Physics of Life Reviews 56 (2026) 61–63

Contents lists available at ScienceDirect

Physics of Life Reviews

journal homepage: www.elsevier.com/locate/plrev

A promising new foundation for conflict and control: Bridging the gap to verification. Comment on "Active inference and cognitive control: Balancing deliberation and habits through precision optimization" by Riccardo Proietti, Thomas Parr, Alessia Tessari, Karl Friston, & Giovanni Pezzulo

Antonino Visalli *

Department of Biomedical, Metabolic and Neural Sciences, University of Modena and Reggio Emilia, Viale Antonio Allegri 9 42121, Reggio Emilia, Italy

Despite decades of research, the theoretical landscape of cognitive control remains fragmented, with models proposing multiple, unintegrated functions [1]: from conflict detection [2], error prediction [3] and effort coding [4] to proactive/reactive control modes [5]. Central debates persist on how signals like conflict influence control allocation. Some models suggest continuous modulation [6–8], while others even put in doubt that these effects reflect genuine dynamic control, proposing simpler processes like associative learning [9]. Furthermore, while control allocation is increasingly conceptualized as an optimization problem that balances costs (effort, conflict) and benefits (reward, motivation), how these different values are computationally represented and integrated within hierarchical control systems remains an unresolved issue [4,10].

In this fragmented landscape, the Active Inference framework by Proietti et al. offers a promising path toward unification. The model recasts control allocation as a hierarchical optimization problem, integrating conflict, surprise, effort, and reward signals within a single normative framework. This approach is notable for its theoretical synthesis, and its computational measures serve as strong candidates to investigate neural dynamics. While the proposed framework offers a very original perspective, its core assumptions also raise critical questions that require empirical validation.

1. An original formulation of conflict's role and control's mechanism

The fundamental novelty of the Proietti et al. model lies in how cognitive control is regulated in situations of conflict. In several established models [2,4,6] conflict signals are typically treated as direct inputs that proportionally modulate control intensity. In contrast, the authors treat conflict as an indirect informational input for a higher-order meta-cognitive agent, which makes a discrete, cost-benefit decision on whether to engage deliberation.

This hierarchical approach is necessary to address an impasse that arises from the model's core Active Inference. The critical assumption is that "control" is the precision over the deliberative policy. Crucially, this precision is dynamically adjusted not based on the level of experienced conflict, but on the real-world success or failure of the combined deliberative and habitual policy (i.e.,

DOI of original article: https://doi.org/10.1016/j.plrev.2025.05.008.

* Corresponding author.
E-mail address: antonino.visalli@unimore.it.

https://doi.org/10.1016/j.plrev.2025.11.008
Received 19 November 2025; Accepted 23 November 2025
Available online 24 November 2025

expected free energy prediction error). As the authors demonstrate, this leads to a "vicious circle" where a policy failure paradoxically reduces confidence in the deliberative component. The "optimistic simulation" - a prospective mechanism that calculates a new, optimistic prior - is the specific solution introduced to solve this impasse. This reframes the role of conflict: it is not a direct regulatory signal for control, but rather an indirect trigger for the meta-agent to evaluate the necessity of intervention.

This is a highly original perspective that could lead to novel insights, open new scenarios, and prompt a re-evaluation of previous findings. However, this innovative - and complex - solution is necessitated entirely by the specific AIF assumption regarding the updating of deliberative precision. Therefore, this core assumption demands rigorous experimental verification.

2. The missing link for verification: the need for decision-making dynamics

A crucial link for experimental verification, however, is missing: a mechanistic description of the intra-trial temporal dynamics that lead to policy selection (i.e., the decision-making process). This omission is significant, as experimental data in this field rely fundamentally on reaction times (RTs) and their distributions, not just final choices. This absence prevents the model from explaining core phenomena like the Stroop, Simon, or Flanker effects.

The literature reveals not a unitary mechanism, but a heterogeneous set of processes. Computationally, sequential sampling models built to explain these dynamics propose distinct loci of interference [11,12] and qualitatively different dynamics - such as transient decay for Simon-task conflict versus sustained accumulation for Flanker [13–15]. This heterogeneity is evident in influential measures like delta plots (which map the conflict effect as a function of RT percentiles), which show different profiles: positive for Flanker and Stroop tasks, negative for Simon [13,16–20]. Neural evidence also supports this multiplicity with distinct temporal and spectral profiles [21,22]. This heterogeneity of mechanisms and observed patterns poses a direct challenge to a unifying framework like Proietti et al.'s.

If cognitive control is a single principle of precision optimization, how can this one process generate such radically different temporal profiles? The model requires this missing level of description, one typically provided by sequential sampling accounts, specifying how its signals (e.g., E and G) translate into the temporal dynamics of conflict resolution. Without this bridge, the model's mechanisms remain disconnected from RT distributions, making it difficult to falsify against the evidence from classic conflict tasks.

3. Conclusion

Proietti et al. put forward a framework of significant originality. The elegance of this work lies in its power to formally unify - under a single, normative principle of precision optimization - both pragmatic (e.g., effort, reward) and epistemic (e.g., surprise, conflict) signals. This approach offers a fundamentally new lens through which to conceptualize both the mechanisms of control and the role of conflict, but its core assumptions now require rigorous validation.

This unification is its greatest strength, but it also presents its greatest challenge. As argued, the empirical landscape of cognitive control is defined by a deep heterogeneity, particularly in the decision-making dynamics that classic tasks reveal. The current framework, while conceptually powerful, operates at a level that does not yet explain how its single, elegant principle can generate such diverse and well-documented behavioral profiles. The challenge for this new perspective is not to ignore this complexity, but to explain it. Demonstrating how this unified theory can account for the rich and varied temporal dynamics of conflict remains the most crucial test for its future development and empirical validation.

Declaration of competing interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Vassena E, Holroyd CB, Alexander WH. Computational models of anterior cingulate cortex: at the crossroads between prediction and effort. Front Neurosci 2017;11:316.
[2] Botvinick MM, Braver TS, Barch DM, Carter CS, Cohen JD. Conflict monitoring and cognitive control. Psychol Rev 2001;108:624.
[3] Alexander WH, Brown JW. Medial prefrontal cortex as an action-outcome predictor. Nat Neurosci 2011;14:1338–44.
[4] Shenhav A, Botvinick MM, Cohen JD. The expected value of control: an integrative theory of anterior cingulate cortex function. Neuron 2013;79:217–40.
[5] Braver TS. The variable nature of cognitive control: a dual mechanisms framework. Trends Cogn Sci 2012;16:106–13.
[6] Gonthier C, Braver TS, Bugg JM. Dissociating proactive and reactive control in the Stroop task. Mem Cognit 2016;44:778–88. https://doi.org/10.3758/s13421-016-0591-1.
[7] Viviani G, Visalli A, Montefinese M, Vallesi A, Ambrosini E. Tango of control: the interplay between proactive and reactive control. J Exp Psychol Gen 2024. https://doi.org/10.1037/XGE0001585.
[8] Visalli A, Ambrosini E, Viviani G, Sambataro F, Tenconi E, Vallesi A. On the relationship between emotions and cognitive control: evidence from an observational study on emotional priming stroop task. PLOS ONE 2023;18:e0294957. https://doi.org/10.1371/JOURNAL.PONE.0294957.
[9] Schmidt JR. Is conflict adaptation adaptive? An introduction to conflict monitoring theory and the ecological problems it faces. Q J Exp Psychol 2025;78: 865–83.
[10] Yee DM, Braver TS. Interactions of motivation and cognitive control. Curr Opin Behav Sci 2018;19:83–90.
[11] Kornblum S, Hasbroucq T, Osman A. Dimensional overlap: cognitive basis for stimulus-response compatibility—A model and taxonomy. Psychol Rev 1990;97: 253–70. https://doi.org/10.1037//0033-295X.97.2.253.
[12] Viviani G, Visalli A, Montefinese M, Vallesi A, Ambrosini E. The Stroop legacy: a cautionary tale on methodological issues and a proposed spatial solution. Behav Res Methods 2023. https://doi.org/10.3758/s13428-023-02215-0.

[13] De Jong R, Liang C-C, Lauber E. Conditional and unconditional automaticity: a dual-process model of effects of spatial stimulus-response correspondence. J Exp Psychol Hum Percept Perform 1994;20:731.
[14] Zorzi M, Umiltá C. A computational model of the Simon effect. Psychol Res 1995;58:193–205.
[15] Servant M, Montagnini A, Burle B. Conflict tasks and the diffusion framework: insight in model constraints based on psychological laws. Cognit Psychol 2014;72: 162–95.
[16] Ulrich R, Schröter H, Leuthold H, Birngruber T. Automatic and controlled stimulus processing in conflict tasks: superimposed diffusion processes and delta functions. Cognit Psychol 2015;78:148–74.
[17] Hübner R, Töbel L. Conflict resolution in the Eriksen flanker task: similarities and differences to the Simon task. PloS One 2019;14:e0214203.
[18] Pratte MS. Eriksen flanker delta plot shapes depend on the stimulus. Atten Percept Psychophys 2021;83:685–99.
[19] Ridderinkhof RK. Micro-and macro-adjustments of task set: activation and suppression in conflict tasks. Psychol Res 2002;66:312–23.
[20] Miller J, Schwarz W. Delta plots for conflict tasks: an activation-suppression race model. Psychon Bull Rev 2021;28:1776–95.
[21] 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;22:1097–106.
[22] Wang K, Li Q, Zheng Y, Wang H, Liu X. Temporal and spectral profiles of stimulus–stimulus and stimulus–response conflict processing. NeuroImage 2014;89: 280–8.