Clinical Psychological Science
2015, Vol. 3(3) 374–377

DOI: 10.1177/2167702614567350
cpx.sagepub.com

# Introduction to the Series on Computational Psychiatry

**Tiago V. Maia**
Instituto de Medicina Molecular, Faculdade de Medicina, Universidade de Lisboa, Lisbon, Portugal and Department of Psychiatry, Columbia University, New York, NY

Computational psychiatry is a budding field of research concerned with computational approaches to psychiatry. Computational techniques can be used in a wide variety of contexts in psychiatry, but in the sense of "computational psychiatry" intended in this series and used in recent treatments of the subject (Friston, Stephan, Montague, & Dolan, 2014; Huys, 2013; Maia & Frank, 2011; Montague, Dolan, Friston, & Dayan, 2012; Stephan & Mathys, 2014; Wang & Krystal, 2014), the focus is on using computational approaches to understand the brain, behavior, and especially brain–behavior relations, in psychiatric disorders. Computational psychiatry thus defined builds on computational cognitive neuroscience, which is concerned with the use of computational approaches to understand brain–behavior relations in healthy humans or animals (O'Reilly, Munakata, Frank, & Hazy, 2014). In fact, computational psychiatry and computational cognitive neuroscience (or computational neuroscience more generally) share many tools and techniques; the main difference between them is that computational psychiatry is concerned not only with the healthy brain but also with the disturbances that underlie psychiatric disorders. Computational psychiatry therefore uses an extended set of tools and techniques that can address topics that are central to research in psychiatry—for example, the ability to detect differences in the models or model parameters that best fit the neurobehavioral processes that characterize different groups (Maia & Frank, 2011; Rigoux, Stephan, Friston, & Daunizeau, 2014), the ability to automatically diagnose patients using neuroimaging data (Klöppel et al., 2012), or the ability to automatically find subgroups that may differ from standard diagnostic criteria but nonetheless prove meaningful from a diagnostic perspective (Brodersen et al., 2014; Wiecki, Poland, & Frank, 2015).

Computational psychiatry can be used in two conceptually different, albeit non–mutually exclusive, ways: (a) as a set of techniques for sophisticated data analysis and (b) as a framework for the development of better theories. The first use of computational psychiatry is perhaps more familiar for scientists outside of this field. In this use, computational approaches are not very different from standard statistical approaches; in fact, they often use or extend statistical approaches. Many of the techniques used come from machine learning, Bayesian statistics, and related fields, but they may also draw on classical statistics. The goal, as in regular statistics, is to answer specific questions about a given set of data.

The second way in which computational approaches can be applied to psychiatry is not concerned with data analysis per se but rather with theory development. For this purpose, computational psychiatry uses computational models, typically based on mathematical equations, to describe the phenomena of interest. To some extent, these models are akin to the equations that are used in classical physics: They capture relations between variables in rigorous ways. The reason for the use of computational models is that the phenomena of interest typically cannot be characterized by closed-form solutions: The system being modeled might even be characterized by a relatively small set of equations, but the behavior of those equations typically cannot be characterized with closed-form solutions, so one has to resort to computational simulations.

A common misunderstanding about the use of computational models for theoretical purposes is that one gets out only what one puts in, so the whole approach is sterile. The reality, however, is that the models can predict novel, unanticipated relations that are entailed by the mathematical characterizations and would be difficult, if not impossible, to anticipate without modeling. For example, when changing a variable in a model (say, the level of a neurotransmitter), we often have no way of predicting a priori what will happen to the other variables (e.g., reaction time) without running the model. The models, like the systems that they describe, are often too complicated for

**Corresponding Author:**
Tiago V. Maia, Instituto de Medicina Molecular, Faculdade de Medicina, Universidade de Lisboa, Av. Prof. Egas Moniz, 1649-028 Lisbon, Portugal
E-mail: Tiago.V.Maia@gmail.com

our limited cognitive resources to be able to perform such calculations and inferences unaided: They may be highly nonlinear, include complex feedback processes, or involve thousands of interacting variables (e.g., the activities of thousands of neurons), among many other possible complexities.

Without the support of a mathematical/computational framework for theoretical development, psychiatry often resorts to overly simplistic explanations: for example, attention-deficit/hyperactivity disorder involves low dopamine, depression involves low serotonin, and so on. These explanations can and do tend to get more elaborate as research accumulates, but they often continue to suffer from the same fundamental limitation: trying to bridge too wide a gap between local changes to one or a small set of variables (as effected, for example, by a medication) and their effects on other, sometimes causally distant variables (e.g., inattention scores). Computational models help to bridge this gap and tame the intervening complexity. Using these models allows us to trace the full causal pathway from a change in one or a set of variables to the effects on the other variables (assuming, of course, that the relevant intervening relations are appropriately captured in the model). Furthermore, the models can often integrate different levels of analyses by showing how certain variables depend on, or affect, variables at other levels (e.g., how changing levels of a certain neurotransmitter may lead to changes in the responsivity of neurons, which may lead to changes in processing in certain brain areas, which may lead to changes in reaction times). In so doing, the models provide an integrated mechanistic understanding of the phenomena under study.

Although the two uses of computational psychiatry described thus far—sophisticated data analysis and theory development—are conceptually different, their combined use is especially powerful. There are several model-selection and model-fitting techniques that can determine which theoretical model or models best characterize an empirical data set, and under which parameterizations (Daunizeau, Adam, & Rigoux, 2014; Daw, 2011; Rigoux et al., 2014; Stephan, Penny, Daunizeau, Moran, & Friston, 2009), and these techniques allow several questions of interest for psychiatry to be addressed. For example, one may assess whether the behavior or brain activity of different groups—for example, patients versus controls, patients with different disorders, medicated versus unmedicated patients, and so on—follows the same theoretical model or different models, whether groups differ in one or more model parameters that relate to specific neurobiological or cognitive processes, whether there is a relation between one or more such parameters and symptom severity, or whether the models or model parameters that best characterize each subject cluster in subgroups that may be meaningful clinically.

The range of approaches, techniques, and applications of computational psychiatry is vast and growing quickly; this article series is intended to showcase some of this richness. In the first article in the series, Wiecki et al. 2015) explain how computational psychiatry may help to overcome some of the challenges currently facing psychiatry and present a set of methods that can be used to address several questions of interest in computational psychiatry. They test these methods by applying them to two data sets and, notably, find that these methods, which use computational models to infer latent processes, outperform standard methods based on applying standard statistics to the measured variables. In the next article, Huys, Guitart-Masip, Dolan, and Dayan (2015) use a normative account of decision making based on Bayesian decision theory to identify the types of "fault lines" along which decision-making processes may break. They show that specific deviations from normative processes, or even the application of normative processes on uncharacteristic patterns of experience, may lead to specific deficits that underlie different types of symptoms. In the next article, Lu et al. (2015) use machine-learning methods to classify children with autism spectrum disorder versus control children on the basis of the response of the cingulate cortex to the presentation of a single "self" stimulus, as assessed using functional magnetic resonance imaging (fMRI). The finding that single-stimulus fMRI may provide valuable diagnostic information, if replicated in further studies, would be very good news for the clinical application of fMRI, as it drastically reduces scanning time, thereby cutting costs. In the next article, Anticevic, Murray, and Barch (2015) provide a comprehensive review of computational approaches to schizophrenia that shows how models of different types and at different levels of abstraction—including biophysical, connectionist, and normative (or seminormative) models—can shed light on multiple aspects of this disorder. Schizophrenia is perhaps the disorder in which there has been more work from a computational perspective; this review therefore helps to showcase the richness and breadth of computational methods that can be applied to understand psychiatric disorders. In the final article in the series, Cano-Colino and I (Maia & Cano-Colino, 2015) use a biophysical model of the effects of serotonin on neuronal membrane currents to explain mechanistically how low serotonin leads to an increased tendency to develop obsessions and to get trapped in existing obsessions in obsessive-compulsive disorder (OCD). The model also elucidates the mechanisms underlying the effects of medications that act on the serotonergic system in OCD and suggests that serotonergic medications can be useful to treat OCD even if the primary abnormality is glutamatergic, rather than serotonergic.

The articles in this series illustrate the diversity of approaches, methods, and applications of computational psychiatry. The model types used or reviewed include biophysical (Anticevic et al., 2015; Maia & Cano-Colino, 2015), connectionist (Anticevic et al., 2015), reinforcement-learning (Anticevic et al., 2015; Wiecki et al., 2015), drift-diffusion (Wiecki et al., 2015), and Bayesian decision (Huys et al., 2015) models. The disorders addressed include addiction (Huys et al., 2015), autism (Lu et al., 2015), depression (Huys et al., 2015), OCD (Maia & Cano-Colino, 2015), Parkinson's disease (Wiecki et al., 2015), and schizophrenia (Anticevic et al., 2015; Huys et al., 2015; Wiecki et al., 2015). The empirical phenomena addressed include psychopharmacology (Anticevic et al., 2015; Maia & Cano-Colino, 2015), fMRI (Lu et al., 2015), deep-brain stimulation (Wiecki et al., 2015), and multiple aspects of behavior and brain–behavior relations (Anticevic et al., 2015; Huys et al., 2015; Maia & Cano-Colino, 2015; Wiecki et al., 2015). Finally, machine-learning methods are used both for classification (Lu et al., 2015; Wiecki et al., 2015) and for clustering (Wiecki et al., 2015).

This series is, to the best of my knowledge, the first collection of articles specifically devoted to computational psychiatry. Recently, there have been several reviews of computational psychiatry (Friston et al., 2014; Huys, 2013; Maia & Frank, 2011; Montague et al., 2012; Stephan & Mathys, 2014; Wang & Krystal, 2014) and a growing number of meetings devoted to the topic. The time had come for an article series that brought together a range of approaches, techniques, and applications of computational psychiatry. The fact that even the diverse set of articles included in this series does not—and could not aim to—cover the full breadth of computational psychiatry is a testament to the vigor of this research field. The aforementioned reviews provide an excellent complementary perspective on the field. These are exciting times for those interested in computational approaches to psychiatry, and I hope that this series does its part in helping to consolidate this young but vibrant and extremely promising field.

## Author Contributions

T. V. Maia is the sole author of this article and is responsible for its content.

## Acknowledgments

I am very grateful to all of the authors for agreeing to participate in this series and to Alan E. Kazdin, the editor of *Clinical Psychological Science*, for his unwavering enthusiasm for, and support of, this series.

## Declaration of Conflicting Interests

The author declared no conflicts of interest with respect to the authorship or the publication of this article.

## References

Anticevic, A., Murray, J. D., & Barch, D. M. (2015). Bridging levels of understanding in schizophrenia through computational modeling. *Clinical Psychological Science*, *3*, 433–459.

Brodersen, K. H., Deserno, L., Schlagenhauf, F., Lin, Z., Penny, W. D., Buhmann, J. M., & Stephan, K. E. (2014). Dissecting psychiatric spectrum disorders by generative embedding. *NeuroImage: Clinical*, *4*, 98–111. doi:10.1016/j.nicl.2013.11.002

Daunizeau, J., Adam, V., & Rigoux, L. (2014). VBA: A probabilistic treatment of nonlinear models for neurobiological and behavioural data. *PLOS Computational Biology*, *10*, e1003441. doi:10.1371/journal.pcbi.1003441

Daw, N. D. (2011). Trial-by-trial data analysis using computational models. In M. R. Delgado, E. A. Phelps, & T. W. Robbins (Eds.), *Decision making, affect, and learning: Attention & performance XXIII* (pp.). Oxford, England: Oxford University Press. doi:10.1093/acprof:oso/9780199600434.003.0001

Friston, K. J., Stephan, K. E., Montague, R., & Dolan, R. J. (2014). Computational psychiatry: The brain as a phantastic organ. *Lancet Psychiatry*, *1*, 148–158. doi:10.1016/S2215-0366(14)70275-5

Huys, Q. J. M. (2013). Computational psychiatry. In D. Jaeger & R. Jung (Eds.), *Encyclopedia of computational neuroscience* (pp.). New York, NY: Springer. doi:10.1007/978-1-4614-7320-6_501-2

Huys, Q. J. M., Guitart-Masip, M., Dolan, R. J., & Dayan, P. (2015). Decision-theoretic psychiatry. *Clinical Psychological Science*, *3*, 400–421.

Klöppel, S., Abdulkadir, A., Jack, C. R., Koutsouleris, N., Mourão-Miranda, J., & Vemuri, P. (2012). Diagnostic neuroimaging across diseases. *NeuroImage*, *61*, 457–463. doi:10.1016/j.neuroimage.2011.11.002

Lu, J., Kishida, K., Asis-Cruz, J. De Lohrenz, T., Treadwell-Deering, D., Beauchamp, M., & Montague, P. R. (2015). Single-stimulus functional MRI produces a neural individual difference measure for autism spectrum disorder. *Clinical Psychological Science*, *3*, 422–432.

Maia, T. V., & Cano-Colino, M. (2015). The role of serotonin in orbitofrontal function and obsessive-compulsive disorder. *Clinical Psychological Science*, *3*, 460–482.

Maia, T. V., & Frank, M. J. (2011). From reinforcement learning models to psychiatric and neurological disorders. *Nature Neuroscience*, *14*, 154–162. doi:10.1038/nn.2723

Montague, P. R., Dolan, R. J., Friston, K. J., & Dayan, P. (2012). Computational psychiatry. *Trends in Cognitive Sciences*, *16*, 72–80. doi:10.1016/j.tics.2011.11.018

O'Reilly, R. C., Munakata, Y., Frank, M. J., & Hazy, T. E. (2014). *Computational cognitive neuroscience*. Retrieved from http://ccnbook.colorado.edu

Rigoux, L., Stephan, K. E., Friston, K. J., & Daunizeau, J. (2014). Bayesian model selection for group studies—Revisited. *NeuroImage*, *84*, 971–985. doi:10.1016/j.neuroimage.2013.08.065

Stephan, K. E., & Mathys, C. (2014). Computational approaches to psychiatry. *Current Opinion in Neurobiology*, *25*, 85–92. doi:10.1016/j.conb.2013.12.007

Stephan, K. E., Penny, W. D., Daunizeau, J., Moran, R. J., & Friston, K. J. (2009). Bayesian model selection for group studies. *NeuroImage*, *46*, 1004–1017. doi:10.1016/j.neuroimage.2009.03.025

Wang, X.-J., & Krystal, J. H. (2014). Computational psychiatry. *Neuron*, *84*, 638–654. doi:10.1016/j.neuron.2014.10.018

Wiecki, T. V., Poland, J., & Frank, M. J. (2015). Model-based cognitive neuroscience approaches to computational psychiatry: Clustering and classification. *Clinical Psychological Science*, *3*, 378–399.