A Window into the Rational Mind:
The Neural Underpinnings of Human Reasoning

Chad C. Williams*, Folkert Van Oorschot, and Olave E. Krigolson

The Theoretical and Applied Neuroscience Laboratory, University of Victoria, Victoria, British
Columbia, V8W 2Y2, Canada

*Corresponding author: Chad C. Williams, The Theoretical and Applied Neuroscience
Laboratory, University of Victoria, P.O. Box 17000 STN CSC, Victoria, British Columbia,
Canada, V8W 2Y2
Tel: 1-250-858-4682; Fax: 1-250-721-6601; E-mail address: ccwillia@uvic.ca

Abstract

Humans reason intuitively by relying on gut hunches or rationally through analytical contemplation. The majority of research on human reasoning has relied on behavioural data and thus the neural underpinnings of this process remain unclear. To address this, we had participants perform a classic reasoning task while electroencephalographic (EEG) data was recorded. Within our reasoning task, participants completed a series of base-rate word problems wherein their decisions were either biased by a provided stereotype or based on statistical probability. Post experiment, we defined participant rationality as the percentage of responses that were made based on likelihood. We then examined frontal theta neural oscillations and found that increased power in this frequency range was associated with increased rationality. Our findings imply that theta oscillations are sensitive to rationality and further that rational reasoning involves a diverse brain network relative to intuitive reasoning.

NEUROIMAGING RATIONALITY

Reasoning is an art that often fails us. We all, on occasion, have acted instinctively and ended up kicking ourselves in hindsight for making faulty judgments. To save ourselves from poor decision making and potential embarrassment, should we abandon intuitive thinking in favour of rationality? Of course not, as we have all also analytically overthought a decision, and still made the wrong choice. A balance between intuitive and rational reasoning is necessary for optimal decision making.

Intuitive reasoning is fast and effortless but can lead to mistakes^{1,2}. In contrast, rational reasoning is slower and more accurate but takes considerable effort^{1,2}. We should not discredit intuitive reasoning, however, simply because it is potentially less accurate. Indeed, we rely on intuitive reasoning for the majority of our decisions as it most often leads to an acceptable outcome^{1,3}. Yet, intuitive reasoning can fail when an unexpected or difficult decision requires more thought and consideration³⁻⁵. In these instances, we typically turn to rational reasoning to arrive at a suitable decision. As such, there is an intimate balance between intuitive and rational reasoning where we operate to conserve energy until we must exert effort when faced with a difficult decision^{6,7}.

Our understanding of intuitive and rational decision making mostly stems from a large body of research focused on the resolution of word problems. For example, Frederick's⁸ classic widget problem: *"It takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?"* Such problems have two common answers: one intuitive and incorrect (i.e., 100 minutes) and the other rational and correct (i.e., 5 minutes). Another example of reasoning problems are base-rate problems^{9,10}: *"There are clowns and accountants. Person A is funny. There are 30 clowns and 70 accountants. Is person A a clown or an accountant?"* Here, both stereotype (Person A is funny) and base-rate (there are more accountants than clowns)

information are presented – whereas an intuitive response adheres to the stereotype information, a rational response follows the base-rate information. Unlike Frederick's⁸ widget problem, base-rate problems do not have right or wrong answers – the person being a clown or an accountant are both possible – but instead these problems measure people's tendency to reason intuitively or rationally depending on the piece of information they base their decision on⁹. When the presented stereotype and base-rate information are incongruent, strictly intuitive reasoners will respond using the stereotype information and strictly rational reasoners will respond using the base-rate information. Reasoners can also fall in between these two extremes – sometimes making decisions using the stereotype information and other times using the base-rate information. Thus, people who make the majority of their decisions using base-rate information are proposed to reason more rationally than those that rely more on stereotype information.

Neuroimaging has begun to provide insight into the neural systems that underlie intuitive and rational reasoning. For example, Bago and colleagues¹¹ used electroencephalography (EEG) to examine the neural underpinnings of human reasoning during the deliberation of base-rate problems. In this task, the stereotype and base-rate information may be congruent or incongruent, depending on whether they indicate the same response or not, respectively. Although the authors found neural responses that distinguished congruent from incongruent trials, their analyses did not specifically investigate differences between intuitive and rational reasoning (see also Banks¹²). Paralleling these findings, Vartanian and colleagues¹³ determined via functional magnetic resonance imaging (fMRI) that activity within the anterior and posterior cingulate cortices differed between congruent and incongruent base-rate problems (see also De Neys et al.¹⁴). However, they too did not examine differences in neural activity between intuitive and

rational responses. As such, the neural systems that underlie intuitive and rational reasoning, while hypothesized, are still not clear.

To address this gap, in the current study we used electroencephalography to probe the neural correlates of human rationality. We accomplished this by having participants complete base-rate problems (e.g., Bago et al.¹¹) so that we could examine whether neural oscillations are sensitive to intuitive and rational reasoning¹⁵. Furthermore, neural oscillations are theorized to correspond to the degree of communication across the brain – fast oscillations reflect localized brain activity and slow oscillations reflect the coordination of structures across a diverse brain network¹⁶. As rational thinking involves coordination across multiple brain regions, we focused our analyses on neural oscillations in the theta band (4 – 8 Hz)^{15,17} and found a strong relationship between these oscillations and rationality.

Materials and Methods

Participants

Thirty-three undergraduate students participated in this study. One participant was removed due to excessive noise in their EEG data and two others were removed as outliers determined via an evaluation of Cook's distances during analyses (see below). Thus, here we report 30 participants ($M_{age} = 20.53$ years old [19.61 years old, 21.46 years old]; 15 female, 15 male). Cognitive control and reward learning literature indicate theta effect sizes to be large and thus require sample sizes of 10¹⁸ and 23¹⁹, respectively, to achieve 95% power – confirming our sample size which exceeds these calculations. All participants were recruited through an online sign-up system wherein they earned course credit within psychology courses, were native English speakers, and had normal or corrected-to-normal vision. All participants provided

informed consent and this study was approved by the Human Research Ethics Board at the University of Victoria (Ethics Protocol Number: 16-428).

Apparatus and Procedure

Participants sat in a dark, sound-dampened room in front of a 22" LCD computer monitor and responded to the task using a ResponsePixx controller (VPixx, Vision Science Solutions, Quebec, Canada). The task (written in MATLAB version 8.6, Mathworks, Natick, MA, using the Psychophysics Toolbox Extension version 3.0.8²⁰) consisted of a series of base-rate questions taken from work by Pennycook and colleagues⁹. Base-rate questions introduce two populations (e.g., clowns and accountants), provides stereotype information (e.g., Person A is funny), provides base-rate information (e.g., there are 5 clowns and 995 accountants), and ask the participant to determine which population the indicated target (Person A) is from. With base-rate problems, the stereotype and base-rate information may be congruent or incongruent. For example, a congruent problem would indicate that Person A is funny and that there are 995 clowns and 5 accountants, while an incongruent problem would indicate that Person A is funny but that there are 5 clowns and 995 accountants. Within the congruent condition, there is an easy and obvious response; however, within the incongruent condition a participant may formulate their response dependent on the stereotype or the base-rate information.

On each trial, population information, stereotype information, base-rate information, and response options were presented sequentially with each lasting 1900 to 2100 ms. Problem information was presented sequentially with new information being appended to previously presented information. Presented information was spaced so that the base-rate information was presented in the center of the monitor (where participants were instructed to keep their gaze). Participants were provided up to 3000 ms to indicate (left, right on response controller) which

population (e.g., accountant or clown) the target person was from. If they did not respond within this time limit, they were told they were ‘TOO SLOW’ via feedback presented on the computer display; note that too slow trials were removed from all analyses. Base-rate information was manipulated across extreme, moderate, and non-informative conditions: within the extreme condition, base-rates were 994/6, 995/5, 996/4, 6/994, 5/995, 4/996; within the moderate condition, base-rates were 69/31, 70/30, 71/29, 31/69, 30/70, 29/71; within the non-informative condition, base-rates were 50/50. Conditions were pseudo-randomly selected each trial across 11 blocks of 18 problems with the restriction that all conditions were presented 66 times, half of which were congruent and the other half incongruent. Prior to the task, participants were presented two practice problems. The current article considers a subset of data of the larger project just described. As such, the current analyses only consider the extreme and moderate base-rate conditions.

Data Acquisition and Processing

Behavioural data were collected and recorded using the ResponsePixx response box and MATLAB, respectively. EEG data were collected using a 32-electrode system with a standard 10-20 layout (ActiCAP, Brainproducts GmbH, Munich, Germany) and recorded using Brain Vision Recorder (Version 2.1., Brainproducts GmbH, Munich Germany). EEG data were sampled at 500 Hz, amplified, and filtered using an antialiasing low-pass filter of 245 Hz (ActiCHamp, Revision 2, Brainproducts GmbH, Germany). To ensure data quality, electrode impedances were on average kept below 10 k Ω , and to ensure temporal accuracy of event markers we used a DATAPixx stimulus timing unit (VPixx, Vision Science Solutions, Quebec, Canada).

Processing of EEG data was conducted using custom MATLAB scripts which can be found on github.com/neuro-tools (MATLAB-EEG-fileIO toolbox, MATLAB-EEG-preProcessing toolbox, and MATLAB-EEG-timeFrequencyAnalysis toolbox) and functions from EEGLAB²¹. First, excessively noisy or faulty electrodes were removed, data were re-referenced to an averaged mastoid electrode, and data were filtered using a Butterworth filter (passband: 0.1 to 30 Hz, 4th order) and a notch filter (60 Hz, 2nd order). Next, eye blinks were removed using infomax independent component analysis (ICA) where ICA components were first determined and identified as eye blinks via visual inspection and then EEG data were reconstructed without the eye blink components. Then, removed electrodes in step one were interpolated using spherical splines, data was segmented from -700 to 1500 ms (note that the window of interest was -200 to 1000 ms and that we here added 500 ms on either side of this range to accommodate for time-frequency edge artifacts) surrounding markers of interest (the onset of the base-rate information), and baseline corrected using a -200 to 0 ms time window. Trials that violated artifact rejection criteria of 150 μ V max-min were removed (total percentage of trials removed: 16% [12%, 20%]). After processing, we transformed EEG data into time-frequency data using a Gaussian-windowed complex Sine wave with a Morlet parameter of 6 cycles, a baseline correction of -200 to 0 ms, and normalization into 30 frequencies in linear steps from 1 to 30 Hz. Here, we only considered theta frequencies (4 – 8 Hz).

Data Analysis

The experimental paradigm afforded us with two within-subject factors: congruency (congruent, incongruent) between the stereotype and base-rate information and base-rate extremity (extreme, moderate, non-informative). As we were here investigating behavioural and neural responses when presented two sources of information (stereotype, base-rate), the non-

informative base-rate conditions were not considered. Thus, we were left with congruent extreme, incongruent extreme, congruent moderate, and incongruent moderate conditions.

First, we determined participants' behavioural tendencies to respond intuitively (i.e., focusing on the stereotype information in incongruent trials) or rationally (i.e., focusing on the base-rate information in incongruent trials). We determined the percentage of rational responses as the percentage of times participants responded in line with the base-rate information on incongruent trials. Thus, 0% means that participants always responded in accord with stereotype information, 100% means that participants always responded using the base-rate information, and 50% means that participants responded with equal investment in both. We also extracted reaction time data for each participant as the average reaction time of incongruent extreme and moderate conditions (the same conditions used to determine the percentage of rational responses). To determine whether there was a relationship between rationality and reaction time, we conducted a Pearson R correlation (using the *corrcoef* function in MATLAB, $\alpha = .05$). Assumptions of normality and homoskedasticity were met for these analyses.

Here, we focused our research question to determine if EEG activity was in general related to participant's tendency to respond rationally. EEG data extraction involved two steps: 1) determining clusters of interest, and 2) extracting oscillatory activity on a participant level. To determine clusters of interest, we first extracted participant level time-frequency activity by averaging each condition separately and then baseline correcting the incongruent conditions with the corresponding congruent conditions (e.g., incongruent moderate minus congruent moderate). These data were then averaged across conditions and participants and time-frequency clusters were determined as any data greater than 0.10 dB. We restricted clusters to frontal theta activity (4-8 Hz at electrode FCz) given our *a priori* hypotheses. Theta power was then extracted and

averaged (across frequency and time) for each participant using the identified cluster. To determine whether there was a relationship between rationality and reaction time/theta power, we performed Pearson R correlation analyses (using the *corrcoef* function in MATLAB, $\alpha = .05$). Assumptions of normality and homoskedasticity were met for these analyses.

Results

No Relationship Between Rationality and Reaction Times

To determine whether rationality was reflected in behavioural observations, we compared the percentage of times that participants responded rationally ($M = 62\%$ [54%, 70%], range = 8% to 98%) with reaction times. We found no relationship between rationality and reaction times, $r(28) = 0.07$, $p = .7042$, see Figure 1.

Strong Relationship Between Rationality and Theta Activity

Next, we determined whether participant rationality was related to frontal theta activity. Indeed, we found a theta cluster of interest at electrode FCz with the frequency range of 4 to 8 Hz and the time range of ~100 to ~600 ms post-base-rate information onset (see Figure 2 and Figure 3). There was a strong positive relationship between this frontal theta activity and participants' rationality, $r(28) = 0.64$, $p = .0001$ (see Figure 4).

Discussion

Our principal finding was that frontal theta oscillations predicted rationality. Specifically, increased frontal theta power was associated with increased rationality and vice versa. The relationship between theta oscillations and rationality that we observed here reinforces the proposition that high-level cognitive mechanisms including cognitive control and working memory play a critical role in reasoning^{15,22–24}. Furthermore, as slow-wave brain oscillations such as those in the theta band are posited to reflect the communication of disparate brain

regions, the relationship between theta oscillations and rationality also implies that rational reasoning involves increased coordination across the whole-brain in comparison to intuitive reasoning¹⁶.

Our findings are in line with recent work¹⁵ replicating and extending Kahneman and colleagues'²⁵ seminal findings on reasoning. Kahneman et al. presented participants with four numbers and had them either report those same four numbers (add-zero condition) or report the four numbers after adding one to each of them (add-one condition). Their pupillometry findings determined the add-one condition to require more effortful and rational thinking than the add-zero condition. Williams and colleagues¹⁵ replicated these findings and further determined frontal theta activity to be larger for the add-one condition than the add-zero condition, signifying the involvement of cognitive control and working memory in reasoning. Moreover, Cavanagh and colleagues²⁶ investigated the neural underpinnings of conflict detection, a precursor to cognitive control, in a Simon task. This task had participants making rightward and leftward responses contingent on the presented shape. These shapes may cause conflict when they are presented on the opposite side of the screen than the response. Indeed, frontal theta activity was enhanced in the conflict condition relative to the non-conflict condition, implying the need for cognitive control. Congruent with our findings here, these aforementioned studies concluded rational thinking to involve mechanisms of cognitive control and working memory as well as a coordination across the brain.

Our findings add to a growing body of EEG and fMRI literature^{11–14} investigating the neural basis of reasoning. Our results are also in line with studies examining cognitive control and executive functioning that have probed the underlying mechanisms of reasoning by employing niche tasks to assess specific theorized mechanisms²⁷. For example, the Stroop task

has people reading the name of a colour that is printed in either the same or a different colour as the word; findings have shown reaction times to be longer when the name-colour pairings were incongruent²⁸. This task is theorized to investigate focused attention, a core mechanism of reasoning²⁸. Although the field of executive functioning is invaluable, the distilled nature of their corresponding tasks and findings can only anecdotally describe real-world reasoning²⁷. As such, it is important to expand this field of research by investigating natural reasoning, as we did here.

In summary, we demonstrated here that frontal theta oscillations were predictive of rationality. As such, theta activity is a neural measure of rationality and can be used in future research to further decipher the mental operations of reasoning. Moreover, as slow wave oscillations such as theta imply long-range communication across the brain, our results indicate that rational reasoning requires a diverse whole-brain network in comparison to intuitive reasoning.

Acknowledgements

Chad Williams would like to acknowledge support from Natural Sciences and Engineering Research Council of Canada (CGSD3 - 518118 - 2018) and all authors would like to acknowledge support from the Natural Sciences and Engineering Research Council of Canada (RGPIN 2016-094). We would also like to acknowledge Dr. Gordon Pennycook for providing the necessary material for conducting this research.

Competing Interests Statement

The authors declare no competing financial interest.

References

1. Kahneman, D. *Thinking, Fast and Slow*. (Macmillian, 2011).
2. Evans, J. St. B. T. & Stanovich, K. E. Dual-Process Theories of Higher Cognition: Advancing the Debate. *Perspect Psychol Sci* **8**, 223–241 (2013).
3. Norman, G. R. *et al.* The Causes of Errors in Clinical Reasoning. *Acad Med* **92**, 23–30 (2017).
4. Pennycook, G. A perspective on the theoretical foundation of dual - process models. in *undefined* vol. Dual Process Theory 2.0 5–27 (Psychology Press, 2017).
5. DeNeys, W. & Pennycook, G. Logic, Fast and Slow: Advances in Dual-Process Theorizing. *Curr Dir Psychol Sci* **28**, 503–509 (2019).
6. Inzlicht, M. & Schmeichel, B. J. What Is Ego Depletion? Toward a Mechanistic Revision of the Resource Model of Self-Control. *Perspect Psychol Sci* **7**, 450–463 (2012).
7. Inzlicht, M., Schmeichel, B. J. & Macrae, C. N. Why self-control seems (but may not be) limited. *Trends Cogn Sci* **18**, 127–133 (2014).
8. Frederick, S. Cognitive Reflection and Decision Making. *J Econ Perspect* **19**, 25–42 (2005).
9. Pennycook, G., Trippas, D., Handley, S. J. & Thompson, V. A. Base Rates: Both Neglected and Intuitive. *J Exp Psychology Learn Mem Cognition* **40**, 544–554 (2014).
10. Kahneman, D. & Tversky, A. On the psychology of prediction. *Psychol Rev* **80**, 237–251 (1973).
11. Bago, B. *et al.* Fast and Slow Thinking: Electrophysiological evidence for early conflict sensitivity. *Neuropsychologia* **117**, 483–490 (2018).
12. Banks, A. P. Comparing dual process theories: Evidence from event - related potential. in *Dual Process Theory 2.0* (ed. Neys, W. D.) 66–81 (2017).

13. Vartanian, O. *et al.* The Reflective Mind: Examining Individual Differences in Susceptibility to Base Rate Neglect with fMRI. *J Cognitive Neurosci* **30**, 1011–1022 (2018).
14. Neys, W. D., Vartanian, O. & Goel, V. Smarter Than We Think. When Our Brains Detect That We Are Biased. *Psychol Sci* **19**, 483–489 (2008).
15. Williams, C. C., Kappen, M., Hassall, C. D., Wright, B. & Krigolson, O. E. Thinking theta and alpha: Mechanisms of intuitive and analytical reasoning. *Neuroimage* **189**, 574–580 (2019).
16. Dai, Z. *et al.* EEG Cortical Connectivity Analysis of Working Memory Reveals Topological Reorganization in Theta and Alpha Bands. *Front Hum Neurosci* **11**, 237 (2017).
17. Williams, C. C., Ferguson, T. D., Hassall, C. D., Wright, B. & Krigolson, O. E. Dissociated neural signals of conflict and surprise in effortful decision Making: Theta activity reflects surprise while alpha and beta activity reflect conflict. *Neuropsychologia* **155**, 107793 (2021).
18. Cohen, M. X. & Donner, T. H. Midfrontal conflict-related theta-band power reflects neural oscillations that predict behavior. *J Neurophysiol* **110**, 2752–2763 (2013).
19. Williams, C. C., Ferguson, T. D., Hassall, C. D., Abimbola, W. & Krigolson, O. E. The ERP, frequency, and time–frequency correlates of feedback processing: Insights from a large sample study. *Psychophysiology* **58**, e13722 (2021).
20. Brainard, D. H. The Psychophysics Toolbox. *Spatial Vision* **10**, 433–436 (1997).
21. Delorme, A. & Makeig, S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Meth* **134**, 9–21 (2004).
22. Cavanagh, J. F. & Frank, M. J. Frontal theta as a mechanism for cognitive control. *Trends Cogn Sci* **18**, 414–421 (2014).
23. Hsieh, L.-T. & Ranganath, C. Frontal midline theta oscillations during working memory maintenance and episodic encoding and retrieval. *Neuroimage* **85**, 721–729 (2014).

24. Loof, E. D. *et al.* Preparing for hard times: Scalp and intracranial physiological signatures of proactive cognitive control. *Psychophysiology* **56**, (2019).
25. Kahneman, D., Peavler, S. & Onuska, L. Effects of verbalization and incentive on the pupil response to mental activity. *Can J Psychology Revue Can De Psychologie* **22**, 186–196 (1968).
26. Cavanagh, J. F., Zambrano-Vazquez, L. & Allen, J. J. B. Theta lingua franca: A common mid-frontal substrate for action monitoring processes. *Psychophysiology* **49**, 220–238 (2012).
27. Cohen, M. X. Neurophysiological Oscillations and Action Monitoring. in *The Wiley Handbook of Cognitive Control* 242–258 (John Wiley & Sons, Incorporated, 2017).
28. Monahan, J. S. Coloring Single Stroop Elements: Reducing Automaticity or Slowing Color Processing? *J Gen Psychology* **128**, 98–112 (2001).

Figures and Captions

Figure 1. No relationship between rationality and reaction time. Participant rationality was determined as the number of responses a participant made in line with base-rate rather than stereotype information in the incongruent trials. Blue line corresponds to a linear regression with a 95% confidence interval.

Figure 2. Two and three-dimensional time-frequency wavelet plots demonstrating a frontal theta cluster of interest at electrode FCz. Activity are in decibel units. The cluster border is designated as any activity greater than 0.10 dB within the theta range (4 – 8 Hz). To better illustrate theta effects, the data within this figure was scaled using an asymmetric Hamming window which peaked at 5 Hz. An interactive supplemental figure for this data can be found at <https://osf.io/sb62z/>.

Figure 3. Three-dimensional topographic map of theta activity illustrating activity to be frontal-central. An interactive supplemental figure for this data can be found at <https://osf.io/sb62z/>.

Figure 4. A strong positive relationship between rationality and frontal theta activity. Participant rationality was determined as the number of responses a participant made in line with base-rate rather than stereotype information in the incongruent trials. Theta activity was extracted as the cluster of activity at electrode FCz as illustrated in Figure 2. Blue line corresponds to a linear regression with a 95% confidence interval. An interactive supplemental figure for this data can be found at <https://osf.io/sb62z/>.