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Beyond Brain Mapping: Using Neural Measures to Predict Real-World Outcomes

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Abstract

One goal of social science in general, and of psychology in particular, is to understand and predict human behavior. Psychologists have traditionally used 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 neuroscientific knowledge has reached a point where it can complement other existing psychological measures in predicting behavior and other important outcomes. This *brain-as-predictor* approach integrates traditional neuroimaging methods with measures of 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 have demonstrated that brain measures can predict outcomes (e.g., purchasing decisions, clinical outcomes) over longer timescales in ways that go beyond what was previously possible with self-report data alone. This approach can be used to reveal the connections between neural activity in laboratory contexts and longer-term, ecologically valid outcomes. We describe this approach and discuss its potential theoretical implications. We also review recent examples of studies that have used this approach, discuss methodological considerations, and provide specific guidelines for using it in future research.

Keywords

brain-as-predictor, prediction, neuroscience, ecological validity, brain-behavior relationship

Each year, television studios spend millions of dollars to develop pilot episodes for new shows. The development process includes gathering feedback from potential viewers through surveys, interviews, and focus groups. The studios use this input under the assumption that people are capable of accurately reporting what they like and don't like and, in turn, 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 are canceled 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 in to 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. In this article, we argue that knowledge gained from decades of work in cognitive neuroscience about the mapping between mental process and brain function (Cabeza & Nyberg, 2000; Kober et al., 2008; Lieberman, 2010; Montague & Berns, 2002) can be leveraged to predict meaningful outcomes beyond the laboratory (Fig. 1). Indeed, we recently found that viewers' brain activation while watching a set of commercials in a "neural focus group" predicted the success of the commercials in the media markets where they were aired, and did so better than viewers' reports of the ads' effectiveness (Falk, Berkman, & Lieberman, 2012).

This is one example of a more general *brain-as-predictor* approach, which treats neural measures (e.g., activation, structure, connectivity) as independent variables in models that predict longitudinal outcomes as dependent variables. The adoption of the brain-as-predictor approach represents a paradigm shift for research in neuroscience, complementing traditional *brain-mapping* studies in which psychological processes are manipulated and the resulting neural activity is observed as the dependent measure (note the bidirectional relationships shown in Fig. 1). Decades of neuroscientific research aimed at

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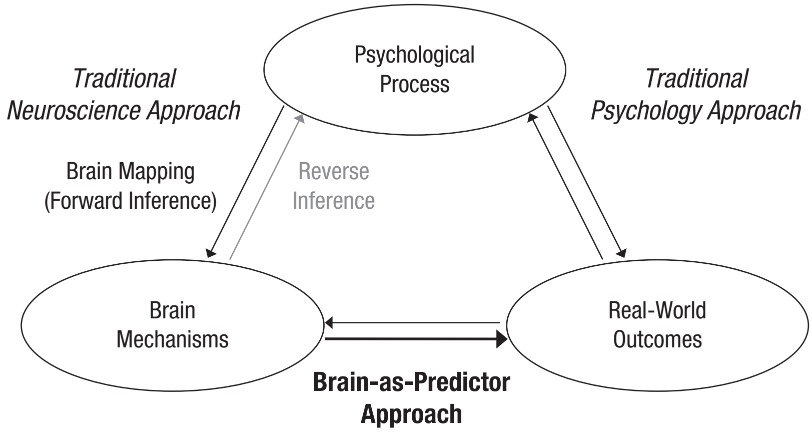

Fig. 1. The brain-as-predictor approach. Traditionally, psychologists have been interested in mapping the relationship between psychological processes (e.g., cognitions, emotions) and real-world outcomes (e.g., health behaviors, discrimination). In contrast, neuroscientists have traditionally used neuroimaging tools to map the relationship between psychological process and brain mechanisms. The *brain-as-predictor* approach integrates these methods by using brain systems that previously have been linked to specific psychological processes to predict meaningful outcomes beyond the confines of the laboratory. This approach offers new ways to explain previously unaccounted variance in behavioral outcomes and to test whether hypothesized psychological processes (via their neural associates) are predictive of those outcomes. Bidirectional arrows emphasize 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. Note that arrows in this figure indicate conceptual relationships between independent and dependent variables rather than causality; manipulation of brain function (e.g., using transcranial magnetic stimulation or in clinical lesion studies) is necessary in order to establish causal relationships between brain measures and behavior.

establishing brain-behavior relationships and integrating results from 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 brain-as-predictor approach differs from approaches taken in this earlier work, however, in the level of specificity of the hypothesized neural systems and targeted outcomes.

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

Potential for Theoretical and Applied Advances

In the brain-as-predictor framework, the brain is viewed as an additional window into psychological processes that complements other measures, such as self-reports 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, we have used neural measures as an alternative way to study psychological processes that unfold during exposure to ads and that are difficult to capture using other methods. Our results illustrate how neuroimaging can add to the understanding of social influence and can also be applied practically to the problem of designing more efficient health campaigns.

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. The following sections highlight the advantages of the brain-as-predictor framework in several areas in psychology.

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 separate sample moves the focus of research from brain mapping to testing the predictive validity of measures from 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 the 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 predicting the population-level success of 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 (Falk, Berkman, Mann, Harrison, & Lieberman, 2010) and reductions in smoking (Falk, Berkman, Whalen, & Lieberman, 2011) in groups exposed to relevant public service announcements. 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) were tested as predictors in subsequent, conceptually related studies (e.g., studies investigating individual behavior change in a different domain or the population-level success of different ad 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 in a "neural focus group" framework, in which neural activation in a small group predicts outcomes in a larger population (Falk et al., 2012).

However, we note that independent samples of participants are not always necessary; ROIs may also be defined using an independent psychological *localizer* task, which isolates the brain regions associated with a process of interest for each subject within a single group of subjects. 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 (Chua et al., 2011).

The brain-as-predictor approach can also be used to examine relationships between basic social, cognitive, and affective processes and health-relevant outcomes to reveal 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 6 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) outside of the scanner on the basis of 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 have also suggested 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; for 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 the deployment of multilevel models containing both kinds of data. This logic can also be extended to incorporate neural data from hypothesized ROIs into structural-equation models, nonparametric models, and other statistical models as they are developed.

A Guide to the Brain-as-Predictor Approach

Procedure

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

First, hypothesis generation, in which candidate brain regions or networks are identified and a priori ROIs defined using any means for identifying neural regions associated with the hypothesized psychological constructs. In the study described in our opening example, we hypothesized on the basis of prior results that neural activity in the brain's medial prefrontal cortex would predict the success of ad campaigns (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 or machine-learning techniques (Mur, Bandettini, & Kriegeskorte, 2009; Norman, Polyn, Detre, & Haxby, 2006) can also be used to identify ROIs.

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

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, or endocrine data) and assessing whether the neural data provide additional predictive power. For instance, in the earlier example in which neural responses to health communications predicted subsequent reductions in smoking, 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 addition, 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 with other types of variables. Neuroimaging data can have high test-retest reliability depending on factors including the hardware used to obtain the data, the length of the test-retest interval, and the complexity of the cognitive processes tested (Berkman, Cunningham, & Lieberman, in press; Miller et al., 2009). However, the reliability of neuroimaging data, like that of any other kind of data, must be evaluated in light of the study design and other available measures.

Predictor selection

In the brain-as-predictor approach, 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 on the basis of psychological theory and prior brain-mapping results. Because predictor regions represent the operationalization of a mental process that will be used for theory testing, their careful selection is critical, akin to selecting a behavioral task or self-report measure to tap a construct. In this sense, the brain-as-predictor approach relies on the same scientific logic as any other predictive approach in psychology (e.g., predicting behavior change from intention) but with a different independent variable.

Iterative process

The brain-as-predictor approach is only one part of an iterative cycle of exploratory and confirmatory hypothesis testing designed to advance theory (Fig. 1): Brain-mapping and brain-as-predictor approaches can be used together to triangulate the relationships among neural, mental process, and behavioral variables. Traditionally, studies have identified candidate regions for a given psychological process (e.g., self-control); brain-as-predictor studies employ confirmatory predictive analyses that test the involvement of ROIs in that process and identify conditions under which brain activity 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 (e.g., 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 neuroscientific 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 brain activity above and beyond other measures is explicitly quantified.

We have 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 neuroscientific 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.

Recommended Reading

Cabeza, R., & Nyberg, L. (2000). (See References). A review of neuroimaging studies of cognition that will be useful for generating predictive networks.

Falk, E. B., Berkman, E. T., & Lieberman, M. D. (2012). (See References). An early demonstration that data from a small "neural focus group" can predict population-level outcomes.

Lindquist, K. A., Wager, T. D., Kober, H., Bliss-Moreau, E., & Barrett, L. F. (2012). The brain basis of emotion: A meta-analytic review. *Behavioral and Brain Sciences*, *35*, 121–143. A comprehensive review and meta-analysis of the neural basis of emotions, and a potential source of predictive regions.

Poldrack, R. A. (2008). The role of fMRI in cognitive neuroscience: Where do we stand? *Current Opinion in Neurobiology, 18*, 223–227. A thoughtful critique of "reverse inference" and the inferential limits of fMRI for psychological theory.

Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C., & Wager, T. D. (2011). (See References). Describes the development of a database for the automated meta-analysis of cognitive neuroscience studies.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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