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Fast and slow thinking: Electrophysiological evidence for early conflict sensitivity

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ABSTRACT

Popular dual process models have characterized reasoning as an interplay between fast, intuitive (System 1) and slow, deliberate (System 2) processes, but the precise nature of the interaction between the two systems is much debated. Here we relied on the temporal resolution of electroencephalogram (EEG) recordings to decide between different models. We adopted base-rate problems in which an intuitively cued stereotypical response was either congruent or incongruent with the correct response that was cued by the base-rates. Results showed that solving problems in which the base-rates and stereotypical description cued conflicting responses resulted in an increased centro-parietal N2 and frontal P3. This early conflict sensitivity suggests that the critical base-rates can be processed fast without slow and deliberate System 2 reflection. Findings validate prior EEG work and support recent hybrid dual process models in which the fast System 1 is processing both heuristic belief-based responses (e.g., stereotypes) and elementary logico-mathematical principles (e.g., base-rates).

1. Introduction

For centuries, human thinking has been conceived as an interplay between more intuitive and deliberate processes. In the last decades dual process models that are inspired by this classic dichotomy have moved to the center stage in the cognitive and economic sciences (Evans and Stanovich, 2013; Greene, 2013; Kahneman, 2011; Rand, et al., 2012). At the heart of these dual process models lays the idea that human reasoning relies on two different types of thinking - often referred to as System 1 and System 2 processing (Stanovich, 1999). System 1 is assumed to operate quickly and effortlessly whereas System 2 is assumed to be slower and more effortful. It is System 1 (often also called the intuitive or heuristic system) that is supposed to mediate intuitive thinking whereas System 2 (often also called the deliberate or analytic system) is supposed to mediate more deliberate thinking.

Despite the popularity of dual process models, the approach is also criticized (e.g., De Neys and Glumicic, 2008; Gigerenzer and Regier, 1996; Keren and Schul, 2009; Osman, 2013). One key concern is that the framework lacks a precise processing specification of the two systems. A critical issue is the fact that the nature of the interaction between the two systems is not clear. Traditionally there has been some debate between proponents of a serial and parallel view. The parallel view entails that both systems are always activated simultaneously from the start of the reasoning process (Epstein, 1994; Sloman, 1996). The serial model entails that people initially only activate System 1 and optional System 2 activation occurs later in the reasoning process (Evans and Stanovich, 2013; Kahneman, 2011). More recently, so-called hybrid models have been put forward (e.g., Bago and De Neys, 2017; Banks, 2017; De Neys, 2012; Handley and Trippas, 2015; Pennycook et al., 2015; Thompson and Newman, 2017; Trippas and Handley, 2017a). Simply put, these hybrid models posit that the response that is traditionally expected to be calculated by System 2 can also be cued by System 1. System 1 would generate different types of intuitions such that possible conflict between them can be detected early in the reasoning process without slow System 2 computations.

To illustrate these different views, consider the following reasoning problem: You are told that there is a sample of 995 females and 5 males. Next, you're told that one person ("Person X") got drawn randomly

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from the sample and you're informed that we know that this person X is a surgeon. You are then asked whether it is more likely that Person X is male or female. This example is based on Tversky and Kahneman's (1974) famous base-rate neglect problems. Intuitively, many people will tend to say that Person X is a male based on stored stereotypical associations cued by the descriptive information ("Surgeons are male"). In case your only piece of information would be the job description of the person that might be a fair guess. In general, there are more male than female surgeons. However, there are also female surgeons and in the problem premises you were explicitly told that there were far more females than males in the sample where Person X was drawn from. If you take this extreme base-rate information into account this should push the scale to the "female" side. However, decades of studies have shown that people often fail to respect elementary logical considerations such as the base-rate principle and give the intuitive or so-called "heuristic" response that is cued by their stereotypical prior beliefs (e.g., Kahneman, 2011).

Traditional serial and parallel dual process models have typically assumed that taking logico-mathematical principles into account and giving the response favored by the base-rates, for example, requires System 2 deliberation. The key idea is that because System 2 operations are demanding and slow, most people will not wait for the slow process to complete or will simply refrain from engaging in it altogether. Consequently, they end up being biased and give the heuristic System 1 response. The hybrid model entails that people can also process the logical response intuitively. Hence, System 1 will cue at least two intuitive responses: a "heuristic" response based-on stereotypical associations and a "logical" intuitive response based on automatically activated elementary knowledge of logico-mathematical principles. Both the hybrid and traditional models can explain that the heuristic response will typically dominate: the traditional models because the logical response will not (yet) be computed at the time of decision; the hybrid model because the heuristic response can have a higher activation level (Bago and De Neys, 2017; Pennycook et al., 2015). However, the key difference is that the intuitive processing of logical features in the hybrid model implies that it allows reasoners to detect instantly that there are conflicting responses at play early on in the reasoning process without any engagement of the slow System 2.

Recent behavioral studies that aimed to test these different models have provided some initial support for the hybrid view (e.g., Franssens and De Neys, 2009; Johnson et al., 2016; Nakamura and Kawaguchi, 2016; Pennycook et al., 2014b; Thompson and Johnson, 2014; Trippas et al., 2016; Trippas et al., 2017b). For example, conflict detection studies have contrasted how people process classic reasoning problems in which an intuitively cued heuristic response conflicts with elementary logical considerations (i.e., conflict problems) and control no-conflict problems. In the control versions small content transformations guarantee that the intuitively cued heuristic response is also logically correct. For example, one can easily create a no-conflict control version of the introductory base-rate problem by switching the base-rates around (e.g., you are told that person X is a surgeon but is drawn from a sample with 995 males and 5 females). In this case both base-rate considerations and stereotypical associations triggered by the job description cue the exact same response.

Results show that people are sensitive to the presence of conflict as evidenced by increased response times (e.g., De Neys and Glumicic, 2008), decreased confidence (e.g., De Neys et al., 2011), or activation of brain regions that have long been known to mediate conflict detection (e.g., Anterior Cingulate Cortex, e.g., De Neys et al., 2008; Simon et al., 2015; Vartanian et al., 2018). Critically, these effects are observed even when people are put under time-pressure or cognitive load so that possible System 2 processing is experimentally minimized (e.g., Bago and De Neys, 2017; Franssens and De Neys, 2009; Howarth et al., 2016; Johnson et al., 2016; Newman et al., 2017; Pennycook et al., 2015; Thompson and Johnson, 2014). In sum, these conflict sensitivity findings suggest that base-rates and other logico-mathematical aspects of the reasoning problem are processed even when System 2 processing is minimized. This conclusion has been validated with a range of behavioral paradigms (e.g., Handley and Trippas, 2015; Trippas et al., 2016; Trippas et al., 2017b; but see also Mata et al., 2017; Pennycook et al., 2012; Travers et al., 2016).

However, all these behavioral studies face an intrinsic limitation: by definition, they are all response dependent. For example, confidence measures are typically collected post response. Likewise, response time measurements require overt response generation. Consequently, even when applying time pressure manipulations or minimal "rapid-response" task versions designed to allow for fast response generation (e.g., Pennycook et al., 2014a), it still takes at the very least a second or more before an overt response has been selected in a reasoning task. However, if the fast System 1 is indeed processing base-rate and other logical task features intuitively, it should be possible to find signs of early conflict sensitivity much earlier in the reasoning process, *before* the actual response has been given.

Banks and Hope (2014) were the first to realize the potential of electroencephalogram (EEG) recordings and their unique temporal resolution in this respect. Banks and Hope presented participants with syllogisms in which the logical validity of the conclusions could conflict with a heuristic response cued by the believability of the conclusion. For example, an illustration of a conflict problem would be a valid syllogism with an unbelievable conclusion (e.g., "All mammals can walk. Whales are mammals. Therefore, whales can walk."). An illustration of a no-conflict problem would be a valid syllogism with a believable conclusion (e.g., "All flowers need light. Roses are flowers. Therefore, roses need light"). By time-locking an event-related potentials (ERPs) analysis to the presentation of the last word of the conclusion (i.e., the exact point at which belief-logic conflict could occur), Banks and Hope could test whether early electrophysiological activation differed as a function of the conflict status of the problem. Such early conflict sensitivity would be expected if fast System 1 operations process the logical status of the problem. If slow System 2 processing is required, then detection of logic/belief conflict should occur much later in the reasoning process.

Results pointed to very early conflict sensitivity after a mere 200 ms were elapsed: In contrast with no-conflict problems, the conflict trials gave rise to a reduced N2 and enhanced P3 component. The N2 and P3 are well-known negative and positive deflections that occur between 200 and 350 ms and 300–500 ms after the event, respectively, and have been associated with information monitoring, control, and updating processes (e.g., Borst et al., 2013; Folstein and Van Petten, 2008; Polich, 2007; Ullsperger et al., 2014; Yeung and Summerfield, 2012).

Banks and Hope (2014) early conflict sensitivity findings indicate that logical reasoning—a process that is traditionally believed to require slow System 2 computations—can be literally accomplished in a split second. This fits with the hybrid dual process model's postulation of intuitive logical processing (Banks, 2017). However, to draw strong theoretical conclusions it is important to establish whether the results are robust. To avoid confusion, Banks and Hope (2014) were obviously not the first to study reasoning processes with EEG per se (e.g., Bonnefond et al., 2014; Bonnefond and Van der Henst, 2009, 2013, Luo et al., 2008, 2013; Luo et al., 2011; Malaia et al., 2015). However, the problem is that these prior studies were not specifically designed to test between different dual process models. For example, many studies used a design that was time-locked to the response generation (e.g., Luo et al., 2013) or initial presentation of the problem premises (e.g., Luo et al., 2011, 2008). This complicates testing for early conflict sensitivity (i.e., participants are still reading the premises or already responded). In addition, many studies did not manipulate belief-logic conflict experimentally (e.g., Bonnefond et al., 2014; Bonnefond and Van der Henst, 2009, 2013; Malaia et al., 2015).

In sum, to draw clear conclusions it is important to test the generalizability and robustness of the initial Banks and Hope (2014) findings. The present paper addresses this issue. We focused on the popular base-rate task and tested whether the N2 and P3 showed early sensitivity to the intrinsic conflict between the response cued by the base-rates and the stereotypical description. Our rationale for choosing the base-rate task was that the task has been extensively used in behavioral conflict detection studies. These studies presented abundant behavioral evidence for the intuitive nature of the base-rate processing in the task (e.g., Bago and De Neys, 2017; Franssens and De Neys, 2009; Pennycook et al., 2014b; Thompson and Johnson, 2014). Hence, if Banks and Hope are correct in that the N2 and P3 reflect early conflict sensitivity, we should a fortiori observe it in the base-rate task.

A second objective of the study was to test whether correct and incorrect responders show differential conflict sensitivity. As most reasoning and EEG studies, Banks and Hope's (2014) work only focused on correctly solved trials. However, behavioral studies have indicated that intuitive conflict sensitivity is not only observed for correct but also for incorrect conflict responses (e.g., Bago and De Neys, 2017; Franssens and De Neys, 2009; Pennycook et al., 2015; Thompson and Johnson, 2014; but see also Aczel et al., 2016; Mata et al., 2017; Travers et al., 2016). Hence, by including both correctly and incorrectly solved conflict trials in our analysis we wanted to test whether the N2 and P3 effects were observed irrespective of response accuracy.

2. Method

2.1. Participants

In total, 31 participants took part in this experiment (27 female, M = 23.4 year, SD = 4.2 year). All participants were right handed and had normal or corrected vision. None of them reported to have had neurological surgery or any known neurological or psychiatric problems. All of the participants were native English speaking North-American current or former university students. All participants provided written informed consent and were tested in accordance with national and international norms governing the use of human research participants.

2.2. Material and procedure

Reasoning task. Participants solved a total of 132 base-rate problems. All problems were taken from Pennycook et al. (2015). In each problem participants received a description of the composition of a sample (e.g., “This study contained I.T. engineers and professional boxers”), base-rate information (e.g., “There were 995 engineers and 5 professional boxers”) and a description that was designed to cue a stereotypical association (e.g. “This person is strong”). Participants' task was to indicate to which group the person most likely belonged.

The problem presentation format was based on Pennycook et al.'s (2014) rapid-response paradigm. In this paradigm, the descriptive information consists of a neutral name (“Person L”) and a single word personality trait (e.g., “strong” or “funny”) that was designed to trigger the stereotypical association. The following illustrates the full problem format:

This study contains clowns and accountants. Person 'L' is funny.

There are 995 clowns and 5 accountants.

Is Person 'L' more likely to be:

1) A clown

2) An accountant

Each trial started with the presentation of a fixation cross for 1000 ms. After the fixation cross disappeared, the sentence which specified the two groups appeared for 2000 ms. Then the descriptive information appeared for another 2000 ms while the first sentence remained on the screen. Finally, the last sentence specifying the base-rates appeared together with the question and two response alternatives. Note that we presented the base-rates and question together (rather than presenting the base-rate for 2000 ms first) to minimize the possibility that some participants would start solving the problem during presentation of the base-rate information. Once the base-rates and question were presented participants were able to select their answer by pushing a button corresponding to the selected response. There was a 7000 ms response deadline on each problem. Note that in 0.6% of the trials participants missed the deadline. These trials were discarded from further analysis.

Half of the presented problems were conflict items and the other half were no-conflict items. In no-conflict items the base-rate probabilities and the descriptive information cued the same response. In conflict items the descriptive information and the base-rate probabilities cued different responses. As Pennycook et al. (2014a) we used three slightly altered base-rate levels (i.e., 997/3, 996/4, 995/5) to make the task less repetitive. Each ratio was used with equal frequency. Problems were presented in random order.

All material was extensively pretested (see Pennycook et al., 2015). Pennycook et al. made sure that words that were selected to cue a stereotypical association consistently did so while avoiding extremely diagnostic cues. Such a non-extreme, moderate association is important. For convenience and consistency with prior work we label the response that is in line with the base-rates as the correct response. Critics of the base-rate task (e.g., Gigerenzer et al., 1988) have long pointed out that if reasoners adopt a Bayesian approach and combine the base-rate probabilities with the stereotypical description, this can lead to interpretational complications when the description is extremely diagnostic. For example, imagine that we have an item with males and females as the two groups and give the description that Person ‘A’ is ‘pregnant’. Now, in this case, one would always need to conclude that Person ‘A’ is a woman, regardless of the base-rates. The more moderate descriptions (such as ‘kind’ or ‘funny’) help to avoid this potential problem. In addition, the extreme base-rates (997/3, 996/4, or 995/5) that were used in the current study further help to guarantee that even a very approximate Bayesian reasoner would need to pick the response cued by the base-rates (see De Neys, 2014).

As in Pennycook et al. (2015) we created a no-conflict version of each conflict problem (and vice versa) by presenting the opposing personality trait from the pilot study (e.g., hippies and computer programmers were paired with “nerdy” in one case and with “unconventional” in the other). The conflict and no-conflict versions of each item were presented in two different blocks (and half of the problems in each block were conflict and no-conflict problems). Participants could take a short break between the two blocks.

EEG recording and preprocessing. The electroencephalogram (EEG) was recorded from a 256-channel HydroCel Geodesic Sensor Net (Electrical Geodesics Inc., Eugene, Oregon, USA) containing electrodes imbedded in small sponges soaked in a potassium chloride saline solution. Continuous EEG was acquired through a DC amplifier (Net Amps 300 1.0.1, EGI) and digitized at a sampling rate of 500 Hz. A common reference at the vertex was used during acquisition and electrode impedances was kept below 100 kΩ. Eye-blinks and eye-movements were monitored via pairs of channels (included in the net) covering the face area.

All processing stages described below were performed using EEGLab (Delorme and Makeig, 2004). Activity from all electrodes was re-referenced to the average. The raw EEG data was passed through a high pass filter (0.5 Hz) and a low pass filter (30 Hz). Muscular artefacts and ocular artefacts were removed from continuous EEG data using Artefact Subspace Reconstruction (ASR implemented in the EEGLab plugin “clean_rawdata”, see Mullen et al., 2015). The continuous EEG was then segmented from −200 to 700 ms relative to the onset of the presentation of the base-rates. The epochs were baseline corrected using the mean prestimulus voltage in the 200 ms prestimulus period. N2 and

P3 amplitudes were defined as the average voltage in pre-specified time windows. The N2 was defined as the average in the 175–250 ms time interval, while the P3 was defined as the average voltage in the 300–500 ms interval following stimulus onset (see Rietdijk et al., 2014). As in previous work (e.g., Banks and Hope, 2014) we calculated the mean amplitudes at frontal central and parietal electrode sites (roughly corresponding to Fz, Cz and Pz) where N2 and P3 are typically maximal. As we had 256 electrodes, when calculating the amplitude averages for each electrode site we took into account all electrodes which were located directly next to the electrode in question. Hence, we took into account the following electrodes (numbers corresponding to the electrode map of the HydroCel Geodesic Sensor Net; Parietal (Pz, 89, 100, 110, 119, 128, 129, 130), Central (Cz, 9, 45, 81, 132, 186), Frontal (Fz, 13, 14, 20, 22, 27, 28)).

We performed a trial-based analysis, using mixed effect models and the lmerTest package in R (Kuznetsova et al., 2015). Note that this trial based analysis does not change the ERP averages compared to a more traditional ERP analysis where the averages are first calculated at the individual level. However, it increases the probability of detecting real effects as it takes into account individual trials and thus increases statistical power (Baayen et al., 2008; Quené and Van den Bergh, 2008; for applications with ERP data, see: Tremblay and Newman, 2015). We entered the random effect of participants and the random effect of electrodes in the model to filter for noise introduced by individual electrodes or participants.

3. Results

3.1. Behavioral results

Accuracy. Overall conflict problem accuracy reached 66.4% (SD = 47.2). Note that although this indicates that participants were frequently biased in our study, the accuracy rate is slightly higher than what has been observed in previous behavioral studies with the same task (e.g., Bago and De Neys, 2017; Pennycook et al., 2014a, 2015). This might suggest that our sample of participants had a stronger predisposition to focus on the base-rates than participants in previous behavioral work. As expected, accuracy on the no-conflict problems in which the stereotypical and base-rate response agreed was at ceiling with an overall accuracy rate of 97.6% (SD = 15.3), χ^2 (1) = 1008.4, $p < 0.0001$, $b = 4.06$.

Note that in all remaining behavioral and ERP analyses we discarded the few (i.e., 2.4%) incorrectly solved no-conflict trials. In no-conflict trials, the base-rates and stereotypical information point to the same correct response. Therefore, incorrect responses cannot be interpreted unequivocally and are typically discarded in conflict detection studies (De Neys and Glumicic, 2008; Pennycook et al., 2015). We will refer to the correct no-conflict problems as the baseline problems.

Latencies. All latencies were logarithmically (log10) transformed prior to analysis. Table 1 shows the results. We found that participants took overall more time to solve conflict than the baseline no-conflict trials, χ^2 (1) = 116.44, $p < 0.0001$, b = -0.07. More critically, we found the increase both for correctly, χ^2 (1) = 113.51, $p < 0.0001$, b = -0.08, and incorrectly, χ^2 (1) = 69.35, $p < 0.0001$, b = -0.08., solved conflict problems. Increased latencies for conflict vs baseline no-conflict problems are typically taken as evidence for conflict sensitivity[1] (De Neys and Glumicic, 2008; Pennycook et al., 2015). Hence, at the behavioral level our latency results replicate previously established evidence for conflict sensitivity with this task (De Neys, 2012; Pennycook et al., 2014a, 2015).

[1] To recap, the rationale is that in no-conflict problems, the base-rates and stereotypical information cue the same response. If people take longer to solve the problems in which they cue conflicting responses, this supports the claim that presence of conflict goes not undetected: it slows people down.

Table 1
Overview of the latency results. The table shows the geometrical means (SD, and SE for mean differences) as well as the difference between no-conflict correct (baseline) trials and correctly and incorrectly solved conflict trials.

	Correct	Incorrect
Conflict	1929.2 ms (1.8)	1706.7 ms (2.1)
No-conflict	1556.1 ms (1.8)	2124.5 ms (2.2)
Difference score	− 361.1 ms (0.06)	− 150.6 ms (0.09)

3.2. ERP amplitudes

Fig. 1 gives a general overview of the grand average ERP waveforms for conflict and no-conflict baseline trials at our three electrode locations. Fig. 2 shows the corresponding scalp topography for the 175–250 ms (N2) and 300–500 ms (P3) time window.

N2 amplitude. We first analyzed the overall contrast between no-conflict baseline and conflict problems (irrespective of conflict accuracy). As for statistical testing, we added electrode location (Frontal, Central, Parietal), conflict (conflict or no-conflict problem), and their interaction to the model. We found a significant effect of electrode location, χ^2 (2) = 30.76, $p < 0.001$, a significant effect of conflict, χ^2 (3) = 13.71, $p < 0.001$, and also a significant interaction effect, χ^2 (5) = 6.34, $p = 0.04$. As we had a significant interaction, we analyzed each electrode site separately. We found a significant difference between conflict and no-conflict trials at the Central, χ^2 (1) = 14.7, $p < 0.001$, b = -0.37, and Parietal groups, χ^2 (1) = 13.46, $p < 0.001$, b = -0.48, but not for the Frontal group, χ^2 (1) = 0.44, $p = 0.51$, b = -0.08. In all of these groups, the N2 amplitude was more negative on conflict trials then on no-conflict trials. Hence, the presence of conflict between base-rates and description resulted in a more pronounced centro-parietal N2 which supports the idea that reasoners show early conflict sensitivity.

Next, we also ran an exploratory analysis in which we separated the conflict trials by their accuracy to test whether the N2 findings differed for correct and incorrect responses. Thus, instead of conflict, we entered a variable "response category" with 3 levels (no-conflict correct responses, conflict correct and conflict incorrect responses) into the model. Results showed that both the main effect of electrode site, χ^2 (2) = 30.76, $p < 0.001$, and response category, χ^2 (4) = 13.72, $p < 0.001$, but not their interaction, χ^2 (8) = 13.71, $p = 0.07$, significantly improved model fit. Follow-up test for the response category effect showed that in comparison with the no-conflict baseline trials the N2 across the 3 electrode sites was more negative for both correct conflict responses, b = -0.25, t = -3.26, $p = 0.001$, and incorrect conflict responses, b = -0.25, t = -2.36, $p = 0.018$. However, visual inspection of Fig. 3 suggests that this effect might not be equally strong on all electrode locations; while there is a clear effect on the centro-parietal Central and Parietal groups, the effect on the Frontal group seems weaker. Given that the model interaction was marginally significant and the overall analysis also pointed to stronger conflict effects on centro-parietal electrodes, we analyzed the effect of response category at each electrode location separately. Consistent with the visual trend, results showed that there were significant effects for the Parietal, χ^2 (2) = 14.89, $p < 0.001$, and Central, χ^2 (2) = 15.33, $p < 0.001$, sites but not at the Frontal one, χ^2 (2) = 0.46, $p = 0.79$.

P3 amplitude. We used the same analysis approach as for the N2 amplitude. Hence, we first analyzed the overall contrast between no-conflict baseline and conflict problems (irrespective of accuracy). We added electrode location (Frontal, Central, Parietal), conflict (conflict or no-conflict problem) and their interaction to the model. Results pointed to a significant effect of electrode location χ^2 (2) = 34.68, $p < 0.001$, but no effect of conflict, χ^2 (3) = 3.57, $p = 0.06$, and also a significant effect of their interaction, χ^2 (5) = 16.6, $p = 0.04$. Given the interaction, we analyzed each electrode site separately. We found a significant difference between conflict and no-conflict trials at the

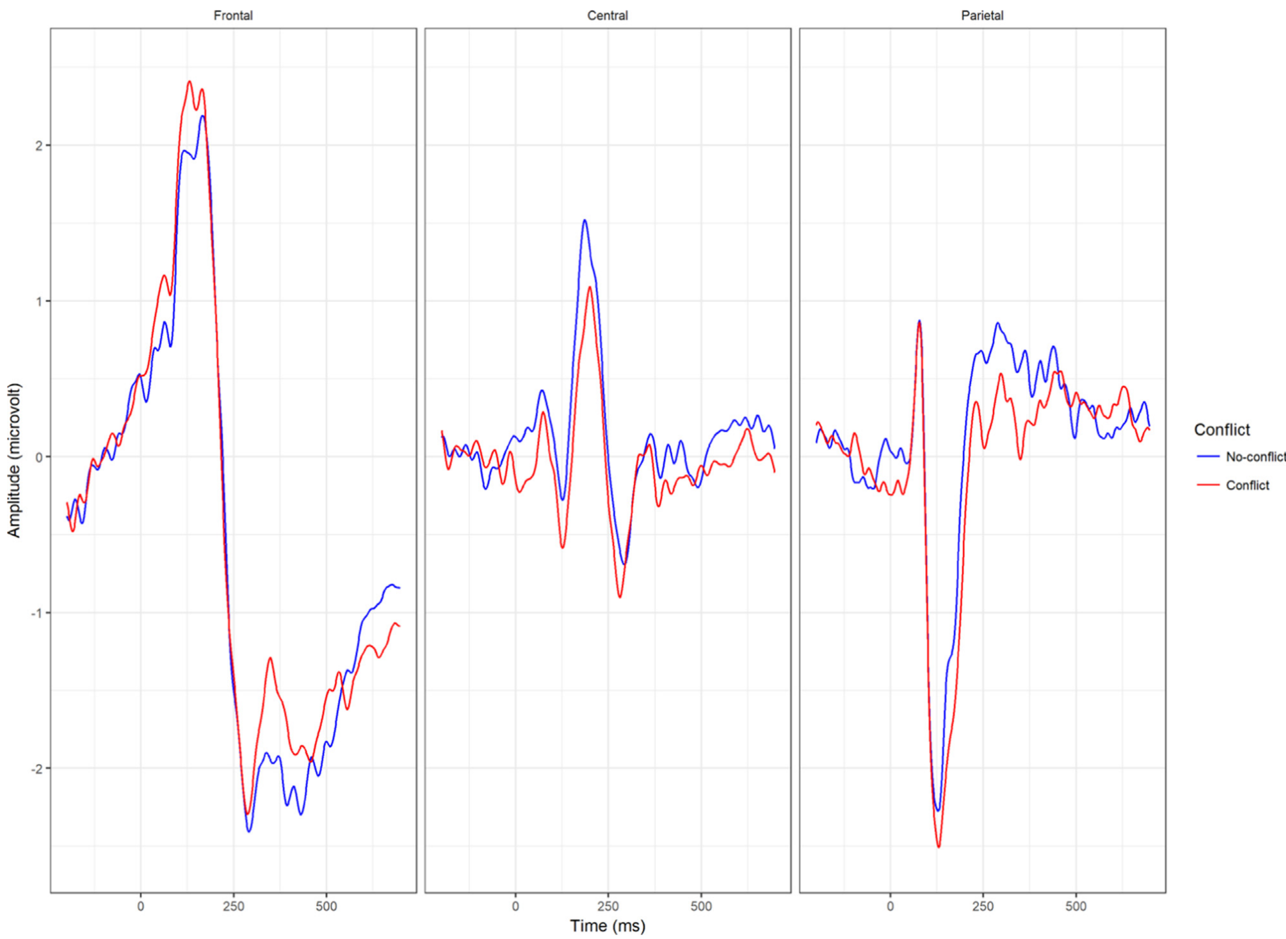


Fig. 1. Grand average ERP waveforms for conflict and no-conflict baseline trials at each of the three electrode locations of interest (Frontal, Central, Parietal).

Frontal group, χ^2 (1) = 13.47, p = 0.001, b = 0.38, but not on the Central, χ^2 (1) = 0.92, p = 0.34, b = -0.08, or Parietal groups, χ^2 (1) = 3.4, p = 0.07, b = -0.21. Hence, P3 findings point to a more frontal conflict sensitivity following the centro-parietal N2.

Next, we also ran an analysis in which we separated the conflict trials by their accuracy. As with the N2, we therefore entered a variable "response category" with 3 levels (no-conflict correct responses, conflict correct and conflict incorrect responses) into the models. We found a significant effect of electrode location, χ^2 (2) = 34.7, p < 0.001, an effect of category, χ^2 (4) = 11.2, p = 0.004, and a significant interaction, χ^2 (8) = 20.3, p < 0.001. Analysis of the individual electrode sites indicated that there was no effect of category at Central, χ^2 (2) = 2.2, p = 0.33, and Parietal sites, χ^2 (2) = 4.37, p = 0.11. Consistent with the overall analysis, response category did have a significant effect at the Frontal site, χ^2 (2) = 24.6, p < 0.001. Follow-up test showed that P3 was significantly more positive for correct conflict trials than in the no-conflict baseline, b = 0.59, t = 4.86, p < 0.001. Although P3 amplitude was also more positive for incorrectly solved conflict than baseline no-conflict trials, the trend did not reach significance, b = -0.01, t = -0.09, p = 0.93. Hence, the frontal P3 conflict effect was specifically driven by correctly solved conflict trials.

4. General discussion

In the present paper we used EEG to test for early conflict sensitivity during reasoning. We adopted base-rate problems in which a cued stereotypical response was either congruent or incongruent with the correct response that was cued by the base-rates. Results showed that solving problems in which the base-rates and stereotypical description cued conflicting responses resulted in an increased centro-parietal N2 and frontal P3. This early conflict sensitivity suggests that the critical base-rates can be processed fast without slow and deliberate System 2 reflection. Consistent with previous EEG work (Banks and Hope, 2014), these results lend credence to recent hybrid dual process models entailing that the fast System 1 is processing both heuristic belief-based responses (e.g., stereotypes) and elementary logical principles (e.g., base-rates).

Results also suggest that the early conflict sensitivity is observed both for correct and incorrect conflict responses. Although the P3 results did not reach significance for incorrect responders, the earlier N2 was observed regardless of response accuracy. Hence, this tentatively suggests that even incorrect responders manage to readily process the base-rate information. This supports earlier behavioral findings on the base-rate and other tasks suggesting that incorrect responding does not necessarily result from a failure to detect conflict (De Neys, 2012; Pennycook et al., 2015).

Overall, our EEG results corroborate the findings of Banks and Hope (2014). Both studies indicate that the N2 and P3 show early sensitivity to heuristic/logic conflict during reasoning at the neural level. This lends general credence to the robustness of the initial Banks and Hope findings. However, for completeness we should point out that there were also some differences between the two studies. One example concerns the directionality of the N2 findings. Although Banks and Hope found that the N2 was affected by conflict, it was not in the direction they initially expected: the N2 was larger (more negative) for no-conflict than for conflict problems. The monitoring and control processes that the N2 is often believed to index typically result in a more negative N2 amplitude in those conditions where one is faced with cognitive conflict (e.g., Folstein and Van Petten, 2008; Ullsperger et al., 2014; Yeung and Summerfield, 2012). Banks and Hope suggested

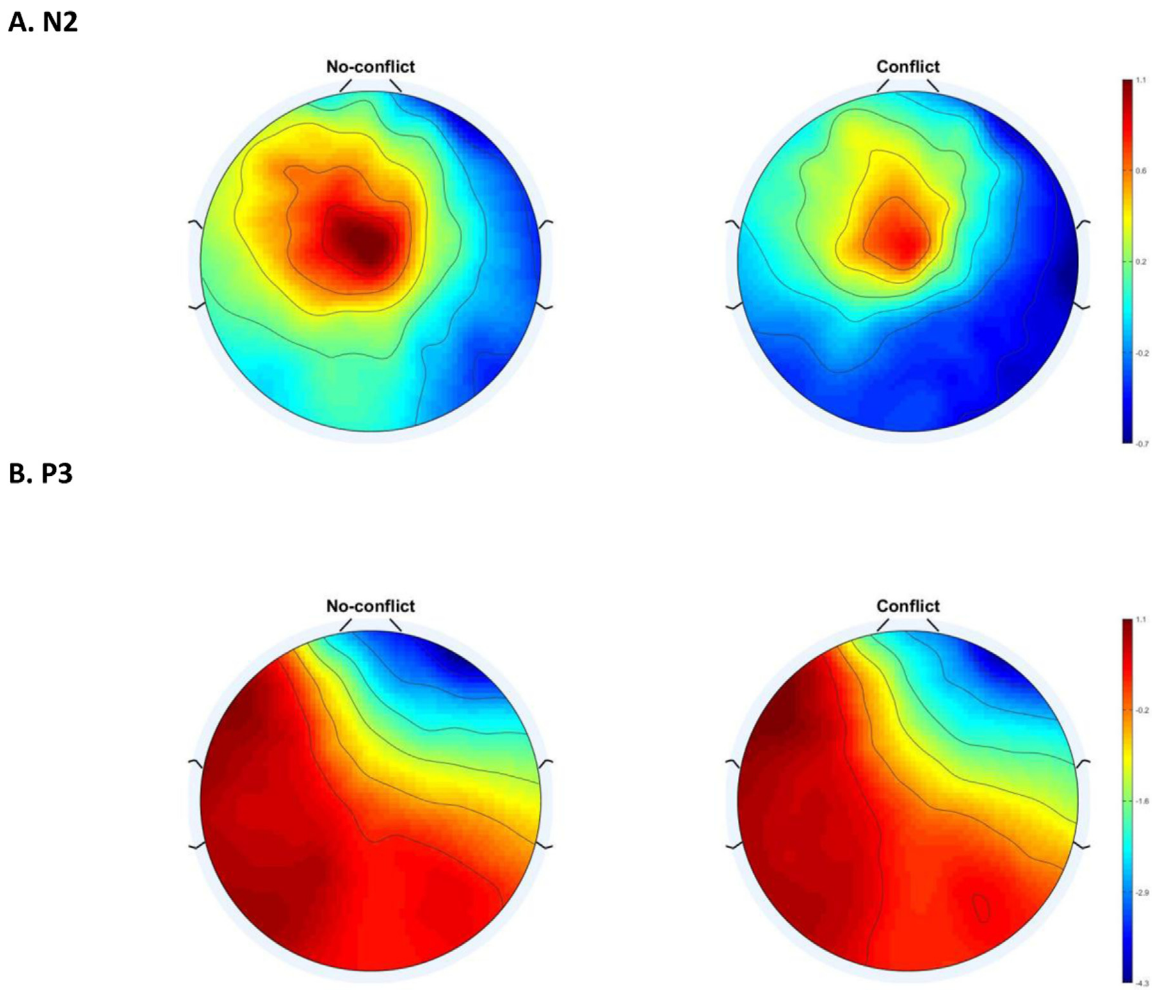


Fig. 2. Scalp topography in the 175–250 ms (N2) and 300–500 ms (P3) time window for conflict and no-conflict baseline trials.

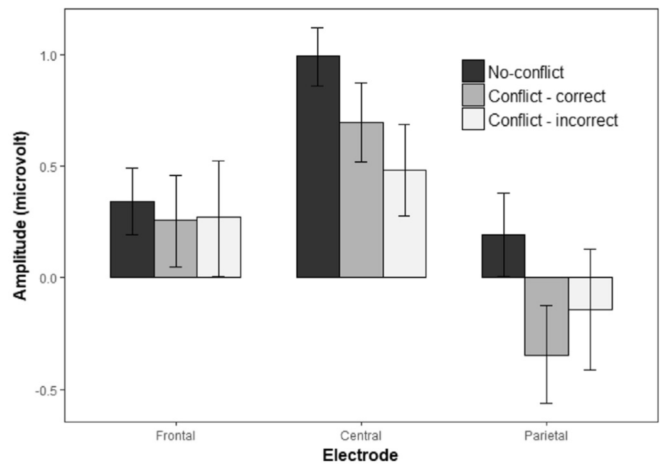
that their finding might result from the peculiarities of the specific paradigm they adopted and might not be reliable. We simply note in this respect that in the present study the N2 did show the expected pattern and was more negative on the conflict than no-conflict problems.

One interesting question for further research concerns the precise nature of the cognitive processes that gave rise to the N2 and P3 potentials. We noted that the N2 and P3 have been frequently linked to control processes such as monitoring, updating, and response inhibition (e.g., Borst et al., 2013; Folstein and Van Petten, 2008; Polich, 2007; Ullsperger et al., 2014; Yeung and Summerfield, 2012). All these processes can be conceived to be implicated in the detection of conflict between a cued stereotypical and base-rate response: In order to detect such conflict, monitoring processes must be engaged, detection of conflict might require updating of one's problem representation, and generation of a single answer can imply inhibition of one of the conflicting responses. The present study does not allow us—and was not designed to—make more specific claims about the precise contribution of each component and to disentangle different hypotheses. For example, we observed that in contrast to correct conflict problem responders, incorrect responders' initial N2 was not followed by a (significant) P3. Based on the assumption that the N2 primarily signals presence of conflict and the P3 response inhibition, one very tentative explanation is that incorrect responders detect conflict but are subsequently less efficient at recruiting inhibitory processing (e.g., Houdé, 2000; Houdé and Borst, 2015; Simon et al., 2015). However, Banks (2017), Banks and Hope (2014) reasoned that the P3 would rather reflect an updating process (e.g., Polich, 2007). Hence, the non-significant P3 for incorrect responders might as well indicate that incorrect responders are struggling with this updating process.

A related point concerns the precise interpretation of our N2 potential. On the basis of the grand average waveforms (Fig. 1) one could argue that this potential might be conceived as a reduced positivity (P2) rather than increased negativity (N2) for the conflict problems. Interestingly, the P2 has been associated with anticipation and selective attention processes (Luck and Hillyard, 1994; Ma et al., 2015; Philips and Takeda, 2009). Studies suggest that an increase in selective attention results in a decreased P2; task conditions that require more selective attention typically give rise to a reduced P2 (Luck and Hillyard, 1994; Philips and Takeda, 2009). Hence, in this light one might note that rather than conflict detection per se, our early "N2/P2" might reflect the selective attention increase that enables or accompanies successful detection.

Although these are interesting questions for further research the key point that was tested in the present study was whether during high-level reasoning we see an early divergence in the ERP signal in cases in which reasoners are confronted with conflict between cued heuristics and base-rate considerations. It is such early sensitivity—in combination with convergent behavioral findings—that presents a strong case against the assumption that taking the base-rates into account and detecting conflict with the cued heuristic response requires slow and demanding System 2 reflection.

In closing, we believe that the present study nicely demonstrates how the temporal resolution of EEG can be used to inform fundamental



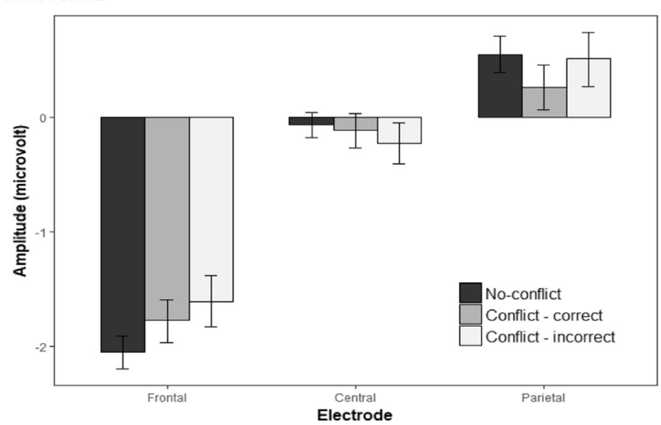


Fig. 3. Average ERP amplitudes for N2 (A) and P3 (B) for all of the three response categories (No-conflict baseline, correct conflict, incorrect conflict) at each electrode location of interest (Frontal, Central, Parietal). Error bars are 95% confidence intervals.

theoretical debates in the reasoning field. Different dual process models make in essence different predictions about the time-course of intuitive and deliberate interaction (Bago and De Neys, 2017; De Neys, 2017; Evans, 2007; Travers et al., 2016). We hope that the current study further illustrates the potential of EEG and will lead to a more general adoption of the methodology in dual process research (Banks, 2017). We conclude that the presently available EEG evidence provides good support for a hybrid dual process model in which the fast System 1 cues both heuristic belief-based responses (e.g., stereotypes) and elementary logico-mathematical principles (e.g., base-rates). In general, this requires us to upgrade the role of System 1 and questions the long-held belief that taking basic logico-mathematical principles into account necessarily requires us to engage in slow deliberative thinking.

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