Convocatoria 2019 - «Proyectos de I+D+i»

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IP 2 (Nombre y apellidos)**:**

TÍTULO DEL PROYECTO (ACRÓNIMO): CUANTIFICACIÓN DE LA INFORMACIÓN CONTEXTUAL EN EL CONTROL COGNITIVO: MODELADO DE EVIDENCIA CONDUCTUAL Y ELECTROFISIOLÓGICA (MIND.CONTEXT)

TITLE OF THE PROJECT (ACRONYM): QUANTIFYING CONTEXTUAL INFORMATION FOR COGNITIVE CONTROL: MODELING OF BEHAVIORAL AND ELECTROPHYSIOLOGICAL EVIDENCE (MIND.CONTEXT)

1. PROPUESTA CIENTÍFICA - *SCIENTIFIC PROPOSAL*

1.1. Background, Current State-Of-The-Art and Justification.

Cognition is context-sensitive, as the same sensory information is processed differently depending on its context (e.g., on its probabilistic association with goal-directed actions and their outcomes). However, the concept of context in studies of higher-order cognition is often simplified to nominal stimulus categories (like comparing a target with a distractor). The main objective of this proposal is to quantify contextual information for a more accurate modeling of cognitive demands. There can be many benefits in quantifying contextual information in tasks of cognitive control. First, this can provide novel insights into the nature of cognitive control. Second, it can help operationalize cognitive control as simple probability models offer a tool for quantifying contextual information at different levels in the putative neural hierarchy of cognitive control, and these values can then be entered as regressors to describe and predict rapidly changing trial-by-trial neural dynamics. In the following, I briefly describe the logic of using context-sensitive measures of cognitive control and highlight recent studies that do so using information theory metrics and Bayesian statistics under the Bayesian brain hypothesis (Barceló & Cooper, 2018a,b; Friston, 2010; Parr et al., 2019).

A recent research hypothesis states that the dynamic interaction between exogenous and endogenous sources of information underwriting cognitive control can be defined in probabilistic terms, with formal models of information processing based on information theory and Bayesian probability models (Barceló, Bestmann and Yu, 2012; Koechlin and Summerfield, 2007; Friston, 2005, 2010). These models allow us to accurately quantify the cognitive demands in a task, as well as to model the behavioral and brain responses associated with different experimental conditions. Our recent findings are consistent with this hypothesis about the probabilistic nature of the relationship between exogenous and endogenous variables responsible for cognitive control (Barceló et al., 2008; Barceló and Cooper, 2018; Periáñez and Barceló, 2009). These works suggest that the brain acquires and maintains an approximate representation of the uncertainty associated with the stimuli and responses of the experimental task (the "task-set"), and that this uncertainty influences both the allocation of attentional resources, as well as other processes such as working memory, learning and decision-making (e.g., Friston, 2005; Glimcher, 2004; Yu, 2007). This recent hypothesis has renewed interest in knowing the role played by the processing of uncertainty in cognitive control, using different formalisms derived from the Theory of Information and Bayesian Probability (Koechlin and Summerfield, 2007; Barceló, Bestmann and Yu, 2012; Parr et al., 2019). These findings suggest an amazing capacity of the human brain for probabilistic inference, and can help describe and predict behavioral and brain responses in tasks of cognitive control (Miller, 1956; Sutton et al., 1965). These probabilistic models can help design better cognitive tasks and offer a frame of reference to compare the results obtained across different experimental paradigms, as well as between individuals of different age and condition (Barceló et al., 2008; Barceló and Knight, 2007). The calibration of neuropsychological tasks using a universal scale, independent of the sensory and motor parameters specific to each task, would allow us to reach more generalizable conclusions and compare the results from different neuropsychological tests (Miller, 1956; Barceló et al., 2008). The mathematical formalization of the concept of cognitive control can therefore serve not only to describe more precisely the spatio-temporal neural dynamics of executive control, but also to improve the neuropsychological assessment of cognitive deficits associated with age and those caused by brain injuries (Barceló & Knight, 2007; Nyhus & Barceló, 2009).

Our research group has pioneered the electrophysiological study of cognitive control through “task switching” paradigms inspired by the Wisconsin card sorting test (WCST), a classic neuropsychological test of prefrontal executive function (Miller, 2000). In the last twenty years, we have developed a modified adaptation of the WCST (known as the Madrid Card Sorting Test, MCST; Barceló, 2003), which allows the simultaneous recording of behavioral and electroencephalographic (EEG) responses (Barceló, 1999, 2001; Barceló et al., 1997, 2000, 2002a, 2002b, 2003, 2006; see Figure 1). This adaptation of the original WCST offers several advantages to explore the interaction between the neural mechanisms of exogenous (e.g., “bottom-up” responses to distractors) and endogenous (e.g., “top-down” control of cued attention) executive attention. The MCST adaptation offers the excellent temporal resolution of electroencephalographic (EEG) recordings, which combined with our modeling work has shown that the activation of the frontoparietal network involved in cognitive control is a function of the informative content (entropy) of the sensory stimulus for response selection, over and above the novelty, mean probability of occurrence, or the instructed task relevant (i.e., target) or irrelevant (i.e., distracter) nominal labels given to those stimuli (cf., Barceló et al., 2008; Barceló & Cooper, 2018b; Nyhus and Barceló, 2009). These findings have led us to reconceptualize the functional significance of the endogenous P300 cortical potential (Donchin and Coles, 1988), since at least one of its elements (traditionally known as the “P3a”, or “novelty P3” component), seems to index phasic activation across the frontoparietal network for cognitive control during the memory updating of the context of stimulus-response associations necessary for the selection of responses in a proactive or anticipatory fashion (Barceló et al., 2002, 2006; Barceló & Cooper, 2018a,b). The explanation of these previous results has led us to formalize a computational model that links the information content of stimuli with the allocation of resources in working memory (cf., Barceló and Nyhus, 2009; Miller, 1956). To date, this model has allowed us to examine individual differences in EEG activation across frontoparietal scalp regions responsible for implementing task-switching, and have begun to describe them formally in probabilistic terms (Adrover-Roig and Barceló, 2010, cf., Barceló & Cooper, 2018a,b).

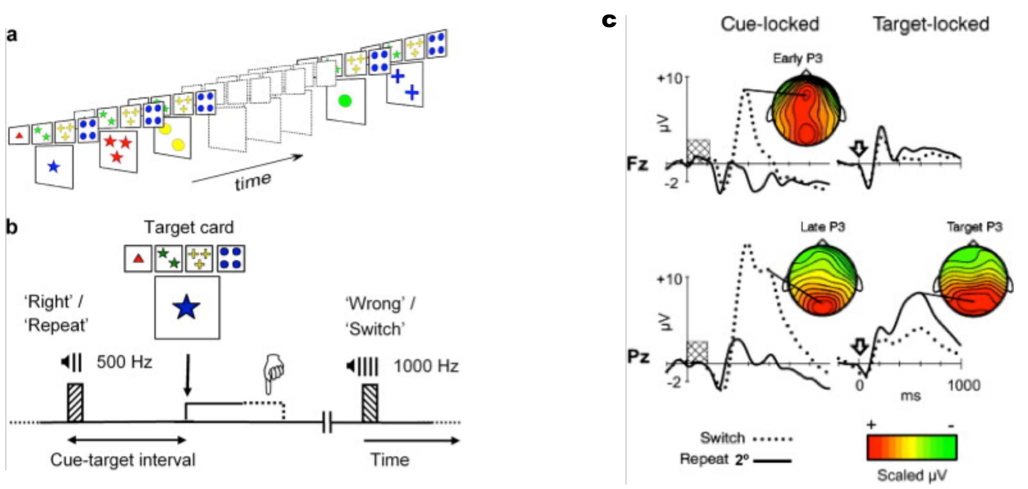

Figure 1. MCST protocol. (a) Trial sequence, (b) task cues and target card displays, y (c) Event-related potentials (ERPs) obtained to contextual cues and target cards along one MCST classification series (cf., Nyhus y Barceló, 2009).

The purpose of this proposal is to advance the mathematical formalization of a computational model of cognitive control initiated with a previous project (ref. PSI2013-44760-R), and verify its validity and generality with new behavioral and electroencephalographic (EEG) evidence obtained with two classic neuropsychological tasks of cognitive control (i.e., our MCST adaptation and a task-switching paradigm). In addition, this project involves the empirical examination of the modeling work in two samples of healthy young adults (20-35 years; N = 60) and older people (60-85 years; N = 60), all of which will be classified according to their scores ("high" or "low") in a battery of neuropsychological tests of cognitive control following the procedure described in Adrover-Roig and Barceló (2010). The ultimate purpose of this project is to improve the neuropsychological diagnosis of cognitive deficits associated with age and, in particular, to verify the extent to which these are comparable with deficits caused by lesions in the prefrontal cortex (e.g., hypothesis of frontal aging; West, 1996, 2005).

Probabilistic models of cognitive control

The computational work developed in our earlier MICINN projects (refs. SEJ2007-61728 and PSI2013-44760-R), combines an integrative model of prefrontal function (Miller, 2000), with a formal model of cognitive control based on Information Theory (see Figures 2 & 3). However, in recent years, formalisms based on Bayesian models of probability have also been used for the same purpose (Baldi, 2002, 2005; Parr et al., 2019). The present project aims to develop further this model using both the formalisms of the Theory of the information, as well as the Bayesian theory of probability (Barceló, Bestmann and Yu, 2012). For this purpose we take as a starting point published works (Barceló et al., 2008; Barceló & Cooper, 2018a), as well as the current probabilistic approach to the human mind and brain (Behrens et al., 2007; Friston, 2005; Mars et al., 2008; Yu et al., 2009). The model of Koechlin and Summerfield (2007) is briefly outlined below, and the relationship between the concepts of information theory and those used in Bayesian probability models is explained further below.

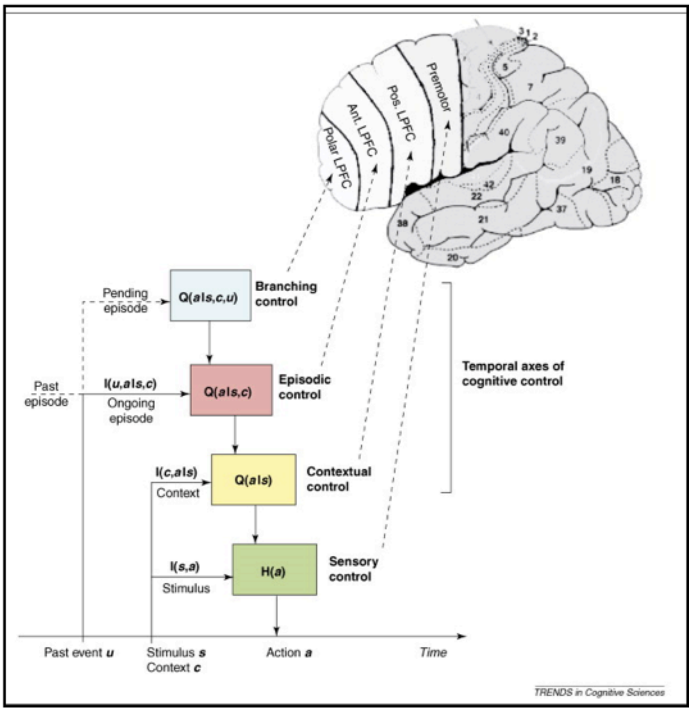

Figure 2. Probabilistic model of cognitive control (adapted from Koechlin and Summerfield, 2007).

Koechlin & Summerfield's (2007) model. These authors used concepts from Information Theory to describe and explain the functional architecture of executive control in the lateral prefrontal cortex. The model is based on functional magnetic resonance data, and one of its most important tenets is that the selection of actions is guided by control signals organized hierarchically along an antero-posterior axis within the prefrontal cortex. However, today there are hardly any studies that have tried to validate this model using EEG activity in humans (cf., Barceló et al., 2008; Barceló & Knight, 2007).

Adopting formalisms from the Theory of Information such as other authors did before (Miller, 1956), the model in Fig. 2 computes the total amount of information H(a) necessary to select an action 'a' associated with a stimulus 's' by estimating the sum of two terms (Fig. 1 and Box 1, Ec. 1): (i) the 'mutual information' $I(s, a)$ between the stimulus 's' and the 'a' action; and (ii) the remaining portion of information Q (a | s) (that is, the 'conditional information' necessary to select action 'a' but that is independent from stimulus 's'). Koechlin refers to I(s, a) as 'sensorimotor control' and describes the term Q (a | s) as 'cognitive control'. The distinction between sensorimotor and cognitive control is compatible with most theories that dissociate two control modes, one exogenous and controlled by the data, and another endogenous and controlled by the goals. Koechlin and Summerfield (2007) similarly explain the difference between higher levels in the control hierarchy: contextual and episodic. Recent neuroimaging evidence provides support for this hierarchical model (e.g., Badre & D'Esposito, 2009).

By combining the models of Miller (2000) and Koechlin and Summerfield (2007) we can get some clues for understanding cognitive control across many tasks such as the WCST and task-switching paradigms. According to our estimates of transmitted information between sensory and motor aspects in Figure 3, the amount of information $H(r_j)$ necessary to select the correct response r_2 to a card with 'a blue star', s_3, corresponds to the sum of: (i) the information for the 'sensorimotor control' provided by stimulus s_3 on response r_2 (Box 1, Ec. 2), which depends on the set of all stimuli { S } and responses { R } present in the task, as well as their probabilistic dependencies (Ec. 3), and (ii) residual control processes (Ec. 4) that need to be invoked when the sensorimotor control (that is, the current stimulus-response mappings) are not enough to produce adaptive behavior (Nyhus & Barceló, 2009). In other words, some additional control is needed to process contextual signals, c (error feedback, or switch task cues), which prompt for a change in higher order units of the task set, ts (Ec . 4).

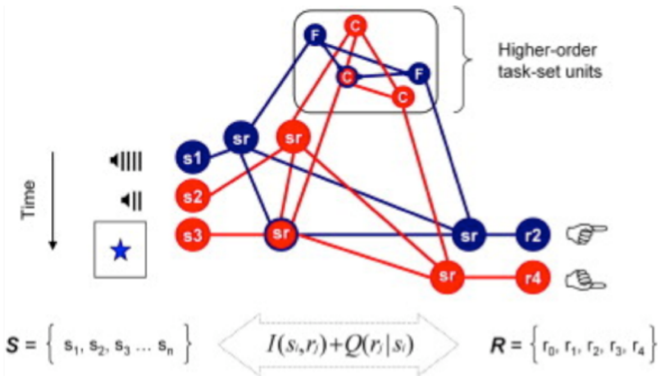

Figure 3. Probabilístic model of cognitive control applied to modelling of the Madrid card sorting test (adapted from Nyhus & Barceló, 2009).

Box 1. (Nyhus & Barceló, 2009)

$$H(r_j) = I(s_i, r_j) + Q(r_j|s_i) \quad (1)$$

$$I(s_j, r_i) = \log \frac{p(s_j, r_i)}{p(r_i)p(s_j)} \quad (2)$$

$$I(S; R) = \sum_i \sum_j p(s_j, r_i) \log \frac{p(s_j, r_i)}{p(r_i)p(s_j)} \quad (3)$$

$$Q(r|s) = I(c, r|s) \equiv I(c, ts) \quad (4)$$

This formal model allows us to examine relevant hypotheses such as, for example, whether the memory demands linked to the processing of a sensory stimulus, and its associated brain activations, depend on control processes at low (bottom-up), rather than at high order (top-down) levels in the hierarchy of control. For example, switch and repetition cues in the MCST transmit similar amounts of information for the low-order 'sensorimotor control' of their associated 'nogo' responses. However, switch cues also transmit additional information at high-order levels in the hierarchy prompting for a switch in the perception-action rules. This notion is illustrated in Figure 4, where a switch cue with a low probability of occurrence (P = 0.05) conveys the same amount of information for the selection of its 'nogo' response than a repetition cue with a high probability of occurrence (P = 0.45). On the contrary, it becomes clear that the cognitive demands associated with a switch cue increase depending on the number of latent higher order units (i.e., task rules) kept active in working memory (Fig. 4, Ec. 4). The greater informative content of the cues associated with a greater number of rules entails an increase in the response costs and in the amplitude of P3a/novelty P3 to those cues, in tasks where two or three rules are handled, compared to single tasks with only one task rule (Barceló et al., 2008). This quantification of contextual information helps formalize the intuitive idea that sensory processing depends on the task context, and it also suggests that the amount of information provided by an unexpected sensory distractor, error feedback, or a task switch cue, depends in part on the temporal and sensorimotor (task-related) uncertainty of those sensory stimuli for response selection (Barceló & Cooper, 2018a,b).

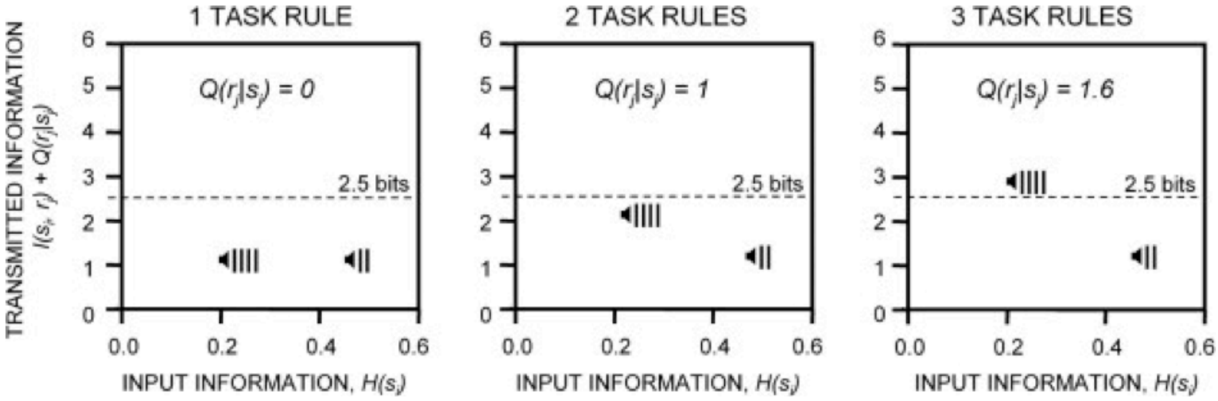

Figure 4. Estimates of transmitted information between auditory task cues and associated "*nogo*" responses as a function of sensory entropy (0.25 y 0.50 bits for high and low tones, respectively), and the number of high order latent task rules that are actively maintained in working memory (adapted from Nyhus & Barceló, 2009).

Uncertainty, novelty, surprise and cognitive control

The probabilistic approach to cognition (Chater and Oaksford, 2008) links the concept of cognitive control to the concepts of uncertainty, novelty and surprise (Baldi, 2005). Indeed, an old problem in Cognitive Neuroscience has been to find a definition of novelty or surprise that is both precise and widely accepted, which has generated a lot of conceptual confusion in the search for the neural generators of brain activations (Sokolov, 1963; Donchin, 1981). The new probabilistic models could offer a solution to this dilemma, helping to formalize the concepts of surprise and relevance as they are linked to the neural dynamics of exogenous and endogenous cognitive control (cf., Friston, 2005, 2010). The amount of surprise in any sensorimotor task can be measured as the difference between the probability distributions before and after the occurrence of each event (Barceló & Cooper, 2018a,b; Yu et al., 2009). Bayesian formalisms are more adequate than Information Theory for these dynamic trial by trial estimates (Baldi, 2005). The formal concept of surprise provides a simple formula to redefine the relevance of a stimulus (Baldi, 2005, p. 24). To the extent that attention is a rapid process modulated by exogenous ("bottom-up") signals, we can compute surprise to detect disparities between these exogenous signals and any internal expectations or ("top-down") prior hypotheses induced by the task context, or explicitly imposed by the task instructions (Baldi, 2005, p. 24; Friston, 2005). According to this, during task performance the brain is generating a representation of the probabilistic relationships between task events (i.e., the task context or "task-set"), in order to identify any highly informative surprising events. It is important to emphasize that these principles are very general, and are applicable to all tasks, from task switching (Figure 5b), to oddball paradigms (Barceló & Knight, 2007).

The endogenous component P300 and the resolution of uncertainty

To date few studies have tried to quantify the fluctuations in the level of surprise throughout the trials of a cognitive control task, in order to examine its influence on brain and behavioral responses (e.g., Barceló et al., 2008; Mars et al., 2008; Visalli et al., 2019). These studies have shown that EEG activity in a wide network of fronto-parietal cortical regions is a function of the amount of surprise associated not only with the stimuli of sensorimotor tasks, but also with their associated responses and further intermediate and latency-variable sensorimotor processes (cf., Brydges & Barceló, 2018). These results are relevant, for example, to understand the significance of the endogenous P300 brain potential, which has been related to the uncertainty generated by unexpected and surprising stimuli since its discovery (Sutton et al., 1965). New evidence suggests that the modulations of P300 measured from trial to trial (and perhaps also of other ERP components) depend on the probabilistic associations between task events. Therefore, probabilistic models could help explain part of the variability in brain and behavioral responses in cognitive tasks (Friston, 2005, 2010).

An important advantage of probabilistic models of cognitive control is that they allow the interpretation of the behavioral results and brain activations obtained from different versions of the WCST to be integrated with results from other cognitive control tasks (cf., Miller, 1956). This approach provides a common interpretive framework for the control processes involved in responding to novel distractors in oddball-type tasks, to temporarily unexpected task switch cues, and to error feedback cues in the conventional WCST. All these situations require a fast and transient change in the high-order representations responsible for goal-directed behavior. The mechanisms of task-set switching are fast and transitory, and seem to depend on the integrity of the prefrontal cortex (Miller, 2000; Shallice et al., 2008), as well as on a distributed anatomical network of cortical and subcortical structures necessary for the processing of novelty and surprise at different levels of neural representation. Even if this mechanism is activated only during a few milliseconds, it is surely accompanied by other additional processes, as lesion studies have suggested (Barceló & Knight, 2007; Shallice et al., 2008). Likewise, other slow negative ERP components of the evoked potential also accompany the P3a/novelty P3 responses to contextual cues that prompt a switch in tasks (Barceló et al., 2006; Kopp et al., 2006; Kieffaber & Hetrick, 2005).

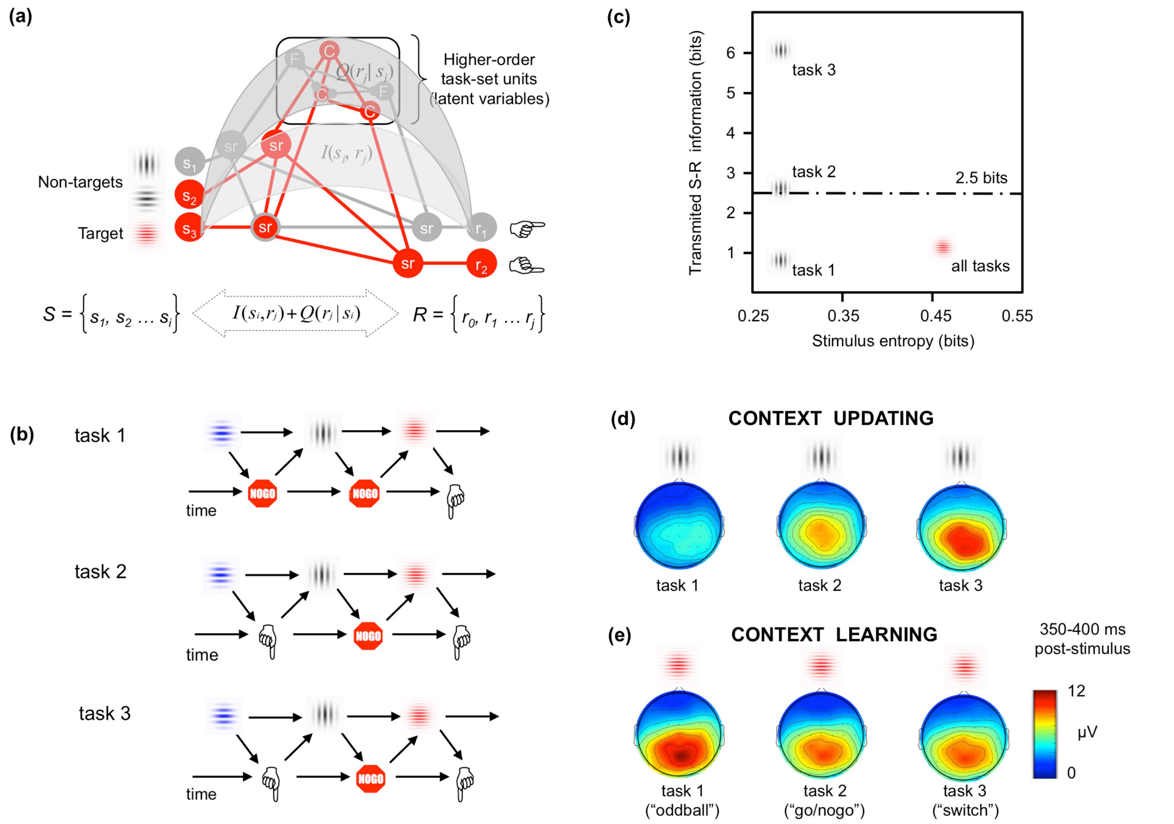

***Figure 5.* Formal modeling of contextual information.** *(a) Hierarchies of cognitive control*. Information theory can be used to quantify the contextual dependencies characterizing cognitive control in simple target detection tasks, as well as in more complex tasks involving hypothetical high-order latent variables (here, Color and Form task rules). Mean probability of task events (i.e., $P = 0.2$ for gray non-targets, $P= 0.8$ for colored targets) cannot fully convey the complex contextual contingencies driving behavioral and brain responses in studies on cognition. Information theory metrics such as stimulus entropy, and information transmission between sets of task stimuli (S) and responses (R) –both at lower [$I(s_i, r_j)$] and higher [$Q(r_j |s_i)$] ordered levels in the neural hierarchy of control (Koechlin and Summerfield, 2007), offer better ways to parametrize the numerous sources of contextual information that modulate behavioral and brain responses in studies of cognition. *(b) Time dynamics of sensorimotor loops*. Examples of three cognitive tasks where the stimulus context was kept constant while manipulating motor and sensorimotor demands (cf., Barcelo & Cooper, 2018a). Task 1 ("*oddball task*") involved detection of visual targets using one-forced choice responses ("press a button to red gratings"); Task 2 ("*go/nogo task*") required two-forced choice responses ("press button 1 for red gratings and button 2 for blue gratings"); In Task 3 ("*switch task*") infrequent vertical and horizontal gray gratings instructed participants to switch and repeat the active task rule (i.e., "Color" *vs.* "spatial Frequency"), respectively. *(c) Quantifying contextual information*. Transmitted sensorimotor (S-R) information was modeled at two levels in the hypothetical neural hierarchy shown in Fig. 1a, and plotted as a function of mean stimulus entropy. This simple model predicted maximal task differences in contextual information among the temporarily surprising non-target stimuli, and no differences in task-averaged transmitted information for the temporarily predictable target stimuli. *(d) Context updating*: Scalp-recorded "context P3" responses to the surprising non-target "nogo" stimuli (300-450 ms) captured the graded differences in cognitive demands across all tasks, as predicted by the model in Fig. 1c. The largest "context P3" intensities were observed in the task with the largest sensorimotor entropy, a condition conveying maximal contextual uncertainty about upcoming actions. Similar context-sensitive brain responses have also been reported with auditory and somatosensory stimulation (Donchin, 1981). *(e) Context learning*: The intensity of "target P3" responses to temporarily predictable target "go" stimuli was slightly larger in the task conveying less sensorimotor entropy, whose contextual information could be quickly learned. These findings pointed to a common fronto-parietal cortical network for cognitive control showing different functional dynamics during two temporarily distinct context updating and context learning stages of processing (cf., Barcelo & Cooper, 2018b).

Relevant bibliography

Adrover-Roig, D., & Barceló, F. (2010). Individual differences in aging and cognitive control modulate neural indexes of context updating and maintenance in task switching. *Cortex, 46*, 434-450.

Baldi P (2002) A computational theory of surprise. In: *Information, coding, and mathematics* (Blaum M, ed), pp 1-26. Amsterdam: Kluwer.

Baldi P (2005). Surprise: A shortcut for attention. In: *Neurobiology of Attention* (Itti L, Rees G, Tsotsos JK, eds), pp 24-28. San Diego: Elsevier Academic Press.

Badre, D., y D'Esposito, M. (2009). Is the rostro-caudal axis of the frontal lobe hierarchical? *Nat Rev Neurosci*, 10(9), 659-69.

Barceló, F., & Cooper, P. S. (2018). An information theory account of late frontoparietal ERP positivities in cognitive control. *Psychophysiology, 55*, e12814. doi:10.1111/psyp.12814

Barceló, F., & Cooper, P. S. (2018). Quantifying contextual information for cognitive control. *Frontiers in Psychology, 9*, 1693. doi:10.3389/fpsyg.2018.01693

Barceló F, & Knight RT (2007) An information theoretical approach to contextual processing in the human brain: evidence from prefrontal lesions. *Cerebral Cortex* 17:i51-i60.

Barceló F, Bestmann S, Yu A. (Eds.) (2012). Cognitive control, uncertainty and the brain. Special Research Issue in *Frontiers in Human Neuroscience*. http://www.frontiersin.org/humanneuroscience/specialtopics/67/

Barceló, F. (1999) Electrophysiological evidence of two different types of error in the Wisconsin Card Sorting Test. *NeuroReport*, 10, 1299-303.

Barceló, F. (2003). The Madrid card sorting test (MCST): a task switching paradigm to study executive attention with event-related potentials. *Brain Res. Protocols*, 11(1), 27-37.

Barceló, F., Muñoz-Céspedes, J. M., Pozo, M. A., y Rubia, F. J. (2000). Attentional set shifting modulates de target P3b response in the Wisconsin card sorting test. *Neuropsychologia*, 38(10), 1342-1355.

Barceló, F., Sanz, M., Molina, V. y Rubia, F.J. (1997) The Wisconsin Card Sorting Test and the assessment of frontal function: A validation study with event-related potentials. *Neuropsychologia*, 35, 399-408.

Behrens TE, Woolrich MW, Walton ME, Rushworth MF. (2007). Learning value of information in an uncertain world. *Nat Neurosci,* 10:1214-21.

Braver, T.S., y Barch, D.M. (2002). A theory of cognitive control, aging cognition, and neuromodulation. *Neurosci Biobehavi Rev*, 26, 809-17.

Brydges, C. R., & Barceló, F. (2018). Functional dissociation of latency-variable, stimulus- and response-locked target P3 sub-components in task-switching. *Frontiers in Human Neuroscience, in press*. doi:10.3389/fnhum.2018.00060

Chater N, Oaksford M. (Eds.) (2008). *The Probabilistic mind: prospects for bayesian cognitive science.* New York: Oxford University Press.

Donchin, E. (1981). Surprise! Surprise? *Psychophysiology*, 18, 493-513.

Donchin E, Coles MHG. (1998). Context updating and the P300. *Behavioral and Brain Sciences*, 21(1), 152-153.

Doya K, Ishii, S, Pouget A, Rao, RPN. (2007) *Bayesian brain: probabilistic approaches to neural coding*. Cambridge, MA: MIT Press.

Friston, K. (2005). A theory of cortical responses. *Philosophical Transactions of the Royal Society of London. B. Biological Sciences*, 360(1456), 815-836.

Friston, K. (2010). The free-energy principle: a unified brain theory? *Nature Reviews in Neuroscience*, 11(2), 127-138.

Friston KJ, Kiebel S. (2009). Predictive coding under the free-energy principle. *Philos Trans R Soc Lond B Biol Sci* 364, 1211-1221.

Fuster, J. M. (2015). *The prefrontal cortex* (5th ed.). London: Academic Press.

Garcia-Garcia, M., Barcelo, F., Clemente, I. C., & Escera, C. (2010). The role of the dopamine transporter DAT1 genotype on the neural correlates of cognitive flexibility. *European Journal of Neuroscience, 31*(4), 754-760. doi:10.1111/j.1460-9568.2010.07102.x

Garcia-Garcia, M., Barcelo, F., Clemente, I. C., & Escera, C. (2011). COMT and ANKK1 gene-gene interaction modulates contextual updating of mental representations. *Neuroimage, 56*(3), 1641-1647. doi:10.1016/j.neuroimage.2011.02.053

Glimcher, P. W. (2004). *Decisions, uncertainty and the brain*. New York: Bradford books.

Kieffaber, P.D., y Hetrick, W.P. (2005). Event-related potential correlates of task switching and switch costs. *Psychophysiology*, 42(1), 56-71.
Koechlin, E., y Summerfield, C. (2007). An information theoretical approach to prefrontal executive function. *Trends in Cognitive Sciences*, 11(6), 229-235.
Kopp, B., Tabeling, S., Moschner, C., & Wessel, K. (2006). Fractionating the neural mechanisms of cognitive control. *Journal of Cognitive Neuroscience*, 18(6), 949-965.
Miller, G.A. (1956). The magical number seven plus or minus two: some limits on our capacity for processing information. *Psychological Review*, 63(2), 81-97.
Miller, E.K. (2000). The prefrontal cortex and cognitive control. *Nat. Rev. Neurosci*, 1, 59-65.
Monsell, S. (2017). Task set regulation. In T. Egner (Ed.), *The Wiley handbook of cognitive control* (pp. 29-49). Chichester, West Sussex: Wiley.
Nyhus E, Barceló F (2009). The Wisconsin Card Sorting Test and the cognitive assessment of prefrontal executive functions: A critical update. Brain and Cognition 17:437–451.
Oaksford M, Chater N. (2007). *Bayesian rationality: the probabilistic approach to human reasoning*. New York: Oxford University Press.
Ouyang, G., Herzmann, G., Zhou, C., & Sommer, W. (2011). Residue iteration decomposition (RIDE): A new method to separate ERP components on the basis of latency variability in single trials. *Psychophysiology, 48*(12), 1631-1647. doi:10.1111/j.1469-8986.2011.01269.x
Ouyang, G., Hildebrandt, A., Sommer, W., & Zhou, C. (2017). Exploiting the intra-subject latency variability from single-trial event-related potentials in the P3 time range: A review and comparative evaluation of methods. *Neurosci Biobehav Rev, 75*, 1-21.
Parr, T., Rikhye, R. V., Halassa, M. M., & Friston, K. J. (2019). Prefrontal Computation as Active Inference. *Cereb Cortex, in press*. doi:10.1093/cercor/bhz118
Periáñez JA, Barceló F (2009). Updating sensory versus task representations during task-switching: Insights from cognitive brain potentials in humans. *Neuropsychologia* 47:1160–1172.
Shallice T, Stuss DT, Picton TW, Alexander MP, Gillingham S (2008) Mapping task switching in frontal cortex with neuropsychological group studies. *Frontiers Neurosci.* 2: 79-85.
Sokolov, E.N. (1963). *Perception and the conditioned reflex*. Oxford: Pergamon Press.
Strange, B.A., Duggins, A., Penny, W., Dolan, R.J., y Friston, K.J. (2005). Information theory, novelty and hippocampal responses: unpredicted or unpredictable? *Neural Networks,* 18(3), 225-30.
Sutton S, Braren M, Zubin J, John ER (1965). Evoked-potential correlates of stimulus uncertainty. *Science* 150:1187-1188.
Visalli, A., Capizzi, M., Ambrosini, E., Mazzonetto, I., & Vallesi, A. (2019). Bayesian modeling of temporal expectations in the human brain. *Neuroimage, 202*, 116097.
West R. (2005). The neural basis of age-related declines in prospective memory. In: *Cognitive neuroscience of aging: linking cognitive and cerebral aging*, ed. R Cabeza, L Nyberg, D Park, pp. 246-66. New York: Oxford University Press.
West, R. (1996). An application of prefrontal cortex function theory to cognitive aging. *Psychol Bull*, 120(2), 272-92.
Yu AJ, Dayan P, Cohen JD. (2009). Dynamics of attentional selection under conflict: toward a rational Bayesian account. *J Exp Psychol Hum Percept Perform*.; 35(3):700-17.
Yu AJ, Dayan P.(2005). Uncertainty, neuromodulation, and attention. *Neuron*, 46(4):681-92.
Yu AJ. (2007). Adaptive behavior: humans act as Bayesian learners. *Curr Biol.,* 17:R977-80.

1.2. General Objectives

Recent research suggests that there is a conceptual and methodological confusion regarding the measurement of the endogenous P300 component recorded in simple target detection tasks with homogenous stimulus-response mappings (i.e., oddball tasks). This conceptual and methodological confusion is partly due to the absence of a numerical quantification of the amount of contextual information being updated, which is assumed to modulate this component according to the widely accepted "context-updating" hypothesis (Donchin, 1981; Donchin & Coles, 1988; Sutton et al., 1965). Another related problem is the existence of not just one, but a multiplicity of P300-like sub-components differently linked with proactive (anticipatory) and reactive control of target detection (Barceló & Cooper, 2018a, b). Even during reactive target detection, target P3 can be functionally decomposed into stimulus-locked, response-locked and latency variable sub-components (Brydges & Barceló, 2018).

This methodological confusion has prevented reaching a consensus on the functional significance of this and other related endogenous ERP components, and on their role in human information processing and cognition (Barceló & Cooper, 2018b).

Our general starting hypothesis is that context-sensitive cognition can be described and explained by formally quantifying and modeling contextual information using the metrics of information theory and Bayesian probability theory (Barceló & Cooper, 2018b). Likewise, this formal approach can allow us to model more accurately brain activity, since the brain also seems to follow probabilistic laws to represent the dynamic interaction between exogenous (sensory input) and endogenous control processes (prior knowledge, goals and expectations; cf., Baldi, 2005; Doya et al., 2007; Koechlin and Summerfield, 2007; Yu and Dayan, 2005). In this respect, this proposal is consistent with the theory that the brain has evolved to infer and represent the causes of sensory stimulation, minimizing prediction errors in perceptual inference, learning and decision-making (Friston, 2005, 2010). These prediction errors can be quantified in terms of information surprise represented at both low- and high-order levels across the putative hierarchy of neurocognitive processes in our brains (see Figure 5a).

1.3. Specific Objectives

The purpose of this project is to complete the mathematical formalization of a computational model of cognitive control developed in our earlier MICINN projects (refs. SEJ2007-61728 and PSI2013-44760-R). We also want to test the predictive validity of the model with new behavioral and electroencephalographic data from healthy young and old people obtained using two classic tasks of cognitive control (namely, an adaptation of the WCST and a task-switching paradigm). This general objective can be broken down into four specific objectives:

Objective 1. To complete a formal model of the WCST from a predictive processing account, using Information Theory and Bayesian probability metrics (Barceló et al., 2008; Parr et al., 2019) in line with recent studies (Adrover-Roig & Barceló, 2010; Barceló & Cooper, 2018). In this modeling work, those parameters known to mostly affect the behavioral and cerebral indexes of executive attention, such as the probability of target and distracting stimuli, inter-stimulus and inter-trial intervals, etc., will be of particular interest. This objective will be achieved through the development of Work Package 1 (see Work Plan).

Objective 2. To validate the generalizability of the model to other cognitive control tasks, and in particular, we will extend the modeling to a task-switching paradigm used in our recent work (Barceló & Cooper, 2018). The same parameters as with our WCST adaptation will be modeled for the task-switching paradigm, and especially those known to mostly affect the behavioral and brain indexes of executive control (i.e., inter-stimulus and inter-trial intervals). The fulfillment of this objective will be guaranteed through Work Package 2 (see Work Plan).

Objective 3. Examine the validity of the proposed model in new data already recorded but not yet published. The new behavioral and EEG data correspond to two behavioral paradigms of cognitive control (MCST, task-switching), and comprise two large samples of young adults (20-35 years; N = 60) and healthy older (60-85 years; N = 60), who have been previously classified according to their score (“high” or “low”) in a battery of neuropsychological tests of cognitive control (cf., Adrover-Roig & Barceló, 2010). This objective will involve the modeling of both behavioral and electroencephalographic data, and will allow us to advance in our work of functional segregation of the fronto-parietal network involved in cognitive control (Periáñez & Barceló, 2009; Brydges & Barceló, 2018). This objective is relevant because it will aim the modeling of temporal EEG dynamics in the WCST and during task switching. The fulfillment of this objective will be pursued through Work Packages 3 and 4 for the modified MCST and task-switching protocols, respectively (see Work Plan).

Objective 4. To validate the predictive and diagnostic capacity of the model in people with brain damage who had our task-switching protocol administered in previous collaborative work at the University of Cambridge university. The explanatory and predictive value of the model will also be achieved by comparing the behavioral results of N = 33 patients with lesions in the prefrontal cortex with a sample of controls (N = 24). The fulfillment of this objective will be guaranteed through the development of Work Package 5 (see Work Plan).