

# Cognitive Control Promotes Either Honesty or Dishonesty, Depending on One's Moral Default

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Cognitive control is crucially involved in making (dis)honest decisions. However, the precise nature of this role has been hotly debated. Is honesty an intuitive response, or is will power needed to override an intuitive inclination to cheat? A reconciliation of these conflicting views proposes that cognitive control enables dishonest participants to be honest, whereas it allows those who are generally honest to cheat. Thus, cognitive control does not promote (dis)honesty per se; it depends on one's moral default. In the present study, we tested this proposal using electroencephalograms in humans (males and females) in combination with an independent localizer (Stroop task) to mitigate the problem of reverse inference. Our analysis revealed that the neural signature evoked by cognitive control demands in the Stroop task can be used to estimate (dis)honest choices in an independent cheating task, providing converging evidence that cognitive control can indeed help honest participants to cheat, whereas it facilitates honesty for cheaters.

**Key words:** cognitive control; decision-making; dishonesty; EEG; morality; replication

## Significance Statement

Dishonesty causes enormous economic losses. To target dishonesty with interventions, a rigorous understanding of the underlying cognitive mechanisms is required. A recent study found that cognitive control enables honest participants to cheat, whereas it helps cheaters to be honest. However, it is evident that a single study does not suffice as support for a novel hypothesis. Therefore, we tested the replicability of this finding using a different modality (EEG instead of fMRI) together with an independent localizer task to avoid reverse inference. We find that the same neural signature evoked by cognitive control demands in the localizer task can be used to estimate (dis)honesty in an independent cheating task, establishing converging evidence that the effect of cognitive control indeed depends on a person's moral default.

## Introduction

Dishonesty imposes a lasting social toll by undermining personal relationships as well as sabotaging trust in social institutions. Although dishonesty may be ubiquitous, it is clear that not everybody is a cheater; there are considerable individual differences in our moral flexibility. When given the opportunity, individuals differ considerably in how much they cheat (Gino et al., 2012, 2014; Speer et al., 2020; Gerlach et al., 2019).

When tempted to cheat, clearly the prospective gains are an important determinant of whether someone will succumb (Becker, 1968; Allingham and Sandmo, 1972; Abe and Greene, 2014; Seuntjens et al., 2019; Speer et al., 2020). However, behaviors such as altruism, reciprocity, and honesty suggest that most

individuals do not only consider the (financial) rewards when tempted to cheat. Converging evidence indicates that our self-concept, our perception of ourselves as moral beings (Aronson, 1969; Bem, 1972; Baumeister, 1998), motivates us to be honest (Mazar et al., 2008; Speer et al., 2020).

An fMRI study by Speer et al. (2020) investigated how the brain accomplishes the task of arbitrating between obtaining rewards and upholding a moral self-concept. The study showed that brain regions associated with cognitive control helped dishonest participants to be honest, whereas they enabled cheating for more honest participants, suggesting that cognitive control is not required to be honest or dishonest per se but that it is contingent on an individual's moral default.

However compelling these and other neuroimaging studies on dishonesty thus far are, two issues stand out. The first is that they have relied on reverse inference to infer the neurocognitive processes underlying (dis)honest decisions, where the cognitive operations are inferred from activation in an observed region of the brain. Although informative, reverse inference should be interpreted with caution depending on how selectively these areas of interest are activated by a specific cognitive process (Poldrack, 2006).

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A second issue is that a single finding cannot be taken as sufficient support for any novel theory or hypothesis. The importance of conducting replications has been highlighted as several authors have questioned the validity of numerous findings in neuroscience and psychology (Ioannidis, 2005; Button et al., 2013; Botvinik-Nezer et al., 2020). The most promising way of addressing these issues is to attempt to replicate findings as the probability of a finding being true increases with the number of replications.

Here, we attempt to replicate previous findings (Speer et al., 2020) with a different neuroimaging method in combination with a localizer task to circumvent reverse inference problems. Using a different modality has the potential to substantially increase the convergent validity of the previous finding as it allows us to capture different aspects of the underlying neural processes because of the higher temporal resolution of electroencephalogram (EEG).

We elicited the neural patterns associated with cognitive control by means of recording the EEG of participants while they performed the Stroop task, which is a well-established task requiring cognitive control. Subsequently, participants engaged in the Spot-The-Difference task (Gai and Puntoni, 2021; Speer et al., 2020), which allows participants to cheat repeatedly, deliberately, and voluntarily while their EEG was recorded. If we observe the same neural patterns in both tasks, we can deduce with empirical support that the neural patterns we observe in our cheating task do indeed reflect cognitive control processes relating to the inhibition of a default response. Our study thus contributes by more rigorously testing the neural mechanisms underlying dishonest decisions and reducing issues of reverse inference.

## Materials and Methods

### Participants

EEG recordings were obtained from 35 participants. One participant completed the Spot-The-Difference task, but not the Stroop task, so for the Stroop task there were 34 participants. The data of two participants had to be discarded because for these participants 27 or more channels (of 64) were identified as bad channels by the Autoreject algorithm (see below, EEG acquisition and preprocessing; Jas et al., 2017), which classified them as outliers (interquartile range rule, 2 SD rule). The reported analyses are based on the remaining 33 (32 for the Stroop task) participants (18 female; age, 18–29 years;  $M = 21$ ,  $SD = 2.6$ ), recruited from an online community for university students, where students can sign up for experiments. An initial screening interview ensured that all participants were right-handed with normal or corrected-to-normal vision, spoke English fluently, were not on any psychoactive medication influencing cognitive function, and had no record of neurologic or psychiatric illness. The study was approved by the university's Internal Review Board and was conducted in accordance with the Declaration of Helsinki.

### Determination of the appropriate sample size

To determine the appropriate sample size, we focused on previous studies using the Stroop task because no EEG studies have been conducted with the Spot-The-Difference task so far. We consulted three previous studies, Hanslmayr et al. (2008), Tang et al. (2013), and Kovacevic et al. (2012). The sample sizes in these ranged from 16 to 22 participants, all reporting significant effects of incongruency on power in the theta range over midfrontal channels. The effect sizes calculated based on the statistics reported in those studies range from  $d = 1.28$  to 1.62, which corresponds to a recommended sample size (at  $\alpha = 0.05$ , two sided) of 8–11 participants to obtain a power of 95% to detect a significant effect between congruent and incongruent trials in the Stroop task. Previous neuroimaging studies using voluntary (dis)honest choice paradigms such as the coin-flip task or the sender receiver game (Ding et al., 2013,

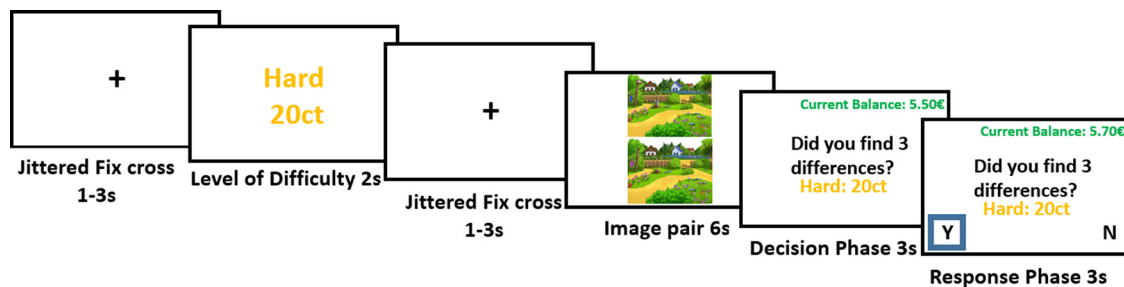
$N = 18$ ; Abe and Greene, 2014,  $N = 28$ ; Hu et al., 2015,  $N = 26$ ; Shuster and Levy, 2020,  $N = 33$ ; Speer et al., 2020,  $N = 40$ ) ranged in sample size from 18 to 40 participants. So we reasoned that for this study, 35 participants should be sufficient to detect the electrophysiological correlates of (dis)honesty.

### Task and stimuli

**Spot-The-Difference task.** In the Spot-The-Difference task, participants were presented with pairs of images and told that there were always three differences between the image pairs. Differences consisted of objects that were added to or removed from an image or objects that differed in color between images. However, images could actually contain one, two, or three differences. Participants were instructed to find three differences between the images. Because reward (see below) was contingent on participants reporting that they had found all three differences without having to point them out, this design allowed and encouraged cheating behavior (i.e., reporting having found all three, even when objectively fewer than three differences were present in the images). In 25% of the trials there were only two differences, and in 25% there was only one difference. All stimuli were standardized in size and were presented on a white background on a computer screen. The ratio of 50 to 50% (three differences versus less than three differences) was chosen based on the results of pilot studies that indicated this ratio to be optimal in reducing suspicion that the pairs did not always contain three differences.

Trials were further categorized into normal (50%), hard (25%), and very hard trials (25%), for which participants could receive 5, 20, and 40 cents, respectively. All the trials with three differences (the filler trials) were categorized as normal trials, whereas trials with fewer than three differences (the trials of interest) were randomly categorized as hard or very hard trials. Consequently, the reward was independent of the number of differences in the image pair for the trials of interest, which is important to be able to disentangle the effects of reward and cheating magnitude (the actual number of differences) on cheating behavior. The different levels of difficulty were added to reduce suspicion about the real purpose of the task. It was assumed that if trials are labeled hard or very hard, it would be more credible to the participant if the image pair actually contained three differences, but they were just too hard to spot. In addition, levels of difficulty were introduced to eliminate possible demand effects. We wanted participants to cheat for monetary reward and not prevent them from seeming incompetent, which may be associated with different underlying neural mechanisms and consequently confound the analysis. The maximum amount of money earned in case a participant cheated on all cheatable trials was ~35 Euros, whereas in case a participant would not cheat at all he or she would earn ~7.50 Euros. After completion of the full study, participants were debriefed, and to be fair to all participants, they were all paid the maximum amount regardless of their actual cheating behavior.

Participants were informed that the purpose of the study was to investigate the underlying neural mechanisms of a visual search for marketing purposes such as searching for a product in an assortment or information on a Web page. To increase credibility of this marketing story a simple visual search task was added at the beginning of the experiment (Speer et al., 2020). Further, participants were instructed that the neurocognitive effect of motivation, elicited by monetary reward, on speed and accuracy of the visual search would be investigated. To further reduce suspicion about the purpose of the study, we added 12 point-and-click trials in which participants used a mouse to click on the location in the images where they spotted the differences. Consequently, cheating was not possible on the point-and-click trials. Participants always knew before the start of a trial whether it was a point-and-click trial, indicated by a screen requesting participants to click on the image. This ensured that participants would not refrain from cheating on all other trials while still reducing the suspicion about the real purpose of the study. Participants were told that only 10% of trials were point-and-click trials because it would take too much time to point out the differences for every pair. In sum, there were 144 regular trials (72 of which were cheatable trials) and 12 point-and-click trials.



**Figure 1.** One trial of the Spot-The-Differences paradigm. Participants viewed a screen indicating the difficulty and value of the trial, then the image pair appeared for 6 s, and participants were asked to indicate whether they spotted all three differences.

Each trial started with a fixation cross that was presented for a variable amount of time between 1 and 3 s (Fig. 1). Subsequently, the Level of Difficulty screen was presented for 2 s informing the participants about the level of difficulty of the upcoming trial. This screen also displayed how much money could be earned on that trial. As a result, participants were constantly aware of the potential gains of cheating. Next, an image pair was presented for 6 s, a length determined by behavioral pilots (Speer et al., 2020), and participants engaged in the visual search. Afterward, the participants were asked whether they spotted all three differences (yes or no response). On this decision phase screen, again the potential reward for this trial was presented to make the reward more salient and increase cheating behavior. After 3 s the response phase started in which participants' responses were recorded. In the decision phase and the response phase, the current balance was also shown, which was done to demonstrate to the participants that if they stated they had found the three differences, their current balance increased immediately. It was assumed that this direct noticeable effect of behavior on the increase of the current balance would further motivate participants to cheat.

The buttons corresponding to yes and no were switched across trials to reduce a possible response bias associated with the side where the response options were presented. Once the participants responded, the choice was highlighted by a blue box for 500 ms to indicate that the response was recorded, and the trial ended. If no response was made, the trial ended after 3 s. In addition, there were five practice trials in which participants became acquainted with the task. Stimulus presentation and data acquisition were performed using Presentation software (version 18.0, Neurobehavioral Systems, <https://www.neurobs.com>).

**Stimuli for the Spot-The-Difference task.** Stimuli for the task consisted of 144 Spot-The-Difference image pairs that were downloaded from the Internet. Cartoon images of landscapes containing several objects were selected to make them engaging and challenging enough for the participants. Landscapes were chosen as they generally satisfied the necessary criterion of containing several different objects. The stimuli consist of pairs of images that are identical, apart from a certain number (1–3) of differences that were created using Adobe Photoshop. Differences included objects added to or removed from the landscape picture or changed colors of objects. Differences were fully randomized across all pairs of images, which means that all image pairs could be presented with either one, two, or three differences. To make sure that participants would be able to find the differences between the images in a reasonable amount of time, we ran a pilot study on Amazon Mechanical Turk ( $N = 205$ ) to test the difficulty in spotting the differences between the images and to determine the optimal duration of the picture presentation (Speer et al., 2020).

**Stroop task.** The Stroop task was used to localize the neural signature of cognitive control. The use of a localizer task is a common approach in fMRI research and is becoming increasingly used in EEG research as well to reduce issues of reverse inference (Niccolai et al., 2014; van Driel et al., 2014; Brooks et al., 2017; Dutra et al., 2018; Eijlers, et al., 2020; Lee and Kang, 2020; Soh and Wessel, 2021). In the Stroop task participants view names of colors written in different colors of ink and are instructed to indicate the color of the ink as fast as possible. In incongruent trials, color names and the color of the ink do not match, whereas in congruent

trials the name of the color and the color of the ink match. On the incongruent trials, participants must inhibit the predominant response of reading the word and instead focus on the ink color. Thus, the overlearned response of reading interferes with successful task performance.

The Stroop task was selected over the Stop-Signal or GoNoGo tasks because we assumed that overriding the default response of reading the words is more similar to overriding default (im)moral behavior than, for example, motor inhibition elicited by the Stop-Signal or GoNoGo task because of top of inhibiting a motor response, the more cognitive process of automatically reading needs to be suppressed. Intuitively, this process seems more similar to the type of control needed to inhibit default (dis)honest behavior.

To allow conducting the Stroop task without participants speaking, which would cause artifacts in the EEG signal, we adapted a version developed by Zysset et al. (2007). Participants were told that they would see two words vertically arranged (Fig. 2) and would have to decide, by pressing a button (yes or no), whether the color of the word at the top corresponds to the name of the color written at the bottom. There were 72 trials in total. Half of the trials were corresponding, meaning that the color of the top word matched the meaning of the bottom word. There were 36 congruent and 36 incongruent trials. In congruent trials the color of the top word matched the meaning of that word. For incongruent trials this was not the case.

Each trial started with a fixation cross with a duration that jittered between 1 and 2 s. Subsequently, to prevent subjects from focusing on the bottom word and blurring the top word, the top word was presented 150 ms before the word on the bottom. As a result, visual attention shifted automatically to the top word, and participants were forced to read the top word, enabling interference. Next, the bottom word and a white fixation cross were presented. The white fixation cross turned orange as soon as a response was made to signal to the participant that the response had been recorded. After the words were on the screen for 3 s the feedback was presented (Fig. 2).

**Experimental procedure.** Before the experiment started, participants were told the marketing story and were introduced to the tasks, and they signed the informed consent form. During the EEG data collection, participants were seated in a slightly reclining chair positioned in front of a 19 inch PC monitor in a sound-attenuated, electrically shielded, dimly lit room. Participants first completed practice trials for both visual search tasks. Afterward, the participants completed the simple visual search task (5 min) followed by the Spot-The-Difference task, which took ~40 min. Subsequently, participants completed practice trials for the Stroop task and the actual Stroop task, which lasted ~7 min. After completing all tasks, participants left the EEG room and completed a short questionnaire that included questions about their thoughts on the purpose of the task on a computer in a separate testing room.

#### EEG acquisition and preprocessing

We recorded EEGs from 64 active scalp electrodes using a Biosemi Active Two system. Additional flat-type electrodes were placed on the right and left mastoid and in the eye region to record eye movements or electro-oculograms (EOGs). Electrodes were placed below and above the left eye in line with the pupil to record vertical EOGs and at the outer canthi of both eyes to record horizontal EOGs. The EEG and EOG

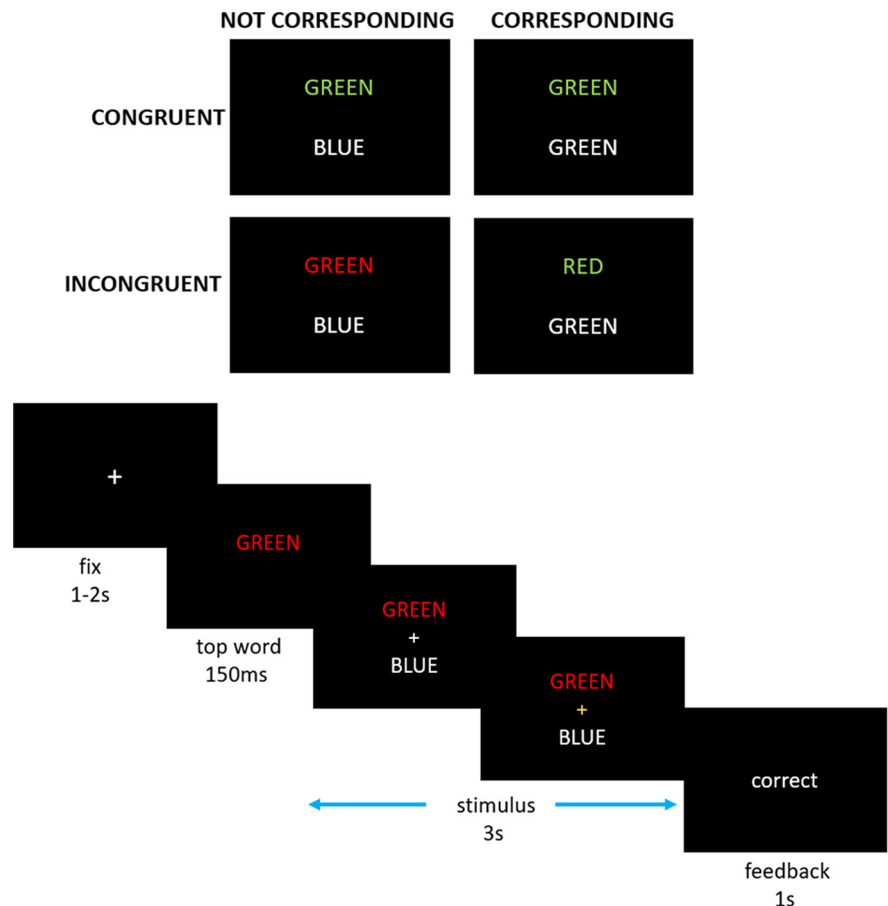


signals were sampled at a rate of 512 Hz. All preprocessing was done using MNE-Python software (Gramfort et al., 2013). EEG data were filtered with a low cutoff filter of 1 Hz to remove slow drifts and a notch filter of 50 Hz to remove line noise.

Subsequently, bad and noisy channels were detected using several different approaches as implemented in the PREP pipeline (Bigdely-Shamlo et al., 2015). First, by means of correlation, we checked how well a given channel is correlated with all other channels (categorized as bad at  $r < 0.4$ ); second, we checked by using the robust  $z$ -score deviation aggregates per channel (categorized as bad at  $z > 5$ ); third, by using the robust  $z$ -score estimates of high-frequency noise per channel (categorized as bad at  $z > 5$ ); and finally, we checked by using the random sample consensus (RANSAC) channel correlations, which is the correlation for each channel with itself across the original data versus the RANSAC predicted data (categorized as bad at  $r < 0.75$ ) as implemented in the PREP pipeline (Bigdely-Shamlo et al., 2015). After detection, these channels were removed from the data and subsequently interpolated (i.e., estimated from surrounding channels). Interpolation was performed using the spherical spline method (Perrin et al., 1989) as implemented in MNE-Python, which projects the sensor locations onto a unit sphere and interpolates the signal at the channels identified as bad on the signals for the good channels. The EEG data were then rereferenced to the average signal across channels. As a next step, ocular artifacts were removed by performing an independent component analysis on the data and then correlating the resulting components with the EOG channels to see which of the components represented the ocular artifacts. The component that correlated the highest with the EOG channels was then removed from the EEG data.

#### Epoching and artifact rejection for the Spot-The-Difference task

The EEG data from the Spot-The-Difference-Task was then segmented into 3 s epochs, time locked to the onset of the decision phase. The epochs were baseline corrected using the last second of the fixation period preceding the presentation of the image pair, which occurred 7–6 s before the decisions phase. The resulting epochs were then subjected to Autoreject, an automated artifact detection algorithm based on machine-learning classifiers, and cross-validation to estimate the optimal peak-to-peak threshold (Jas et al., 2017). On average, 3% of trials (~4 trials of 144 trials, SD = 5%) were rejected. This algorithm was implemented to remove artifacts not identified by previous preprocessing steps, and depending on the number of bad sensors for a given trial, either repairs the trial based on interpolation or excludes it from further analysis. The preprocessed data were then submitted to a morlet wavelet analysis to transform the data into the time-frequency domain with 18 log-scaled frequency bins ranging from 4 to 40 Hz to have higher sensitivity in lower frequency ranges such as the theta band. To optimize both spectral and temporal resolution, the number of cycles to include in the sliding time window were defined by dividing each individual frequency by two. After transforming the data to the time-frequency domain, the data were decimated by a factor of four (sampling every fourth time point) to increase computational efficiency.



**Figure 2.** An example trial of the Stroop task. Participants were asked whether the color of the top word corresponds with the meaning of the bottom word. Top, The four conditions of the Stroop task. Bottom, The sequence of a trial in the Stroop task.

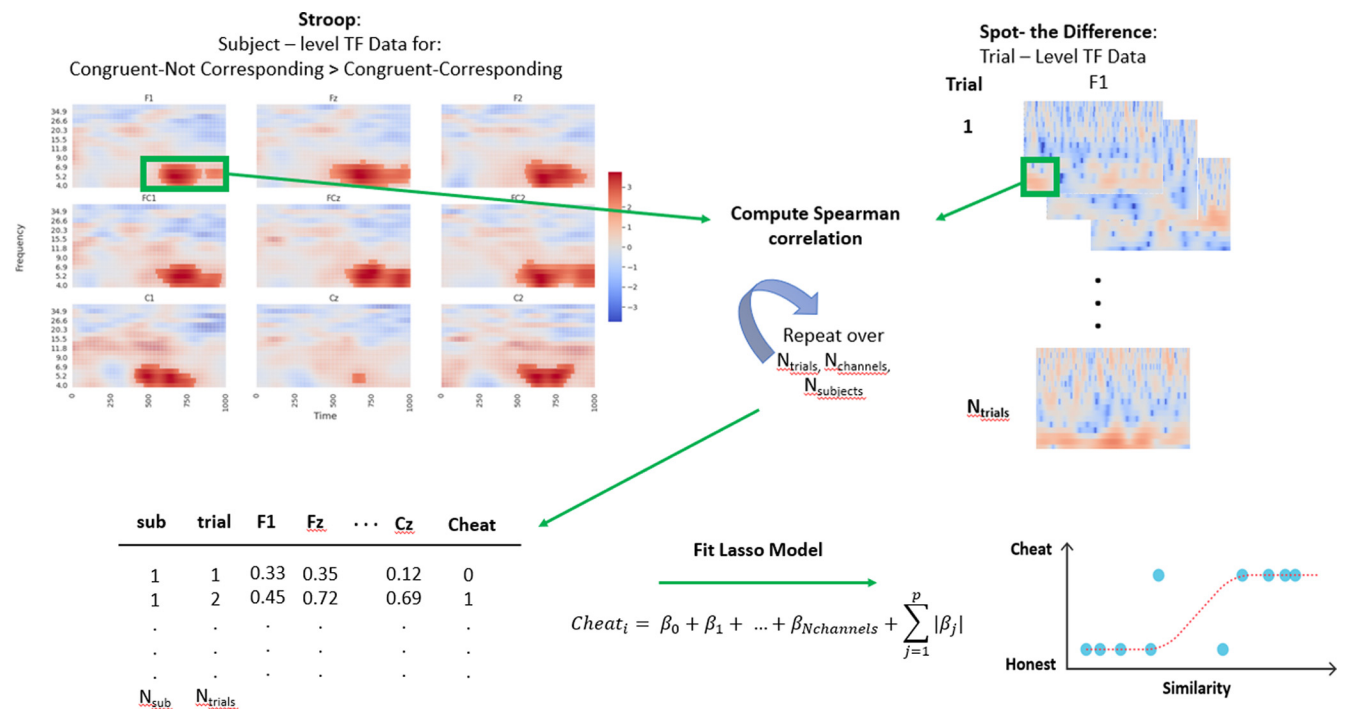
#### Epoching and artifact rejection for the Stroop

Following the same preprocessing steps as described above, the EEG data from the Stroop task were segmented into 2 s epochs, time locked to the presentation of the second word on the screen. The epochs were baseline corrected in the second preceding the onset of the second word. The same artifact rejection as described above was applied to the Stroop task, and in this task on average 2% (SD = 4%) of trials for each subject was rejected. The same morlet wavelet analysis was used to transform the data to the time-frequency domain.

#### Statistical analysis

**Contrasting conditions in the Stroop task.** To localize the neural correlates of cognitive control related to inhibiting the default response in the Stroop task, we conducted a multilevel analysis contrasting the EEG data from the conditions of the Stroop task with the highest behavioral difference (congruent/corresponding vs congruent/noncorresponding; see above, Task and stimuli). Previous research has found that the EEG correlates of cognitive control are typically observed in the theta (4–8 Hz) frequency range on midfrontal channels (Fz, FCz; Wang et al., 2005; Cohen et al., 2008; Womelsdorf et al., 2010; Cohen and Cavanagh, 2011; Cavanagh et al., 2012; Nigbur et al., 2012). However, the exact reported frequencies and channels vary a bit among studies, so we conducted a relatively broad search on all midfrontal channels (F1, Fz, F2, FC1, FCz, FC2, C1, Cz, C2), and across the entire frequency spectrum to localize the EEG correlate of cognitive control in our task.

At the first level (i.e., the participant level), we computed the averaged time-frequency maps for each of the two conditions. We then tested the resulting averaged maps at the second level for significant group effects, using a paired sample  $t$  test. We used cluster-based



**Figure 3.** For the similarity-based analysis, we computed the similarity between the last 500 ms of each participant’s time-frequency data for the difference between congruent/noncorresponding trials and congruent/corresponding trials and the first 500 ms of the time-frequency map for each trial, each channel, and each participant in the Spot-The-Difference task.

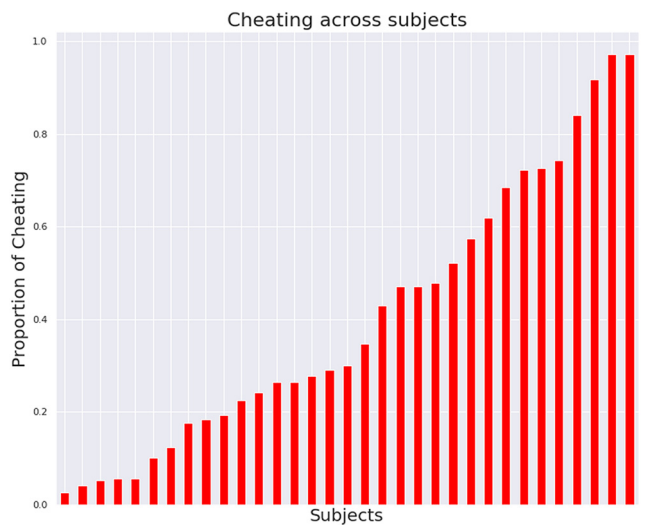
permutation testing as a stringent control for multiple comparisons (Maris and Oostenveld 2007). Specifically, for every sample across the nine channels, we quantified the experimental effect by a *t* value. We selected samples for which the *t* value was larger than a given threshold ( $p < 0.05$ ) for potential inclusion in a cluster. It should be noted that the threshold used does not affect the false alarm rate of the final statistical test; it only sets a threshold for considering a sample as a candidate member of a cluster. We subsequently clustered selected samples in connected sets based on temporal and spectral adjacency, and we computed cluster-level statistics by taking the sum of the *t* values within every cluster. Subsequently, we performed permutation testing using the Monte Carlo method to compute the posterior significance probability of our observed effect (Maris and Oostenveld, 2007). This analysis results in a cluster of adjacent data points across time, frequencies, and channels, which significantly differs in activity between conditions that demand high versus low levels of cognitive control.

*Contrasting cheatable versus noncheatable trials*

To test whether the same neural signature of cognitive control found in the Stroop task could be observed when participants are exposed to the opportunity to cheat, we first created a mask consisting of the channels and frequencies as identified by the analysis of the Stroop task. We then performed a cluster-based permutation test on these channels and frequencies, which reduces the multiple-comparisons problem and thus increases the sensitivity of the analysis (Maris, 2012). Specifically, we computed the averaged time-frequency maps of cheatable trials and noncheatable trials for each subject. We then selected the channels and frequencies that were significant in the Stroop task (i.e., the spectral points within the channels found to be significant in the analysis of the Stroop effect). For group-level analysis we then conducted the cluster-based permutation testing procedure described above on the masked contrast maps to test whether there is a significant cluster within the cognitive control mask that distinguishes between cheatable and noncheatable trials.

*Trial-by-trial analysis*

To test whether power in the channels and frequencies that were found to be significantly different between cheatable and noncheatable trials in the previous analysis could be used to estimate the actual decision to cheat



**Figure 4.** Individual differences in the proportion of cheating on the Spot-The-Difference task ( $N = 33$ ).

or to be honest, we conducted a trial-by-trial analysis. Based on the findings from the analysis above, we focused particularly on the time window that most strongly differentiated cheatable and noncheatable trials. We used this time window to test whether we can estimate (dis)honesty on each trial. We extracted trial-by-trial power from the channels, time window, and frequencies of interest by extracting the first factor from an exploratory factor analysis. A factor analysis (without rotation) was used to extract the most amount of variance from the time window of interest. The advantage of using a factor analysis over using the mean is that different items (time points) can be given different weights to maximize the correlation between time points in this time period (DiStefano et al., 2009). This resulted in one data frame where the rows represent trials, and the columns represent the channels of interest.

Given the nested structure of the data (trials among participants), we then conducted a multi-level analysis to estimate trial-by-trial cheating. The dependent variable was the binary response with a logit link (cheating = 1, honest = 0). The power in the frequency range of interest within the time window of interest for each of the channels of interest served as trial-level regressors. In addition, the average cheatcount (number of times a participant cheated) was added as a subject-level regressor. To reduce multicollinearity between the regressors and to explore which of the channels is most important in estimating cheating on the trial level, we performed variable selection for generalized linear mixed models by means of L1-penalized estimation. This was implemented using the *glmmlasso* package in R, which applies a gradient ascent that enables us to maximize the penalized log likelihood, yielding models with reduced complexity (Groll and Tutz, 2014). The lasso regression adds a penalty term to the equation, which shrinks less important coefficients in the model to zero and thus reduces complexity of the model and multicollinearity of regressors (Tibshirani, 1996). In this way it also selects the most important regressors in the model.

#### Similarity analysis

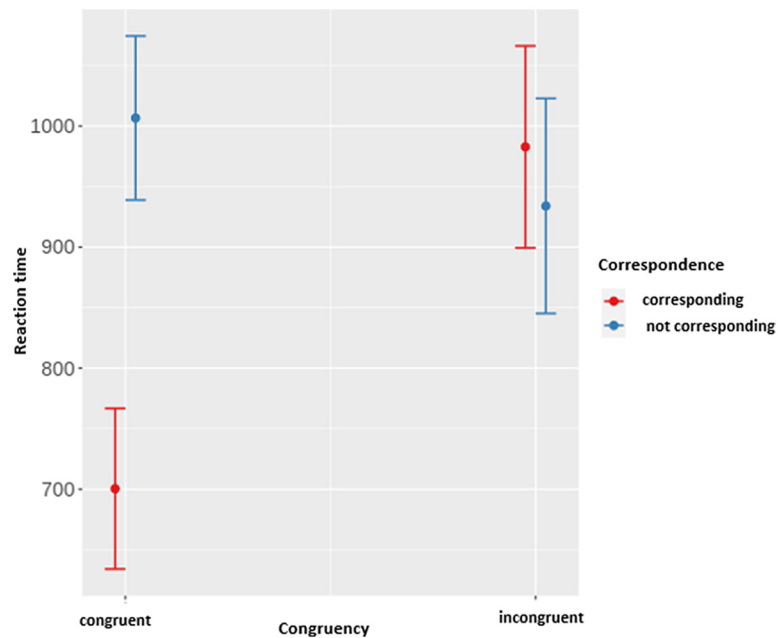
To further establish a link between the patterns of activation in the Stroop task and patterns of activation related to trial-level cheating, we conducted a similarity analysis (Fig. 3). For each participant we subtracted the average time-frequency data for congruent/corresponding trials from the average time-frequency data for incongruent/noncorresponding trials for all channels of interest, resulting in a time-frequency spectrum representing the neural signature of cognitive control as derived from the Stroop task (Fig. 3). We then computed the Spearman correlation between this neural signature of cognitive control and the time-frequency map for each subject on each of the trials and for each channel in the Spot-The-Difference task. After computing the Spearman correlations, a Fisher *z*-transformation was applied to obtain normally distributed predictors. This resulted in a data frame with a Spearman correlation on each row for each subject, trial, and channel. We then entered these data into a multilevel lasso regression model with the binary response (cheating = 1, honest = 0) as a dependent variable.

## Results

### Large individual differences in cheating

Substantial individual differences in the total amount of cheating were observed (mean = 41%, median = 30%, SD = 29%; Fig. 4). Some participants cheated no more than three times in 72 trials (6% of participants), whereas others only missed one or two opportunities to cheat (also 6%).

We investigated how different task characteristics of the Spot-The-Difference task influenced cheating behavior. Because of the nested structure of our data (trials with different numbers of differences and rewards among participants), we applied a multilevel logistic regression analysis on our behavioral data. This analysis considered cheatable trials only. The dependent variable was the binary response (cheating vs honest) with a logit link (cheating = 1, honest = 0). The number of differences, trial number, and level of reward served as trial-level regressors. The model allowed for random intercept among participants. Replicating findings from a previous study (Speer et al., 2020), this analysis revealed a significant effect of the number of differences on cheating behavior ( $b = 1.02$ , SE = 0.08,  $z = 12.86$ ,  $p <$



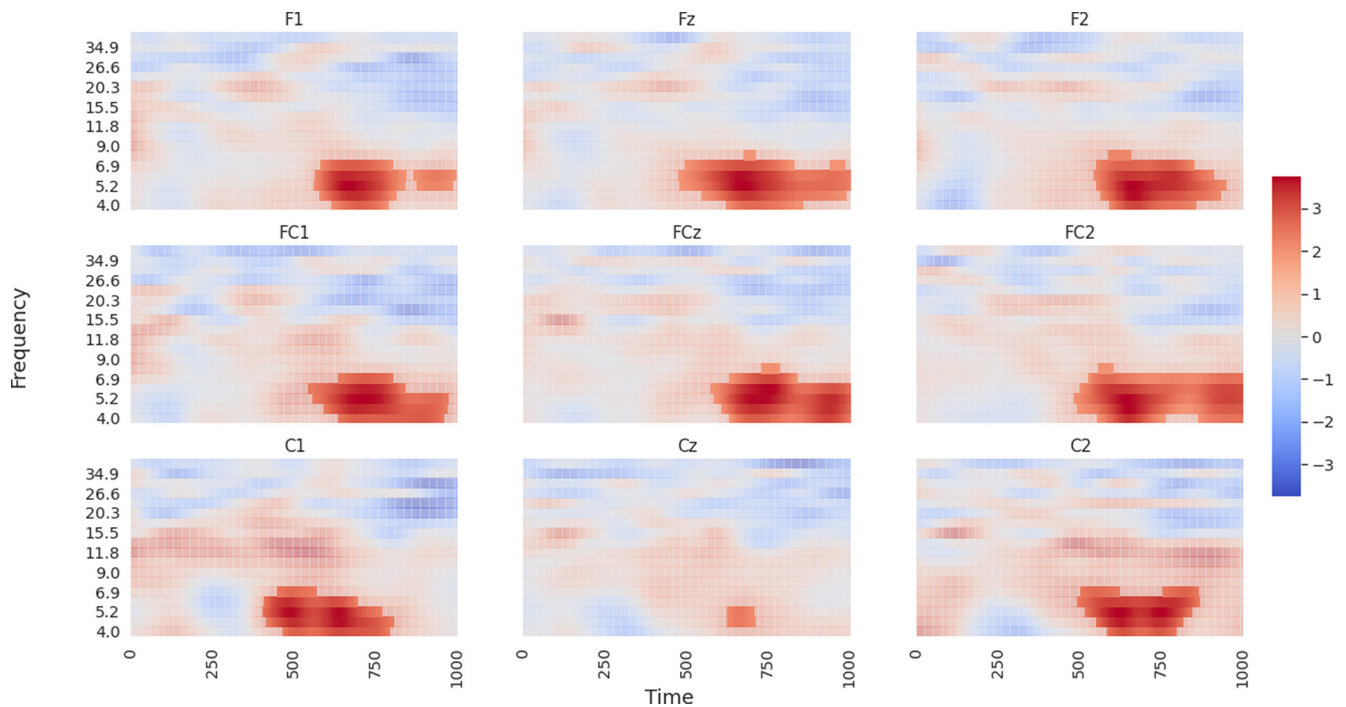
**Figure 5.** The effect of Congruency and Correspondence on Reaction time in the Stroop task.

0.001). This indicates that participants cheated more frequently when the crime was smaller (i.e., they claimed to have found three differences more often when there were two differences compared with only one). As in the previous study (Speer et al., 2020), no significant effect of reward magnitude (see above, Materials and Methods) on cheating behavior was found. Further, no significant effects of reaction time on cheating were found, which is probably because participants had 3 s to make up their mind and form a decision before the response options appeared and a response could be made (see above, Materials and Methods). Also, the trial number regressor, testing for possible fatigue or habituation effects, did not have a significant effect.

### Effects of congruency and correspondence on reaction time in the Stroop task

To test whether there were significant differences in cognitive control demands between the different conditions of the Stroop task, we tested the effects of the conditions, namely congruency (whether the color of the top word matched the meaning of the top word) and correspondence (whether the color of the top word matched the meaning of the bottom word), and the interaction of the conditions with reaction times. Here, the assumption is that longer reaction times reflect higher cognitive control demands. Because of the nested structure of the data, a multilevel regression model was used. The analysis revealed that both Congruency ( $b = 282.09$ , SE = 23.55,  $t = 11.99$ ,  $p < 0.001$ ) and Correspondence ( $b = 306.20$ , SE = 21.27,  $t = 14.39$ ,  $p < 0.001$ ) had a significant effect on reaction times. In addition, the interaction effect between Congruency and Correspondence was found to be significant ( $b = -354.98$ , SE = 25.09,  $t = -14.15$ ,  $p < 0.001$ ). The results show that incongruent as well as noncorresponding trials resulted in significantly higher reaction times than the congruent and corresponding trials. The combination of incongruent and noncorresponding words also led to significantly higher reaction times (Fig. 5). Thus, congruent and corresponding trials had significantly lower cognitive control demands than any of the other conditions (Fig. 5). For parsimony, from now on we only focus on the difference between





**Figure 6.** The electrophysiological signature of cognitive control in the Stroop task. Significant clusters in the midfrontal channels can be observed in theta band (4–8 Hz) between 500 and 1000 ms after stimulus onset. The clusters plotted in solid colors are significant at  $p < 0.05$  (corrected for multiple comparisons using a cluster-based permutation test,  $N_{\text{perm}} = 1000$  across channels). The transparent colors are insignificant. The legend represents  $t$  values.

congruent/corresponding and congruent/noncorresponding trials because this is the contrast where the largest difference in reaction time between conditions was observed. In congruent/noncorresponding trials, the meaning of the top word is congruent with the ink color of the top word, leaving participants particularly inclined to categorize this trial as a corresponding trial. To respond accurately, they must override this intuitive impulse, which demands a high degree of cognitive control, resulting in the longest reaction times. We also repeated the neural analysis for the congruency contrast (incongruent/corresponding trials vs congruent/corresponding trials) and found similar results.

#### The neural correlates of cognitive control in the Stroop task

Our time-frequency analysis over the midfrontal channels (F1, Fz, F2, FC1, FCz, FC2, C1, Cz, C2) revealed there was a significant increase in power on congruent/noncorresponding trials on all midfrontal channels in the theta band (4–8 Hz), starting at ~500 ms after the onset of the bottom word (Fig. 6), consistent with previous findings. The timing of our findings also aligns well with previous studies using time-frequency analysis, which found effects of cognitive control appear ~470–1000 ms after stimulus onset (Hanslmayr et al., 2008; Kovacevic et al., 2012; Tang et al., 2013). Consequently, it can be assumed that this difference in power in the theta band reflects cognitive control processes related to the processing of cognitive conflict. To test the robustness of these findings, the analysis was repeated for the congruency effect (contrasting all congruent vs incongruent trials), revealing similar results.

#### Conflict processing when exposed to the opportunity to cheat

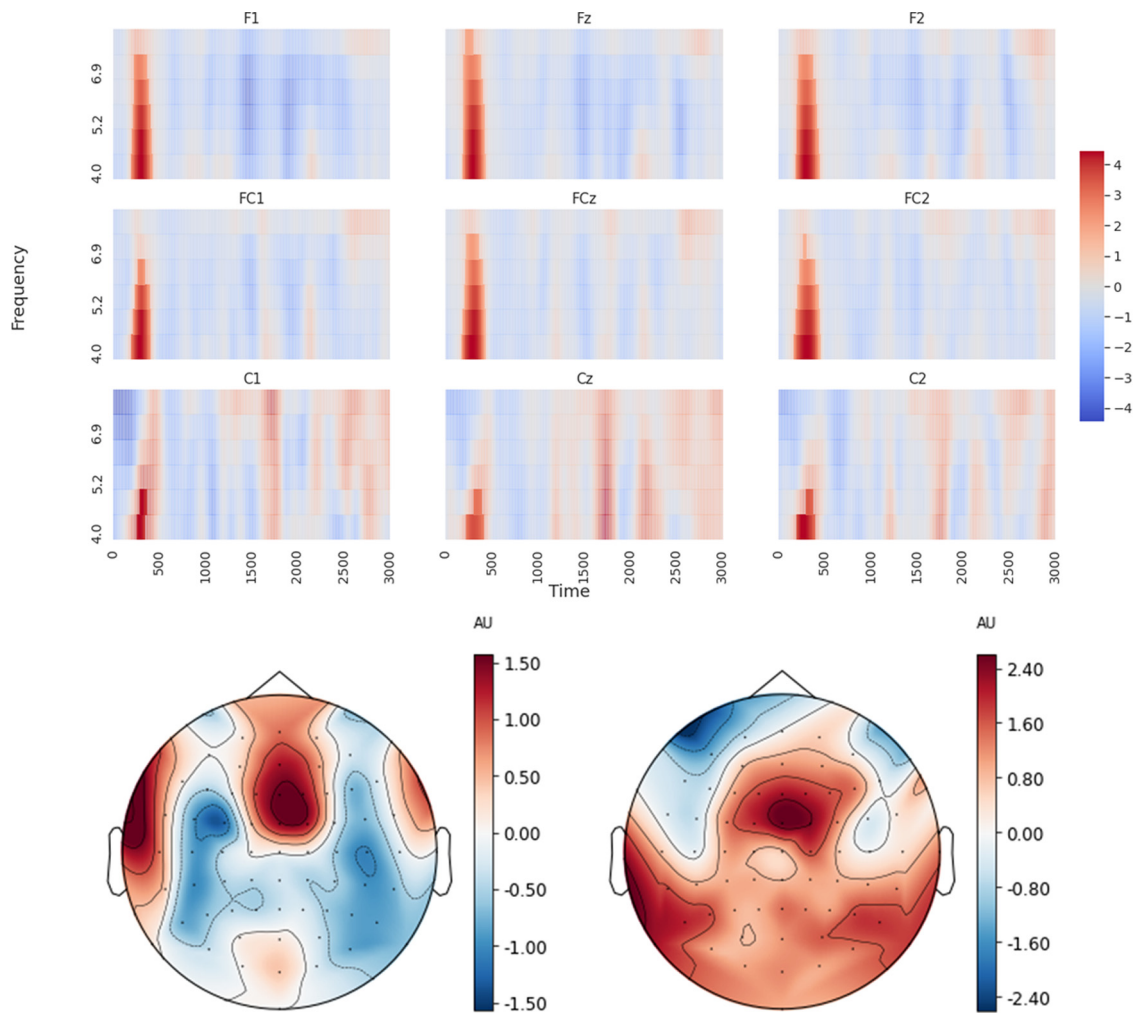
Using the channels (F1, Fz, F2, FC1, FCz, FC2, C1, Cz, C2) and frequencies (4–8 Hz) derived from the analysis of the Stroop task, we then contrasted cheatable with noncheatable trials (see

above, Materials and Methods). The analysis revealed there was a significant cluster spanning all the channels in the theta band in the first 500 ms of the decision phase (Fig. 7), suggesting that conflict associated with the temptation to cheat is detected relatively early in the decision phase.

We also more quantitatively tested the similarity between the Stroop contrast for correspondence (congruent/noncorresponding > congruent/corresponding) and the contrast between cheatable and noncheatable trials in the Spot-The-Difference task. Specifically, we computed the Spearman correlation between the last 500 ms of the time-frequency map for the correspondence effect in the Stroop task and the first 500 ms of the time-frequency map for cheatable versus noncheatable trials in the Spot-The-Difference task across channels, time, and frequency, resulting in a correlation of  $r = 0.56$ . To estimate the significance of this correlation, we then repeated this procedure 5000 times, shuffling the values for one of the maps, to create a null distribution of correlations expected by chance. Comparing the empirical correlation with the null distribution, we observed that the correlation is significant at  $p < 0.001$ . The same holds when we calculate the correlation for each of the channels individually (F1:  $r = 0.49$ ,  $p < 0.001$ ; Fz:  $r = 0.62$ ,  $p < 0.001$ ; F2:  $r = 0.71$ ,  $p < 0.001$ ; FC1:  $r = 0.49$ ,  $p < 0.001$ ; FCz:  $r = 0.75$ ,  $p < 0.001$ ; FC2:  $r = 0.71$ ,  $p < 0.001$ ; C1:  $r = 0.31$ ,  $p < 0.001$ ; Cz:  $r = 0.37$ ,  $p < 0.001$ ; C2:  $r = 0.64$ ,  $p < 0.001$ ). These findings show that the patterns of activation related to cognitive control in the Stroop task are indeed similar to the patterns of activation when one decides whether to cheat.

#### Power in the theta band is associated with trial-by-trial cheating

Entering the power in the theta range within the first 500 ms for each of the channels of interest together with participants'



**Figure 7.** The electrophysiological signature of conflict processing when tempted to cheat. Top, Significant clusters in the midfrontal channels can be observed in theta band (4–8 Hz) in the first 0.5 s of the decision period. The clusters plotted in solid colors are significant at  $p < 0.05$  (corrected for multiple comparisons using a cluster-based permutation test,  $N_{\text{perm}} = 1000$ , corrected for multiple comparisons across channels using false discovery rate at  $p < 0.05$ ). The transparent colors are insignificant. Bottom, Topoplots of the first 0.5 s of the Spot-The-Difference task (left) and the last 250 ms of the Stroop task (right) in the theta band.

cheatcount into a multilevel lasso model revealed that the cheatcount ( $b = 1.61$ ,  $SE = 0.07$ ,  $p < 0.001$ ) and the interaction effect between the cheatcount and theta power on Fz ( $b = -0.17$ ,  $SE = 0.06$ ,  $p < 0.05$ ) were significantly associated with trial-level cheating. Scrutinizing the plot depicting the interaction effect (Fig. 8), we see that for participants who cheat a lot (light blue lines), a higher power on Fz was associated with lower probabilities of cheating, whereas for more honest participants (dark blue lines), a higher theta power on Fz is associated with a higher probability of cheating. These findings suggest that the effect of midfrontal theta on cheating is contingent on whether a participant is, by default, more inclined to be honest or dishonest. We also conducted a robustness check for these results in which we averaged over all channels (F1, Fz, F2, FC1, FCz, FC2, C1, Cz, C2). This robustness analysis revealed there was a significant main effect of cheatcount ( $b = 1.60$ ,  $SE = 0.07$ ,  $p < 0.001$ ) and a significant interaction effect between the average of all electrodes and the cheatcount ( $b = -0.31$ ,  $SE = 0.14$ ,  $p < 0.05$ ).

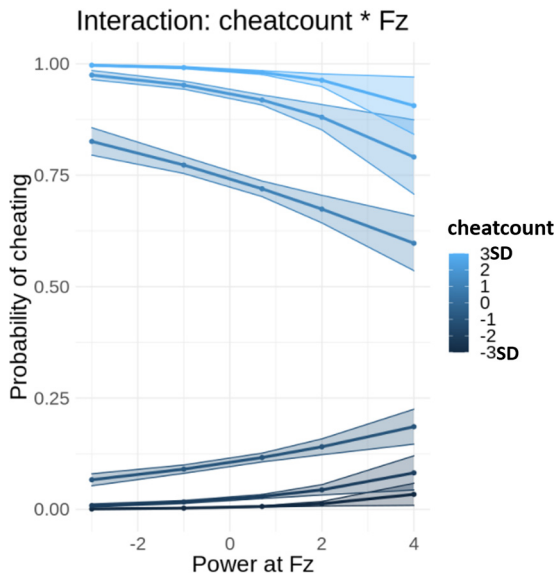
#### Similarity to cognitive control signature is associated with trial-by-trial cheating

To further establish a link between the patterns in the Stroop task and cheating, we conducted a similarity analysis. We

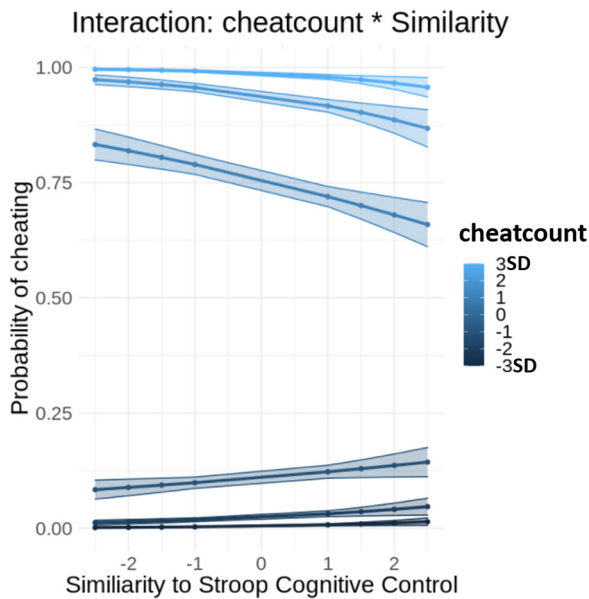
computed for each participant and for each channel the correlation between the average time-frequency map in the last 500 ms of the difference between congruent/noncorresponding trials (representing high cognitive control demands) and congruent/corresponding trials (representing low cognitive control demands) and the first 500 ms of the time-frequency map for each trial, channel, and participant in the Spot-The-Difference task. We then entered the resulting correlation, together with each participant's cheatcount in a multilevel lasso regression model to predict trial-by-trial cheating. This analysis revealed that the cheatcount ( $b = 1.62$ ,  $SE = 0.07$ ,  $p < 0.001$ ) and the interaction effect between the cheatcount and the similarity between the Stroop and Spot-The-Difference tasks on FC1 ( $b = -0.16$ ,  $SE = 0.07$ ,  $p < 0.05$ ) were significantly associated with trial-level cheating (Fig. 9).

These results indicate that for cheaters the more similar their brain response is to that of applying cognitive control in the Stroop task, the less likely it is they will cheat. On the other hand, the more similar the brain response is to that of cognitive control in the Stroop task for more honest participants, the more likely it is they will cheat. These results establish a direct link between the neural signature of cognitive control identified in the Stroop task and trial-level cheating in the Spot-The-Difference task,





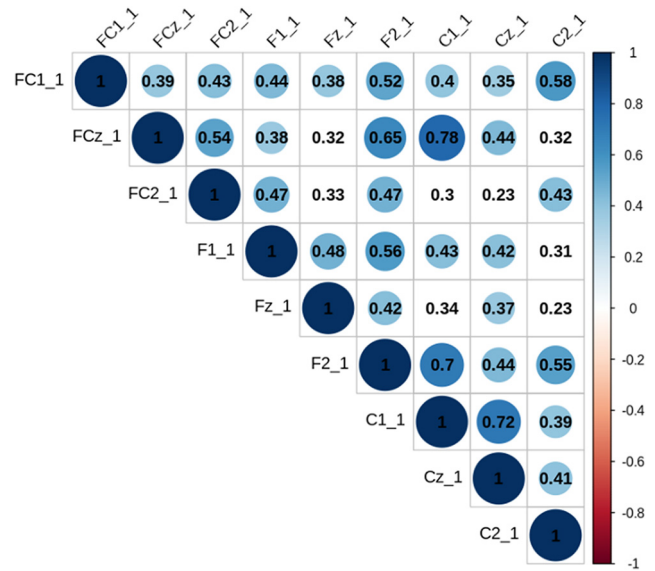
**Figure 8.** Interaction effect between cheatcount and theta in Fz in estimating the probability of cheating. The lines that are shown are the fitted values for participants 3 SD (lightest blue), 2 SD (light blue), and 1 SD (blue) above the mean of the cheatcount, and for participants 1 SD (dark blue), 2 SD (darker blue), and 3 SD (darkest blue) below the mean of the cheatcount.



**Figure 9.** Interaction effect between cheatcount and similarity in the FC1 between trial-level time-frequency data from the Spot-The-Difference task and subject-level time-frequency data representing the neural signature of cognitive control in the Stroop task in estimating the probability of cheating. The lines shown are the fitted values for participants 3 SD (lightest blue), 2 SD (light blue), and 1 SD (blue) above the mean of the cheatcount, and for participants 1 SD (dark blue), 2 SD (darker blue), and 3 SD (darkest blue) below the mean of the cheatcount.

supporting our hypothesis that the role of cognitive control in cheating behavior depends on one’s moral default.

The fact that in this analysis the FC1 and not the Fz (as in the previous analysis) was observed to be the most predictive channel might be because the similarities between Spot-The-Difference and Stroop data were highly correlated across channels. The lasso chose the most important predictor; however, the



**Figure 10.** Correlation among similarities across channels.

other channels were also highly correlated (Fig. 10) and, consequently, could have also been selected with a high likelihood. This suggests that the cluster of midfrontal channels represents engagement of the same underlying process.

### Discussion

In the current study we replicated previous findings (Speer et al., 2020) that the role of cognitive control in (dis)honest decisions depends on an individual’s moral default. Specifically, combining EEG with the Stroop task as a localizer we identified the neural signature of cognitive control in the theta band (4–8 Hz) on mid-frontal channels (F1, Fz, F2, FC1, FCz, FC2, C1, Cz, C2). Subsequently, we observed higher power on these channels and this frequency range in the first 500 ms of the decision-making phase of the Spot-The-Difference task when participants were exposed to the opportunity to cheat compared with the absence of this temptation. In addition, we find that higher theta power on these channels in the first 500 ms is associated with a higher probability of cheating for honest participants, whereas it increased honesty for cheaters. Finally, we found that the similarity between trial-level power in the Spot-The-Difference task and the subject-level neural signature of cognitive control derived from the Stroop task is associated with trial-level cheating.

Our findings align well with the literature on the electrophysiological signature of cognitive control, which has consistently found that cognitive control demands modulate power in the theta range over the midfrontal cortex (Wang et al., 2005; Cohen et al., 2008; Womelsdorf et al., 2010; Cohen and Cavanagh, 2011; Cavanagh et al., 2012; Nigbur et al., 2012). Furthermore, our findings from the Stroop task are in accordance with previous research showing that cognitive control demands related to the Stroop interference can be observed ~470–1000 ms after stimulus onset (i.e., presentation of both words; Hanslmayr et al., 2008; Kovacevic et al., 2012; Tang et al., 2013).

Previous research has deduced the involvement of cognitive control in moral decision-making through relating observed activations to those observed for cognitive control tasks in prior studies (Greene and Paxton, 2009; Abe and Greene, 2014) or with the help of meta-analytic evidence (Speer et al., 2020) from

the Neurosynth platform (Yarkoni et al., 2011). This approach, which relies on reverse inference, must be used with caution because any given brain area may be involved in several different cognitive processes, which makes it difficult to conclude that activation observed in a particular brain area represents one specific function (Poldrack, 2006). Here, we extend prior research by providing more rigorous evidence by means of explicitly eliciting cognitive control in a separate localizer task and then demonstrating that this same neural signature can be identified in the Spot-The-Difference task when participants are exposed to the opportunity to cheat. Moreover, using similarity analysis we provide a direct link between the neural signature of cognitive control, as elicited by the Stroop task, and (dis)honesty by showing that time-frequency patterns of cognitive control demands in the Stroop task are indeed similar to those observed when tempted to cheat in the Spot-The-Difference task. These results provide strong evidence that cognitive control processes are recruited when individuals are tempted to cheat.

We observed that the detection of cognitive conflict occurs in the first 500 ms of the decision phase, regardless of whether participants were honest or dishonest. This suggests that moral conflict is detected relatively early in the decision process. This may indicate that the decision to cheat or not relies on the immediate engagement of cognitive control on a given trial, rather than a later readjustment of an intuitive response to be (dis)honest. Alternatively, the outcome of the decision may depend on intrinsic fluctuations of cognitive control over time (Leber et al., 2008); when control is high when a particular choice is presented, participants are better equipped to go against their default than when control is relatively low at that point in time. To rule out the possibility that differences in cognitive control can be attributed to differences in mental effort exerted during a visual search rather than moral conflict during choice, we tested whether differences in cognitive control between conditions could already be detected during the visual search phase. No significant differences between conditions (cheatable vs noncheatable) were found in the search phase.

Importantly, we replicate the previous results from an fMRI. Using EEG instead of fMRI, evoking cognitive control by means of a well-validated localizer and using a different sample, we provide further evidence that validates the notion that cheaters require cognitive control to be honest, whereas generally honest participants require cognitive control to cheat. This replication is significant as the reproducibility of many findings in (cognitive) neuroscience and psychology have been questioned (Ioannidis, 2005; Button et al., 2013; Botvinik-Nezer et al., 2020). To avoid building further research on fragile ground, replications are necessary to validate novel insights and hypotheses (Barch and Yarkoni, 2013; Botvinik-Nezer et al., 2020). Importantly, the data and code this article is based on are publicly available to allow other labs to reproduce our findings or facilitate replication in new samples and in different labs.

#### Data availability

Data and scripts used in the task are available in the following public repository: <https://doi.org/10.25397/eur.15194658.v1>.

Some limitations of this study are worth addressing. Here, we focused mainly on more rigorously investigating the effect of cognitive control on (dis)honest decisions by applying a localizer specifically designed to investigate the neural mechanisms underlying conflict detection and the inhibition of a default response. In a previous study (Speer et al., 2020), it was revealed that cognitive control helps to reconcile the conflict

between the anticipation of reward and the maintenance of a positive self-concept. Therefore, future studies may benefit from also designing localizer tasks to elicit the neural processes underlying the anticipation of reward and self-referential thinking to more rigorously explore the interaction between these processes.

Furthermore, although neuroimaging can provide insights into which neural processes are associated with (dis)honest decisions, it cannot determine whether there is a causal relationship. To test the causality of the effect of cognitive control on dishonesty, methods such as transcranial direct current stimulation or transcranial magnetic stimulation could be used to directly manipulate activity in the cognitive control network in honest participants and cheaters to test whether the interaction effect can be causally induced. Similarly, the causal relationship between moral default, cognitive control, and cheating could be examined with the help of behavioral interventions to induce cognitive load or evoke acute stress (Wood et al., 1984), which have been found to reduce cognitive control capacity (Shiv and Fedorikhin, 1999; Schwabe and Wolf, 2009; Yu, 2016).

To conclude, the current study shows that the role of cognitive control does not enable cheating or honesty per se but is contingent on one's moral default. By using a well-established localizer task for cognitive control, we provide further validation of the differential effect of cognitive control on (dis)honesty. In addition, the high temporal resolution provided by EEG allowed us to show that cognitive control has an impact on decisions involving dishonesty relatively early in the decision-making process, which may indicate that the decision to cheat or not relies on the immediate engagement of cognitive control on a given trial or, alternatively, that the outcome of the decision may depend on probabilistic fluctuations of cognitive control over time so that when control is high, participants are better equipped to go against their default than when control is relatively low at that point in time. Future studies may extend this work by causally manipulating cognitive control to investigate both the intersubject and intrasubject variability in cheating behavior.

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