Box 1. Recommendations and Best Practices for Clinical Neuroscience Research

1. Dimensional phenotypes. *Diagnostic and Statistical Manual of Mental Disorders, 5th Edition* (DSM-5) diagnoses present barriers to the development of useful neuromarkers (marked heterogeneity and comorbidity, poor inter-rater reliability) [12]. Narrower dimensional phenotypes (e.g., anxiety, anhedonia) offer substantial increases in reliability and power and opportunities to understand transdiagnostic mechanisms.

2. Big and broad data. Mega-cohorts encompassing diverse measures provide increased power and more precise and realistic estimates of brain–disease associations. They afford opportunities for assessing generalizability, controlling potential confounds (e.g., motion artifact in imaging studies), and identifying disease- and risk-relevant relevant environments.

3. Aggregate. Machine learning approaches, actuarial risk calculators, and related techniques that aggregate multiple sources of neural (e.g., activity, connectivity, and anatomy) and non-neural information are more likely to yield clinically useful tools than isolated 'hot spots' of brain function or structure (or focusing on the brain alone).

4. Cross-validate. Absent adequate cross-validation procedures, estimates of neuromarker performance are likely to be inflated. Separate cohorts for model training/discovery and testing/replication are the gold standard and serve as an important brake on premature application based on overly rosy preliminary results.

5. Incremental validity. Simple paper-and-pencil measures of personality and actuarial approaches that leverage readily available demographic/clinical information (e.g., smoking status) often outperform more sophisticated and expensive neuromarkers. Absent head-to-head tests of 'incremental validity,' the clinical value of neuroimaging remains unknown.

6. Reliability. In contrast to clinical measures, the test–retest reliability of most neuromarkers is unclear. Reliability is typically assessed in small, nonrepresentative samples, precluding definitive conclusions. We urge investigators to assess and report reliability in larger, more diverse samples.

reasons, from screening and diagnosis to treatment stratification and monitoring [3]. Developing neuromarkers that more seriously reckon with the complex interactions of human brains, contexts, and outcomes would accelerate the development of new therapeutics and the repurposing of existing ones [11]. H&P remind us that this is a major challenge, one that will require substantial time and resources, new kinds of multidisciplinary collaborations and training models, and a sober assessment of what particular kinds of neuromarkers really can and cannot do for patients and clinicians.

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[1]Department of Psychology, University of Maryland, College Park, MD 20742, USA

[2]Neuroscience and Cognitive Science Program, University of Maryland, College Park, MD 20742, USA

[3]Maryland Neuroimaging Center, University of Maryland, College Park, MD 20742 USA

[4]Department of Psychology, University of California, Davis, CA 95616, USA

[5]California National Primate Research Center, University of California, Davis, CA 95616, USA

[6]Both authors contributed equally to this work; the order of authors was determined by a coin flip

*Correspondence:
shackman@umd.edu (A.J. Shackman) and
dfox@ucdavis.edu (A.S. Fox).

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Letter

Is the Type 1/Type 2 Distinction Important for Behavioral Policy?

Nick Chater[1,]*

Melnikoff and Bargh provide a powerful critique of the Type 1/Type 2 distinction as a typology of cognitive processes. But such a distinction may, nonetheless, be useful in highlighting the need for behaviorally inspired public policy.

Melnikoff and Bargh [1] make a persuasive case concerning the dangers of dividing cognitive processes into two categories: Type 1 (putatively unintentional, uncontrollable, unconscious, and efficient) and Type 2 (putatively intentional, controllable, conscious, and inefficient). They note that the underlying dimensions need not align with each other and that each dimension may itself fragment into subdimensions. Their argument strengthens the viewpoint that the Type 1/Type 2 divide (and the even stronger claim that these processes are organized into distinct mental 'systems') should be treated as no more than a helpful metaphor [2].

As Melnikoff and Bargh point out, recent influential policy reports and discussions in the framework of behavioral economics have adopted, and recommended, this metaphor [3,4]. Policy makers are not, and probably need not be, concerned about detailed typologies of mental processes. They are, though, concerned about which policy levers are likely to work, and which are likely to be irrelevant – and here, broad-brush distinctions can prove useful.

Consider chess as a metaphor for the complexities of real-world decisions. Suppose that we wish to explain the pattern of play in top-quality chess games. We need to know the legal moves of the game, the objective of the players, and to assume that the players will choose from among the 'best' moves available. Perfect rationality is, of course, impossible, but explanation in terms of rational deliberation is the best we can do. For example, we can explain why Grandmaster X did not move his castle by noting that this would have led to a devastating response by Grandmaster Y. Usually it does not help much to refer to either Grandmaster's cognitive frailties or pay attention to their psychological processes at all [5]. Indeed, our explanations will be unchanged if we discover the Grandmaster is actually not a human, but a chess-playing computer. This is because our explanation in top-quality chess primarily concerns the rational structure of the game.

Consider, too, how one player can influence another in this 'hyper-rational' setting. Suppose that White wishes to encourage Black to attack. In top-quality chess, White's only option is to play moves to which Black's attack is the best response: White needs to, in economic language, 'incentivize' Black to attack. By contrast, extraneous interventions, such as reminding players of the rules of the game, moving the game to a computer screen, or playing martial music may have surprisingly little impact. A Grandmaster will attack when and only when it is judicious to do so.

By contrast, suppose we consider chess among extreme novices. Here, neither player is quite sure of the rules, of the identity of the pieces, or what counts as winning. Thus, the rational structure of chess is only partially constraining the players' actions. Now, nonrational factors, such as the visual similarity between bishops and pawns, might be relevant to explaining why one player thinks pawns always move diagonally; the fact that some rules were in small print may explain why another player has missed crucial points. Now, a 'rational' approach to modifying players' behavior will be ineffective: White cannot encourage Black to attack by incentivizing Black, because Black cannot judge when attack is the best course of action. Besides, martial music may encourage attacking play; after all, neither player has any idea whether attack is rationally good or bad, so the mere reminder of the possibility of aggression might be enough to trigger a player to 'give it a go'.

The policy significance marked by the Type 1/Type 2 distinction is, in terms of this analogy, simply stated: policy makers often treat firms and/or consumers as Grandmasters (Type 2), when, in reality, they are abject novices (Type 1). Thus, policy makers may assume that subtle changes in regulation or taxation (subtly modifying the 'rules of the game' and hence its rational structure) will cause firms or consumers to respond optimally [6]. They may assume, too, that rationally irrelevant factors should be of marginal importance (e.g., the layout, or wording, of a tax letter should only marginally impact tax compliance, although see [7]). Indeed, a Type 2 viewpoint can even reinterpret apparent self-destructive behavior as indicating unexpected preferences, such as an inherent love of gambling, or a strong preference for mild present pleasures over much greater foregone future pleasures [8]. Legal scholars, liberal political theorists and especially neoclassical economists, have taken this line; and policy makers have frequently taken their lead.

Yet in many domains of life (gambling, buying a mortgage, or choosing whether to marry) we are all novices: the open-ended, incredibly complex world presents us with challenges for which we have little idea about how to calculate the 'rational' course of action [9,10]. Indeed, the incoherence and incomplete character of our preferences and beliefs in open-ended domains cast doubt on whether rational action is even well-defined in many real-world domains [9,11]. In such cases, Type 1, nonrational, forces may dominate how citizens make choices. Thus, whether a policy is implemented as a tax, a subsidy, or a fine, how a form is worded or designed, and the look-and-feel of a product may be of decisive importance [3]. Irrespective of the shaky theoretical foundations of the Type 1/ Type 2 distinction as a taxonomy of cognitive processes, the implications of this sort of distinction may still be considerable for developing a behaviorally informed public policy [12].

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[1]Behavioural Science Group, Warwick Business School, Coventry, UK

*Correspondence: nick.chater@wbs.ac.uk (N. Chater).
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Spotlight

Birds of a Feather Synchronize Together

Matthew D. Lieberman[1,*]

The multitudinous thoughts, feelings, and perceptions that constitute each person's phenomenological awareness, their subjective experience, might be seen as that which most deeply distinguishes us from one another. We can never fully know one another's experiences and words fail all but the greatest wordsmiths in communicating this experience adequately. Yet new data suggests that the ineffable might be effable after all. And rather than being what separates us from others, our way of seeing the world is a remarkable predictor of who we will connect with.

Over the last decade, the study of neural synchrony, or intersubject correlations, has provided an exciting new way to use neuroimaging to examine the human mind [1]. Rather than focusing on whether activity levels in particular brain regions are responsive to different tasks, neural synchrony examines the conditions under which fluctuations in brains regions correlate from one person to the next. If two people have a conversation, will their brains synchronize? Yes, but one must consider the temporal lag between one person producing speech and the other understanding it [2]. If two people watch the same video, will their brains synchronize? Yes, but how much depends on the quality of video [3]. Effective messages produce more synchrony than less effective messages because effective messaging induces people to see something in the particular way that the messenger wants. In addition, those who are presented with ambiguous information will show greater synchrony with others who see it the same way they do [4,5].

Parkinson, Kleinbaum, and Wheatley's new study [6] is one of only a handful of neural synchrony studies to use machine learning algorithms, such that neural synchrony is actually being used to predict something about the people whose brains are synchronized. But rather than predicting one's experiences and memories [7,8], Parkinson *et al*. predicted the social structure of a large novel group from the similarity of their neural responses.

Parkinson *et al*. obtained social network data from all first year students in an MBA program ($n = 279$). The network was characterized based on mutual nominations in response to a question about 'the people with whom you like to spend your free time.' If two people each checked the other from the list of all students, then this dyad was denoted as 'friends' with an 'edge' directly connecting them in the network and assigned a social distance of 1. If two people were not directly connected, but shared a mutual friend, then they were considered 'friends of friends' and were assigned a social distance of 2. Friends of friends of friends were assigned a 3 and beyond this was coded as a 4.

A subset of this social network ($n = 42$) participated in a second study that involved watching videos ranging from 1.5 to 5 minutes each on a variety of topics (sports, comedy, politics, science), while lying in an MRI scanner. Parkinson *et al*. parcellated the brains of each participant into 80 distinct regions. The time course of activity in response to the video clips in each of these 80 regions was correlated across each of the 861 possible dyadic pairings, with each pair receiving an overall neural similarity score.

The results revealed strong links between neural similarity and social distance within the MBA social network. As neural similarity increased by one standard deviation, a pair was 47% more likely to be friends in real life. Strikingly, this 47% was observed after controlling for gender, ethnicity, nationality, and age – other factors likely to be drivers of social connection. Although this analysis was done by aggregating across all regions of the brain, subsequent analyses indicated that these effects were driven primarily by regions associated with shared perspective taking, attention, and affective processing.

Finally, using machine learning, Parkinson *et al*. trained a classifier on part of the data to try to predict which of the four levels of social distance characterized new dyads within the study. The classifier succeeded at significantly better than chance levels (41%; chance = 25%) and classified close to 50% of friends as friends, rather than as one of the other three levels of social distance.

This study elegantly demonstrates that our private experiences of ordinary everyday events, like YouTube videos, are powerful predictors of who we will spend our time with and come to care about. This study did not attempt to assess the direction of causality, but its findings are consistent with the idea that our unique personal way of seeing the world is so central to who we are, that those who show signs of being our phenomenological comrades would be highly valued by us.