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Dissociated neural signals of conflict and surprise in effortful decision Making: Theta activity reflects surprise while alpha and beta activity reflect conflict

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A B S T R A C T

What makes a decision difficult? Two key factors are conflict and surprise: conflict emerges with multiple competing responses and surprise occurs with unexpected events. Conflict and surprise, however, are often thought of as parsimonious accounts of decision making rather than an integrated narrative. We sought to determine whether conflict and/or surprise concurrently or independently elicit effortful decision making. Participants made a series of diagnostic decisions from physiological readings while electroencephalographic (EEG) data were recorded. To induce conflict and surprise, we manipulated task difficulty by varying the distance between a presented physiological reading and the category border that separated the two diagnoses. Whereas frontal theta oscillations reflected surprise – when presented readings were far from the expected mean, parietal alpha and beta oscillations indicated conflict – when readings were near the category border. Our findings provide neural evidence that both conflict and surprise engage cognitive control to employ effort in decision making.

1. Introduction

We make countless decisions every day - some of which are easy while others are difficult. But what makes a decision difficult? It turns out that this is a complicated question entrenched in debate. Consider a clinician. Clinicians assess patient symptoms to develop diagnostic hypotheses. A sore throat may indicate a cold, a flu, or the measles. Measles is uncommon and can often be disregarded, but cold and flu are both likely diagnoses and a clinician may be conflicted when deciding between them. Likewise, clinicians are predisposed with expectations of what symptoms their patients may exhibit even prior to meeting them. Just by sheer statistics, clinicians may, for example, expect the average patient to arrive with a cough and a runny nose. When patients exhibit uncommon symptoms, however, the decision-making process becomes more complicated.

We then return to the pressing question: what makes a decision difficult? Decision difficulty refers to judgments that require additional cognitive effort and two key factors contributing to the effort of a decision are conflict and surprise. On one hand, conflict occurs when two or more options are similarly likely (Botvinick and Cohen, 2014; Egner, 2011, 2017; Nigg, 2017) – for example, when the clinician was first deliberating between a cold and a flu. To make a decision we consider different response options (e.g., diagnoses) each with a likelihood (or value) (Krajbich et al., 2010; Krajbich and Rangel, 2011; Tajima et al., 2016) and typically choose the most likely option over less likely options. However, if the likelihood for response options are similar it is difficult to choose between them and response conflict arises (Botvinick and Cohen, 2014; Egner, 2011, 2017; Nigg, 2017). On the other hand, we become surprised with unexpected events (Alexander and Brown, 2011; Brown, 2013; Brown and Alexander, 2017; Vassena et al., 2020; Vassena et al., 2017a,b) – such as when a patient demonstrates rare symptoms. In other words, easy decision making can rely on intuitive heuristics (De Neys, 2017; Evans and Stanovich, 2013; Kahneman, 2011; Pennycook, 2017), but this strategy only functions as long as there is a clear response (i.e., no conflict) and everything subscribes to what is expected (i.e., nothing surprising). If conflict or surprise are present, intuitive decision systems are superseded by analytical decision systems that engage cognitive control (Evans and Stanovich, 2013; Kahneman, 2011).

Neural decision systems determine whether it is necessary to exert effortful top-down control (e.g., to resolve conflict or surprise) and, if so, direct the brain in doing so (Egner, 2017). One computational framework of decision making posits that determining whether to exert control involves a cost-benefit assessment (Alexander and Brown, 2011;

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Brown and Alexander, 2017; Kool et al., 2017; Kool and Botvinick, 2018; Shenhav et al., 2013; 2014; Vassena et al., 2020; Vassena et al., 2017a, b). Whereas cost refers to the expenditure of resources needed to make a difficult decision, benefit is the progress that would be achieved by exerting top-down influence. This model describes that if the benefit outweighs the cost, cognitive control and top-down bias is exerted, but if the cost outweighs the benefit, decisions are made without additional effort (Alexander and Brown, 2011; Brown and Alexander, 2017; Kool et al., 2017; Kool and Botvinick, 2018; Shenhav et al., 2013; 2014; Vassena et al., 2020; Vassena et al., 2017a,b).

Within this cost-benefit framework, conflict operates as a cost of decision making – enforcing the need for increased incentives in fear of relying on faulty intuitions (Shenhav et al., 2014). Surprise signals, on the other hand, affect decision making in a nuanced way. As described by another computational framework of decision making (Alexander and Brown, 2011), humans have a pre-determined degree of effort which we expect to employ during decision making. If these predictions are mistaken, surprise signals index a discrepancy between our expected effort and the actual needed effort and we update our expectations for future decision making.

In sum, computational accounts of decision making posit that conflict signals may operate to resolve decision making in the moment (Shenhav et al., 2014) and surprise signals may function to reduce future difficulty (Alexander and Brown, 2011). With that said, rather than considering conflict and surprise in parallel, researchers have pitted them against each other in pursuit of a single account of effortful decision making (Alexander and Brown, 2011; Brown and Alexander, 2017; Kool et al., 2017; Kool and Botvinick, 2018; Shenhav et al., 2013; 2014; Vassena et al., 2020; Vassena et al., 2017a,b). For example, during an investigation using fMRI, Vassena and colleagues (Alexander and Vassena, 2020; Vassena et al., 2020) discerned patterns of conflict and surprise through computational modelling wherein conflict was modelled using the Expected Value of Control (EVC) framework (Shenhav et al., 2013) and surprise was modelled as the Predicted Response Outcome (PRO) framework (Alexander and Brown, 2011). Their intent was to determine which of these frameworks independently explained neural patterns of effortful decision making. They concluded their neural data to fit the PRO model rather than the EVC model and thus effortful decision making to reflect surprising events rather than conflicting responses. Others have, however, re-interpreted their findings to have reflected a combination of conflict and surprise (Shenhav et al., 2020), indicating a need to further consider both mechanisms in parallel.

In the current study, we examined whether conflict and surprise signals independently or concurrently influence control demands and the employment of effort in decision making. In other words, we investigated whether one of conflict or surprise guides effortful decision making alone or whether the two operate in parallel. Participants were to diagnose virtual patients with one of two diseases based on a physiological reading. Each disease was characterized by a unique range of the reading and task difficulty was manipulated as the distance between the presented reading and the category border that separated the two diseases (see Fig. 1). Thus, difficulty was highest near this border and decreased as readings diverged from it.

Our analyses first focused on determining whether our task varied control demands, which would prompt the adjustment of decision making strategies via cognitive control (Jiang et al., 2015). The demand for control increases when there exists conflict between responses (Shenhav et al., 2013) – in our task the two diagnoses conflicted when the readings were near the category border (i.e., when difficulty was high). Moreover, demands change with changing contexts (Shenhav et al., 2013). In our task, these changes take the form of congruency sequence effects wherein changing demands across trials (incongruent trials, e.g., a conflict trial preceded by a no-conflict trial) elicit increased need for control than consistent demands across trials (congruent trials, e.g., a conflict trial preceded by a conflict trial) (Egner, 2007). Indications of changing control demands correspond to decreased accuracy rates and increased reaction times in the presence of conflict relative to no-conflict as well as in the presence of incongruent relative to congruent consecutive trials (Egner, 2007; Shenhav et al., 2013). Accordingly, we hypothesized that accuracy rates and reaction times would index changing demands in our task by adopting these patterns.

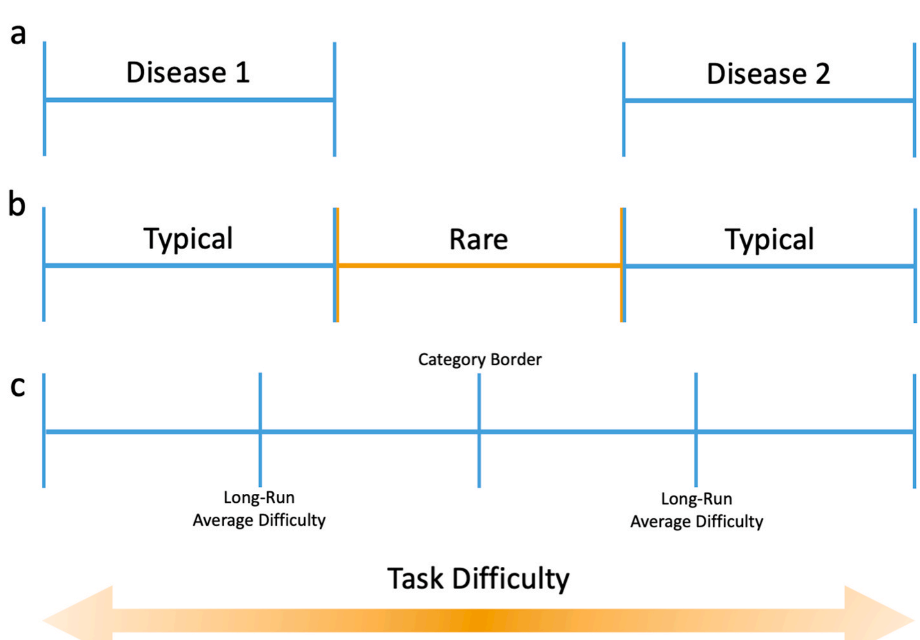

Fig. 1. Depictions of disease ranges in the learning phase (a) and the decision making phase (b) and how they correspond to task difficulty (c). Category border signifies where the range of one disease ended and the other began. The double-sided arrow is a model where the brightness corresponds to the degree of difficulty. [Colour should be used for this figure]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Next, we considered whether neural components of decision making reflected conflict and/or surprise. Within our task, conflict was highest when the presented physiological reading was near the category border and decreased as a function of the distance from this border (see Fig. 1). Conflict was highest at the category border because these readings almost equally corresponded to each diagnosis and was lowest away from this border because one diagnosis was increasingly more likely than the other. Correspondingly, conflict was low at the lowest extreme of the disease 1 range, increased to a maximum at the category border, and then decreased back to low at the highest extreme of the disease 2 range (see Fig. 1c). Statistically, this pattern of conflict could be described as a quadratic polynomial (see Fig. 2).

In addition, as the physiological readings were determined randomly from a uniform distribution on each trial, the long-run average difficulty, and thus the most expected and least surprising readings, for the diagnoses would be within the center of each diagnostic range (see Fig. 1c). Surprise was lowest in the center of each range because participants learned to expect an average difficulty (or level of needed effort) of the task, and deviations from this expectations were unexpected and surprising. Thus, surprise was lowest within the middle of each disease's range and increased as the readings deviated from the center – i.e., towards the outer extremes and towards the category border. Statistically, this pattern of surprise could be described as a quartic polynomial (see Fig. 2).

Here, we investigated oscillatory patterns in the brain corresponding to theta (3–8 Hz), alpha (8–14 Hz), and beta (14–20 Hz) rhythms while participants made decisions as modulations of these EEG rhythms have all been linked to the engagement of cognitive control (Cavanagh and Frank, 2014; De Loof et al., 2019; Lin et al., 2018; Williams et al., 2019). Although there has been neural evidence for both conflict and surprise signals within effortful decision making (Cavanagh and Frank, 2014), they are rarely dissociated and investigated concurrently (Lin et al., 2018; Vassena et al., 2020). Our research here was exploratory thus we had no *a priori* hypothesis as to whether there would be individual or concurrent neural signals of conflict and surprise when making difficult, or else more effortful, decisions. Informally, however, in line with past research (Cavanagh et al., 2012; De Loof et al., 2019; Engel and Fries, 2010; Lin et al., 2018; Williams et al., 2019) we predicted that theta would be positively associated with conflict and surprise and that alpha and beta would be negatively associated with conflict but not associated with surprise.

2. Experimental methods

2.1. Participants

Thirty-three undergraduate students from the University of Victoria participated in the experiment. Three participants were removed due to excessively noisy frontal data leaving us with thirty participants (21.47 years old [19.60, 23.33], 19 female, 10 male, 1 undisclosed). All participants had normal or corrected-to-normal vision and volunteered for extra course credit in a psychology course. Participants all provided informed consent approved by the Human Research Ethics Board at the University of Victoria.

2.2. Experimental design

Participants were seated in a sound dampened room, viewed stimuli on a 19" LCD computer monitor, and responded using a handheld 5-button RESPONSEPixx controller (VPixx, Vision Science Solutions, Quebec, Canada). The task was written in MATLAB (version R2017b, Mathworks, Natick, U.S.A.) using the Psychophysics Toolbox extension (Version 3.0.14; Brainard, 1997).

Participants completed a simplified version of a decision making task used by Williams and colleagues (Williams et al., 2018; see also Bannister et al., 2016; Burak et al., 2015; Horrey et al., 2016; Kazoleas, 2016; Tang et al., 2016). On each trial, they were presented with a simulated medical case including one physiological measure, Alkaline Phosphatase, and were to decide whether their virtual patient had general hepatocellular liver disease or cholestatic intrahepatic biliary disease (see Fig. 3). Here, we use the term 'medical case' to be consistent with the aforementioned research. Although the current cases contained a physiological reading that is pertinent in diagnosing these diseases in real-world settings, we would like to note that the simplicity of what is presented in this research does not adequately reflect the variety of information used to diagnose real patients. Each disease had a unique range of readings (see Fig. 1a) and on each trial a reading for the current disease was randomly determined from a uniform distribution of the corresponding disease range. The ranges were each 115 values wide and were shifted by a random number between 0 and 654 so that no two participants conducted the task with the same readings. Further, the diseases to which each range were representative of were counterbalanced across participants. Although participants were informed that each disease was represented by a range of numbers, they were not told

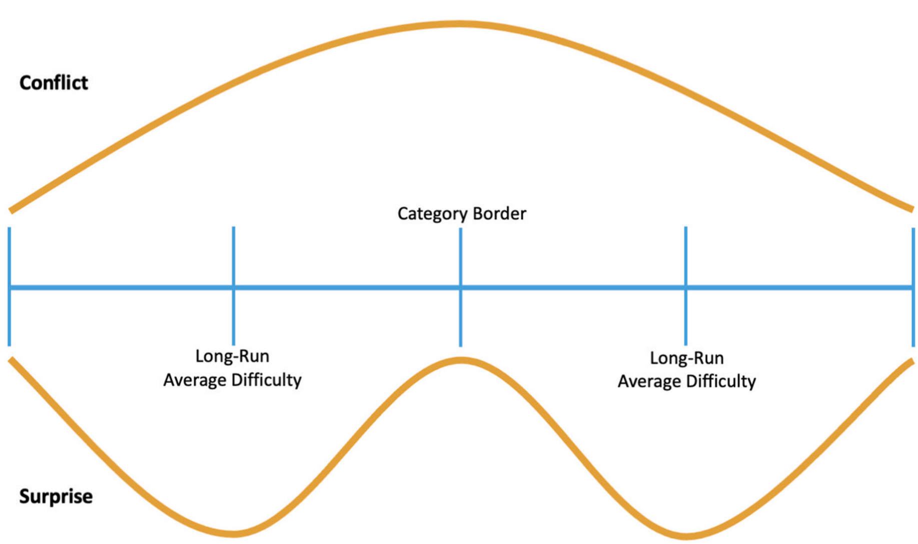

Fig. 2. Polynomials describing predictions of conflict (top orange line) and surprise (bottom orange line). The x-axis corresponds to task difficulty as depicted in Figure. [Colour should be used for this figure]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

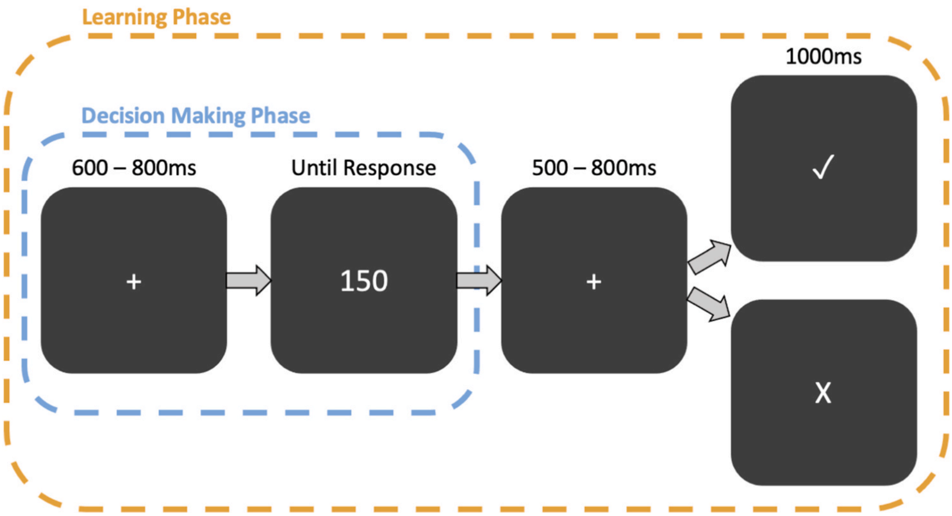

Fig. 3. Task paradigm demonstrating stimuli and timing for both the learning phase (orange) and the decision making phase (blue). [Colour should be used for this figure]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the corresponding ranges, nor the range widths.

On each trial, participants saw a white fixation cross on a dark grey background for 600–800 ms which was followed by a white number representing the physiological measure of the patient. With no time limit, they were to then select one of the two diseases by pressing the left or right button on the response box. Which button represented which disease was counterbalanced and at the beginning of each block participants were reminded which button corresponded to which disease. The experiment was separated into two phases: a learning phase and a decision making phase (see Fig. 3). In the learning phase participants would then see another white fixation cross for 500–800 ms which was followed by a 1 s presentation of a white ✓ or X indicating correct or incorrect, respectively. When participants achieved two consecutive blocks of twenty trials with an accuracy rate of 90% or higher, they moved into the decision making phase of the experiment.

Within the decision making phase, no feedback was presented and participants saw both typical and rare medical cases. Specifically, the readings presented to participants varied as a function of whether they were from the same ranges as in the learning phase (typical cases) or from a new range that had not previously been learned (rare cases), see Fig. 1b. To avoid confusion, we want to emphasize that when using the terms typical and rare, we do not mean frequent and infrequent stimuli, but are rather using terminology that is coherent with the medical literature. The rare cases consisted of physiological readings that fell in between the two ranges that had been previously learned. Participants were told that this phase of the experiment was simply to practice what they had learned and were not told that the ranges of the diseases had been broadened nor that there would be unfamiliar cases. In this phase, participants completed ten blocks of twenty trials, half of which were typical cases and the other half rare cases. Although they were not presented feedback of their performance on each trial, they were informed of their performance after five blocks and at the end of the ten blocks.

2.3. Data acquisition and processing

Accuracy rates and reaction times were recorded using the response box. Behavioural responses were analyzed as markers of changing control demands. First, the typical cases and rare cases were analogous to conflict. In line with categorization literature, there exists a category border wherein readings equally activate each response option (Ratcliff et al., 2016). Rare cases straddle this border, resulting in conflict between the responses. In contrast, the typical cases encompass highly trained readings far from this border and result in no conflict. Thus, to confirm the manipulation of control demands in our paradigm, accuracy rates must decrease and reaction times increase for conflict relative to no conflict trials (Shenhav et al., 2013). Second, an additional marker of changing demands is the congruency sequence effect (Egner, 2007). Congruent trial types (i.e., typical – typical or rare – rare) result in higher accuracy rates and quicker reaction times than incongruent trial types (i.e., typical – rare or rare – typical). Thus, to further confirm changes of demand in our task would be to observe these behavioural patterns. Finally, we additionally analyzed these behavioural measures across task difficulty but describe these procedures below in section 2.4. Statistical Analyses.

EEG data were recorded from a 32 electrode EEG system (ActiCAP, Brain Products, GmbH, Munich, Germany) using Brain Vision Recorder (Version 1.10, Brain Products GmbH, Munich, Germany). Electrodes were all initially referenced to a common ground, impedances were on average kept below 20 kΩ, data were sampled at 500 Hz, and filtered using an antialiasing low-pass filter of 245 Hz through an ActiCHamp amplifier (Revision 2, Brain Products GmbH, Munich, Germany). To ensure precise temporal resolution, we synced EEG markers and stimuli through a DataPixx processing box (VPixx, Vision Science Solutions, Quebec, Canada).

All EEG data were first processed in Brain Vision Analyzer (version 2.1.2.327, Brain Products GmbH, Munich, Germany). Excessively noisy or damaged electrodes were removed, and data was down-sampled to 250 Hz, re-referenced to an average mastoid, run through a dual-pass Butterworth filter (pass band: 0.1 Hz–30 Hz, 4th order), and a notch filter of 60 Hz. To identify and remove blink artifacts, data were put through a restricted infomax independent component analysis (ICA) with classic PCA sphering, components were visually identified by component head maps and related factor loadings, and artifacts were removed via an ICA back transformation. Electrodes that had initially been removed were then interpolated using spherical splines.

All EEG data were then exported to a MATLAB format where the remainder of processing took place. Within MATLAB, data were segmented −500 to 1500 ms centered on markers of interest. The markers of interest coincided with the onset of medical cases. Next, artifact rejection with absolute difference of 200 μV and/or 20 μV/ms gradient criteria was applied. We then conducted wavelet analyses on individual trial data (Gaussian-windowed complex sine wave with a Morlet parameter of 6 for frequencies 1 to 30 in 30 linear steps, no baseline was used; script can be found at www.github.com/neuro-tools; also see Cohen et al., 2008; Cohen, 2014), and standardized the data within each participant. Standardization was completed for each electrode at each frequency within each participant by subtracting the mean of each frequency across conditions and dividing the output by the standard deviation of each frequency across conditions.

Within the time-frequency wavelet data, we first determined clusters of interest using the collapsed localizer approach (Luck and Gaspelin, 2017). This approach consists of averaging data across all conditions and identifying time-frequency clusters of interest. The frequency and time-width of these clusters were constrained to the contour lines of the plotted data (see Results). This approach resulted in two clusters of interest. The first cluster was at electrode FCz spanning frequencies 3–8 Hz within the time range of ~250–750 ms. Although this cluster's frequency range is in line with the theta band, we here caution from using frequency band terminology as it may constrain our ability to interpret time-frequency analyses (Haller et al., 2018). Hereafter, we will simply refer to this cluster as the frontal cluster. The second cluster was maximal at electrode POz and spanned frequencies 7–20 Hz within the time range of ~350–650 ms. This frequency range corresponds to frequency bands alpha and beta. Hereafter, this cluster will be referred to as the parietal cluster.

The task difficulty of each trial was then determined as the difference between the physiological reading presented and the category border, see Fig. 1c. This measure corresponded to response conflict wherein readings near the category border would indicate both diseases as likely diagnoses. As the readings moved away from this border, one response became increasingly more favourable than the other, reducing task difficulty. This resulted in a measure of task difficulty on a continuous scale which we then segmented into 21 bins.

2.4. Statistical analysis

All statistics were conducted in R (Version 4.0.0, the R Foundation, Vienna, Austria; R Team, 2016) using RStudio (Version 1.1.463, RStudio Inc., Boston, U.S.A.)(RStudio Team, 2016). All figures were created using the R package ggplot2 (Wickham, 2016) with the exception of the time-frequency wavelets and topographic maps which were created in MATLAB using EEGLab (Version, 2019; Delorme and Makeig, 2004).

For accuracy rates and reaction times, conflict and congruency sequence effects were determined with two-tailed, repeated-measures *t*-tests (alpha = .05), 95% within-subject credible intervals (Nathoo et al., 2018), and a Cohen's *d* effect size. The assumption of normality was violated for both analyses of accuracy rates, and the assumption of homogeneity of variance was violated for accuracy analyses of conflict. For consistency, all behavioural analyses were then conducted using a Welch's *t*-test.

Our manipulation of task difficulty provided opportunity to determine whether behavioural data confirmed that our task involved changing control demands and whether neural signals reflected conflict and/or surprise. For the former, changes in demand would be confirmed as any relationship between behavioural measures and task difficulty. For the latter, whereas conflict signals would decrease proportionally to the distance from the category border, or in other words via a second order quadratic polynomial, surprise signals would increase with deviations from the long-run average task difficulty, or else a fourth order quartic polynomial, see Fig. 2. For accuracy rates, reaction times, frontal oscillatory clusters, and parietal oscillatory clusters, then, we employed linear mixed-effects modelling techniques (lme4 package; Bates et al., 2015); lmerTest package (Kuznetsova et al., 2017) to determine quadratic fits:

$$Measure \sim \beta_0 + \beta_1 Bin + \beta_2 Bin^2 + (1|Participant) + \varepsilon \quad (1)$$

and quartic fits:

$$Measure \sim \beta_0 + \beta_1 Bin + \beta_2 Bin^2 + \beta_3 Bin^3 + \beta_4 Bin^4 + (1|Participant) + \varepsilon \quad (2)$$

where *Measure* referred to accuracy, reaction time, frontal cluster activity, and parietal cluster activity and *Bin* referred to the binned task difficulty. To determine the fit of each model to neural data, we conducted a model comparison with a null model using chi-square difference tests:

$$Measure \sim \beta_0 + (1|Participant) + \varepsilon \quad (3)$$

For behavioural data, we determined that the presence of a significant quadratic and/or quartic fit would confirm that these measures are sensitive to task difficulty and thus provide additional evidence that our task elicited changing control demands. For neural data, we compared the quadratic model to the quartic model using chi-square difference tests to determine whether they reflected conflict or surprise signals. Although quadratic and quartic polynomials were the focus of our neural analyses due to their description of conflict and surprise, respectively, we also conducted linear mixed-effects modelling investigating linear and cubic polynomial fits. One note is that alpha and beta activity, as encompassed within the parietal cluster, are negatively associated with cognitive control (De Loof et al., 2019; Engel and Fries, 2010; Williams et al., 2019) – increased activity within the parietal cluster signifies reduced control. Correspondingly, the patterns reflected in Fig. 2 would then need to be interpreted inversely when considering the parietal cluster activity.

2.5. Data and code availability

In line with open science policies, all data and scripts (analysis, plotting, and statistics) used for this manuscript can be found at www.osf.io/a65sh/.

3. Results

3.1. Behavioural findings confirm the recruitment of cognitive control

First, we sought to determine whether our paradigm engaged cognitive control in relation to changing control demands. Participants made a diagnostic decision between one of two diseases based on a physiological reading for a virtual patient. Each disease was characterized by a specific value range for the physiological reading and thus we manipulated task difficulty by varying the distance to which the presented readings was from the category border (see Fig. 1). This manipulation of task difficulty afforded us the ability to investigate both conflict and congruency sequence effects. Specifically, readings near the category border would elicit conflict between the two diagnostic responses (conflict condition), and readings far from the border would not (non-conflict condition). Moreover, trials could be considered as congruent (e.g., conflict – conflict) or incongruent (e.g., non-conflict – conflict) depending on the demands of the preceding trial.

Effects of accuracy rate and reaction time when manipulating both conflict and trial-to-trial congruency, confirmed the manipulation of control demands (see Fig. 4). Specifically with regard to conflict manipulations, accuracy rates were greater in the non-conflict condition (97% [96%, 98%]) relative to the conflict condition (80% [77%, 84%]), $M_d = 17\%$ [13%, 20%], $t(29) = 7.94$, $p < .0001$, $d = 1.71$ [1.03, 2.39]. Correspondingly, reaction times were quicker for the non-conflict condition (689 ms [646 ms, 733 ms]) relative to the conflict condition (783 ms [725 ms, 841 ms]), $M_d = -93$ ms [-123 ms, −63 ms], $t(29) = -5.31$, $p < .0001$, $d = -0.51$ [-0.71, −0.30]. Similarly, accuracy rates were higher in congruent trials (90% [88%, 92%]) relative to incongruent trials (88% [85%, 90%]), $M_d = 2\%$ [1%, 4%], $t(29) = 2.73$, $p = .0105$, $d = 0.31$ [0.08, 0.54]. Lastly, reaction times were quicker for congruent trials (716 ms [670 ms, 763 ms]) than for incongruent trials (755 ms [703 ms, 807 ms]), $M_d = -39$ ms [-58 ms, −19 ms], $t(29) = -3.41$, $p = .0019$, $d = -0.23$ [-0.37, −0.09].

In addition to these analyses, we investigate accuracy rates and reaction times in a continuous manner using linear mixed-effects models. For these analyses the assumptions of linearity and homoskedasticity

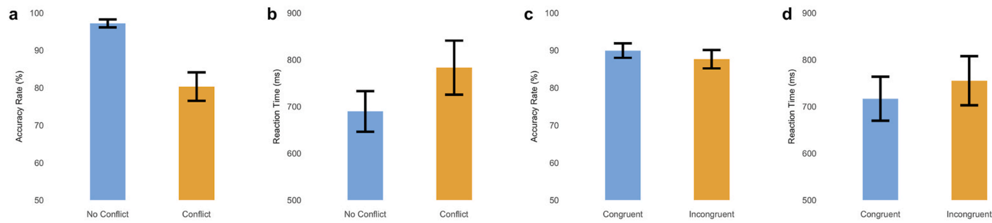

Fig. 4. Behavioural results reflect common findings of cognitive control – i.e., conflict effects (a and b) and congruency sequence effects (c and d). The behavioural effects confirm the recruitment of cognitive control within the task. [Colour should be used for this figure]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

were met; however, the assumption of normality of residuals was violated. As linear mixed-effects models are robust to violations of residual normality (Winter 2013), no corrections were made. These analyses present additional evidence that our task indeed elicited changing demands as demonstrated by both quadratic and quartic fits for accuracy rates (quadratic: $AIC = 52{,}976$, $X^2(2, n = 30) = 356.61$, $p < .0001$; quartic: $AIC = 52{,}753$, $X^2(4, n = 30) = 583.97$, $p < .0001$) and reaction times (quadratic: $AIC = 81{,}304$, $X^2(2, n = 30) = 109.13$, $p < .0001$; quartic: $AIC = 81{,}291$, $X^2(4, n = 30) = 126.08$, $p < .0001$), see Fig. 5.

3.2. *Frontal activity reflects surprise and parietal activity reflects conflict*

Our task affords us the opportunity to investigate task difficulty as a continuous function of the deviation between the readings and the category border with difficulty increasing as readings approached the border (see Fig. 1c). Conflict signals could then be considered continuously in proportion to task difficulty and surprise signals could be considered as deviations from average task difficulty. Recall that conflict is highest at the category border because these readings almost equally indicate both diagnoses and decreases as the readings deviate from this border. Also recall that the best predictor of each diagnosis is the mean of their corresponding range, thus these values are most certain to participants and deviations from each range's center increases surprise. Statistically then, conflict would fit a quadratic pattern in the data while surprise would fit a quartic pattern (see Fig. 2).

EEG time-frequency measures were fit to polynomials reflecting decision making model predictions using linear mixed-effect models. Specifically, frontal cluster power (reflective of theta band activity) and parietal cluster power (reflective of alpha and beta band activity) were identified (see Fig. 6) and fit to quadratic and quartic polynomials to determine their correspondence with conflict and surprise, respectively (see Fig. 7). The assumptions of linearity and homoskedasticity were met for all models, and the assumption of normality of residuals was violated for all models. As linear mixed-effects models are robust to violations of this latter assumption (Winter 2013), no corrections were made.

Frontal power was best fit by the quartic polynomial (quadratic: $AIC = 15{,}575$, $X^2(2, n = 30) = 3.69$, $p = .1581$; quartic: $AIC = 15{,}568$, $X^2(4, n = 30) = 14.71$, $p = .0053$; quartic versus quadratic: $\Delta AIC = -7.02$, $X^2(2, n = 30) = 11.02$, $p = .0040$). Parietal power was best fit by the quadratic polynomial (quadratic: $AIC = 15{,}570$, $X^2(2, n = 30) = 9.69$, $p = .0079$; quartic: $AIC = 15{,}574$, $X^2(4, n = 30) = 9.91$, $p = .0420$; quartic vs quadratic: $\Delta AIC = 3.78$, $X^2(2, n = 30) = 0.22$, $p = .8939$). We also provide a full complement of analyses comparing linear, quadratic, cubic, and quartic trends (1) to a null model and (2) to each other in Tables 1 and 2, respectively. Note that alpha and beta bands of the parietal cluster activity are inversely related to cognitive control, thus higher scores indicate lower control.

4. Discussion

Research has struggled to parsimoniously describe the factors that lead to effortful decision making (Alexander and Brown, 2011; Brown and Alexander, 2017; Kool and Botvinick, 2018; Shenhav et al., 2013; 2014; Vassena et al., 2020; Vassena et al., 2017a,b). Here, we had participants make diagnostic decisions based on a physiological reading of a series of virtual patients while we recorded EEG data. The proximity between the presented physiological reading and the category border served as a manipulation of task difficulty. Specifically, when the presented reading was near the border that distinguished one diagnosis from the other, the likelihood of each diagnosis being correct was near equal and thus the decision was more difficult. In contrast, readings that were further from this border resulted in one diagnosis being more likely than the other thus making the decision easier. As such, our manipulation afforded us the ability to assess predictions of conflict and surprise in that conflict signals increased proportionally to task difficulty and surprise signals increased as a factor of deviation between the presented reading difficulty and the overall average task difficulty.

First, we determined that our paradigm indeed manipulated control

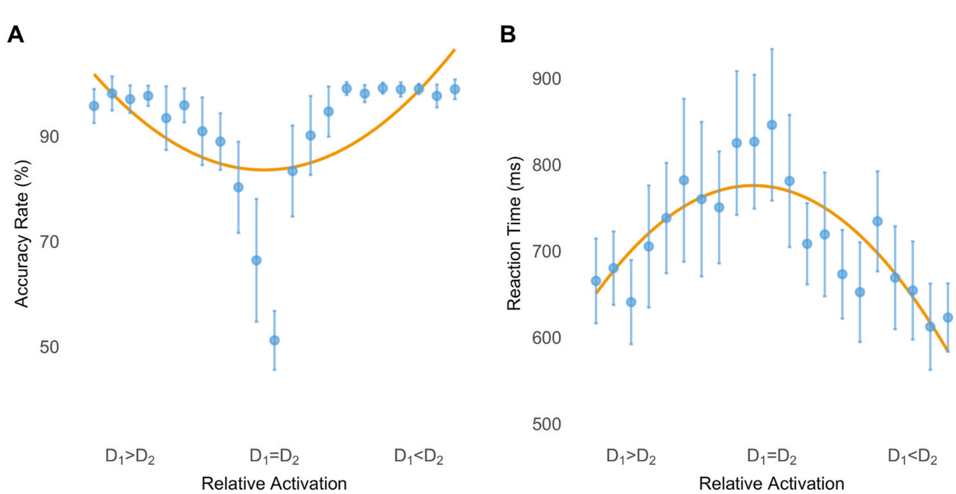

Fig. 5. Accuracy and reaction time reflect changing task difficulty. The x-axis corresponds to twenty-one bins of task difficulty as depicted in Fig. 1c, ranging from favour for disease one to favour for disease two. Each point corresponds to a mean with 95% within-subject credible intervals. Orange lines reflect quadratic polynomials. [Colour should be used for this figure]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

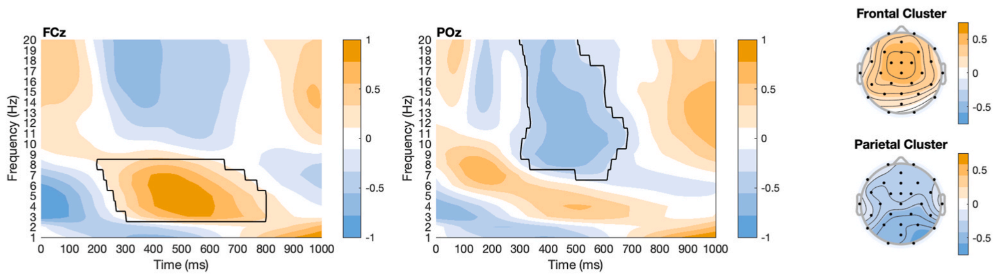

Fig. 6. Two clusters of interest at frontal (FCz) and parietal (POz) locations of the scalp. Standardized time-frequency wavelets correspond to data averaged across all trials. The frontal cluster reflects activity within the theta band (3–8 Hz) and the parietal cluster reflects activity within the alpha and beta bands (7–20 Hz). Black contour lines correspond to extracted regions for analysis. Topographic map values were extracted from time-frequency analyses in correspondence with the contour lines. Colour bars are in units of power (μV^2). [Colour should be used for this figure]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

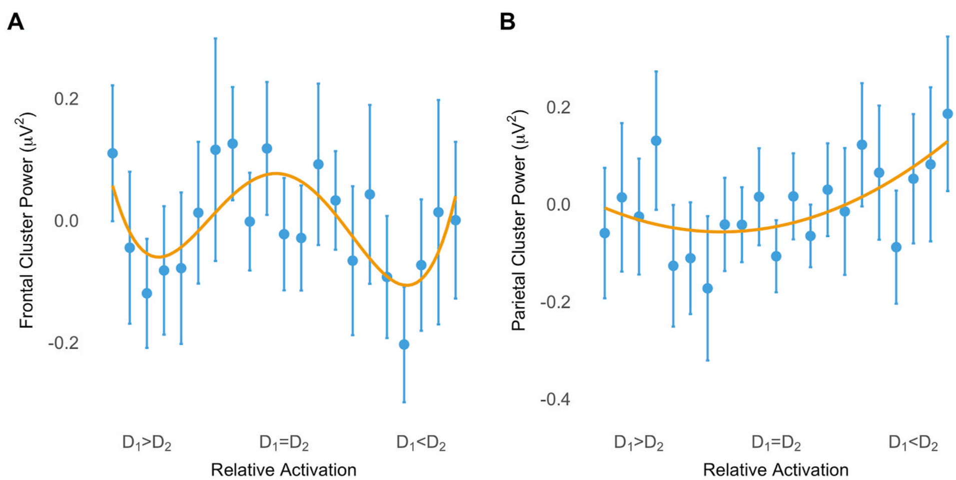

Fig. 7. Frontal cluster power (electrode FCz, frequencies 3–8 Hz) reflects surprise and parietal cluster power (electrode POz, frequencies 7–20 Hz) reflects conflict. Standardized power for the frontal and parietal cluster were determined by the clusters of Fig. 6. The x-axis corresponds to twenty-one bins of task difficulty as depicted in Fig. 1c, ranging from favour for disease one to favour for disease two. Each point corresponds to a mean with 95% within-subject credible intervals. Orange lines are best fit polynomials. [Colour should be used for this figure]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1

Model fits of linear, quadratic, cubic, and quartic trends for frontal and parietal neural clusters. Chi-squared and p-values correspond to model comparison results with a null model. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion.

	AIC	BIC	X^2	*p-value*
Frontal Cluster				
Linear	15,575	15,601	1.58	.2092
Quadratic	15,575	15,608	3.69	.1581
Cubic	15,576	15,616	3.87	.2759
Quartic	15,568	15,614	14.71	.0053
Parietal Cluster				
Linear	15,573	15,599	5.05	.0247
Quadratic	15,570	15,603	9.69	.0079
Cubic	15,572	15,612	9.74	.0209
Quartic	15,574	15,620	9.91	.0420

demands and thus elicited effortful decision making by inspecting behavioural tendencies between the conflict and no-conflict conditions as well as between congruent and incongruent trials. Specifically, accuracy rates were lower and reaction times were higher for conflict trials relative to no-conflict trials, as well as, for incongruent trials relative to congruent trials. Changing control demands were additionally confirmed as accuracy rates and reaction times varied continuously across task difficulty. Next, we identified two oscillatory EEG patterns of interest: a frontal cluster of EEG activity within the theta range and a parietal cluster of EEG activity within the alpha and beta ranges. For each of these, we determined their reflection of conflict (as reflected by a quadratic polynomial) and surprise (as reflected by a quartic polynomial) via linear mixed-effects modelling. Frontal activity fit a quartic function rather than a quadratic function, indicating that it reflected signals of surprise rather than conflict. In contrast, parietal activity fit a

Table 2

Model fits differences and statistical results when comparing across linear, quadratic, cubic, and quartic trends for accuracy, reaction time, the frontal neural cluster, and the parietal neural clusters. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion.

	ΔAIC	ΔBIC	X^2	*p-value*
Frontal Cluster				
Linear vs Quadratic	0	−7	2.11	.1461
Linear vs Cubic	−1	−15	2.29	.3178
Linear vs Quartic	7	−13	13.13	.0044
Quadratic vs Cubic	−1	−8	0.18	.6710
Quadratic vs Quartic	7	−6	11.02	.0040
Cubic vs Quartic	8	2	10.84	.0010
Parietal Cluster				
Linear vs Quadratic	3	−4	4.64	.0312
Linear vs Cubic	1	−13	4.69	.0957
Linear vs Quartic	−1	−21	4.87	.1820
Quadratic vs Cubic	−2	−9	0.05	.8186
Quadratic vs Quartic	−4	−17	0.22	.8939
Cubic vs Quartic	−2	−8	0.17	.6785

quadratic function above a quartic function, determining that it reflected signals of conflict rather than surprise. Thus, there existed a concurrent and dissociable account of conflict and surprise within effortful decision making.

Our findings demonstrate that neither conflict nor surprise in themselves define what makes a decision difficult (i.e., more effortful). Further, they are neither able to independently account for the recruitment of cognitive control and the exertion of effort in decision making – indicating that cognitive control and effort are complex cognitive phenomena that are elicited by a range of factors. Both conflict and surprise need to be considered in parallel and with our findings we now have dissociated neural indicators of each.

Thus, we add to the neural evidence of concurrent contributing factors of cognitive control and effortful decision making. For example, Lin et al. (2018) demonstrated both conflict and surprise signals in decision making. In their task, participants decided between an immediate reward and a delayed reward and task difficulty was manipulated as the subjective difference between the immediate and delayed reward magnitudes. They found that theta activity was highest when the subjective rewards of the options were similar (i.e., conflict was highest) and decreased with the degree to which the options diverged (i.e., decreasing conflict). They also presented participants with a small subset of surprising trials – i.e., no-brainer trials – which were designed so that the immediate reward was undoubtedly better than the delayed reward. They found heightened theta activity with no-brainer trials. As these trials were much easier than what the participants were used to, they concluded that theta was also indicative of surprise. As theta activity varied proportionally to conflict and was large to unexpected no-brainer trials, Lin and colleagues' (2018) findings demonstrate concurrent neural signals of conflict and surprise.

Our findings extend the work of Lin and colleagues by analyzing both conflict and surprise on a continuous scale – demonstrating patterns of both of these signals across task difficulty. With that said, one discrepancy between our findings and those of Lin et al. (2018) is that our frontal EEG activity exclusively reflected a surprise signal whereas Lin and colleagues' found that frontal theta reflected both conflict and surprise. These deviations, however, may simply be due to the different task demands between studies – Lin et al. (2018) manipulated task difficulty as the relative subjective value of the immediate and delayed rewards and we manipulated task difficulty as the relative likelihood of each diagnosis.

In addition to our current findings and those of Lin et al. (2018), Vassena et al. (2020) determined concurrent patterns of surprise and conflict while measuring brain activity via fMRI imaging. In their research, participants were to select one of two pairs of stimuli, each indicating a reward magnitude. Vassena and colleagues manipulated task difficulty, and thus conflict, as the discrepancy between the two option values wherein difficulty and conflict was highest when the magnitudes were similar. In addition, they signified that participants developed an expectation of presented rewards as the long-run averaged reward across trials and thus determined surprise to increase as values diverged from this expectation. They found that activity within the dorsal anterior cingulate cortex corresponded to surprise signals and activity within the ventral medial prefrontal cortex reflected control signals (similar to conflict in our findings). Curiously, despite finding the presence of both conflict-like and surprise signals, Vassena et al. (2020) concluded surprise as the sole contributor to the recruitment of cognitive control – a conclusion criticized by others who posited their findings to provide evidence for both conflict and surprise in effortful decision making (Shenhav et al., 2020).

Together, our findings with those of Lin (2018), Vassena (2020), and their colleagues demonstrate dissociable and concurrent signals of conflict and surprise during effortful decision making. Although it is beyond the scope of the current manuscript, different computational models, such as the Expected Value of Control (EVC; Grahek et al., 2020; Musslick et al., 2017; Shenhav et al., 2013) and the Predicted Response Outcome (PRO; Alexander and Brown, 2011; Brown and Alexander, 2017; Vassena et al., 2020), may afford an explanation as to how our findings of dissociable conflict and surprise signals may affect decision making through the engagement of cognitive control and the employment of effort (Alexander and Brown, 2011; Shenhav et al., 2013). The EVC model posits that expected benefits and costs are utilized to determine whether to initiate cognitive control and the degree of effort to be enforced (Kool et al., 2017; Kool and Botvinick, 2018; Shenhav et al., 2013, 2016, 2020). Thus, control costs (e.g., to resolve conflict) as determined by this model explicitly function to influence action selection. Concurrently, the PRO model tracks expectations and determines alignment with the environment (Alexander and Brown, 2011; Brown and Alexander, 2017; Vassena et al., 2020; Vassena et al., 2017a,b). If discrepancies exist (a surprising event), control is initiated with the function of updating expectations to reduce future difficulty. Thus, conflict signals may recruit cognitive control to reactively address immediate action selection, while surprise signals may recruit cognitive control to proactively account for environmental demands via context-updating.

In conclusion, here we demonstrate dissociable and concurrent signals of conflict and surprise, indicating that neither alone could explain the complexities of effortful decision making. Our findings indicate the complexity of recruiting factors and functions of cognitive control. Specifically, conflict may recruit cognitive control for action selection and surprise may recruit cognitive control to update expectations. We posit that future research may benefit by considering these signals as simultaneous contributors for the recruitment of cognitive control and the employment of effort in decision making as opposed to debating which of them should be considered as the lone contributor.

Author credit statement

C.W. designed the experiment, collected and analyzed the data, conducted statistical analyses, and wrote the manuscript. T.F. and C.H. aided in collecting the data and provided technical expertise on the design of the experiment and the writing of the manuscript. B.W. provided technical expertise on the design of the experiment and the writing of the manuscript. O.K. is the senior author on the project.

Declaration of competing interest

The authors declare no competing interests.

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