



Research Report

Stabilizing expectations when shifting from analytical to intuitive reasoning: The role of prediction errors in reasoning

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ABSTRACT

As humans, we rely on intuitive reasoning for most of our decisions. However, when there is a novel or atypical decision to be made, we must rely on a slower and more deliberative thought process—analytical reasoning. As we gain experience with these novel or atypical decisions, our reasoning shifts from analytical to intuitive, which parallels a reduction in the need for cognitive control. Here, we sought to confirm this claim by employing electroencephalographic (EEG) measures of cognitive control as participants performed a simple perceptual decision-making task. Specifically, we had participants categorize “blobs” into families based on their visual attributes so we could examine how their reasoning changed with learning. In a key manipulation, halfway through the experiment we introduced novel blob families to categorize, thus temporarily increasing the need for analytical reasoning (i.e., cognitive control). Congruent with past research, we focused our EEG analyses on frontal theta activity as it has been linked to cognitive control and analytical thinking. As hypothesized, we found a transition from analytical to intuitive decision-making systems with learning as indexed by a decrease in frontal theta power. Further, when the novel blobs were introduced at the midpoint of the experiment, we found that decisions about these stimuli recruited analytical reasoning as indicated by increased theta power in comparison to decisions about well-practiced stimuli. We propose our findings to reflect prediction errors to decision demands—a monitoring process that determines whether our expectations of demands are met. Shifting from analytical to intuitive reasoning thus reflects the stabilization of our expectations of decision demands, which can be violated with unexpected demands when encountering novel stimuli.

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1. Introduction

As humans, we avoid putting out effort whenever we can (Kool, McGuire, Rosen, & Botvinick, 2010). As a result, we rely on gut-hunches and heuristics to guide us in everyday decisions and only put forth effort when something important comes along; we reluctantly take some extra time to ensure we are making the best possible decision (DeNeys & Pennycook, 2019; Evans & Stanovich, 2013; Kahneman, 2011). Dual-process decision-making theory describes this as the trade-off between intuitive and analytical reasoning (DeNeys & Pennycook, 2019; Evans & Stanovich, 2013; Kahneman, 2011). Within this framework, the majority of our decisions are governed by heuristics. For example, on our commute home from work, we instinctively turn onto our street. But sometimes we must think something through and spend effort in doing so. For instance, when we deliberate whether to move to a new city for a job. In general, intuitive reasoning is thought to be faster but less accurate than analytical reasoning—but this is an acceptable trade-off because most of our intuitive decisions work out (Evans & Stanovich, 2013; Norman et al., 2017). That is, intuitive reasoning is effective when everything is familiar and our responses are well-practiced, a situation that defines most of our daily decisions.

If intuition is so great, why do we ever need to be analytical? As noted above, intuitive reasoning fails when a situation is unfamiliar or uncertain and we do not have a rehearsed response. Another way of putting this is that intuitive reasoning fails us when we encounter something that is novel or atypical (Cavanagh & Frank, 2014; Williams et al., 2021a). Let us say, on a walk to get coffee you are texting on your cellphone, and you take the wrong turn. You end up lost in an unknown neighbourhood. Because intuitions rely on our past knowledge (Croskerry, 2009, 2017; Evans & Stanovich, 2013; Lin, Saunders, Hutcherson, & Inzlicht, 2017), in this novel neighbourhood you are going to have to start thinking and looking for signs that will help you find your way out. This is, of course, effortful and analytical. However, just finding your way out does not mean that the next time you end up in this same neighbourhood you will be able to rely on intuitions because it is still an atypical place for you to be (Ericsson, Krampe, & Tesch-Römer, 1993; Williams et al., 2021a). Considerable experience is needed for something to become intuitive (Ericsson et al., 1993).

Indeed, experience allows us to shift from making analytical to intuitive decisions (Ericsson et al., 1993). We have all heard that *practice makes perfect* and that is exactly what we are talking about here. Let us think about learning a new skill, such as driving. The first time you sat behind the wheel of a car, you likely had more to think about than your brain could handle. You were confronted with a load of gauges, the pedals, and of course the steering wheel. Moreover, you do not know what to pay attention to, so you try and pay attention to all of it. Every decision you make—for example pulling onto the street from your driveway—is a stressful process requiring cognitive effort. However, driving gets easier with practice

and now as an expert driver you can hold a conversation with your passenger while listening to the radio and drinking a coffee all as you commute along a busy highway.

So, what dissociates intuitive and analytical thinking—or in other words, what changes as you practice making decisions? Emerging research suggests that analytical decision making requires cognitive control (Kool, Shenhav, & Botvinick, 2017; Pennycook, Fugelsang, & Koehler, 2015; Williams et al., 2019, 2021a, 2021b) — a mechanism that functions to coordinate cognitive processes. ¹²Neuroimaging research has described cognitive control to coordinate brain networks and recent electroencephalographic (EEG) research has explicitly linked neural signals of cognitive control to analytical thinking (Cavanagh, Figueroa, Cohen, & Frank, 2012; Cavanagh & Frank, 2014; Cavanagh & Shackman, 2015; Eisma, Rawls, Long, Mach, & Lamm, 2021; Umemoto, Inzlicht, & Holroyd, 2019; Williams et al., 2019, 2021a, 2021b). According to Cavanagh and Frank, a neural brain oscillation, specifically frontal theta band activity (4–7 Hz), reflects cognitive control (Cavanagh & Frank, 2014; Cavanagh & Shackman, 2015; Eisma et al., 2021) and has been linked to control demands (Cavanagh & Shackman, 2015; Eisma et al., 2021). Work by our laboratory has elaborated on these findings by linking theta oscillations (i.e., cognitive control) to analytical thinking. For example, in 2019 (Williams et al., 2019) we showed increased frontal theta power corresponded to analytical rather than intuitive reasoning. In 2021 (Williams et al., 2021a), we further demonstrated that, during reasoning, increased theta power was an indicator of surprise, which reflected a novel or atypical environment and thus also the need to recruit cognitive control to reason analytically. Further in 2021 (Williams et al., 2021b), we linked theta power to a person's tendency to respond analytically when completing word problems. Altogether, frontal theta oscillations are related to analytical thinking. However, our previous work contrasted the neural activity of people when placed in situations where they either needed to reason analytically or not. What is yet to be investigated is how cognitive control, as reflected by theta oscillations, changes with learning.

Here we sought to investigate how neural signals of cognitive control change as someone shifts from reasoning analytically to reasoning intuitively. To examine this, we had participants classify complex shapes—which we call *blobs*—into different families. We investigated how cognitive control, as indexed by theta power, changed with experience. We hypothesized that theta power, and thus cognitive control, would decrease with learning, implying the transfer from analytical to intuitive reasoning. In a critical manipulation, halfway through the experiment we introduced two new families of blobs to determine whether these novel stimuli would elicit increased cognitive control relative to stimuli which the participants had already learned. Here, we hypothesized that the introduction of novel stimuli at the halfway point of the study would be associated with increased theta power when making decisions about these new stimuli relative to decisions about previously learned stimuli.

2. Materials and methods

2.1. Participants

Fifteen undergraduate students ($\bar{X}_{age} = 19.60$ years [SD: 3.26 years], 14 female, 1 male) from Dalhousie University participated in this study for course credit via the online sign-up system. All participants had normal or corrected-to-normal vision and provided informed consent approved by the Research Ethics Board at Dalhousie University. Although we did not compute an *a priori* power computation prior to data collection, we here conducted a hypothetical *a priori* analysis in G-Power for a one-way repeated measures ANOVA (one group with three levels) design, searching for a large effect size ($\eta_p^2 = .14$), using an alpha of .05, across three levels of power (.80, .90, .95). The remaining G-Power arguments were left at default (i.e., correlation among repeated measures = .5, and nonsphericity correction = 1). The required sample sizes for a large effect were 12, 15, and 18, for a power of .80, .90, and .95, respectively. Thus, our design afforded us the ability to detect a large effect at a power of .90.

2.2. Sample size and exclusion statement

We report how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study.

2.3. Apparatus and procedure

Participants sat in a dark, sound attenuated room in front of a 19" LCD computer monitor and responded to the task using a Logitech game controller. The task (written in MATLAB version, 8.3, Mathworks, Natick, MA, using the Psychophysics Toolbox (Brainard, 1997)) consisted of participants classifying different families of polygons, or more casually *blobs*. Six families of blobs were constructed in the same way as

Krigolson and colleagues (Krigolson, Pierce, Holroyd, & Tanaka, 2009) wherein six prototype blobs were created by dividing a circle into 20 vertices, randomly placing the vertices within 30–70% of the original circles radius and interconnecting them to form a closed polygon. Each family prototype was then modulated into one hundred exemplars by randomly adjusting the radius of each vertex by $\pm 20\%$, thus creating six families of blobs.

In this task, participants had to learn the blob-family pairings through trial and error. Specifically, they saw a blob and a family name underneath it and their task was to indicate whether that family name was true to the blob or not. Once they responded, they were told whether they were right or wrong. Over trials, they learned to match the blobs to the correct family. In detail, on each trial, participants first viewed a fixation cross for 500–1000 ms, followed by a blob presented in the center of the screen (see Fig. 1). After a 1000–1500 ms delay, a family label (families were named from A to F) was presented underneath the blob and the participants were to report whether the blob fit into the family. Participants made their selection using the green and red button on the Logitech game controller where the green button indicated that the blob and family matched, and the red button indicated that they did not. The label was a correct match 50% of the time. Following this, a second fixation cross appeared for 500–1000 ms and correct or incorrect feedback was presented as a checkmark or an X, respectively, for 1000 ms. There were two phases in this experiment in that the first half of the experiment presented four families of blobs for participants to learn and the second half of the experiment presented two ‘old’ families of blobs that were present in the first half of the experiment and two ‘new’ families of blobs that participants had not yet seen. Note that the order of presentation of blob families were randomly determined across participants so that the ‘old’ and ‘new’ blob families were not always the same. Each half of the experiment consisted of three blocks of 100 trials and thus there were a total of 600 trials in this experiment. Our analyses will focus on early trials of each half of the experiment (when learning was highest) and categorize

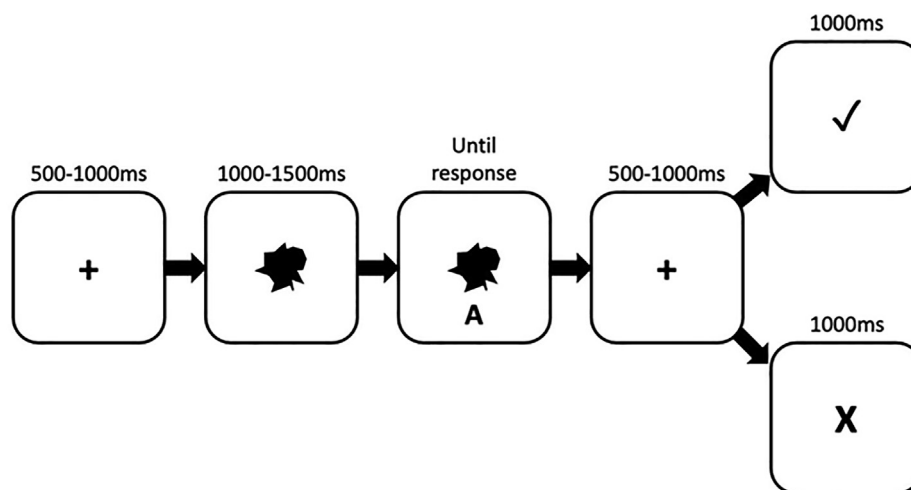


Fig. 1 – Task presentations with timing. On each trial, participants see a fixation cross followed by a blob stimulus. After a delay, a blob family label is presented (here, the ‘A’ family) until the participant indicates whether the family and blob match. Upon their response, a fixation cross precedes feedback (checkmark = correct, X = incorrect).

three conditions. The ‘Early’ condition reflects the initial four families of blobs in the first half of the experiment, the ‘Old’ condition reflects the two families of blobs within the second half of the experiment that were extensively learned in the first half, and the ‘New’ condition reflects the two families of blobs introduced in the second half of the experiment. Thus, we are able to contrast practice effects on decision making by comparing the Early and Old conditions and by comparing the New and Old conditions.

2.4. Data acquisition and processing

Behavioural data were collected using a Logitech game controller and were recorded using MATLAB. EEG data were collected using a 64-electrode system with a 10–20 layout (ActiCAP, Brainproducts GmbH, Munich, Germany) and recorded using Brain Vision Recorder (Brainproducts GmbH, Munich, Germany). Data were recorded with a sampling rate of 500 Hz and filtered with an antialiasing low-pass filter of 245 Hz via an ActiCHamp amplifier (Brainproducts GmbH, Germany). Electrode impedances were, on average, below 10 k Ω .

Although the data were collected in 2014, they were analyzed in 2021 using MATLAB (version, 9.9, Mathworks, Natick, MA) and custom MATLAB scripts and toolboxes (github.com/neuro-tools: MATLAB-EEG-fileIO toolbox, MATLAB-EEG-preProcessing toolbox, and MATLAB-EEG-timeFrequencyAnalysis toolbox), which rely on EEGLAB (Delorme & Makeig, 2004). All data were referenced to averaged mastoids, except for two participants whose mastoid electrodes were faulty and as such data were referenced to an averaged electrode, filtered using a Butterworth passband filter (.1–30 Hz with a 4th order) and a notch filter (60 Hz, 2nd order). Next, eye blinks were corrected using independent component analyses (ICA) wherein ICA blink components were visually identified by factor loadings and scalp topographies and EEG data were reconstructed after removing these components. Data were then segmented from –500 to 1500 ms respective of events of interests. The events of interests were the onset of blob stimuli in the Early, Old, and New conditions. Data were then baseline corrected using 200 ms prior to event onset and run through an artifact rejection algorithm with a 150 μ V max-min criteria. Any electrode that exceeded rejection rates of 20% were tagged as noisy or faulty for removal. Thus far, we have described the first pass of data processing, which we use to identify faulty electrodes. Our second pass of data processing was exactly as just described except with the removal of faulty electrodes at the beginning and the introduction of re-constructing faulty electrodes using topographic interpolation with spherical splines prior to segmentation.

Data were then transformed into time-frequency representations using a Gaussian-windowed complex sine wave with a normalized 6 cycle Morlet parameter to result in frequencies from 1 to 30 Hz. As time-frequency transformations create edge artifacts we then re-segmented data to be –200 to 1000 ms respective of events of interest. Further, we only here present data from 1 to 20 Hz and focus our analyses within theta frequencies (roughly 4–8 Hz).

2.5. Data analysis

There were three conditions of interest considered in this manuscript. The first is named the ‘Early’ condition wherein we investigate the four blob families presented in the first half of the experiment. Two of these four blob families are re-investigated within the second half of the experiment, and this is the ‘Old’ condition. Finally, two new families of blobs are introduced within the second half of the experiment and investigated as the ‘New’ condition. Although the families share lots of features and as such are difficult to categorize, participants performed better than we expected from pilot research. The new blob families in the second half of the experiment were learned at a very quick pace, likely due to generalizability effects of what was learned in the first half of the experiment. As such, we had to focus our analyses to early trials of each experimental half and thus behavioural and neural data for each condition and participant reflected the average of the first five trials of the first/second half of the experiment.

Our paradigm has participants make difficult classifications of complex stimuli and thus would recruit effortful decision making systems of the brain to do so early in learning. As participants become well practiced with learning, they rely less heavily on effortful decision making systems in favour of recruiting effortless decision making systems. As such, we can investigate the effects of learning in two ways. First, we can determine how decision making for a family of blobs changes from the first half (Early condition) to the second half (Old condition) of the experiment, and second we can compare how decision making differs between learned blob families (Old condition) and unlearned blob families introduced in the second half of the experiment (New condition). In other words, we will use the Old condition as an indicator of learned and effortless decision making and compare this to the two unlearned and effortful decision making conditions, namely the Early and New conditions.

Behavioural measures of accuracy rates and reaction times were determined for each condition (see Fig. 2A&B). To determine significant differences in our data, we conducted repeated-measures one-way ANOVAs and then planned comparisons. The planned comparisons were repeated-measures, two-tailed, *t*-tests ($\alpha = .05$) conducted to compare the Early and the New conditions to the Old condition. Additionally, we provide effect sizes in the form of 95% confidence intervals, η_p^2 (for the ANOVAs), and Cohen's *d* measures (for the planned comparisons).

Neural measures of decision making required the extraction of frontal theta components. First, we created grand averaged time-frequency representations for each condition (see Fig. 3A–C). For each comparison (i.e., Early versus Old and New versus Old), we created difference time-frequency representations by subtracting the Old condition from each of the Early and New conditions (see Fig. 3D&E). At electrode FCz (Williams et al., 2019, 2021a, 2021c), we then extracted a cluster of theta activity for each of the comparisons. For the Early-Old contrast, this resulted in a cluster that ranged from 4

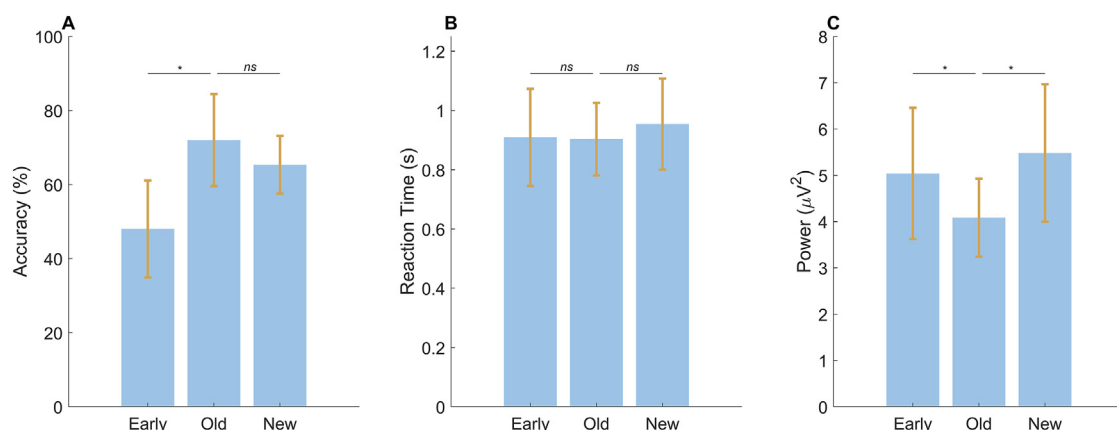


Fig. 2 – Accuracy rates (A), reaction times (B), and frontal theta power (C) across conditions. Bars indicate means with 95% confidence intervals. Asterisk indicates significant effect and ns indicates non-significant effect.

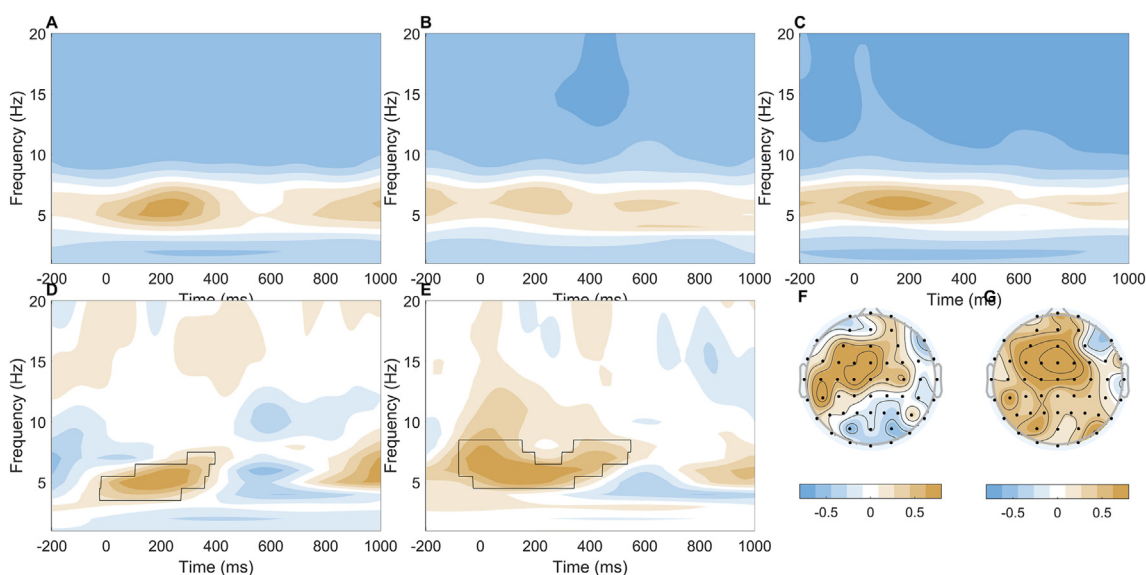


Fig. 3 – Time-frequency plots of the Early (A), Old (B), and New (C) conditions, as well as of the difference between Early minus Old (D) and the difference between New minus Old (E) – contour lines demonstrate theta clusters of interest. To exemplify theta effects of interest, we applied an asymmetric Hamming window which peaked at 5 and 6 Hz. In addition, topographic plots of the theta clusters of the difference between Early and Old (F) and the difference between New and Old (G) across electrodes.

to 8 Hz and from ~0 to ~400 ms post-blob stimulus onset (see Fig. 3D). For the New-Old contrast, this ranged from 5 to 8 Hz and from ~-50 to ~-600 ms post-blob stimulus onset (see Fig. 3E). Note that both components peak at similar frequencies and times and that the latter extends prior to the onset of the blob stimulus (i.e., 0 ms) due to temporal smearing, an artifact of time-frequency transforms (Cohen, 2014).

We then extracted theta activity for each participant and for the Early and New conditions by using their respective clusters. We also extracted theta activity for each participant for the Old condition by using the combination of both clusters to ensure that the Old condition was consistent across both contrasts (see Fig. 2C). First, we conducted a repeated measures one-way ANOVA and then planned comparisons. Planned comparisons were conducted as repeated-measures, two-tailed, *t*-tests

($\alpha = .05$) for each contrast and we also provide 95% confidence intervals, η_p^2 , and Cohen's *d* effect sizes.

2.6. Code and data availability

Our ethics package did not include the collection of consent from our participants for the sharing of raw data; however, we have made summary data and all code available at <https://osf.io/vznqs/>. Furthermore, we are unable to share task presentation code as these have been in part lost since the collection of data in 2014.

2.7. Pre-registration

No part of the study procedures or analyses were pre-registered prior to the research being conducted.

3. Results

For accuracy rates, reaction times, and frontal theta activity, we conducted one-way, repeated measures ANOVAs, and then planned comparisons by contrasting the Early and New conditions with the Old condition, see Fig. 2. An ANOVA revealed a significance in our accuracy data, $F(2,28) = 5.40$, $P = .0104$, $\eta_p^2 = .28$, in that early accuracy rates ($\bar{X} = 48\%$ [35%, 61%]) were statistically lower than Old accuracy rates ($\bar{X} = 72\%$ [60%, 84%]), $\bar{X}_d = -24\%$ [-43%, -5%], $t(14) = -2.67$, $P = .0183$, $d = -.98$, see Fig. 2A. In contrast, New accuracy rates ($\bar{X} = 65\%$ [57%, 73%]) were not statistically different from Old accuracy rates, $\bar{X}_d = -7\%$ [-22%, 8%], $t(14) = -.96$, $P = .3535$, $d = -.35$, see Fig. 2A. An ANOVA did not reveal a significant effect in our reaction time data, $F(2,28) = .31$, $P = .7355$, $\eta_p^2 = .02$, in that early reaction times ($\bar{X} = 909$ ms [745 ms, 1,073 ms]) were not different from Old reaction times ($\bar{X} = 903$ ms [781 ms, 1,026 ms]), $\bar{X}_d = 6$ ms [-143 ms, 155 ms], $t(14) = .08$, $P = .9361$, $d = .03$, see Fig. 2B. Similarly, New reaction times ($\bar{X} = 954$ ms [800 ms, 1,107 ms]) were not statistically different from Old accuracy rates, $\bar{X}_d = 50$ ms [-80 ms, 181 ms], $t(14) = .83$, $P = .4215$, $d = .30$, see Fig. 2B.

Neural analyses first required the identification of frontal theta clusters for each contrast, see Fig. 3. Indeed, we found a theta cluster for each contrast with similar frequency, timing, and scalp topography, see Fig. 3D–G. Generally, these clusters were from 4 to 8 Hz, 0–500 ms post-stimulus onset, and frontal-central. Each cluster was used to extract theta activity for each participant from the corresponding effortful conditions (Early, New). As the old condition serves as a non-effortful contrast for each of the effortful conditions, we extracted data using the combination of both clusters. An ANOVA revealed a significance in our theta power data, $F(2,28) = 3.46$, $P = .0455$, $\eta_p^2 = .20$, in that the Early theta activity ($\bar{X} = 5.03\mu\text{V}^2$ [3.62 μV^2 , 6.45 μV^2]) was statistically larger than theta activity in the Old condition ($\bar{X} = 4.08\mu\text{V}^2$ [3.24 μV^2 , 4.93 μV^2]), $\bar{X}_d = .95\mu\text{V}^2$ [.04 μV^2 , 1.86 μV^2], $t(14) = 2.24$, $P = .0419$, $d = .82$, see Fig. 2C. The New theta activity ($\bar{X} = 5.48\mu\text{V}^2$ [3.99 μV^2 , 6.97 μV^2]) was also statistically larger than the Old condition's theta activity, $\bar{X}_d = 1.40\mu\text{V}^2$ [.26 μV^2 , 2.54 μV^2], $t(14) = 2.63$, $P = .0198$, $d = .96$, see Fig. 2C.

4. Discussion

As expected, we found a decrease in theta power across learning and propose this as neural evidence of a transfer from analytical to intuitive reasoning over practice. Further corroborating these findings is that we found a theta power dissociation between novel and practiced decisions, suggesting the change in theta activity were linked to learning. As a reminder, novel and atypical decisions rely on the engagement of cognitive control (Evans & Stanovich, 2013; Pennycook et al., 2015; Williams et al., 2019, 2021a, 2021b) – a neural mechanism that facilitates decision-making and increases the coordination of different brain regions. With practice of the same decisions, we see a shift of effortful

analytical reasoning to effortless intuitive reasoning—or in other words, a reduction in the need for cognitive control (DeNeys & Pennycook, 2019; Pennycook, 2017, pp. 5–27; Pennycook et al., 2015). Here we demonstrated this shift by measuring frontal theta activity—an EEG signal thought to reflect the engagement of cognitive control (Cavanagh & Frank, 2014; Cavanagh & Shackman, 2015; Lin, Saunders, Frieze, Evans, & Inzlicht, 2020; Williams et al., 2019, 2021a, 2021b). Specifically, we found that frontal theta oscillations decreased with learning. We also introduced novel stimuli halfway through the experiment and found that making classification decisions about them required cognitive control (i.e., analytical reasoning) as evidenced by increased theta activity relative to the well-practiced stimuli, which relied on effortless intuitive thinking.

These findings are even more interesting when considering accuracy rates. As might be expected, we observed an increase in accuracy with learning, yet we did not see reduced accuracy for the novel stimuli introduced in the second half of the experiment. To explain this, we propose that participants were able to generalize their knowledge from the first half of the experiment to the decisions made with these novel stimuli. But what is interesting is that there was still a need for cognitive control and analytical thinking, as evidenced by increased theta oscillations, for the novel stimuli. As such, the implementation of cognitive control and analytical thinking for novel stimuli, as reflected by the proposed functionality of theta activity (Pennycook et al., 2015; Proudfit, 2015; Umemoto et al., 2019; Williams et al., 2019, 2021a, 2021b), without decreased performance (as was the case with early stimuli) implies that these signals are not simply a reflection of poor performance but a reflection of effortful contemplation (Evans & Stanovich, 2013; Kahneman, 2011).

Earlier we discussed getting lost in an unfamiliar neighbourhood as an example of when you would need to employ analytical decision-making to find your way out. Now, let us say you have just moved and the neighbourhood you were previously lost in is your new neighbourhood. At first, you would need to employ analytical decision-making to navigate your new environment, but over time you would learn the streets and landmarks and eventually you could rely on intuitive heuristics. As we are only human, we would most likely only (eventually) learn a single route out of our neighbourhood and stick to it. But what if one day there is unexpected construction, and your normal route is blocked off? Well, you would again need to rely on your analytical reasoning system to find a novel path. If the construction lasted long enough, then the need for analytical reasoning would diminish and you would eventually know that novel path like the back of your hand, navigating it intuitively.

In the present study, we have shown evidence that we can quantify this shift from analytical to intuitive reasoning, and subsequent re-engagement of analytical reasoning when it is needed. Here, these shifts were quantified as frontal theta oscillations and associated with a person's previous experience with an item or event. We propose that, during reasoning, theta oscillations reflect a prediction error—a monitoring process wherein expectations are compared to actual events (Alexander & Brown, 2011; Krigolson, 2018; Proudfit, 2015; Williams et al., 2021c). Specifically, prediction

errors emerge in response to unexpected decision demands—i.e., if a decision is more or less demanding than expected. For example, walking along your normal neighbourhood path has become your expectation, yet the disruption of this path by construction elicits a prediction error, as your path is now going to be more demanding than usual.

Here, when we introduced novel families of blobs, demands of the task became more difficult than expected and prediction errors emerged. As such, the increased frontal theta activity to novel stimuli during reasoning reflected prediction errors concerning the demands of a decision. Indeed, our findings are in line with research describing frontal theta activity to be a signal of surprise in decision making (Lin, Saunders, Hutcherson, & Inzlicht, 2018; Williams et al., 2021a). Here, any unexpected event elicits a prediction error and thus is surprising. Further, the Predicted Response Outcome (PRO) model posits that these surprising events are the consequence of a monitoring process that tracks the likelihood of events, such as stimuli, responses, and their outcomes (Alexander & Brown, 2011; Brown & Alexander, 2017; Vassena, Deraeve, & Alexander, 2020; Williams et al., 2021a).

In line with the PRO model, we provide evidence that these prediction errors are a consequence of monitoring decision making demands. Here, prediction errors emerge when decision demands are not as expected—e.g., when participants encountered unexpected novel blob families to learn. As such, increased theta activity is an indication of a prediction error that recruits cognitive control to update one's expectations of decision demands for future reasoning (Alexander & Brown, 2011; Brown & Alexander, 2017). Consequently, the shift from analytical to intuitive reasoning then involves this monitoring process that stabilizes our expectations of decision demands. Further, if a well-practiced decision presents unexpected characteristics, then a prediction error emerges, and cognitive control is employed to update our expectations.

Again, we pose that the prediction errors we are here considering reflect a deviation of our expectations of the decision's demands; however, it's important to note that this is different from the literature investigating prediction errors of outcome feedback (see Williams, Ferguson, Hassall, Abimbola, & Krigolson, 2021 (Williams et al., 2021c) for a detailed description of prediction errors of feedback). Wherein prediction errors of decision demands reflect deviations from our expectations about the characteristics (e.g., the costs and benefits) of a decision, prediction errors of outcomes reflect deviations from our expected performance. Critically, these two prediction errors would occur at different time points during the reasoning process where the former would occur when faced with a judgment and the latter would occur when faced with feedback of our performance in that judgment.

Although distinct, these two types of prediction errors are related. If we encounter a prediction error when considering a judgment, this could indicate that we are less certain about the decision to be made. If this is the case, then we may expect a decrease in performance for these judgments. Indeed, past work (Krigolson, Hassall, & Handy, 2014) has demonstrated this link where prediction errors of feedback propagated back in the decision process to the judgment onset across learning.

As such, with well-practiced judgments, we may confidently know our performance prior to getting feedback, but with novel or less familiar judgments, we must rely on feedback as we are uncertain about the decision to be made.

There is indeed another theoretical implication of our findings. Here, we present evidence towards a shift from analytical towards intuitive reasoning, signifying that these modes of reasoning are then, in fact, the two extremes of a continuum. This highlights a heated debate within the literature: whether intuitive and analytical reasoning are distinct systems or part of a continuum within a single system (Evans & Stanovich, 2013; Keren, 2013; Keren & Schul, 2009; Kruglanski, 2013; Kruglanski & Gigerenzer, 2011; Osman, 2013; Thompson, 2013). Indeed, the cognitive control literature is depicted as a continuum (Alexander & Brown, 2011; Botvinick & Cohen, 2014; Egner, 2017; Shenhav, Botvinick, & Cohen, 2013) and some dual-process theorists are now describing a continuum that depends on personal experience with a decision (Bago & Neys, 2017; Neys & Pennycook, 2019; Thompson, Pennycook, Trippas, & Evans, 2018). However, we are here limited with how much we can indeed speak towards one or the other theory and as such look forward to seeing future research to further the debate.

5. Conclusion

To summarize, in the present study we ^{7,12,13}demonstrated that changes in theta oscillations reflected a transition from analytical to intuitive reasoning with practice. Additionally, we saw that introducing novel decisions in a well-practiced environment also recruited cognitive control (i.e., increased theta oscillations) to reason analytically and achieve accuracy. We propose that the transition from analytical to intuitive reasoning involves a process wherein our expectations of decision demands are stabilized. Further, if an intuitive decision presents atypical characteristics, we recognize this in the form of a prediction error to recruit cognitive control and update our expectations.

Credit author statement

Chad Williams: Data Curation; Formal Analysis; Investigation; Methodology; Visualization; Writing—original draft. Cameron Hassall: Conceptualization; Investigation; Methodology; Writing—review & editing. Olave Krigolson: Conceptualization; Funding Acquisition; Investigation; Supervision; Writing—review & editing.

Declaration of competing interest

The authors declare no competing financial interest.

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REFERENCES

- Alexander, W. H., & Brown, J. W. (2011). Medial prefrontal cortex as an action-outcome predictor. *Nature Neuroscience*, 14, 1338–1344.
- Bago, B., & Neys, W. D. (2017). Fast logic?: Examining the time course assumption of dual process theory. *Cognition*, 158, 90–109.
- Botvinick, M. M., & Cohen, J. D. (2014). The computational and neural basis of cognitive control: Charted territory and new frontiers. *Cognitive Sci*, 38, 1249–1285.
- Brainard, D. H. (1997). The Psychophysics toolbox. *Spatial Vision*, 10, 433–436.
- Brown, J. W., & Alexander, W. H. (2017). Foraging value, risk avoidance, and multiple control signals. *How the Anterior Cingulate Cortex Controls*. Arxiv, (10), 1656–1673.
- Cavanagh, J. F., Figueroa, C. M., Cohen, M. X., & Frank, M. J. (2012). Frontal theta reflects uncertainty and unexpectedness during exploration and exploitation. *Cerebral Cortex*, 22, 2575–2586.
- Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. *Trends Cogn Sci*, 18, 414–421.
- Cavanagh, J. F., & Shackman, A. J. (2015). Frontal midline theta reflects anxiety and cognitive control: Meta-analytic evidence. *J Physiology-paris*, 109, 3–15.
- Cohen, M. X. (2014). *Analyzing neural time series data: Theory and practice*. MIT Press.
- Croskerry, P. (2009). A universal model of diagnostic reasoning. *Academic Medicine: Journal of the Association of American Medical Colleges*, 84, 1022–1028.
- Croskerry, P. (2017). A model for clinical decision-making in medicine. *Medical Sci Educ*, 27, 9–13.
- Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Meth*, 134, 9–21.
- DeNeys, W., & Pennycook, G. (2019). Logic, fast and slow: Advances in dual-process theorizing. *Curr Dir Psychol Sci*, 28, 503–509.
- Egner, T. (2017). Past, present, and future of the congruency sequence effect as an index of cognitive control. In *The Wiley handbook of cognitive control* 64–78. John Wiley & Sons.
- Eisma, J., Rawls, E., Long, S., Mach, R., & Lamm, C. (2021). Frontal midline theta differentiates separate cognitive control strategies while still generalizing the need for cognitive control. *Sci Rep-uk*, 11, Article 14641.
- Ericsson, K. A., Krampe, R. T., & Tesch-Römer, C. (1993). The Role of deliberate practice in the acquisition of expert performance. *Psychological Review*, 100, 363–406.
- Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspect Psychol Sci*, 8, 223–241.
- Kahneman, D. (2011). *Thinking, fast and slow*. Macmillian.
- Keren, G. A. (2013). Tale of two systems: A scientific advance or a theoretical stone soup? Commentary on Evans & Stanovich (2013). *Perspect Psychol Sci*, 8, 257–262.
- Keren, G., & Schul, Y. (2009). Two is not always better than one: A critical evaluation of two-system theories. *Perspect Psychol Sci*, 4, 533–550.
- Kool, W., McGuire, J. T., Rosen, Z. B., & Botvinick, M. M. (2010). Decision making and the avoidance of cognitive demand. *J Exp Psychology Gen*, 139, 665–682.
- Kool, W., Shenhav, A., & Botvinick, M. M. (2017). Cognitive control as cost-benefit decision making. *The Wiley Handbook of Cognitive Control*, 167–189. <https://doi.org/10.1002/9781118920497.ch10>
- Krigolson, O. E. (2018). Event-related brain potentials and the study of reward processing: Methodological considerations. *Int J Psychophysiol*, 132, 175–183.
- Krigolson, O. E., Hassall, C. D., & Handy, T. C. (2014). How we learn to make decisions: Rapid propagation of reinforcement learning prediction errors in humans. *J Cognitive Neurosci*, 26, 1–10.
- Krigolson, O. E., Pierce, L. J., Holroyd, C. B., & Tanaka, J. W. (2009). Learning to become an expert: Reinforcement learning and the acquisition of perceptual expertise. *J Cognitive Neurosci*, 21, 1833–1840.
- Kruglanski, A. W. (2013). Only one? The default interventionist perspective as a unimodel-commentary on Evans & Stanovich (2013). *Perspect Psychol Sci*, 8, 242–247.
- Kruglanski, A. W., & Gigerenzer, G. (2011). Intuitive and deliberate judgments are based on common principles. *Psychological Review*, 118, 97–109.
- Lin, H., Saunders, B., Friese, M., Evans, N. J., & Inzlicht, M. (2020). Strong effort manipulations reduce response caution: A preregistered reinvention of the ego-depletion paradigm. *Psychological Science*, 31, 531–547.
- Lin, H., Saunders, B., Hutcherson, C. A., & Inzlicht, M. (2017). Midfrontal theta and pupil dilation parametrically track subjective conflict (but also surprise) during intertemporal choice. *Biorxiv*, Article 172122. <https://doi.org/10.1101/172122>
- Lin, H., Saunders, B., Hutcherson, C., & Inzlicht, M. (2018). Midfrontal theta and pupil dilation parametrically track subjective conflict (but also surprise) during intertemporal choice. *Neuroimage*, 172, 838–852.
- Neys, W. D., & Pennycook, G. (2019). Logic, fast and slow: Advances in dual-process theorizing. *Curr Dir Psychol Sci*, 28, 503–509.
- Norman, G. R., Monteiro, S. D., Sherbino, J., Ilgen, J. S., Schmidt, H. G., & Mamede, S. (2017). The causes of errors in clinical reasoning. *Academic Medicine: Journal of the Association of American Medical Colleges*, 92, 23–30.
- Osman, M. A. (2013). Case study: Dual-process theories of higher cognition-commentary on Evans & Stanovich (2013). *Perspect Psychol Sci*, 8, 248–252.
- Pennycook, G. (2017). A perspective on the theoretical foundation of dual-process models. In *Dual process theory 2.0*. Psychology Press.
- Pennycook, G., Fugelsang, J. A., & Koehler, D. J. (2015). What makes us think? A three-stage dual-process model of analytic engagement. *Cognitive Psychol*, 80, 34–72.
- Proudfit, G. H. (2015). The reward positivity: From basic research on reward to a biomarker for depression. *Psychophysiology*, 52, 449–459.
- Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2013). Review the expected value of control: An integrative theory of anterior cingulate cortex function. *Neuron*, 79, 217–240.
- Thompson, V. A. (2013). Why it matters: The implications of autonomous processes for dual process theories-commentary on Evans & Stanovich (2013). *Perspect Psychol Sci*, 8, 253–256.
- Thompson, V. A., Pennycook, G., Trippas, D., & Evans, J. S. B. T. (2018). Do smart people have better intuitions? *J Exp Psychology Gen*, 147, 945–961.
- Umemoto, A., Inzlicht, M., & Holroyd, C. B. (2019). Neuropsychologia Electrophysiological indices of anterior cingulate cortex function reveal changing levels of cognitive effort and reward valuation that sustain task performance. *Neuropsychologia*, 123, 67–76.
- Vassena, E., Deraeve, J., & Alexander, W. H. (2020). Surprise, value and control in anterior cingulate cortex during speeded decision-making. *Nat Hum Behav*, 4, 412–422.
- Williams, C. C., Ferguson, T. D., Hassall, C. D., Abimbola, W., & Krigolson, O. E. (2021). The ERP, frequency, and

- time–frequency correlates of feedback processing: Insights from a large sample study. *Psychophysiology*, 58, Article e13722.
- Williams, C. C., Ferguson, T. D., Hassall, C. D., Wright, B., & Krigolson, O. E. (2021). Dissociated neural signals of conflict and surprise in effortful decision Making: Theta activity reflects surprise while alpha and beta activity reflect conflict. *Neuropsychologia*, 155, Article 107793.
- Williams, C. C., Kappen, M., Hassall, C. D., Wright, B., & Krigolson, O. E. (2019). Thinking theta and alpha: Mechanisms of intuitive and analytical reasoning. *Neuroimage*, 189, 574–580.
- Williams, C. C., VanOorschot, F., & Krigolson, O. E. (2021). A window into the rational mind: The neural underpinnings of human reasoning. *PsyArXiv*, 1–21. <https://doi.org/10.31234/osf.io/gc6u9>