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# Abstract

The relationship between political ideology and brain activity has captured the fascination of scientists and the public alike. Using approaches from cognitive neuroscience to provide insights into deeply held and personal beliefs requires careful navigation, with the application of robust methods that generate replicable results. A hallmark study in this area from Amodio et al. (2007) reported that brain components reflective of conflict monitoring and inhibition (namely the ERN [error-related negativity] and N2) are heightened in individuals who self-identify as liberal compared to conservative. While the study is highly influential and well-cited in the scientific literature, no direct replications of their findings exist and as such, this work was selected as a target replication for the #EEGManyLabs initiative. This cross-cultural multi-site study (N=320) will conduct a thorough replication of the Amodio et al. (2007) study, strictly adhering to the original protocol, namely by administering a Go/No-Go task with simultaneous EEG recording and a one-item scale asking participants to rate the extent to which they are liberal or conservative. We will supplement the original study with new measures that may better correspond to political identity in non-US contexts, such as religiosity, dogmatism, and traditionalism. In line with the original study, we will conduct correlational analyses between self-identified liberalism and ERN/N2 amplitudes. In addition, Bayesian linear regressions will be used to provide robust estimates of the strength of association between other components of political ideology and electrophysiological signals.

# 1. Introduction

Event-related potential (ERP) methods have been indispensable in elucidating important links between brain and behaviour. One such ERP is the error-related negativity (ERN), which occurs as a fronto-central negative deflection 100ms after the execution of an incorrect response during forced-choice reaction time tasks (Gehring et al., 1993) and is likely generated from the anterior cingulate cortex (Miltner et al., 2003). Greater ERN amplitude is reportedly reflective of cognitive advantages beyond error monitoring including enhanced attention, cognitive flexibility, and working memory (Larson & Clayson, 2011). Moreover, the ERN is considered a transdiagnostic marker for psychopathology as atypical signal amplitudes are associated with various psychiatric conditions (Riesel, 2019; Weinberg et al., 2015). Specifically, it is thought to correspond to symptoms of worry and harm avoidance (Kampman, Viikki, Jarventausta, & Leinonen, 2014; Dar & Iqbal, 2015; Yook, Kim, Suh, & Lee, 2010), although recent research suggests that the ERN may not be sensitive to these characteristics in non-clinical populations (Härpfer et al., 2020).

Another well-defined ERP is the N2, corresponding to a negative deflection at fronto-central electrodes peaking between 200-350ms, which reflects conflict arising from the competing decision to either execute or inhibit a response (Nieuwenhuis, Yeung, Van Den Wildenberg, & Ridderinkhof, 2003). A larger N2, elicited when an individual successfully withholds from making a pre-potent but inappropriate response, is a widely accepted proxy for inhibitory control (Falkenstein, Hoorman, & Hohnsbein, 1999; Kok, Ramautar, De Ruiter, Band, & Ridderinkoff, 2004). Like the ERN, the N2 is typically reported to be localised in the anterior cingulate cortex (Bekker et al., 2005; van Veen & Carter, 2002).

Fascinatingly, the ERN and N2 are even found to reflect individual differences in political ideology. In a now widely cited study, Amodio and colleagues (2007) showed for the first time that a more liberal (compared to conservative) orientation was associated with greater ERN and N2 amplitudes, as well as with better performance on a Go/No-Go task. The Go/No-Go task is a classic paradigm which measures one's ability to inhibit a pre-potent response to an infrequent stimulus (termed a No-Go stimulus). Political identity was ascertained via ratings on a single-item scale ranging from -5 (extremely liberal) to +5 (extremely conservative). Results suggested that self-identified liberals were more successful at inhibiting their responses to the No-Go stimulus. The authors interpreted these findings as being consistent with traits commonly associated with liberalism, including greater flexibility and better awareness and processing of potentially conflicting information. In contrast, conservatism seeks to preserve traditional social institutions and practices, traits which perhaps correspond to more rigid and habitual responding on the task.

Attempts to replicate and expand upon these findings have been met with mixed success. On the one hand, recent studies report dampened ERN and N2 in those

who demonstrate traits adjacent to conservatism including stronger religiosity, traditionalism, and resistance to social equality (Good et al., 2015; Inzlicht et al., 2009; Weissflog et al., 2013). Greater conflict-related N2 has also been discovered in children of liberals compared to children of conservatives, suggesting that cognitive styles associated with political ideology may be heritable (Dennis et al., 2015), although this study did not report ERN results. Furthermore, self-reported liberalism is linked to higher grey matter volume in the anterior cingulate cortex (Kanai et al., 2011), which is where the ERN and N2 are generated.

On the other hand, to date, there have been no successful direct replications of Amodio et al.'s (2007) findings. In a sample comprising 34 Canadian undergraduates (Weissflog et al., 2013), there was no significant association between ERN and political identity as measured using the single-item liberalism/conservatism scale used in the original study, although they observed a trend in the direction consistent with Amodio et al.'s findings. More recently, work conducted in 100 university students in the Czech Republic found no relationship between brain conflict monitoring components and liberalism/conservatism on both the single-item scale and an extended questionnaire (Kremláček et al., 2019). Difficulty in reproducing these results could stem from a) the single item liberalism-conservatism scale not being a sensitive enough measure of political ideology, particularly in b) diverse sociocultural contexts apart from the United States.

Such issues are not unique to Amodio et al.'s work and may be representative of a larger ongoing replicability crisis within the field of cognitive neuroscience. From the analysis of 3801 studies, it has been estimated that the rate of false positives in cognitive neuroscience research is over 50% indicated by insufficient sample sizes and low statistical power (Szucs & Ioannidis, 2017). ERP research in particular boasts average sample sizes of 21 per group and statistical power is merely estimated as 0.72–0.98 for a large effect size, 0.35–0.73 for a medium effect, and 0.10–0.18 for a small effect (Clayson et al., 2019), suggesting that most ERP studies are underpowered to detect large effects. These issues have prompted the formation of #EEGManyLabs (Pavlov et al., 2021), a large-scale collaborative project aiming to investigate the replicability of key findings from 20 of the most influential studies in the field. Amodio et al.'s (2007) study serves as one such suitable candidate for replication as the paper has been cited over 800 times hitherto and has influenced the landscape of current political neuroscience research. The present study aims to directly replicate Amodio et al.'s (2007) study while ensuring close adherence to data collection and pre-processing procedures from the original paper. Critically, our study will involve large-scale data collection to ensure adequate statistical power.

The Amodio et al. (2007) study was conducted in the United States (US), where there are clear delineations between conservatism and liberalism. This brand of socio-political division may not be applicable to other countries (particularly non-Western ones), which may explain why past replications not set in the US failed to detect significant associations between conservatism and lowered ERN and N2. Over recent years, political psychology has moved away from studying binary belief systems (e.g., left wing/right wing, nationalistic/globalist, religious/atheist) and is more focused on ideological thinking and behaviour (Rollwage et al., 2018; Schulz et

al., 2020; Zmigrod, 2020, 2021; Zmigrod et al., 2019, 2021). Ideological behaviour describes the extent to which a person rigidly adheres to a doctrine, resists credible evidence when forming opinions, and is antagonistic to individuals who do not follow an ideological group or cause (Zmigrod & Tsakiris, 2021). Such political partisanship appears to have a neurocognitive underpinning; it is linked to reduced cognitive flexibility, regardless of the political party's doctrine and partisan direction (Zmigrod, Rentfrow, & Robbins, 2020). Moreover, dogmatism, a feature of political partisanship which describes the tendency to lay down principles as undeniably true and rejection of conflicting evidence, is associated with inefficient evidence accumulation, higher impulsivity, and lower meta-cognitive insight into their decision-making performance (Rollwage et al., 2018; Schulz et al., 2020; Zmigrod, 2021). These cognitive characteristics are also likely to contribute to lower inhibition and attenuated ERN and N2 on a Go/No-Go task in dogmatic individuals, but research has yet to confirm this.

Cognitive rigidity and inefficient evidence accumulation, moreover, are traits, thought to be linked to intolerance of uncertainty (IU, Schulz et 2020), which describes the tendency to react negatively to uncertain or unpredictable events (Buhr & Dugas, 2002). Indeed, a rigid mind would unlikely have the cognitive resources to flexibly cope with uncertain situations and is more likely to find them aversive. Uncertainty intolerance is classically associated with conservatism (Jost et al., 2007; Jost & Amodio, 2012), but more recently it is reported to be a potential driver of ideological polarisation (van Baar et al., 2021). IU consists of two related but distinct factors, namely prospective (measuring anxiety and the urge to act in the face of uncertainty) and inhibitory IU (measuring avoidance and inhibition of action under uncertainty), the latter of which is associated with reduced ERN and faster response times on a conflict detection task (Jackson et al., 2016) and is hence congruent with electrophysiological findings linked to conservatism (Amodio et al., 2007). Although, a more recent study reports mixed evidence for the link between inhibitory IU and altered ERN (Malbec et al., 2022).

All in all, these non-categorical approaches to identifying neurocognitive correlates of political behaviour is perhaps advantageous as they may be more robust to changing socio-political landscapes over the years as well as differences in ethnicity, social class, and nationality.

Our study will serve as the first direct multi-site replication of Amodio et al. (2007), involving labs from various countries including the US, Germany, Portugal, Canada, Brazil, and Malaysia. Given the diversity in lab locations, we aim to supplement the replication by probing constructs such as religiosity, inhibitory intolerance of uncertainty, and dogmatism that may better capture political ideology in non-US contexts. In addition, we will complement the direct replication method with modern pre-processing and analytical approaches to test the robustness of reported effects.

Our hypotheses, based on Amodio et al. (2007), that would constitute a successful replication are:

1. ERN amplitude is positively correlated with self-reported liberalism;

2. N2 amplitude is positively correlated with self-reported liberalism;

3. Self-reported conservatives make more inhibition errors.

Additionally, given that we will be using other political identity measures aside from the one-item scale, we hypothesise that 4) inhibition errors and lower ERN/N2 amplitudes are positively correlated with measures typically associated with conservatism and cognitive rigidity such as religiosity, traditionalism, dogmatism, and inhibitory intolerance of uncertainty.

# 2. Methods

## 2.1 Sample

The sample to be recruited will also be used for a separate study under #EEGManyLabs which will replicate Amodio et al. (2008), specifically investigating how neural activity is associated with behavioural inhibition and activation.

Amodio et al. (2007) reported that their participants comprised 43 right-handed individuals (63% female) and that they recruited only undergraduate students or recent graduates. Hence, we will only include undergraduate or recent graduates in our replication study.

To determine the minimum target sample size for our study we ran two power analyses using G*Power 3 (Faul, Erdfelder, Lang, & Buchner, 2007). Power was set at 0.90 with $\alpha = .02$ to control for false positives. The effect sizes for the two analyses were respectively based on the reported significant correlations between a) ERN amplitudes and self-reported liberalism [$r(41) = 0.59$, $p < .001$] and b) N2 amplitudes and self-reported liberalism [$r(41) = 0.41$, $p < .01$] in Amodio et al. (2007). These effect sizes were chosen as they are associated with the most theoretically relevant results. The original effect sizes were divided by 2 as replication studies in general have reportedly half the magnitude of original effects (Aarts et al., 2015). The power analyses called for sample sizes of 119 and 256 respectively. We also accounted for the sample size requirement of the Amodio et al. (2008) replication, which requires a sample of N = 320. Based on this, each of the 8 replicating labs will provide data from 40 participants aged 18 years and above resulting in a collective sample size of 320 participants.

In each replicating lab, participants will be recruited via local advertisements or online recruitment systems. Ethical approval for this study within one of the labs has already been granted [Iscte-Instituto Universitário de Lisboa Ethics Committee: 08/2023], while ethics applications in other institutions are currently ongoing.

## 2.2 Questionnaires

Identical to Amodio et al. (2007), we will administer a one-item survey asking participants to rate their political orientation on a scale ranging from Extremely Liberal (–5) to Extremely Conservative (+5), with neutral corresponding to 0. In conjunction, participants will also complete the following questionnaires which will enable further insight into their political ideologies:

1) **Updated Dogmatism Scale** (Shearman & Levine, 2006)**.** An 11-item survey on a 7-point scale (1 = strongly disagree; 7 = strongly agree) will be used to measure dogmatism/political partisanship.
2) **Centrality of Religious Scale – Short Version** (Huber & Huber, 2012)**.** The CRS, to be used as a measure of religious conviction, consists of 5 items divided into five subscales: intellect (e.g., *How often do you think about religious issues?*); ideology (e.g., *To what extent do you believe that God or something divine exists?*); private practice (e.g., *How often do you pray?*); religious experience (e.g., *How often do you experience situations in which you have the feeling that God or something divine intervenes in your life?*); and public practice (e.g., *How often do you take part in religious services?*). Participants will provide ratings on a scale from 1-5.
3) **Intolerance of Uncertainty Scale – Short Version** (Carleton et al., 2007). Twelve-item scale assessing emotional, cognitive, and behavioural reactions to ambiguous situations on a 5-point Likert scale (1 = Not at all characteristic of me; 5 = Entirely characteristic of me). The scale is split into two components: prospective anxiety (e.g., *Unforeseen events upset me greatly)* and inhibitory anxiety (e.g., *The smallest doubt can stop me from acting*).
4) **Social and Economic Conservatism Scale** (Everett, 2013)**.** Twelve-item scale to measure political orientation along a left-right, liberal-conservative continuum. Participants will be asked to indicate the extent to which they feel positive or negative towards specific issues (0 = greater negativity, 50 = neutral, 100 = greater positivity) for instance, abortion, government, and welfare benefits.
5) **Right Wing Authoritarianism 3-Dimensional Scale** (Funke et al., 2005). Twelve-item revised version of the original scale (Altemeyer & Altemeyer, 1996) to measure 3 dimensions of authoritarianism, namely aggression (e.g., *What our country really needs instead of more "Civil rights" is a good stiff dose of law and order*), submission (e.g., *Obedience and respect for authority are the most important values children should learn*), and conventionalism (e.g., *Being virtuous and law-abiding is in the long run better for us than permanently challenging the foundation of our society*). Responses range from 1 (strongly disagree) to 7 (strongly agree).
6) **Social Dominance Orientation Scale-7 (Short Version)** (Ho et al., 2015)**.** Eight-item scale quantifying how much people value egalitarianism (e.g., *No one group should dominate in society*) vs group-based dominance (e.g., *Some groups of people must be kept in their place*)*.* Responses range from 1 (Strongly oppose) to 7 (Strongly favour).

We will also administer questionnaires not related to political orientation, including the Edinburgh Handedness Inventory-Short Form (Veale, 2014) to ensure only right-handed subjects are recruited, and a brief survey on whether participants have consumed psychoactive substances and medications (i.e., foods and drinks including nicotine, caffeine, alcohol, and other stimulants in any form) within 24 hours before the experiment.

Replicating labs who will recruit non-English speaking participants will use validated translated versions of the questionnaires where possible. If not available, we will apply the translation procedure recommended by the Psychological Science Accelerator (Moshontz et al., 2018) that involves forward and back translations followed by cultural adjustments.

## 2.3 Procedure

Our procedure will closely follow the process employed by Amodio et al. (2007). Participants will be given an information sheet and be asked to provide informed consent upon their arrival to the laboratory. They will be seated individually in a private testing room approximately one metre away from a computer monitor. Participants will then complete an online questionnaire in the laboratory consisting of the scales described in the previous section. Experimenters will be blind to the participants' political attitudes.

Next, replicating labs will record 8 minutes of resting-state EEG data and participants will be asked to fill in other brief questionnaires. These data will not be analysed for this study, and instead will be utilised for the separate Amodio et al. (2008) replication as well as for a #EEGManyLabs Resting State EEG spin-off project [https://osf.io/sp3ck/, (Pavlov et al., 2021)].

Participants will then complete the Go/No-Go task whilst undergoing simultaneous EEG recordings (both described below), which will take approximately 20 minutes to complete.

## 2.4 Task

We have programmed a Go/No-Go task (see Figure 1) using Psychopy (Peirce et al., 2019) based on the description of the task in Amodio et al. (2007). On each trial, participants will either be presented with the letter 'M' or 'W' in the centre of a computer monitor screen. Half of the participants will be instructed to make a 'Go' response (via pressing the Spacebar button) when they see 'M' and to withhold responding when they see 'W'; the remaining participants will complete a version in which "W" is the Go stimulus and "M" is the No–Go stimulus. Assignment to either version of the task is based on participant ID number, wherein even-numbered IDs will have "M" as the Go stimulus, while odd-numbered IDs will have "W" as the Go stimulus. Responses will be registered on a computer keyboard placed in front of participants on a table. Each trial will begin with a fixation point presented for 500ms followed by a stimulus for 100ms, and finally a blank screen. Participants will be instructed to respond within 500ms of stimulus onset. Feedback showing 'Too slow!' will appear after responses exceeding this timing, and 'Incorrect' will be shown after any erroneous responses to the No-Go stimulus. No feedback will be given following correct responses.

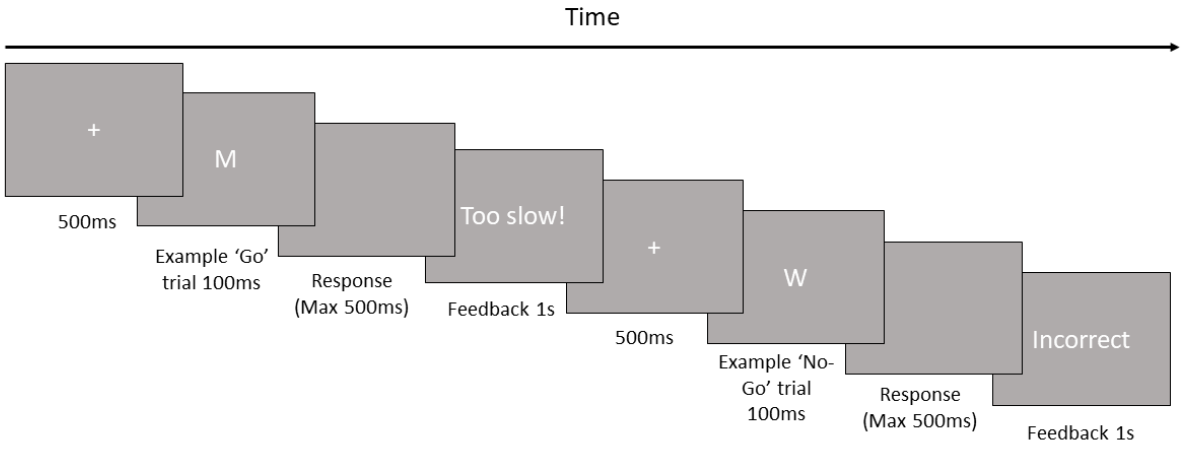


*Figure 1: Diagram of the Go/No-Go Task.*

There was no description of practice trials in Amodio et al. (2007). However, we will include practice trials to ensure participants understand the task's rules and are familiarised with the feedback (e.g., Johnstone et al., 2005; Kamarajan et al., 2005; Nieuwenhuis et al., 2003). Participants will first undergo a practice session of 20 trials, wherein Go and No-Go stimuli are each presented 50% of the time. The main task consists of 500 trials; 80% comprise the Go stimulus and 20% comprise the No–Go stimulus. Participants will receive a two-minute break halfway through the task.

## 2.5 EEG Recordings

Each replicating lab will use different systems for recording EEG. Details of the different systems are outlined in Table 1. Labs that have the equipment available will collect vertical and horizontal electrooculogram (EOG) data to enable removal of blinks and other eye movement artifacts.

Table 1: EEG setup descriptions for each replicating lab

| University | Location | Amplifier | EEG System | Sampling Rate (Hz) | Electrodes + External electrodes | Default reference + Ground | Conductive Gel | Online filter (Hz) | EOG Measure Present (Y/N) | Operating System |
|---|---|---|---|---|---|---|---|---|---|---|
| Sunway University | Malaysia | CGX | CGX Quick-32r (Dry system) | 500 | 32 | Left earlobe | None | 0.1 - 40 | N | Windows 10 |
| University of Bremen | Germany | REFA, TMSi | EASECAP | 512 | 64 + 3 | Left earlobe + cheek | Abralyt HiCl | NA | Y | Windows 7 |
| University of Alabama | USA | Brain Vision actiCHamp Plus | Brain Vision actiCAP Snap | 512 | 64 + 2 | Right earlobe + FPz | EasyCap SuperVisc High Viscosity Electrolyte-Gel | NA | Y | Windows 10 |
| Hamilton College | USA | Biosemi ActiveTwo | Biosemi ActiveTwo | 512 | 64 + 8 | CMS (Common Mode Sense) | SignaGel | NA | Y | Windows 7 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| ISCTE-Instituto Universitário de Lisboa | Portugal | actiCHAMP amplifier | actiCAP slim from Brain Vision | 500 | 32 + 5 | FCz +Fpz | SuperVisc High Viscosity Electrolyte-Gel | NA | Y | Windows 7 |
| University of Toronto | Canada | Advanced Neuro Technology (ANT) TMSi Refa8 | ANT TMSi Refa8 | 512 | 32 + 4 | Left earlobe + right earlobe | Electro-Gel | NA | Y | Windows 8 |
| MSB Medical School Berlin | Germany | Brain Products (brainAmp) System | Brain Products (brainAmp ) System | 1000 | 64 | FCz + FPz | EasyCap SuperVisc High Viscosity Electrolyte-Gel | NA | Y | Windows 10 |
| Universidade Federal do Rio Grande do Sul | Brazil | MITSAR 202 | MITSAR 202 | 500 | 32 | Right earlobe | Neurgel, Spes Medica | 0.1 - 70 | Y | Windows 10 |

## 2.6 EEG pre-processing based on original paper

Our pre-processing procedure will also closely correspond to that of Amodio et al.'s (2007). Offline, we will manually remove segments of data containing eye or muscle movement, and re-reference the data to the average earlobes or mastoids. A bandpass filter set between 1 Hz and 15 Hz will be applied.

For the ERN, an 800 ms response-locked epoch of EEG signal will be selected for each artifact-free trial (from -400 ms to 400 ms). Data will be baseline corrected to -400 to -50 ms prior to response onset. Epochs associated with correct and incorrect 'No-Go' trials will be averaged separately. Most replicating labs will define the ERN as the peak negative deflection occurring between -50 and 150 ms, relative to incorrect responses towards the 'No-Go' stimulus at electrode FCz. One of the labs (Sunway University, Malaysia) will record the ERN at electrode Cz due to their device not having the electrode FCz, with previous work showing that the ERN is captured by Cz as well as FCz (Hanna et al., 2012; Yasuda et al., 2004).

For the N2, a 1000ms epoch of EEG signal will be selected for each artifact free trial (from -200 to 800 ms). Data will be baseline corrected to -100 to 200 ms relative to stimulus onset. Like ERN processing, epochs associated with correct and incorrect 'No-Go' trials will be averaged separately. The N2 will be defined as the peak negative deflection at Cz occurring between 200 and 400ms relative to 'No-Go' stimulus onset on correct trials only.

## 2.7 Updated EEG pre-processing

To ascertain the robustness of results, we will also implement more modern data cleaning methods and compare the results to those obtained following the original study's pre-processing pipeline. This includes 1) applying a bandpass filter of 0.1 to 30Hz (e.g., Härpfer et al., 2020), 2) applying a notch filter of 50/60Hz (depending on lab) to remove any electrical noise, 3) conducting spherical interpolation of channel activity that is invariant or deviates significantly from the activity of other channels based on visual inspection of data and plotting channel spectra maps, 4) cleaning the data for ocular, muscular, or 'bad' channel artifacts using Independent Component Analysis ('runica' implemented in EEGLAB), and 5) rejecting bad epochs, namely those deviating more than 3.29 standard deviations (SD) (Tabachnick & Fidell, 2007) from trimmed normalised means with respect to joint probability, kurtosis or the spectrum. The same epoching and baseline correction measures will be applied here as in the original pipeline.

To guide our selection of independent components for rejection, we will use the SASICA (Semi-Automated Selection of Independent Components of the electroencephalogram for Artifact correction) plugin (Chaumon et al., 2015). The following options will be enabled in SASICA: 'Autocorrelation' to check for muscle components (components reflecting brain data are usually strongly autocorrelated), 'Focal components' (to determine bad channels), 'Focal trial activity' (to check for rare events, namely artefacts occurring with extremely large amplitude), 'Signal to noise ratio' (to reject components with a low signal to noise ratio), and ADJUST (for detection of eyeblinks, and vertical and horizontal eye movements). Final decision to reject components will be based on SASICA's recommendations, as well as visual

inspection of the components' topography and overall component data (using EEGLAB's data scrolling feature). In ambiguous cases, we will also employ the use of ICLabel (Pion-Tonachini, Kreutz-Delgado & Makeig, 2019) and reject components that have a less than 30% probability of being a brain component.

We will quantify the ERN and N2 components (from both original and updated pre-processing pipelines) as peak and mean amplitudes, since peak amplitude values are usually more sensitive to high-frequency noise (Luck, 2014). In addition, the ERN will be further quantified as ΔERN, which refers to the difference between the ERN waveform and a waveform associated with correct 'Go' responses, termed the Correct-related Negativity (CRN). An advantage of this method is that it is thought to better distinguish error-related neural responses from other broad performance monitoring processes reflected in the CRN (Simons, 2010).

The original study did not specify any criterion for participant exclusion, and hence all participant data will be included for the direct replication. However, in the updated pre-processing pipeline, we will remove trials containing response times under 150ms (Nieuwenhuis et al., 2003). Moreover, participants with less than 6 trials for the 'No-Go' incorrect condition and 20 trials for the 'No-Go' correct condition remaining (after removing bad epochs) will be removed from the analysis, as the ERN and N2 requires a minimum of 6 and 20 error trials respectively to be accurately quantified (Olvet & Hajcak, 2009; Rietdijk, Franken, & Thurik, 2014). See Table 2 for a summary of the differences between the original and updated pre-processing steps.

Table 2. *Comparison Between Original and Updated Preprocessing Pipelines*

| Process | Original Pipeline | Updated Pipeline |
|---|---|---|
| Notch Filter | None | 50/60 Hz |
| Bandpass Filter | 1 – 15 Hz | 0.1 – 30 Hz |
| Artifact Handling | Manual removal of continuous data segments | Channel interpolation, ICA, rejection of epochs deviating more than 3.29 SD |

| | | |
|---|---|---|
| Quantification of ERPs | Peak amplitudes for ERN and N2 | Peak and mean amplitudes for ERN, ΔERN, and N2 |
| Outlier handling | None | Trials with responses below 150ms will be removed. Participants will be excluded if they have less than 6 incorrect and 20 correct 'No-Go' trials remaining after removing bad epochs. |

# 3. Statistical Analyses

## 3.1 Direct Replication

First, we aim to reproduce the analysis reported in Amodio et al. (2007), namely by conducting correlation analyses between: (1) political orientation (measured using the 1-item liberalism vs conservatism scale) and ERN amplitudes (ERN in this section will refer to both ERN and ΔERN); (2) political orientation and N2 amplitudes; and (3) political orientation and accuracy on No-Go trials. Peak and mean amplitudes from the original and updated pipelines will be subjected to the correlation analyses and others described in this section.

We plan to conduct Pearson's correlations between measures. These tests will be conducted on data across all replicating labs and significance will be set at $p < .02$ [as outlined in Pavlov et al. (2021)].

To address heterogeneity in EEG devices and samples between labs we will, first, compute effect sizes (correlation coefficients, r) for each individual site and then combine all datasets in a random-effects meta-analysis (with site as a random effect). The correlation coefficients will be Fisher's z transformed before being entered into the meta-analysis. The R function 'metacor' from the 'meta' package (Schwarzer, 2007) will be used for the meta-analysis and a restricted maximum likelihood estimator method will be chosen for estimating $\tau^2$ (a measure of variance in true effects). Forest and funnel plots will be computed. Individual and pooled effect sizes, 95% confidence intervals, number of labs successfully replicating the original effect will be reported. The pooled association will be interpreted following Cohen's convention (small: r = 0.10, medium: r = 0.30, large: r = 0.50; Cohen, 1998) and the significance level will be set at $p < .02$. Between lab heterogeneity will be classified using Higgins & Thompson's $I^2$ statistic and interpreted following Higgins & Thompson (2002) whereby $I^2 = 25\%$, $I^2 = 50\%$, and $I^2 = 75\%$ represent low, moderate, and high heterogeneity respectively.

## 3.2 Further analysis

In addition, we aim to elucidate whether other measures (beyond the one-item scale) of political partisanship and ideology are uniquely related to ERN, N2, and No-Go errors. We will first check for associations between political and ERP/task behavioural measures using Pearson's correlations. Alongside regular p-values, we will report p-values corrected for False Discovery Rates (FDR) following Benjamini & Hochberg's (1995) procedure.

Given the diversity in scales used, we will also conduct a principal component's analysis (PCA) on all questionnaire and sub-scale data to obtain composite measures. Based on prior research, we may expect that scores linked to conservatism, religiosity, dogmatism, and intolerance of uncertainty will emerge as distinct components (van Baar et al., 2021; Zmigrod et al., 2021). The 'prcomp' function in R will be used to run the PCA. Principal components will be extracted based on visual inspection of resulting scree plot and following Kaiser's criterion, whereby we will accept components with eigenvalues of more than 1. Promax rotation will be applied to improve interpretability of the different components by associating each variable to at most one factor/component. Composite scores from each principal component will be extracted.

Next, multivariate Bayesian linear regressions will be used to assess the effects of the principal components on ERN amplitudes, N2 amplitudes, and No-Go errors. These measures will be converted to z-scores before being added as dependent variables into the regression models to enable extraction of standardised coefficients. Possible confounding effects of different laboratory devices will be controlled for by adding 'laboratory' as a fixed effect in the models.

All models will be fitted to data using the brms package (Bürkner, 2018) in R, which uses the programming language *Stan* to implement a Markov chain Monte Carlo (MCMC) algorithm to estimate posterior distributions of parameters of interest. A weakly informative prior (a normal distribution with $\mu = 0$ and $\sigma = 10$) will be used to estimate coefficient distributions while the software default for prior distributions of other model parameters (e.g., standard deviations) will be used, namely a half Student-t prior with 3 degrees of freedom (Bürkner, 2018). Four MCMC chains with random initial values and 4000 iterations (2000 warm-up) will be used for sampling. Convergence of chains will be determined using the potential scale reduction statistic $\hat{R}$. An $\hat{R}$ of 1 denotes perfect convergence and values below 1.2 are typically used as a guideline for convergence (Brooks and Gelman 1998), hence this cut-off will also be applied here. We will assess the goodness-of-fit of the models using the Bayesian $R^2$ (Gelman et al., 2019).

'Significant' relationships between components and dependent variables will be quantified by computing the 95% Bayesian credible interval (CI) for each coefficient. The 95% CI denotes that 95% of possible values of a parameter will fall within the interval. We will inspect the CIs to check if they include 0, denoting no credible effect over the dependent variable. In addition, Bayes factors (BF) will be calculated to quantitatively determine the extent to which the alternative model ($H_1$) has more support over the null model ($H_0$), specifically using the Dickey Savage Density Ratio

(Wagenmakers et al., 2010). We will use the following thresholds to interpret resulting BFs (Andraszewicz et al., 2015); $BF_{10}$ = 1: no evidence for $H_1$, 1 < $BF_{10}$ < 3: anecdotal/weak evidence for $H_1$, 3 < $BF_{10}$ < 10: moderate evidence for $H_1$, 10 < $BF_{10}$ < 30: strong evidence for $H_1$, 30 < $BF_{10}$ < 100: very strong evidence for $H_1$, $BF_{10}$ > 100: extreme evidence for $H_1$.

Lastly, we will compare the standardised coefficients associated with each principal component to determine whether there is a specific facet of political identity that best corresponds to differences in ERN, N2, and No-Go errors.

Analyses described above will be run twice, once with the data cleaned using the Amodio et al. (2007) procedure and once with the data cleaned using modern pre-processing methods as well as removal of any trial data that meet our exclusion criteria. We will check whether similar results are obtained using both data handling procedures to determine the robustness of results.

### 3.3 Software and Code Availability

EEG and ERP data will be processed in MatlabR2021b using EEGLAB2021.1 (Delorme & Makeig, 2004) and the following plugins: ERPLAB9.00 (Lopez-Calderon & Luck, 2014) and SASICA (Chaumon et al., 2015). Further data analysis and visualisation will be conducted in RStudio version 4.0.4 (R Core Team, 2021). All data and code will be made available on the Open Science Framework (https://osf.io/dc437/, Read only link for peer review: https://osf.io/dc437/?view_only=00330400727b4c3db200efdb70fc9ff2).

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