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Comment

Relating computational models and experiments in peripersonal space: Comment on “computational models of peripersonal space representation”, by Bertoni et al.

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Peripersonal space (PPS) refers to the space immediately surrounding the body, and has been shown over the past half century to be represented by a specialised set of neural mechanisms. Research on PPS has used the full range of methods in neuroscience and psychology, incorporating evidence from neurophysiology [1], experimental psychology [2], neuropsychology [3], neuroimaging [4], and as reviewed by Bertoni and colleagues, computational modelling. As the authors note, computational models have important advantages in forcing researchers to explicitly define the functional properties of the systems they are studying. One main problem with proposing theories without a mathematical formalisation is that they are often ambiguous and hard to compare with other theories. This problem can be avoided with computational models, as formalisation is crucial when modelling. In this way it is easier to identify mathematical equivalencies or errors, and explaining underlying mechanisms [5,6].

This review of computational models of PPS is a timely and welcome addition to the field. This is especially true as computational models are often not easily accessible to researchers working on similar topics using other methods. The authors have made a significant effort to establish organisational principles for the models, which is highly useful for a broad range of researchers, not just those focused on PPS. This approach provides a solid approach to computational modelling and offers a concrete application of Marr’s [7] levels-of-analysis framework, which often remains abstract. For researchers working on PPS, it will be highly valuable to have a list of models alongside a framework for interpreting them. Here, we wish to raise some issues relating to the relation between modelling and experimentation, which we believe are important to make the relation between computational models and experimentation on PPS productive and mutually beneficial.

As recent advances in artificial intelligence have made clear, computational models can learn many things, though not always in the same way that humans or other animals would learn them. Bertoni and colleagues review many cases in which neural networks and other computational models can reproduce patterns of results from behavioural, neurophysiological, and neuroimaging studies. It is less clear what status such demonstrations have as evidence. What has been learned when a model successfully replicates a pattern of empirical results? This question is reinforced by observations like Bertoni and colleagues’ own observation that “velocity tuning of PPS spatial properties can emerge from broadly different architectures and conceptual frameworks” (pg. 134). If fundamentally different types of architecture produce similar patterns of results, then collectively they appear to provide little insight into what’s happening in

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actual minds and brains, no matter how well they reproduce experimental results.

A related point concerns model comparison. Bertoni and colleagues describe many computational models that succeed in modelling behavioural and neural data. But the authors say much less about models that fail to do so. But as the authors themselves note, when interpreting a successful model "it is crucial to clearly identify the set of conditions allowing such model predictions to be generated" (pg. 134). It is precisely by comparing the models that do and do not reproduce empirical findings that insight can be gained into what mechanisms might underlie the characteristics of PPS.

A final issue concerns the relation between computational modelling and experimentation. As an experimentalist, it is not always easy to understand how to engage with modelling work in a mutually beneficial way. As Teufel and Fletcher [8] identified in the context of computational models of psychiatric disorders, models can evoke an "evolving feeling of disorientation and puzzlement in some observers of the field". In this respect, it is a great strength that Bertoni and colleagues provide several categories of predictions drawn from several of the models they describe. Many of these predictions are novel, testable, and interesting, such as the prediction that PPS should expand when visual stimuli are noisy.

In other cases, however, the predictions appear less interesting as empirical predictions as such, than as validation of the model. Indeed, Bertoni and colleagues write that "the ability to generate new, testable predictions that are confirmed through empirical testing provides much more compelling validation than merely reproducing known results" (pg. 136). While this is no doubt true, there is a risk of circularity in which the purpose of the model is to generate testable predictions, the purpose of which is to validate the model.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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