to establish whether the article is about politics. It is evident that fEMG is rarely used in political science and is even rarer to be published in a political science journal (6 in total). The list features primarily psychology and communication science journals, in which fEMG is more common. The corrugator measure is the most commonly used fEMG measure, followed by the zygomaticus. Two other fEMG muscles, which are less frequently used, are the levator labii muscle (next to the nose) that measures disgust responses, and the orbicularis oculi muscle (above or below the eye) that measures the so-called startle reflex. One can also analyze the pars orbicularis part next to the eye to measure happiness(Bourgeois and Hess 2008). Since our focus is on valence, we ignore these measures here. In the studies cited here, the orbicularis oculi is used as an alternative measure for emotional arousal, while the levator labii is associated with disgust.

Table A5. Overview of studies on politics using fEMG measures

Authors	Journal	Main title	fEMG measures	N
McHugo *et al.* (1985)	JPSP	Emotional reactions to a political leader's expressive displays	Corrugator, zygomaticus	40
McHugo, Lanzetta, and Bush (1991)	JNB	The effect of attitudes on emotional reactions to expressive displays of political leaders	Corrugator, zygomaticus	100
Marcus, Wood, and Theiss-Morse (1998)	PLS	Linking Neuroscience to Political Intolerance and Political Judgment	Corrugator	21
Ensari *et al.* (2004)	GPIR	Negative Affect and Political Sensitivity in Crossed Categorization	Corrugator	45
Bucy and Bradley (2004)	SSI	Presidential Expressions and Viewer Emotion	Corrugator, zygomaticus	41
Oxley *et al.* (2008)	Science	Political attitudes vary with physiological traits	Orbicularis oculi	48
Bourgeois and Hess (2008)	BioPsy	The impact of social context on mimicry	Corrugator, zygomaticus, levator labii, orbicularis oculi	104
Wang, Morey, and Srivastava (2014)	ComRes	Motivated Selective Attention During Political Ad Processing	Corrugator, zygomaticus	120
Bradley, Angelini, and Lee (2007)	Jadv	Psychophysiological and Memory Effects of Negative Political Ads	Orbicularis oculi	51
Peterson *et al.* (2018)	PLS	Emotional expressivity as a predictor of ideology	Corrugator	342
Fino *et al.* (2019)	SciRep	Unfolding political attitudes through the face	Corrugator, zygomaticus	53
Bakker, Schumacher, and Homan (2020)	PLS	Yikes! Are we disgusted by politicians?	Levator labii, corrugator	108
Bakker *et al.* (2020, NL sample)	NHB	Conservatives and liberals have similar physiological responses to threats	Corrugator	81
Bakker *et al.* (2020, US sample)	NHB	Conservatives and liberals have similar physiological responses to threats	Levator labii, corrugator	202
Goudarzi *et al.* (2020)	NatCom	Economic system justification predicts muted emotional responses to inequality	Corrugator, levator labii	155
Bakker, Schumacher, and Rooduijn (2021)	APSR	Hot politics? Affective responses to political rhetoric	Corrugator, zygomaticus	397
Boyer (2021)	IntJPP	How the News Exacerbates Motivated Reasoning	Corrugator	191
Schumacher, Rooduijn, and Bakker (2022)	Pol Psy	Hot populism? Affective responses to antiestablishment rhetoric	Corrugator, zygomaticus	343
Homan, Schumacher, and Bakker (2022)	Emotion	Do Emotional Displays of Politicians Evoke Mimicry and Emotional Contagion?	Corrugator, zygomaticus	107

11 Full output multilevel models reported in main paper

Table A6. Multilevel model explaining corrugator activity in political vs nonpolitical treatments

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	78.971*	−0.474*	82.628*	−0.950*
	(8.162)	(0.130)	(7.032)	(0.294)
Political treatment	1.745*	0.040*	1.630*	0.102*
	(0.277)	(0.004)	(0.202)	(0.007)
Seconds in experiment	0.092*	0.002*	0.061*	0.003*
	(0.022)	(0.000)	(0.016)	(0.000)
Seconds in treatment	0.060*	0.001*	0.044*	0.002*
	(0.003)	(0.000)	(0.002)	(0.000)
EO	−1.277	−0.027	−0.546	−0.039
	(3.099)	(0.051)	(2.691)	(0.114)
Lab	1.894	0.015	1.341	0.035
	(2.321)	(0.038)	(2.013)	(0.085)
Lowlands	−10.647*	−0.207*	−9.768*	−0.517*
	(2.458)	(0.040)	(2.127)	(0.090)
Nijmegen	−1.454	−0.074	−1.977	−0.195
	(3.049)	(0.050)	(2.644)	(0.112)
Tilburg	2.628	−0.036	1.197	−0.114
	(3.153)	(0.051)	(2.728)	(0.115)
TT Assen	1.510	−0.044	0.612	−0.105
	(4.322)	(0.070)	(3.733)	(0.157)
Temperature	0.937*	0.017*	0.778*	0.040*
	(0.348)	(0.006)	(0.300)	(0.013)
AIC	1538390.918	194353.908	1448166.058	416653.082
BIC	1538540.389	194483.449	1448315.623	416782.704
Log Likelihood	−769180.459	−97163.954	−724068.029	−208313.541
Num. obs.	157108	157108	158100	158100
Num. groups: P	514	514	515	515
Var: P (Intercept)	159.935	0.044	122.653	0.222
Var: P sync.units	0.209		0.110	
Cov: P (Intercept) sync.units	−0.251		−0.234	
Var: Residual	1026.192	0.199	544.793	0.805

*$p < 0.05$

Table A7. Multilevel model explaining zygomaticus activity in political vs nonpolitical treatments

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	130.311*	0.005	114.129*	0.597
	(18.475)	(0.032)	(7.308)	(0.307)
Political treatment	1.559	0.002	1.016*	0.029*
	(1.046)	(0.002)	(0.237)	(0.009)
Seconds in experiment	0.277	0.000*	−0.009	−0.001*
	(0.170)	(0.000)	(0.022)	(0.000)
Seconds in treatment	0.015	0.000	−0.006*	−0.000*
	(0.011)	(0.000)	(0.002)	(0.000)
Lowlands	−26.335*	−0.052*	−18.682*	−0.717*
	(5.111)	(0.009)	(2.020)	(0.085)
Temperature	−0.834	−0.002	−0.417	−0.018
	(0.880)	(0.002)	(0.349)	(0.015)
AIC	1079386.657	−60951.092	814782.766	229563.086
BIC	1079480.752	−60875.815	814876.892	229638.387
Log Likelihood	−539683.328	30483.546	−407381.383	−114773.543
Num. obs.	90179	90179	90461	90461
Num. groups: P	293	293	293	293
Var: P (Intercept)	696.441	0.002	111.663	0.200
Var: P sync.units	7.989		0.119	
Cov: P (Intercept) sync.units	−26.383		−0.532	
Var: Residual	9046.348	0.029	467.578	0.730

*$p < 0.05$

Table A8. Multilevel model explaining corrugator activity in treatments with video, word or pictures

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	81.021*	−0.447*	84.397*	−0.884*
	(8.164)	(0.130)	(7.016)	(0.292)
Video vs picture	1.003*	0.019*	0.933*	0.049*
	(0.284)	(0.004)	(0.207)	(0.007)
Word vs picture	−1.476*	−0.015*	−0.888*	−0.021
	(0.427)	(0.006)	(0.312)	(0.012)
Seconds in experiment	0.071*	0.001*	0.042*	0.003*
	(0.022)	(0.000)	(0.016)	(0.000)
Seconds in treatment	0.052*	0.001*	0.037*	0.002*
	(0.003)	(0.000)	(0.002)	(0.000)
EO	−1.342	−0.026	−0.600	−0.039
	(3.102)	(0.050)	(2.686)	(0.113)
Lab	1.509	0.004	0.863	0.004
	(2.321)	(0.038)	(2.008)	(0.085)
Lowlands	−11.156*	−0.210*	−10.236*	−0.525*
	(2.467)	(0.040)	(2.127)	(0.089)
Nijmegen	−2.239	−0.098*	−2.751	−0.258*
	(3.050)	(0.049)	(2.638)	(0.111)
Tilburg	2.214	−0.038	0.821	−0.120
	(3.159)	(0.051)	(2.724)	(0.114)
TT Assen	0.967	−0.046	0.147	−0.109
	(4.327)	(0.069)	(3.727)	(0.156)
Temperature	0.909*	0.017*	0.758*	0.040*
	(0.348)	(0.006)	(0.299)	(0.012)
AIC	1574077.417	199347.198	1482281.968	427404.205
BIC	1574237.214	199487.020	1482441.864	427544.114
Log Likelihood	−787022.709	−99659.599	−741124.984	−213688.103
Num. obs.	160704	160704	161699	161699
Num. groups: P	514	514	515	515
Var: P (Intercept)	160.669	0.043	122.516	0.220
Var: P sync.units	0.212		0.114	
Cov: P (Intercept) sync.units	−0.337		−0.293	
Var: Residual	1029.513	0.200	548.850	0.811

$^{*}p < 0.05$

Table A9. Multilevel model explaining zygomaticus activity in treatments with video, word or pictures

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	135.122*	0.013	115.689*	0.646*
	(18.331)	(0.032)	(7.082)	(0.301)
Video vs picture	1.444	0.006*	2.461*	0.091*
	(1.178)	(0.002)	(0.269)	(0.010)
Word vs picture	−6.207*	−0.012*	−0.987*	−0.040*
	(1.303)	(0.002)	(0.300)	(0.012)
Seconds in experiment	0.239	0.000	−0.040	−0.002*
	(0.168)	(0.000)	(0.021)	(0.000)
Seconds in treatment	−0.003	−0.000	−0.008*	−0.000*
	(0.011)	(0.000)	(0.002)	(0.000)
Lowlands	−27.551*	−0.054*	−19.709*	−0.739*
	(5.099)	(0.009)	(1.961)	(0.083)
Temperature	−0.960	−0.002	−0.487	−0.021
	(0.873)	(0.002)	(0.338)	(0.014)
AIC	1116688.540	−64595.206	845289.420	239067.293
BIC	1116792.433	−64510.203	845393.347	239152.323
Log Likelihood	−558333.270	32306.603	−422633.710	−119524.646
Num. obs.	93418	93418	93700	93700
Num. groups: P	293	293	293	293
Var: P (Intercept)	676.935	0.002	103.382	0.191
Var: P sync.units	7.795		0.108	
Cov: P (Intercept) sync.units	−24.740		−0.398	
Var: Residual	8910.534	0.029	474.777	0.740

* $p < 0.05$

Table A10. Multilevel model explaining corrugator activity in face vs no face treatments

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	83.647*	−0.416*	86.143*	−0.824*
	(8.158)	(0.130)	(7.029)	(0.294)
Face vs No face	−2.918*	−0.041*	−1.990*	−0.079*
	(0.256)	(0.003)	(0.186)	(0.007)
Seconds in experiment	0.074*	0.001*	0.048*	0.003*
	(0.022)	(0.000)	(0.016)	(0.000)
Seconds in treatment	0.043*	0.001*	0.031*	0.001*
	(0.003)	(0.000)	(0.002)	(0.000)
EO	−1.372	−0.027	−0.608	−0.039
	(3.097)	(0.050)	(2.690)	(0.114)
Lab	0.502	−0.001	0.262	−0.004
	(2.319)	(0.038)	(2.012)	(0.085)
Lowlands	−12.020*	−0.216*	−10.639*	−0.534*
	(2.460)	(0.040)	(2.128)	(0.090)
Nijmegen	−2.702	−0.101*	−3.030	−0.263*
	(3.046)	(0.050)	(2.642)	(0.112)
Tilburg	1.638	−0.043	0.571	−0.125
	(3.153)	(0.051)	(2.728)	(0.115)
TT Assen	0.268	−0.052	−0.169	−0.116
	(4.321)	(0.070)	(3.733)	(0.157)
Temperature	0.880*	0.017*	0.743*	0.040*
	(0.348)	(0.006)	(0.300)	(0.013)
AIC	1538300.387	194335.028	1448116.895	416718.231
BIC	1538449.857	194464.569	1448266.460	416847.854
Log Likelihood	−769135.193	−97154.514	−724043.447	−208346.115
Num. obs.	157108	157108	158100	158100
Num. groups: P	514	514	515	515
Var: P (Intercept)	159.945	0.044	122.711	0.222
Var: P sync.units	0.212		0.113	
Cov: P (Intercept) sync.units	−0.290		−0.261	
Var: Residual	1025.558	0.199	544.589	0.805

*$p < 0.05$

Table A11. Multilevel model explaining zygomaticus activity in face vs no face treatments

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	122.966*	−0.007	113.380*	0.563
	(18.405)	(0.032)	(7.331)	(0.308)
Face vs No face	8.289*	0.013*	1.427*	0.052*
	(1.104)	(0.002)	(0.252)	(0.010)
Seconds in experiment	0.306	0.000*	−0.003	−0.001*
	(0.170)	(0.000)	(0.022)	(0.000)
Seconds in treatment	0.036*	0.000*	−0.005*	−0.000*
	(0.011)	(0.000)	(0.002)	(0.000)
Lowlands	−23.884*	−0.050*	−17.929*	−0.701*
	(5.068)	(0.009)	(2.024)	(0.085)
Temperature	−0.588	−0.001	−0.378	−0.016
	(0.876)	(0.002)	(0.350)	(0.015)
AIC	1079332.408	−60995.828	814768.892	229546.005
BIC	1079426.504	−60920.552	814863.018	229621.307
Log Likelihood	−539656.204	30505.914	−407374.446	−114765.003
Num. obs.	90179	90179	90461	90461
Num. groups: P	293	293	293	293
Var: P (Intercept)	692.614	0.002	112.268	0.201
Var: P sync.units	8.026		0.119	
Cov: P (Intercept) sync.units	−26.883		−0.530	
Var: Residual	9041.056	0.029	467.498	0.730

$^{*}p < 0.05$

Table A12. Multilevel model explaining corrugator activity in treatments with different valence

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	94.916*	−0.077	108.908*	−0.043*
	(13.572)	(0.411)	(3.091)	(0.005)
Positive vs Neutral	−6.267*	−0.190*	18.071*	0.031*
	(0.394)	(0.010)	(1.710)	(0.003)
Negative vs Neutral	5.918*	0.153*	5.088*	0.008*
	(0.299)	(0.008)	(1.317)	(0.002)
Seconds in experiment	0.012	0.001*	0.516	0.001*
	(0.047)	(0.000)	(0.352)	(0.000)
Seconds in treatment	0.064*	0.002*	0.008	0.000
	(0.003)	(0.000)	(0.013)	(0.000)
EO	−4.170	−0.097		
	(2.485)	(0.074)		
Lab	−1.770	−0.058		
	(2.109)	(0.063)		
Nijmegen	−3.896	−0.140*		
	(2.212)	(0.067)		
Tilburg	0.382	0.109		
	(3.363)	(0.095)		
TT Assen	2.306	0.045		
	(5.229)	(0.150)		
Temperature	0.254	−0.001		
	(0.594)	(0.018)		
AIC	731653.847	195398.349	577894.741	−7174.283
BIC	731792.067	195518.223	577973.418	−7113.090
Log Likelihood	−365811.923	−97686.174	−288938.370	3594.142
Num. obs.	74214	74687	46255	46255
Num. groups: P	354	354	156	156
Var: P (Intercept)	75.998	0.069	976.849	0.003
Var: P sync.units	0.444		16.635	
Cov: P (Intercept) sync.units	−1.895		−53.796	
Var: Residual	1100.209	0.791	15361.673	0.050

$^{*}p < 0.05$

Table A13. Multilevel model explaining zygomaticus activity in treatments with different valence

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	108.908*	−0.043*	103.807*	0.129*
	(3.091)	(0.005)	(0.695)	(0.023)
Positive vs Neutral	18.071*	0.031*	5.654*	0.215*
	(1.710)	(0.003)	(0.314)	(0.012)
Negative vs Neutral	5.088*	0.008*	0.936*	0.032*
	(1.317)	(0.002)	(0.242)	(0.009)
Seconds in experiment	0.516	0.001*	0.030	0.003*
	(0.352)	(0.000)	(0.051)	(0.001)
Seconds in treatment	0.008	0.000	−0.005*	−0.000*
	(0.013)	(0.000)	(0.002)	(0.000)
AIC	577894.741	−7174.283	423912.367	122499.474
BIC	577973.418	−7113.090	423991.099	122560.710
Log Likelihood	−288938.370	3594.142	−211947.183	−61242.737
Num. obs.	46255	46255	46537	46537
Num. groups: P	156	156	156	156
Var: P (Intercept)	976.849	0.003	57.749	0.057
Var: P sync.units	16.635		0.316	
Cov: P (Intercept) sync.units	−53.796		−2.416	
Var: Residual	15361.673	0.050	520.848	0.805

* $p < 0.05$

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Table A14. Multilevel model explaining corrugator activity in sound vs no sound treatments

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	80.414*	−0.456*	83.901*	−0.907*
	(8.167)	(0.130)	(7.019)	(0.292)
Sound vs No sound	0.481	0.016*	0.624*	0.046*
	(0.248)	(0.003)	(0.181)	(0.007)
Seconds in experiment	0.084*	0.001*	0.051*	0.003*
	(0.022)	(0.000)	(0.016)	(0.000)
Seconds in treatment	0.054*	0.001*	0.040*	0.002*
	(0.003)	(0.000)	(0.002)	(0.000)
EO	−1.297	−0.026	−0.564	−0.037
	(3.103)	(0.050)	(2.687)	(0.113)
Lab	1.255	0.000	0.661	−0.005
	(2.322)	(0.038)	(2.008)	(0.085)
Lowlands	−10.770*	−0.210*	−9.996*	−0.525*
	(2.466)	(0.040)	(2.127)	(0.089)
Nijmegen	−2.413	−0.102*	−2.957	−0.269*
	(3.052)	(0.049)	(2.640)	(0.111)
Tilburg	2.522	−0.037	1.019	−0.118
	(3.159)	(0.051)	(2.725)	(0.114)
TT Assen	1.389	−0.044	0.430	−0.104
	(4.328)	(0.069)	(3.728)	(0.156)
Temperature	0.937*	0.017*	0.779*	0.041*
	(0.348)	(0.006)	(0.299)	(0.012)
AIC	1574099.686	199352.636	1482299.677	427400.094
BIC	1574249.496	199482.471	1482449.579	427530.009
Log Likelihood	−787034.843	−99663.318	−741134.838	−213687.047
Num. obs.	160704	160704	161699	161699
Num. groups: P	514	514	515	515
Var: P (Intercept)	160.687	0.043	122.502	0.220
Var: P sync.units	0.211		0.113	
Cov: P (Intercept) sync.units	−0.316		−0.278	
Var: Residual	1029.676	0.200	548.926	0.811

$^{*}p < 0.05$

Table A15. Multilevel model explaining zygomaticus activity in sound vs no sound treatments

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	131.931*	0.007	114.415*	0.600*
	(18.246)	(0.032)	(7.103)	(0.301)
Sound vs No sound	−1.946*	−0.001	0.953*	0.039*
	(0.923)	(0.002)	(0.212)	(0.008)
Seconds in experiment	0.308	0.000*	−0.013	−0.001*
	(0.168)	(0.000)	(0.021)	(0.000)
Seconds in treatment	−0.000	−0.000	−0.007*	−0.000*
	(0.011)	(0.000)	(0.002)	(0.000)
Lowlands	−24.809*	−0.051*	−18.525*	−0.715*
	(5.045)	(0.009)	(1.963)	(0.083)
Temperature	−0.819	−0.002	−0.430	−0.018
	(0.869)	(0.002)	(0.339)	(0.014)
AIC	1116710.828	−64569.101	845370.279	239143.902
BIC	1116805.277	−64493.542	845464.757	239219.484
Log Likelihood	−558345.414	32292.551	−422675.139	−119563.951
Num. obs.	93418	93418	93700	93700
Num. groups: P	293	293	293	293
Var: P (Intercept)	672.612	0.002	104.347	0.192
Var: P sync.units	7.847		0.109	
Cov: P (Intercept) sync.units	−25.019		−0.427	
Var: Residual	8912.553	0.029	475.170	0.741

$^{*}p < 0.05$

Table A16. Multilevel model explaining corrugator activity in lab vs no lab treatments

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	80.719*	−0.445*	84.295*	−0.874*
	(8.165)	(0.130)	(7.017)	(0.292)
Lab vs No lab	1.342	0.002	0.772	0.000
	(2.321)	(0.038)	(2.008)	(0.085)
Seconds in experiment	0.089*	0.002*	0.058*	0.003*
	(0.022)	(0.000)	(0.016)	(0.000)
Seconds in treatment	0.052*	0.001*	0.036*	0.001*
	(0.003)	(0.000)	(0.002)	(0.000)
EO	−1.306	−0.026	−0.575	−0.038
	(3.103)	(0.050)	(2.686)	(0.113)
Lowlands	−10.465*	−0.206*	−9.611*	−0.513*
	(2.460)	(0.040)	(2.123)	(0.089)
Nijmegen	−2.246	−0.099*	−2.748	−0.258*
	(3.051)	(0.049)	(2.638)	(0.111)
Tilburg	2.724	−0.033	1.274	−0.108
	(3.157)	(0.051)	(2.723)	(0.114)
TT Assen	1.572	−0.040	0.661	−0.095
	(4.326)	(0.069)	(3.727)	(0.156)
Temperature	0.931*	0.017*	0.772*	0.040*
	(0.348)	(0.006)	(0.299)	(0.012)
AIC	1574100.482	199362.655	1482307.994	427435.984
BIC	1574240.304	199482.503	1482447.903	427555.906
Log Likelihood	−787036.241	−99669.327	−741139.997	−213705.992
Num. obs.	160704	160704	161699	161699
Num. groups: P	514	514	515	515
Var: P (Intercept)	160.687	0.043	122.504	0.220
Var: P sync.units	0.211		0.113	
Cov: P (Intercept) sync.units	−0.320		−0.283	
Var: Residual	1029.689	0.200	548.958	0.811

*$p < 0.05$

Table A17. Multilevel model explaining zygomaticus activity in lab vs no lab treatments

	Outlier removed		Winsorized	
	Preregistered	Adopted	Preregistered	Adopted
Intercept	104.674*	−0.045	97.069*	−0.078
	(22.117)	(0.038)	(8.617)	(0.365)
Lab vs No lab	25.878*	0.051*	18.032*	0.706*
	(5.017)	(0.009)	(1.959)	(0.083)
Seconds in experiment	0.287	0.000*	−0.003	−0.001*
	(0.168)	(0.000)	(0.021)	(0.000)
Seconds in treatment	0.008	−0.000	−0.011*	−0.000*
	(0.010)	(0.000)	(0.002)	(0.000)
Temperatuur	−0.798	−0.002	−0.441	−0.019
	(0.869)	(0.002)	(0.339)	(0.014)
AIC	1116714.951	−64581.429	845387.178	239157.661
BIC	1116799.955	−64515.315	845472.209	239223.796
Log Likelihood	−558348.476	32297.714	−422684.589	−119571.830
Num. obs.	93418	93418	93700	93700
Num. groups: P	293	293	293	293
Var: P (Intercept)	671.999	0.002	104.217	0.192
Var: P sync.units	7.834		0.110	
Cov: P (Intercept) sync.units	−25.021		−0.429	
Var: Residual	8912.960	0.029	475.263	0.741

*$p < 0.05$

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