

How Should We Measure Fear?

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Understanding behavior at an algorithmic level is necessary if we want to adequately explain (mal)adaptive psychological phenomena (1). In this vein, computational psychiatry provides an exciting area of scientific inquiry, where, among other models, computational models are used to better understand mental dysfunction (2). In this issue of *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, Howlett *et al.* (3) provide important data in this direction. The authors used a simple virtual driving task, where participants had to drive a virtual car with a joystick until a stop sign, and fitted a computational model to their data to estimate parameters for present, past, and future error. The results showed that individuals who reported high levels of self-reported fear showed reduced processing of current error (i.e., the difference between the goal position and the current state), a finding that is in line with inhibited approach of valued goals. The same individuals also showed overestimation of future error, in tune with increased corrections after missing a goal. Such findings are useful for both researchers interested in basic decision-making literature and clinical therapists who may be interested in the predictors of (mal)adaptive behavior (e.g., decision making). Another positive characteristic of the study by Howlett *et al.* (3) is that the authors take a modern approach in psychopathology by focusing on different dimensions (e.g., fear and anxiety) rather than categories of symptoms [e.g., anxiety-related disorders; see Research Domain Criteria framework as well as the network models of psychology (4)].

Still, although the authors go to great lengths to decompose participants' performance in different model parameters, Howlett *et al.* (3) fall short in adequately addressing the factors that may predict participants' performance. From among the different factors, I will focus on the concept of fear. The exact definition of fear, and by extension its measurement, is a matter of ongoing debate (5,6). Howlett *et al.* (3) assessed fear via self-reports [assessed with the Positive and Negative Affect Schedule—Expanded Form Fear (7)] and by measuring brain volumes in the insula and the dorsal anterior cingulate cortex. Fear though, as also acknowledged by the authors, may be defined as a conglomerate of physiological, behavioral, and subjective responses, with the different response systems not always converging with each other (8). This nonconvergence implies that the sufficient assessment of fear should ideally entail its measurement at all 3 levels. Importantly, experimental paradigms designed to access fear—e.g., fear conditioning (9)—use a multiassessment approach of fear responses (e.g., by measuring verbal reports together with skin conductance responses and electromyography or action tendencies with approach-avoidance tasks). Of note, highly influential work in the field (10) relies on multiple systems rather than one response system for detecting differences between clinical and healthy samples.

Despite the validity of self-reports in measuring fear, relying on only self-reports reflects only part of how fear may be expressed and implies an assessment of fear on only a conscious level. Also, as acknowledged by the authors, it was unfortunate that the neural data did not include the measurement of other key areas relating to fear/threat (e.g., amygdala) due to the use of surface cortical analyses. Taken together, it remains an empirical question as to whether also the other fear response systems would point to the same direction as the results reported in the article. As such, the present work is an important first step toward better understanding how fear may influence the model parameters estimated by Howlett *et al.* (3), but we should probably wait for more data from studies with a measurement of all levels of fear responses before drawing certain conclusions. Such a multiassessment of fear could be integrated into new computational models, and potentially fresh insights on the interaction between fear and the performance variables could be reached. For example, the different fear responses could be included as separate variables in the model, and their interaction could be used to predict the model parameters. Examinations of these interactions could lead to a deeper understanding of the complexity of pathological behaviors.

To recapitulate, understanding (mal)adaptive behavior at an algorithmic level should focus not only on the estimation of parameters that seem to underline performance at a specific task but also in the correct assessment of the factors that may predict the different parameters. In their article, Howlett *et al.* (3) focused on few of the fear responses. However, and because a consensus on what fear is has yet to be reached (6), it is advisable that researchers assess the different response systems of fear if they want to talk about fear in general and not one of its multiple faces. Importantly, and although here I focus on fear only, the correct conceptualization and measurement of the different predictor variables is an issue that goes beyond fear itself; if the aim is to better understand the predictors of pathological behavior we need to better define, and consequently measure, the possible predictors of interest. This could prove useful in answering key questions in psychology and psychiatry as well as potentially lead to the formal definition of theories of psychopathology.

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