adaptive profiles of coping with adversity, better adherence to health-promoting behaviors, lower frequencies of health-damaging behaviors, better life attainments, better social relations, and even better physical health (in several respects) over extended periods of time (Carver & Scheier 2014; Carver et al. 2010). Unfortunately, this considerable literature on the effects of generalized outcome expectancies was apparently unknown to either the authors or the reviewers of the target article.

This situation is unfortunate, and it illustrates a broader issue. A potential pitfall of multidisciplinary work, or of work that extends one discipline into a topic area that has been well explored by another discipline, is neglecting to consider the various constituencies and failing to review what they have already said. The target article clearly was more grounded in neuroscience and animal research than in human behavioral research and theory, and the failure to thoroughly examine the latter is a serious weakness.

Nonetheless, Kalisch et al. do add to the conceptual conversation. They emphasize that the appraisal processes are not fully conscious, and that they are fluid in operation (we agree with both points; these are ideas that, to our knowledge, have not been widely examined, and they should be). Kalisch et al. appear to be more interested in the neural circuits that support appraisal than in the subjective experience of appraisal, which presumably reflects their background in neuroscience. To their credit, they appropriately acknowledge that there often is a good deal of ambiguity about the meaning of neural activation (sect. 4.3.2). That is, in this case, there is ambiguity (among other ambiguities) about whether neural activation reflects appraisal *contents* or *processes*.

We are not as sanguine as they are about the prospects of gaining useful information about positive appraisals from neuroscience research or from animal research. But it is probably wisest to let a hundred flowers bloom and see what emerges. After all, it is widely known that positive appraisals are generally better than negative ones.

The challenges of forecasting resilience

doi:10.1017/S0140525X14001496, e98

Luke J. Chang, Marianne Reddan, Yoni K. Ashar, Hedwig Eisenbarth, and Tor D. Wager

Department of Psychology & Neuroscience, University of Colorado, Boulder, CO 80309.

luke.chang@colorado.edu
marianne.reddan@colorado.edu
jonathan.ashar@colorado.edu
hedwig.eisenbarth@colorado.edu
tor.wager@colorado.edu
http://cosanlab.com
http://wagerlab.colorado.edu

Abstract: Developing prospective models of resilience using the translational and transdiagnostic framework proposed in the target article is a challenging endeavor and will require large-scale data sets with dense intraindividual temporal sampling and innovative analytic methods.

Kalisch et al. present a thought-provoking translational and transdiagnostic framework for studying resilience. In this commentary, we apply their theoretical framework toward *prospective prediction of* resilient responses to negative life events. Prospective prediction is employed in many domains that depend on accurately forecasting a future state. For example, investors develop models to predict the future value of companies and markets, and epidemiologists develop models to predict the spread of disease. In the area of resilience, a well-formulated model should be able to both forecast the trajectory of an individual's resistance and recovery and generalize across forms of psychopathology and contexts. Such models could transform the study of mental health, but it is not clear how close we are to developing them.

Here, we describe three conceptual challenges for applying Kalisch et al.'s model of resilience in a forecasting framework: (1) resilience is a process unfolding over time, not an outcome that can be measured at a discrete time point; (2) cognitive processes alone are unlikely to predict resilience accurately; and (3) low base rates pose a challenge to predictive accuracy. To help overcome these challenges, we will need studies with large, diverse samples and dense intraindividual temporal sampling.

1. Defining resilient outcomes. Kalisch et al. define resilience as the empirically observed absence of lasting mental health problems following adversity and propose that it can be operationalized as the change in mental health symptoms before and after an adverse event, with a slope of zero indicating a resilient outcome. But at which time points should such a slope be measured? As time passes after a stressful event, the likelihood of returning to a baseline measure becomes greater, increasing the apparent "resilience" independent of any characteristics of the individual. Alternatively, we could estimate the functional form, or shape, of symptom severity as it unfolds across time.

As resilience is likely a dynamic process reflecting multiple mechanisms operating on different timescales, modeling the temporal trajectory may be particularly informative about which mechanisms are involved. This endeavor will require dense sampling of intraindividual data across time and the application of emerging statistical techniques for modeling trajectories, such as functional data analysis (Lindquist & McKeague 2009).

2. Multiple resilient processes. Kalisch et al. adopt a predominantly cognitive view of resilience, proposing a fundamental role for positive appraisal style, which comprises three distinct intrapersonal processes: (1) the initial appraisal, (2) subsequent reappraisal, and (3) inhibiting alternative interfering appraisals. We agree that appraisal and reappraisal are critical (Wager et al. 2008); however, to develop accurate, generalizable models of resilience, we will likely need to incorporate a broader set of mechanisms, including *inter*personal ones. Social support can attenuate negative affective responses (Coan et al. 2006; Master et al. 2009) and has been associated with positive long-term health benefits (House et al. 1988; Uchino et al. 1996). These processes are likely not fully describable in terms of intrapersonal appraisals, but rather will require models of bidirectional, interpersonal feedback loops (Butler & Randall 2013; Schilbach et al. 2013; Zaki & Williams 2013). For example, our feelings of happiness appear to be directly influenced by our peers and can propagate dynamically through our social network over time (Fowler & Christakis 2008).

Therefore, as we move toward prospective models of resilience, it will be important to incorporate both intra- and interpersonal processes. Ensemble algorithms from statistical learning offer a promising approach to integrate multiple mechanisms into a single model (Hastie et al. 2009; Schapire 1990).

3. The base rate problem. One of the challenges of selecting training data for a predictive model is dealing with a very high base rate of resilient outcomes and an extraordinarily low base rate of significant negative life events on a daily basis. To make this more concrete, based on the lifetime prevalence of depression (Kessler et al. 2005), the probability of an individual *not* being depressed on a given day is roughly 99.99%. Using Bayes' rule to combine this high base rate of not being depressed with a low frequency of significant traumatic life events (0.002%; Kessler et al. 1995) reveals a very low conditional probability that an individual will not be depressed given an adverse life event (less than 5%). Therefore, in the general population, resilience defined as a null change across time is actually the standard response, and it will be difficult to identify when true resistance to and recovery from adversity occurs (King & Zeng 2001; Weiss 2004).

To account for these statistical issues, trauma researchers typically have focused on examining resilience to shared traumatic events such as the collapse of the World Trade Center. Such an approach will not be sufficient to develop *predictive* models of resilience, however, as these events are sampled a posteriori rather than prospectively, precluding baseline assessment, and it remains unclear how well mechanisms generalize beyond this experience. Therefore, to increase the predictive power of such forecasting models, it will be necessary to collect large-scale data sets and find a way to increase the frequency of events to train the model (Kanner et al. 1981). Concerted, nationally funded efforts such as the 500,000-person UK Biobank project will help (Allen et al. 2014), and new avenues to large-scale data collection are continually developing with the rapid proliferation of social media, mobile sensing, and cloud computing. For example, using experience sampling of mood from mobile devices, researchers recently collected more than 500,000 samples from approximately 30,000 people (Killingsworth & Gilbert 2010; Rutledge et al. 2014). Furthermore, general public mood can be assessed by mining Twitter feeds, and these metrics appear to modestly predict other global metrics such as the Dow-Jones Industrial Average (Bollen et al. 2011).

4. Conclusion. Though the challenges we have raised in developing predictive models of resilience are substantial, they are inherent to many other problems (e.g., predicting the stock market, forecasting weather, etc.) and are by no means insurmountable. Resilience research can learn from other fields outside of psychology and neuroscience, which have addressed parallel problems with predicting complex and rare events. Billions of dollars are poured into financial markets, and the most powerful supercomputers in the world are continually running simulations to improve our weather forecasts. Why should improving our mental health by predicting resilience be any less important?

Cognitive trade-offs and the costs of resilience

doi:10.1017/S0140525X14001502, e99

Bernard J. Crespi
Department of Biological Sciences, Simon Fraser University, Burnaby, BC V5A 1S, Canada.
crespi@sfu.ca
http://www.sfu.ca/biology/people/profiles/crespi.html

Abstract: Genetic, endocrinological, and psychological evidence demonstrates that resilience commonly trades off with sensitivity. The existence of such trade-offs indicates that resilience bears costs as well as benefits, and that some disorders can best be conceptualized in terms of extremes of trade-offs rather than expression of deficits. Testing for cognitive trade-offs should be a priority for psychiatry, psychology, neuroscience, and genetics.

In the year 2371, the android robot Data from *Star Trek: The Next Generation* has an "emotion chip" installed in his brain, to aid in his quest to understand humanity. The experiment is successful to a fault: Data become overwhelmed with wildly positive, negative, and erratic feelings in response to pleasurable or stressful events. The lesson is clear and supported much further by the empirical evidence described below: Resilience trades off with sensitivity, even at the level of the brain. Why, then, are cognitive trade-offs virtually unstudied in psychology and psychiatry?

Trade-offs can be considered as balances between two beneficial but incompatible phenotypes. Resilience, as conceptualized by Kalisch et al., can be favorable, because it reduces cognitive and emotional sensitivity and vulnerability to stressful events; however, it may also reduce sensitivity to beneficial opportunities. In turn, sensitivity, as a state that trades off with resilience, increases both gains from opportunity and losses from threat. These two opposite concepts form the core of the "vantage sensitivity" model developed by Pluess and Belsky (2013), whereby some individuals are relatively more sensitive than others with

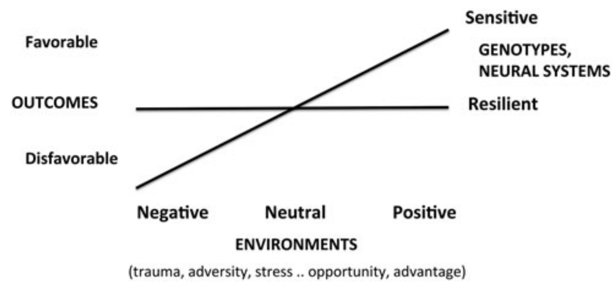

Figure 1 (Crespi). Cognitive trade-offs under a vantage sensitivity model, whereby resilience engenders benefits in poor environments but costs in good ones.

regard to psychological responses to environmental events, whether those events are negative (as in diathesis-stress models) or positive (Fig. 1). Under this paradigm, less-sensitive individuals are simply more resilient. In contrast, the cognitive-resilience model of Kalisch et al., in its reliance on "any mechanism that helps the organism fine-tune stress responses to optimal levels … and remain flexible" (sect. 1.3), implicitly denies the existence of such cognitive trade-offs. So: How important are they?

At the genetic level, cognitive trade-offs are strongly supported by evidence showing that certain genotypes increase liability to psychopathology for individuals in poor environments but confer benefits to individuals in good environments (review in Pluess & Belsky 2013). By contrast, individuals with alternative, "resilience" genotypes at these loci exhibit neither the costs of adversity nor the benefits of advantage. The well-known COMT Val^{158}Met polymorphism provides another case of trade-offs: The Met allele mediates lower flexibility, but increased stability, compared with Val (e.g., Markant et al. 2014); strong trade-offs also have been demonstrated from these alleles for executive compared with emotional tasks (Mier et al. 2010). Comparable results obtain from studies of human polymorphisms in mice: For example, mice bearing the autism-associated R^{451}C mutation exhibit impaired social interactions, but enhanced spatial learning (Tabuchi et al. 2007).

At the level of physiology, trade-offs are controlled by condition-dependent effects of hormones, and for some hormones, these influences extend to the brain. For example, intranasal oxytocin administration leads to reduced analytic thinking, but also increased "holistic processing, divergent thinking and creative performance" (De Dreu et al. 2014, p. 1). Similarly, serum estradiol relative to testosterone exhibits a negative relationship with spatial ability, but a positive association with verbal fluency (Kocoska-Maras et al. 2013).

Finally, at the level of psychiatry, cognitive trade-offs can be analyzed by determining whether increased risks for one disorder coincide with decreased risks for another. For example, three well-documented factors confer protection from schizophrenia: large birth size (Byars et al. 2014), congenital blindness (Silverstein et al. 2013), and duplications of the 22q11.2 copy number locus (Rees et al. 2014). Each of these three factors that reduces schizophrenia risk also *increases* risk for autism (Byars et al. 2014; Hobson & Bishop 2003; Rees et al. 2014), providing evidence that these two disorders trade off in their causes and can be conceptualized as diametric (Crespi & Badcock 2008). More generally, social abilities commonly trade off with spatial skills, in autism as well as neurotypical individuals (e.g., Keehn et al. 2013; Russell-Smith et al. 2012), and schizophrenia genetic risk is positively associated with higher verbal relative to spatial skills (Kravariti et al. 2006). Perhaps most important, these findings also suggest that some disorders themselves represent dysfunctions mediated by extremes of cognitive trade-offs, as between empathizing and systemizing in Baron-Cohen's (2009) model for autism.