UNIVERSITY OF AMSTERDAM

UvA-DARE (Digital Academic Repository)

From model-based perceptual decision-making to spatial interference control

van Maanen, L.; Turner, B.; Forstmann, B.U.

DOI
10.1016/j.cobeha.2014.10.010

Publication date
2015

Document Version
Final published version

Published in
Current Opinion in Behavioral Sciences

License
Article 25fa Dutch Copyright Act (https://www.openaccess.nl/en/policies/open-access-in-dutch-copyright-law-taverne-amendment)

Link to publication

Citation for published version (APA):
van Maanen, L., Turner, B., & Forstmann, B. U. (2015). From model-based perceptual decision-making to spatial interference control. *Current Opinion in Behavioral Sciences*, *1*, 72-77. https://doi.org/10.1016/j.cobeha.2014.10.010

General rights
It is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), other than for strictly personal, individual use, unless the work is under an open content license (like Creative Commons).

Disclaimer/Complaints regulations
If you believe that digital publication of certain material infringes any of your rights or (privacy) interests, please let the Library know, stating your reasons. In case of a legitimate complaint, the Library will make the material inaccessible and/or remove it from the website. Please Ask the Library: https://uba.uva.nl/en/contact, or a letter to: Library of the University of Amsterdam, Secretariat, P.O. Box 19185, 1000 GD Amsterdam, The Netherlands. You will be contacted as soon as possible.

UvA-DARE is a service provided by the library of the University of Amsterdam (https://dare.uva.nl)

Download date:09 Nov 2026

Available online at www.sciencedirect.com

ScienceDirect

Current Opinion in Behavioral Sciences

From model-based perceptual decision-making to spatial interference control

Leendert van Maanen[a], Brandon Turner[b] and Birte U Forstmann[a]

Model-based neuroscience is aimed at understanding latent cognitive processes using quantitative cognitive models in combination with neuroscientific measures. This approach has been successful in the domain of perceptual decision making, in which the properties of accumulator models of choice tasks have been related to neural networks that are involved in decision making. Here, we propose that this approach can also be applied to spatial interference control such as required in the Simon task. Spatial interference control is essential for understanding cognitive control processes. A model-based approach may aid in understanding the latent cognitive processes in spatial interference control. Ultimately this approach may uncover the relationship between decision making that requires interference control and default decision making such as perceptual choice.

Addresses
[a] University of Amsterdam, The Netherlands
[b] The Ohio State University, United States

Corresponding author: Forstmann, Birte U (buforstmann@gmail.com)

Current Opinion in Behavioral Sciences 2015, **1**:72–77

This review comes from a themed issue on **Cognitive neuroscience**

Edited by **Cindy Lustig** and **Howard Eichenbaum**

For a complete overview see the Issue and the Editorial

Available online 25th October 2014

http://dx.doi.org/10.1016/j.cobeha.2014.10.010

2352-1546/© 2014 Elsevier Ltd. All rights reserved.

Introduction

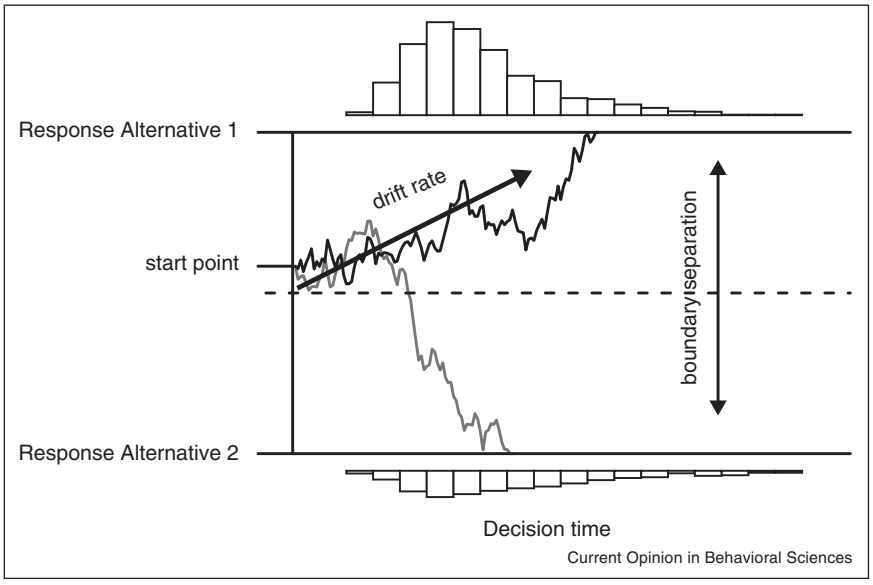
A recent trend in the cognitive neurosciences is the use of formal models of cognition to inform analyses of neural data [1•,2••]. Essentially, this trend entails that theories about the cognitive processes under consideration are explicated in mathematical or computational form, and these formal models are used to make inferences about the neural data. The model-based approach has been successfully applied in perceptual decision neurosciences [3••]. Perceptual decision neurosciences study the neural networks underlying simple perceptual choices. By relating these networks to properties of cognitive models, the model-based neuroscience approach has greatly increased our understanding of how the brain controls the behavioral outcome of simple choices.

A prominent model that has been instrumental in the success of model-based perceptual decision neurosciences is the diffusion model of choice reaction time [4••]. Essentially, the diffusion model assumes that the difference in evidence for two response alternatives is represented by a biased random walk process (Figure 1). The bias in this process is referred to as drift rate. Decisions are made as soon as the random walk hits one of two boundaries, with each boundary representing one response alternative. Because the drift is a random walk process, each boundary can in principle be reached. However, a positive drift rate means that it is more likely that the random walk will be towards the upper boundary, making the associated response more likely. The time required to reach a boundary represents the decision time, which is a function of both the drift rate and the boundary separation. That is, higher drift rates as well as boundaries that are closer together lead to lower decision times. The observed response time is then the sum of the decision time and the time required for additional, non-decision related processes. Crucially, because of the stochastic nature of the random walk process, the diffusion model predicts the proportion in which each boundary is reached, and the distributions of finishing times of the process. Thus, when fit to experimental data, the diffusion model explains both the proportion of correct and erroneous responses, as well as the distribution of response times of each of these response types.

Only recently, the diffusion model and related models have been applied to more complex cognitive behaviors in which control is exerted over a decision (e.g. [5,6•, 7–10]). That is, certain paradigms require that decision makers ignore an interfering irrelevant stimulus feature and focus on a task-relevant feature instead. Often, the irrelevant feature relates to a direct mapping between stimulus and response, making the task to ignore this feature difficult [11].

In this domain, applying the diffusion model holds great promise, because evidence suggests that conflict tasks are best understood when studying the response time distributions [12•]. This is particularly clear for the Simon task. In this task, participants are asked to respond with a left or right hand response to a certain stimulus feature, typically the color of a circle [11]. The stimuli are presented left or right of a central fixation cross. This spatial outline creates a condition in which the location of the stimulus (e.g. left of the fixation cross) is congruent with the required

Figure 1



A graphical representation of the diffusion model. The predicted response time on each trial is the finishing time of the random walk process and an additional parameter representing non-decision related processes such as perception and the motor response.

response (e.g. the color blue should yield a left button press), and a condition in which the location of the stimulus and the required response are incongruent (e.g. a blue circle to the right of the fixation cross, requiring a left button press). The Simon task is demanding because on incongruent trials, participants are confronted with interfering information in the form of the spatial location, but have to respond to the task-relevant feature only. The response time distributions of the Simon task deviate from other conflict tasks in that the time cost of resolving the interfering information is mostly associated with relatively fast responses. That is, most conflict tasks show a greater interference effect for slower responses, but the Simon task shows the greater interference effect for faster responses [13]. This pattern of interference is atypical for most conflict tasks. It suggests that in terms of the cause of interference, more processes are involved than in for example a flanker task [14].

While it is clear that an accumulator model of spatial interference control such as in the Simon task would greatly increase our understanding of cognitive control, as yet no such model has been published. The aim of the current article is to pave the way to use accumulator models to understand latent processes in spatial interference control. That is, based on previous model-based approaches towards the neural basis of perceptual decision making, and previous functional Magnetic Resonance Imaging (fMRI) studies in spatial interference control, we aim to outline the important processes in an accumulator model of spatial interference.

The neural basis of perceptual decision making

In this section we review basic perceptual decision making experiments that have sought to relate diffusion model properties to Blood Oxygen Level Dependence (BOLD) responses. In fact, the two most important properties of the diffusion model can be identified in the brain [3••]. The rate of evidence accumulation has been shown to be positively related to BOLD in dorsolateral prefrontal cortex (DLPFC, e.g. [15–17]) and anterior Insula (aI, e.g. [15–18]). Thus, a high accumulation rate elicits a stronger BOLD response than a low accumulation rate, suggesting that easier perceptual decisions yield a stronger BOLD response in DLPFC than hard perceptual decisions. In addition, some studies report a correlation between the rate of evidence accumulation and the BOLD signal in right inferior frontal gyrus (rIFG, [19,20•]). In particular, in the context of a go/no-go task, White and colleagues [20•] found that accumulation rate and rIFG activation correlated negatively, suggesting that less selective inhibition yields a faster response.

The amount of evidence that is required seems to be modulated by cortical regions such as presupplementary motor area (pre-SMA) and anterior cingulate cortex (ACC, e.g. [21•,22,23,24•,25]). Many studies report that individual differences in pre-SMA BOLD responses correlate with individual differences in boundary setting of diffusion models (e.g. [21•,22]). Also, trial-by-trial fluctuations in pre-SMA BOLD correlate with trial-by-trial estimates of boundary settings under speed-stress [24•]. This means that if there is a need to respond

quickly, participants' ability to adjust the amount of evidence required for a response is reflected in the BOLD response in the pre-SMA. The ACC, an area that is in close spatial proximity to the pre-SMA, has also been associated with the amount of evidence. Van Maanen and colleagues [24•] found that trial-to-trial fluctuations in BOLD response correlated with boundary settings in an accumulator model, but only when the task instruction switched. Similarly, Mansfield *et al.* [22] found a correlation between ACC activation and boundary setting in a task switching paradigm, and Mulder *et al.* [23] found a correlation between ACC activation and the amount of required evidence in a two-alternative forced choice task in which the probability of the choices was manipulated.

Additionally, subcortical nodes in the basal ganglia have been found to be related to boundary settings. In particular, similarly to the pre-SMA, neural activation in striatum has been found to correlate with the boundary setting in the diffusion model or related models. Also, there is some evidence that the subthalamic nucleus plays a role in setting response thresholds [26,22].

The neural basis of spatial interference control

The previous section focussed on studies in which diffusion model properties were related to various regions of interest. In this section, we review work that has studied the BOLD response in spatial interference control tasks. The aim of this section is to identify which diffusion model processes can be expected to be important in an explanation of spatial interference control, given the overlap in regions of interest.

The brain area that is most often reported in relation to interference control is the ACC (for a review see [27]). Although ACC activation is often associated with conflict monitoring or detection [28,29] and therefore should be active during interference tasks, the debate on the specific role of ACC is still open. Besides conflict monitoring [30••,31], people have argued that the ACC is active during anticipatory activation [32–34], in response to errors [35], as an indicator of the likelihood of an upcoming error [36,37], and during task switching [38,39].

In addition to the ACC, it has been argued that the DLPFC is involved in the resolution of conflict [30••,40–43]. However, in general, the DLPFC seems to be involved whenever a decision between multiple difficult stimuli has to be made. For example during a face/house discrimination task, DLPFC activation increases with increasing noise levels of the stimuli [17]. Thus, as the decision becomes more difficult, the DLPFC is more involved.

While many researchers have studied conflict tasks, only a few fMRI studies have focussed on the Simon task, rather than the flanker or Stroop tasks or similar paradigms [44]. However, as argued before, the marked differences between response time distributions in the Simon task relative to these related paradigms warrant a separate discussion. Kerns [43] and Strack and colleagues [34] performed fMRI studies of the Simon task and found that in addition to the ACC and the DLPFC, the pre-SMA also played an important role. Strack and colleagues found that when cued with a symbol indicating the congruency of the upcoming stimulus (i.e. congruent or incongruent), activation was higher in the pre-SMA than in the ACC, as compared to cues indicating the spatial location of the stimulus. Forstmann and colleagues [45,46] studied the relation between various properties of the response time distributions and the BOLD response in the Simon task. They found that BOLD activation in the pre-SMA correlated with the proportion of fast incorrect responses [45]. Additionally, Forstmann and colleagues reported that the decrease in interference for slower responses (i.e. a negative-going *delta plot*, [12•]) was predictive of the amplitude of the BOLD response in rIFG [45,46]. The slope of the delta plot that reflects slow responses has been associated with selective response inhibition [12•]. Thus, this result suggests a role for inhibitory processing for the rIFG in the Simon task, which seems consistent with the literature on the function of the rIFG [47–49].

A subset of studies focussed on the overlap in the BOLD response between the Simon task and related interference tasks [50–52]. These studies found a common involvement of DLPFC, pre-SMA, ACC, and rIFG for both Simon and Stroop tasks. However, these studies reported slight differences in the amplitude of the activation in these areas. The pre-SMA and ACC were found to be more active during the Simon task than the Stroop task; the DLPFC and the rIFG were more activated during the Stroop task than the Simon task. One study also considered the time course of the BOLD response in both the Simon task and the Stroop task [52]. This study found that the increased activation for bilateral IFG during the Stroop task was mainly driven by the first 1.65 s of a trial, whereas the activation in (pre-)SMA that was observed in the Simon task was mainly driven by a later BOLD response.

A diffusion model analysis of the Simon task

Because of the complexity of the response time distributions observed in the Simon task, a formal accumulator model is not straightforward [14]. To deal with this complexity, we hypothesize that the architecture of such a model should align with our understanding of the neural networks involved in spatial interference control. That is, given the involvement of the DLPFC and the rIFG in interference control, we hypothesize that the rate of accumulation, specifying how fast evidence is accrued in favor of a (correct) alternative, is lower for incongruent trials. This would reflect that because the activation in the

DLPFC is increased on incongruent trials — which is associated with conflict resolution — the drift rate is decreased. Moreover, the negative correlation between drift rate and rIFG activation suggests that an increase in the rIFG as observed for slow responses — associated with increased selective suppression — relates to a decrease in the rate of accumulation for incongruent trials as well.

Given the hypothesized role of the pre-SMA in setting response thresholds [3••], the findings by Forstmann and others [45,46] suggest that on incongruent trials in the Simon task, fast errors are made due to an incorrect accumulation towards a low threshold. That is, if the threshold is close to the starting point of accumulation, a fast yet error-prone response is likely to occur, similar to an error in the speed-accuracy trade-off paradigm [53]). The involvement of the ACC suggests a role for model parameters representing the amount of evidence required to make a choice. While typically, this entails boundary setting, preliminary results from fitting accumulator models to data of the Simon task suggest that there exist a differential response caution towards the different response options. This would shed a new light on the specificity of the ACC with respect to response caution.

Conclusion

According to model-based analyses of perceptual decision making, the regions of interest in the Simon task may be the DLPFC, rIFG, pre-SMA, and ACC. BOLD activation in the DLPFC and the rIFG correlates with the accumulation of evidence, which may be hampered in the Simon task due to interfering location information. Activation in the pre-SMA and the ACC correlates with the amount of evidence that is required. This may also vary in the Simon task, for example, due to the congruency of the previous trial, which is thought to play a prominent role in interference tasks [54]. This suggests that the Simon task involves at least two separate processes, represented as two different parameters in a diffusion model. However, a review of the literature on neural activation in conflict tasks also suggests considerable overlap between spatial and non-spatial interference. Consequently, although the behavioral outcome differs between paradigms, the neural networks that mediate a response may be shared.

Conflict of interest statement

The authors declare no conflict of interest.

Acknowledgements

This research was supported by an ERC grant from the European Research Council (ERC) and by a Vidi grant from the Dutch Organization for Scientific Research (NWO).

References and recommended reading

Papers of particular interest, published within the period of review, have been highlighted as:

- • of special interest
- •• of outstanding interest

1. • Forstmann BU, Wagenmakers E-J, Eichele T, Brown SD, Serences JT: **Reciprocal relations between cognitive neuroscience and cognitive models: opposites attract?** *Trends Cogn Sci* 2011, **6**:272-279.

This paper highlights the reciprocal relations that exist between cognitive neuroscience, cognitive psychology, and mathematical psychology.

2. •• Forstmann BU, Wagenmakers EJ (Eds): *Model-based cognitive neuroscience: An introduction*. Springer; 2015. http://www.springer.com/biomed/neuroscience/book/978-1-4939-2235-2.

This book provides an overview of the current state-of-the-art in model-based cognitive neuroscience.

3. •• Mulder M, Van Maanen L, Forstmann BU: **Perceptual decision neurosciences — a model-based review**. *Neuroscience* 2014:872-884.

A concise literature review of the relationships between accumulator model parameters and BOLD responses.

4. •• Ratcliff R, McKoon G: **The diffusion decision model: theory and data for two-choice decision tasks**. *Neural Comput* 2008, **20**:873-922 http://dx.doi.org/10.1162/neco.2008.12-06-420.

The authorative review of the diffusion model.

5. Dambacher M, Hübner R: **Time pressure affects the efficiency of perceptual processing in decisions under conflict**. *Psychol Res* 2014 http://dx.doi.org/10.1007/s00426-014-0542-z.

6. • Hübner R, Steinhauser M, Lehle C: **A dual-stage two-phase model of selective attention**. *Psychol Rev* 2010, **117**:759-784 http://dx.doi.org/10.1037/a0019471.

This paper introduces an accumulator model of attentional control in the flanker task that can be extended to spatial interference control (see [8] for a related model).

7. Servant M, Montagnini A, Burle B: **Conflict tasks and the diffusion framework: insight in model constraints based on psychological laws**. *Cogn Psychol* 2014, **72**:162-195 http://dx.doi.org/10.1016/j.cogpsych.2014.03.002.

8. White CN, Ratcliff R, Starns JJ: **Diffusion models of the flanker task: discrete versus gradual attentional selection**. *Cogn Psychol* 2011, **63**:210-238 http://dx.doi.org/10.1016/j.cogpsych.2011.08.001.

9. White CN, Brown S, Ratcliff R: **A test of Bayesian observer models of processing in the Eriksen flanker task**. *J Exp Psychol Hum Percept Perform* 2012, **38**:489-497 http://dx.doi.org/10.1037/a0026065.

10. Wiecki TV, Frank MJ: **A computational model of inhibitory control in frontal cortex and basal ganglia**. *Psychol Rev* 2013, **120**:329-355 http://dx.doi.org/10.1037/a0031542.

11. Kornblum S, Hasbroucq T, Osman A: **Dimensional overlap: cognitive basis for stimulus-response compatibility — a model and taxonomy**. *Psychol Rev* 1990, **97**:253-270.

12. • Ridderinkhof KR: **Activation and suppression in conflict tasks: empirical clarification through distributional analyses.Common Mechanisms in Perception and Action, Vol. XIX of Attention & Performance**Oxford UP; 2002: 494-519.

This paper describes properties of response time distributions for congruent and incongruent trials. Subsequently a technique called *delta-plots* is introduced that helps to detect inhibitory functioning in the Simon task.

13. Pratte MS, Rouder JN, Morey RD, Feng C: **Exploring the differences in distributional properties between Stroop and Simon effects using delta plots**. *Atten Percept Psychophys* 2010, **72**:2013-2025 http://dx.doi.org/10.3758/APP.72.7.2013.

14. Schwarz W, Miller J: **Response time models of delta plots with negative-going slopes**. *Psychon Bull Rev* 2012, **19**:555-574 http://dx.doi.org/10.3758/s13423-012-0254-6.

15. Domenech P, Dreher J-C: **Decision threshold modulation in the human brain**. *J Neurosci* 2010, **30**:14305-14317 http://dx.doi.org/10.1523/JNEUROSCI.2371-10.2010.

16. Liu T, Pleskac TJ: **Neural correlates of evidence accumulation in a perceptual decision task**. *J Neurophysiol* 2011, **106**:2383-2398 http://dx.doi.org/10.1152/jn.00413.2011.

17. Philiastides MG, Sajda P: **EEG-informed fMRI reveals spatiotemporal characteristics of perceptual decision making**. *J Neurosci* 2007, **27**:13082-13091 http://dx.doi.org/10.1523/JNEUROSCI.3540-07.2007.

18. Ho TC, Brown S, Serences JT: **Domain general mechanisms of perceptual decision making in human cortex**. *J Neurosci* 2009, **29**:8675-8687 http://dx.doi.org/10.1523/JNEUROSCI.5984-08.2009.

19. Rowe JB, Hughes L, Nimmo-Smith I: **Action selection: a race model for selected and non-selected actions distinguishes the contribution of premotor and prefrontal areas**. *Neuroimage* 2010, **51**:888-896 http://dx.doi.org/10.1016/j.neuroimage.2010.02.045.

20. • White CN, Congdon E, Mumford JA, Karlsgodt KH, Sabb FW, Freimer NB, London ED, Cannon TD, Bilder RM, Poldrack RA: **Decomposing decision components in the stop-signal task: a model-based approach to individual differences in inhibitory control**. *J Cogn Neurosci* 2014, **26**:1601-1614.
This work links rIFG activation with the drift rate parameter of the diffusion model in a stop-signal task.

21. • Forstmann BU, Dutilh G, Brown S, Neumann J, von Cramon DY, Ridderinkhof KR, Wagenmakers E-J: **Striatum and pre-SMA facilitate decision-making under time pressure**. *Proc Natl Acad Sci U S A* 2008, **105**:17538-17542.
Shows the relationship between rIFG activation and response time distributions. This relationship is important in conjunction with studies highlighting the role of the rIFG in the accumulator model [20].

22. Mansfield EL, Karayanidis F, Jamadar S, Heathcote A, Forstmann BU: **Adjustments of response threshold during task switching: a model-based functional magnetic resonance imaging study**. *J Neurosci* 2011, **31**:14688-14692 http://dx.doi.org/10.1523/JNEUROSCI.2390-11.2011.

23. Mulder M, Wagenmakers E-J, Ratcliff R, Boekel W, Forstmann BU: **Bias in the brain: a diffusion model analysis of prior probability and potential payoff**. *J Neurosci* 2012, **32**:2335-2343 http://dx.doi.org/10.1523/JNEUROSCI.4156-11.2012.

24. • Van Maanen L, Brown SD, Eichele T, Wagenmakers EJ, Ho TC, Serences JT, Forstmann BU: **Neural correlates of trial-to-trial fluctuations in response caution**. *J Neurosci* 2011, **31**:17488-17495.
In this work, the relationship between model parameters and activation of pre-SMA and ACC is found on a trial-by-trial basis. Thus, momentary fluctuations in the neural response systematically influence the behavioral outcome.

25. Winkel J, Van Maanen L, Ratcliff R, Van der Schaaf M, Van Schouwenburg M, Cools R, Forstmann BU: **Bromocriptine does not alter speed-accuracy tradeoff**. *Front Decis Neurosci* 2012, **6** Article 126.

26. Bogacz R, Gurney K: **The basal ganglia and cortex implement optimal decision making between alternative actions**. *Neural Comput* 2007, **19**:442-477 http://dx.doi.org/10.1162/neco.2007.19.2.442.

27. Ridderinkhof KR, Ullsperger M, Crone E, Nieuwenhuis S: **The role of the medial frontal cortex in cognitive control**. *Science* 2004, **306**:443-447.

28. Botvinick MM, Cohen JD: **The computational and neural basis of cognitive control: charted territory and new frontiers**. *Cogn Sci* 2014, **38**:1249-1285 http://dx.doi.org/10.1111/cogs.12126.

29. Shenhav A, Botvinick MM, Cohen JD: **The expected value of control: an integrative theory of anterior cingulate cortex function**. *Neuron* 2013, **79**:217-240 http://dx.doi.org/10.1016/j.neuron.2013.07.007.

30. •• Botvinick MM, Braver TS, Barch DM, Carter CS, Cohen JD: **Conflict monitoring and cognitive control**. *Psychol Rev* 2001, **108**:624-652.
The conflict monitoring hypothesis introduced in this paper has been extremely influential. It proposes that the ACC is involved in detecting conflicting situations, and describes neural network models that illustrate the use of such a detection mechanism.

31. Carter CS, van Veen V: **Anterior cingulate cortex and conflict detection: an update of theory and data**. *Cogn Affect Behav Neurosci* 2007, **7**:367-379.

32. Aarts E, Roelofs A, van Turennout M: **Anticipatory activity in anterior cingulate cortex can be independent of conflict and error likelihood**. *J Neurosci* 2008, **28**:4671-4678 http://dx.doi.org/10.1523/JNEUROSCI.4400-07.2008.

33. Sohn M-H, Albert MV, Jung K, Carter CS, Anderson JR: **Anticipation of conflict monitoring in the anterior cingulate cortex and the prefrontal cortex**. *Proc Natl Acad Sci U S A* 2007, **104**:10330-10334 http://dx.doi.org/10.1073/pnas.0703225104.

34. Strack G, Kaufmann C, Kehrer S, Brandt S, Stürmer B: **Anticipatory regulation of action control in a Simon task: behavioral, electrophysiological, and fMRI correlates**. *Front Psychol* 2013, **4**:47 http://dx.doi.org/10.3389/fpsyg.2013.00047.

35. Carter CS, Braver TS, Barch DM, Botvinick MM, Noll D, Cohen JD: **Anterior cingulate cortex, error detection, and the online monitoring of performance**. *Science* 1998, **280**:747-749.

36. Brown JW, Braver TS: **Learned predictions of error likelihood in the anterior cingulate cortex**. *Science* 2005, **307**:1118-1121 http://dx.doi.org/10.1126/science.1105783.

37. Magno E, Foxe JJ, Molholm S, Robertson IH, Garavan H: **The anterior cingulate and error avoidance**. *J Neurosci* 2006, **26**:4769-4773 http://dx.doi.org/10.1523/JNEUROSCI.0369-06.2006.

38. Johnston K, Levin HM, Koval MJ, Everling S: **Top-down control-signal dynamics in anterior cingulate and prefrontal cortex neurons following task switching**. *Neuron* 2007, **53**:453-462 http://dx.doi.org/10.1016/j.neuron.2006.12.023.

39. Liston C, Matalon S, Hare TA, Davidson MC, Casey BJ: **Anterior cingulate and posterior parietal cortices are sensitive to dissociable forms of conflict in a task-switching paradigm**. *Neuron* 2006, **50**:643-653 http://dx.doi.org/10.1016/j.neuron.2006.04.015.

40. Egner T, Hirsch J: **Cognitive control mechanisms resolve conflict through cortical amplification of task-relevant information**. *Nat Neurosci* 2005, **8**:1784-1790 http://dx.doi.org/10.1038/nn1594.

41. Fan J, Kolster R, Ghajar J, Suh M, Knight RT, Sarkar R, McCandliss BD: **Response anticipation and response conflict: an event-related potential and functional magnetic resonance imaging study**. *J Neurosci* 2007, **27**:2272-2282 http://dx.doi.org/10.1523/JNEUROSCI.3470-06.2007.

42. Kerns JG, Cohen JD, MacDonald 3rd AW, Cho RY, Stenger VA, Carter CS: **Anterior cingulate conflict monitoring and adjustments in control**. *Science* 2004, **303**:1023-1026 http://dx.doi.org/10.1126/science.1089910.

43. Kerns JG: **Anterior cingulate and prefrontal cortex activity in an fMRI study of trial-to-trial adjustments on the Simon task**. *Neuroimage* 2006, **33**:399-405 http://dx.doi.org/10.1016/j.neuroimage.2006.06.012.

44. Nee DE, Wager TD, Jonides J: **Interference resolution: insights from a meta-analysis of neuroimaging tasks**. *Cogn Affect Behav Neurosci* 2007, **7**:1-17.

45. Forstmann BU, van den Wildenberg WPM, Ridderinkhof KR: **Neural mechanisms, temporal dynamics, and individual differences in interference control**. *J Cogn Neurosci* 2008, **20**:1854-1865 http://dx.doi.org/10.1162/jocn.2008.20122.

46. Forstmann BU, Jahfari S, Scholte HS, Wolfensteller U, van den Wildenberg WPM, Ridderinkhof KR: **Function and structure of the right inferior frontal cortex predict individual differences in response inhibition: a model-based approach**. *J Neurosci* 2008, **28**:9790-9796 http://dx.doi.org/10.1523/JNEUROSCI.1465-08.2008.

47. Aron AR, Robbins TW, Poldrack RA: **Inhibition and the right inferior frontal cortex: one decade on**. *Trends Cogn Sci* 2014, **18**:177-185 http://dx.doi.org/10.1016/j.tics.2013.12.003.

48. Erika-Florence M, Leech R, Hampshire A: **A functional network perspective on response inhibition and attentional control**. *Nat Commun* 2014, **5**:4073 http://dx.doi.org/10.1038/ncomms5073.

49. Berkman ET, Kahn LE, Merchant JS: **Training-induced changes in inhibitory control network activity**. *J Neurosci* 2014, **34**:149-157 http://dx.doi.org/10.1523/JNEUROSCI.3564-13.2014.

50. Fan J, Flombaum JI, McCandliss BD, Thomas KM, Posner MI: **Cognitive and brain consequences of conflict**. *Neuroimage* 2003, **18**:42-57.

51. Liu X, Banich MT, Jacobson BL, Tanabe JL: **Common and distinct neural substrates of attentional control in an integrated Simon and spatial Stroop task as assessed by event-related fMRI**. *Neuroimage* 2004, **22**:1097-1106 http://dx.doi.org/10.1016/j.neuroimage.2004.02.033.

52. Peterson BS, Kane MJ, Alexander GM, Lacadie C, Skudlarski P, Leung HC, May J, Gore JC: **An event-related functional MRI study comparing interference effects in the Simon and Stroop tasks**. *Brain Res Cogn Brain Res* 2002, **13**:427-440.

53. Bogacz R, Wagenmakers EJ, Forstmann BU, Nieuwenhuis S: **The neural basis of the speed-accuracy tradeoff**. *Trends Neurosci* 2010, **33**:10-16.

54. Egner T: **Congruency sequence effects and cognitive control**. *Cogn Affect Behav Neurosci* 2007, **7**:380-390.