Beyond brain mapping: Using the brain to predict real-world outcomes

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Beyond brain mapping: Using the brain to predict real-world outcomes

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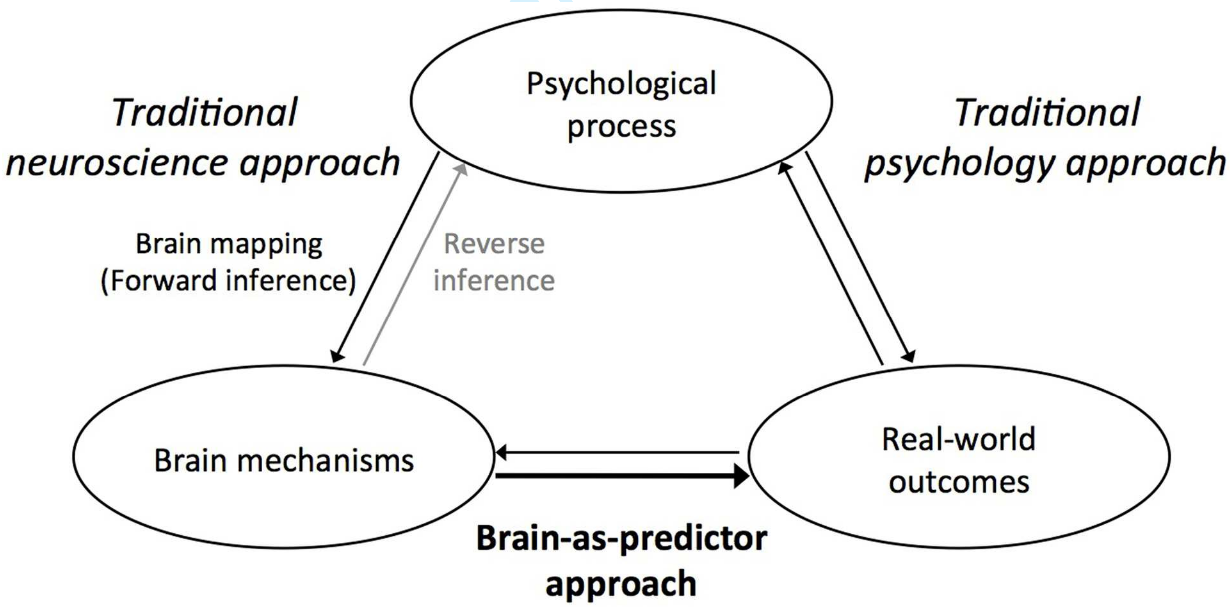
ABSTRACT

One goal of social science in general, and psychology in particular, is to understand and predict human behavior. Psychologists traditionally use self-report measures and performance on laboratory tasks to achieve this end. However, these measures are limited in their ability to predict behavior in certain contexts. We argue that current neuroscience knowledge has reached a point that it can complement other existing psychological measures in predicting behavior and other important outcomes. This *brain-as-predictor* approach integrates traditional neuroimaging methods with behavioral outcomes that extend beyond the immediate experimental session. Previously, most neuroimaging experiments focused on understanding basic psychological processes that could be directly observed in the laboratory. However, recent experiments demonstrate that the brain can predict outcomes over longer time scales (e.g., purchasing decisions, long-term clinical outcomes) in ways that go beyond what was previously possible with self-report alone. This approach can be used to discover the connections between neural activity during laboratory paradigms and longer-term, ecologically valid outcomes. We describe this approach and discuss its potential theoretical implications. We also review recent examples of studies that use this approach, discuss methodological considerations, and provide specific guidelines for using it in future research.

Each year, television studios spend millions of dollars to develop pilot episodes for new shows. The development process includes gathering feedback from potential viewers in the form of surveys, interviews, and focus groups. The studios use this input under the assumption that people are capable of accurately reporting on what they like and don't like, and in turn on what they will and won't watch. However, less than a quarter of pilot episodes become full shows (D'Alessandro, 2012), and the vast majority of those that do fail within the first few years (Stelter, 2012). Why are viewers and network executives alike so poor at judging which shows people will watch? One answer is that the mental processes that give rise to behaviors such as tuning into a TV show are not always accessible to conscious awareness (Dijksterhuis, 2004; Nisbett & Wilson, 1977). A similar argument can be made about why it is so hard to predict the success of health interventions or efforts to get people to save for retirement—people are notoriously limited in their ability to consciously identify why they do what they do. However, the mental processes underlying behavior are nonetheless represented in the brain. Here, we argue that knowledge gained from decades of work in cognitive neuroscience (Cabeza & Nyberg, 2000; Kober et al., 2008; Lieberman, 2010; Montague & Berns, 2002) about the mapping between mental process and brain function can be leveraged to predict meaningful outcomes beyond the laboratory (Figure 1). Indeed, we recently found that brain activation while viewing of a set of commercials in a "neural focus group" predicted the success of the campaigns in the media-markets where they were aired, and did so better than participants' reports of effectiveness (Falk, Berkman, & Lieberman, 2012).

This is one example of a more general *brain-as-predictor* approach, which treats neural markers (e.g., activation, structure, connectivity) as independent variables in models that predict longitudinal outcomes as dependent variables. The brain-as-predictor approach represents a paradigm shift for neuroscience studies, complementing traditional *brain-mapping* studies in which psychological processes are manipulated and the resulting neural activity is observed as the dependent measure (note bidirectional relationships, Figure 1). Decades of neuroscience aimed at establishing brain-behavior relationships and integrating across multiple levels of analysis are foundational to the approach described (e.g., (Cacioppo, Berntson, Sheridan, & McClintock, 2000; Lieberman, 2010). This approach also builds on research on the neural bases of individual differences in personality (e.g., (Canli, 2004; Depue & Collins, 1999)) and responsiveness to clinical treatments (e.g., (Mohr & Mohr, 2001)). The current approach differs from this earlier work, however, in the level of specificity of the hypothesized neural systems and targeted outcomes.



POTENTIAL FOR THEORETICAL AND APPLIED ADVANCES

In this framework, the brain is viewed as an additional window into psychological process that complements other measures such as self-report and other biological measures; its specific role in determining behavior can be examined in the context of those other measures to advance theory and application. For example, in our work predicting the success of ad campaigns, neural measures represent an alternative way to study psychological processes that unfold during ad exposure, which are difficult to capture using other methods. The results illustrate how neuroimaging can add to our understanding of social influence and also apply practically to the problem of more efficiently designing health campaigns.

This conceptualization also improves the ecological validity of neuroimaging experiments by connecting neural measures directly to outcomes beyond the laboratory. For example, a study that predicts treatment outcomes for problem gambling based on activation in regions involved in self-control would provide confirmatory support for the involvement of those regions in control and also suggest ways to improve interventions. In this way, the brain-as-predictor approach broadens our ability to test theory and facilitates translation of basic neuroscience results.

EXAMPLES OF THE BRAIN-AS-PREDICTOR APPROACH

Beyond informing psychological theory, the wide range of outcomes that can be brought into the brain-as-predictor framework represents a compelling new way for neuroscience to interface with other fields such as public health, political science, marketing, sociology, and communication studies. Examples below highlight the advantages of the brain-as-predictor framework in several areas.

Cognition

An early study employing the brain-as-predictor approach predicted intelligence from brain measures (Choi et al., 2008). A model of intelligence based on brain structure and function measured separately in one group explained 45% of the variance in intelligence in a second, independent sample. Identifying regions of interest (ROIs) in advance and examining their involvement in a new sample moves the focus of research from brain-mapping to testing the predictive validity of specified constellations of brain regions. Cognitive neuroscientists have also used neural signals to predict the trajectories of skill acquisition (e.g., language learning (Tan et al., 2011)) and age-related cognitive decline (Woodard et al., 2010)), and to understand overvaluation of short-term benefits relative to long-term costs (Mitchell, Schirmer, Ames, & Gilbert, 2011).

Health

The brain-as-predictor approach has also been applied iteratively to improve the design and selection of health communications and uncover the neural foundations of their effectiveness. For instance, our work (discussed above) predicting the population-level success of health ad campaigns built on previous studies from our lab. The earlier work identified brain regions associated with persuasion, and used activity in those regions to predict increases in sunscreen use in one group (Falk, Berkman, Mann, Harrison, & Lieberman, 2010) and reductions in smoking in a group exposed to relevant public service announcements (Falk, Berkman, Whalen, & Lieberman, 2011). Throughout this program of research, we used a “test-validate” procedure, in which brain-mapping results in one domain (e.g., regions associated with individual behavior change) are tested as predictors in following, conceptually related studies (e.g., individual behavior change in a different domain; population-level success of different campaigns). The use of different participant samples to identify and subsequently interrogate ROIs offers the advantage of conceptual replication across samples. It can also be used within a “neural focus group” framework in which neural activation in a small group predicts outcomes in a larger population (Falk, Berkman, & Lieberman, 2012).

However, we note that independent samples of participants are not always necessary; ROIs may also be defined using an independent psychological 'localizer' task within a group of subjects, which isolates the brain regions associated with a process of interest for each subject. For example, Chua and colleagues used one task to identify neural activity associated with self-related processing in a sample of smokers, and then extracted activity within those regions during a tailored health-message intervention to predict subsequent quitting within the same group of smokers (Chua et al., 2011).

The brain-as-predictor approach can also be used to examine relationships between basic social/cognitive/affective processes and health-relevant outcomes to understand how these psychological processes get 'under the skin'. For example, neural activity during an emotion regulation task predicted daily patterns of release of the stress hormone cortisol in older adults (Urry et al., 2006). Another study showed that activation within the brain's reward system in response to appetitive foods and erotica predicted changes in body mass index and risky sexual behavior (respectively and separately) across six months (Demos, Heatherton, & Kelley, 2012). These studies highlight the potential of brain-as-predictor approaches to link multiple levels of analysis, to examine outcomes beyond observed behavior such as neuroendocrine or immune markers, and to improve prediction.

Economic Decisions

Neuroimaging data have also been used to predict consumer choices (Levy, Lazzaro, Rutledge, & Glimcher, 2011; Tusche, Bode, & Haynes, 2010) and donation behavior (Ma, Wang, & Han, 2011) based on neural responses during protocols in which participants were exposed to stimuli without being asked to judge them. These data suggest that neural signals encode information that predicts subsequent behavior even in the absence of a specific choice or evaluation. Consumer choice studies also suggest that neural data can predict broader population responses (Berns & Moore, 2012).

Clinical, Neurological and Addiction Outcomes

Neural activity during basic laboratory tasks also predicts clinically relevant outcomes. Examples include using brain activation prospectively to predict responsiveness to therapy (e.g., for depression (Costafreda, Khanna, Mourao-Miranda, & Fu, 2009) and anxiety (McClure et al., 2007)), risk for depression (Masten et al., 2011), medical outcomes (e.g., function following stroke (Saur et al., 2010)), and relapse in illicit drug users (Kosten et al., 2006; Paulus, Tapert, & Schuckit, 2005). Along these lines, we used the brain-as-predictor approach to understand the mechanisms that lead to successful regulation of cravings in the context of smoking cessation (Berkman, Falk, & Lieberman, 2011). Neural activation in a self-control network during a self-control task administered at baseline moderated the subsequent hour-to-hour relationship between craving and smoking in the early weeks of quitting. These data provide support for the hypothesis that breaking the link between cravings and smoking involves self-control, which is instantiated in specific, common networks in the brain. This study illustrates the integration of neural measures with experience sampling data and deployment of multilevel models containing both kinds of data. This logic can also be extended to incorporate neural data from hypothesized ROIs in structural equation models, non-parametric models, and other statistical models as they are developed.

A GUIDE TO THE BRAIN-AS-PREDICTOR APPROACH

Procedure

The studies reviewed above, and others like them, provide clues about how to apply a brain-as-predictor approach to a range of outcomes. However, this approach has not yet been formally defined and differentiated from others. We suggest a three-step approach:

First, hypothesis generation, in which candidate brain regions or networks are identified and *a priori* ROIs defined using any means that identify neural regions associated with the hypothesized psychological constructs. In the study described in our opening example, we hypothesized that neural activity within the brain's medial prefrontal cortex would predict the success of ad campaigns based on prior results (Falk, et al., 2010; Falk, et al., 2011). Automated databases that aggregate results of prior research (Yarkoni, Poldrack, Nichols, Van Essen, & Wager, 2011), meta-analyses on the process of interest (Wager, Lindquist, Nichols, Kober, & Van Snellenberg, 2009), or independent tasks within the same sample (Chua, et al., 2011) analyzed with traditional univariate methods or newer multivariate and/or machine learning techniques (Mur, Bandettini, & Kriegeskorte, 2009; Norman, Polyn, Detre, & Haxby, 2006) can each be used to identify ROIs.

Second, data collection, in which neural activation in hypothesized regions is measured and longitudinal outcomes are subsequently collected using methods including but not limited to experience sampling, single-session follow-up or behavioral observation.

Third, hypothesis testing, in which the validity of the hypothesized regions to predict longitudinal outcomes is tested using a predictive statistical model that specifies brain measures as predictors of longitudinal outcomes.

Convergent and Discriminant Validity

A critical consideration is whether neural data contain reliable, predictive information beyond what could be obtained otherwise. Demonstration of discriminant validity requires gathering not only brain data in the second step but also other data that might be predictive (e.g., self-report, behavioral, and/or endocrine), and assessing whether the neural data provide additional predictive power. For instance, in the example above in which neural responses to health communications predicted subsequent smoking reduction, neural activity doubled the amount of variance in behavior change explained relative to a model containing self-report measures alone (Falk, et al., 2011). In other cases, brain and self-report measures overlap in the variance that they explain, which may provide insight into the processes contributing to the predictive relationship (i.e., convergent validity). For example, if the relationship between brain activity in the ROIs and the behavioral outcome were mediated by self-reports of motivation to quit, it would suggest a potential role for this network in motivation and point to a new intervention target. In both cases, psychometric reliability of neuroimaging data is a critical consideration when comparing brain measures to other types of variables. Neuroimaging data can have high test-retest reliability depending on factors including the hardware, test-retest interval, and complexity of the cognitive processes (Berkman, Cunningham, & Lieberman, in press; Miller et al., 2009). However, as with any other kind of data, neuroimaging data reliability must be evaluated in light of the study design and other available measures.

Predictor Selection

In the brain-as-predictor approach, and unlike traditional neuroimaging approaches that generate whole-brain maps as output, the neural predictor must be specified in advance. As suggested by Figure 1, neural predictors presumed to be involved in key mental processes are chosen based on psychological theory and prior brain-mapping results. Careful selection of predictor regions is critical because these regions represent the operationalization of a mental process that will be used for theory testing, akin to selecting a behavioral task or self-report measure to tap a construct. In this sense, brain-as-predictor relies upon the same scientific logic as any other predictive study in psychology (e.g., predicting behavior change from intention) but with a different independent variable.

Iterative Process

Brain-as-predictor is only one part of an iterative cycle of exploratory and confirmatory hypothesis testing designed to advance theory (Figure 1): brain-mapping and brain-as-predictor approaches can be used together to triangulate the relationships among neural, mental process, and behavioral variables. Traditional studies identify candidate regions for a given psychological process (e.g., self-control); brain-as-predictor studies employ confirmatory predictive tests that test the involvement of neural ROIs in that process and identify conditions under which the brain does and does not predict the outcome (e.g., breaking the link between craving and smoking). Brain-as-predictor logic can also be used in neuroimaging studies that employ additional tools designed to facilitate causal inference (such as transcranial magnetic stimulation, which allows manipulation of brain activation (Silvanto & Pascual-Leone, 2012)), and in experiments that manipulate treatment condition and observe subsequent outcomes, with neural function as a hypothesized mediator.

Conclusion

Traditional neuroscience results can be leveraged to uncover unique predictive brain-behavior connections. Though the brain-as-predictor approach is being used more often, researchers rarely call attention to whether neural measures are treated as predictor or outcome variables. Such acknowledgment is essential from a theory building and testing perspective. For example, meta-analyses of both brain-as-predictor and brain-mapping (brain-as-outcome) results would be best served if studies were easily classified as one or the other. In addition, brain-as-predictor “best practices” will emerge more efficiently if researchers can easily track their use in the published literature. Further, the applicability of the approach to fields outside of neuroscience (e.g., medicine, political science) will be most apparent when the predictive capacity of the brain above and beyond other measures is explicitly quantified.

We articulated this brain-as-predictor approach using examples from functional neuroimaging, but the same principles can apply to brain structure, peripheral nervous system function, genes, and other biological measures (Cacioppo, et al., 2000). Future extensions will allow scientists to use neural markers as longitudinal predictors of diverse outcomes across a range of fields. Extending the reach of neuroscience methods beyond exploratory brain-mapping allows for stronger theory testing, sheds light on fundamental neuroscientific questions, and enables prospective prediction of outcomes inaccessible by other means.

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NOTES

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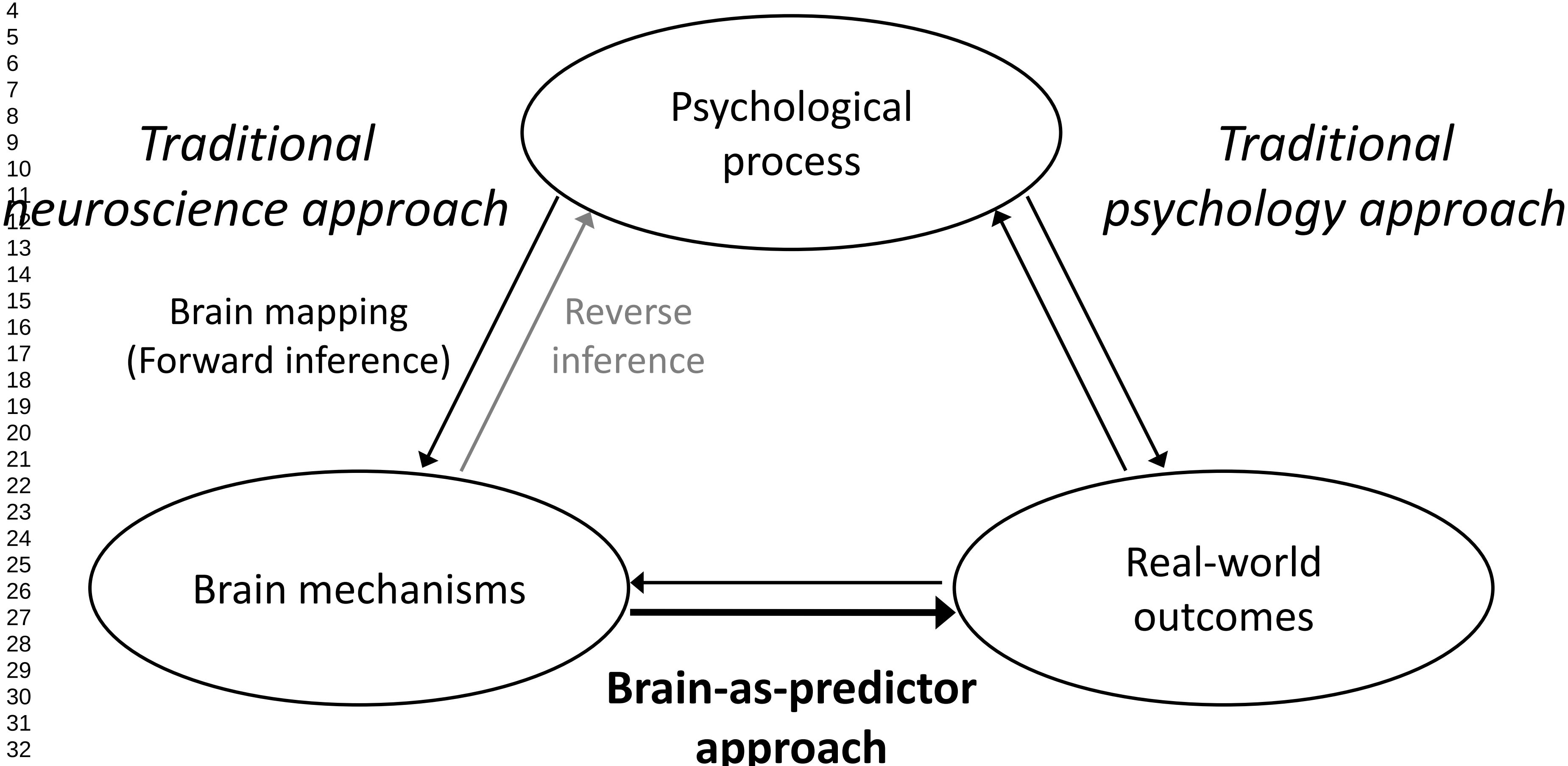
FIGURE CAPTIONS

Figure 1. The brain-as-predictor approach. Traditionally, psychologists have been interested in mapping the relationship between psychological processes (e.g., cognitions, emotions) and real-world outcomes (e.g., health behavior, discrimination), among other things. In contrast, neuroscientists have traditionally used neuroimaging tools to map the relationship between psychological process and brain mechanisms. The *brain-as-predictor* approach integrates these by using brain systems that previously have been linked to a specific psychological process to predict meaningful outcomes beyond the confines of the laboratory. This approach offers new ways to explain unaccounted variance in behavioral outcomes and to test whether hypothesized psychological processes (via their neural associates) are predictive of those outcomes. Bidirectional arrows emphasize the ideas that each construct is likely to affect the others, and that the brain-as-predictor approach complements existing methods for studying the other relationships shown. NB: Arrows in this figure indicate conceptual relationships between independent and dependent variables rather than causality; manipulation of brain function (e.g., using TMS or in natural/clinical lesion studies) is necessary in order to establish causality.


Traditional neuroscience approach
Psychological process
Traditional psychology approach
Brain mapping (Forward inference)
Reverse inference
Brain mechanisms
Real-world outcomes
Brain-as-predictor approach