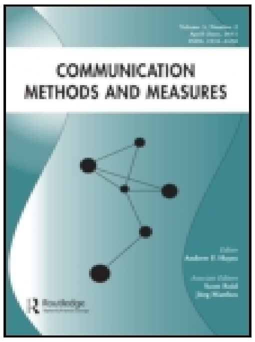

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Neural Prediction of Communication-Relevant Outcomes

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Understanding the mechanisms of effective communication may be advanced by knowledge from social and cognitive neuroscience. We build on prior brain research that mapped mental processes, and describe a brain-as-predictor approach that encompasses studies that treat measures of brain activity in response to communication relevant tasks as: 1) mediators between communication relevant stimuli and outcomes, 2) moderators of the relationship between communication relevant stimuli and outcomes or 3) direct predictors of communication relevant outcomes. In this article, we give a detailed description of the brain-as-predictor approach and provide a guide and checklist for interested authors, reviewers and editors. We discuss how the approach can provide theoretical insights and advance practical applications in communication research. Given its potential for advancing theory and practice, we argue that the brain-as-predictor approach can complement other communication research methods and serve as a valuable addition to the communication science toolbox.

From movie trailers to political ads to health campaigns, companies, governments and nonprofits spend hundreds of billions of dollars each year in the United States alone to produce and distribute media aimed at influencing behavior ("U.S. Total Media Ad Spend Inches Up," 2013). Yet the effects of campaigns are highly variable and small on average (Sethuraman, Tellis, & Briesch, 2011). Among many factors, such variability may arise from the fact that mental processes that lead to influence are not directly observable. Furthermore, individuals are often limited in the extent to which they are willing or able to report accurately on the processes underlying their thoughts, decisions, and causes driving their behaviors (Dijksterhuis, 2004; Fazio & Olson, 2003; Nisbett & Wilson, 1977; Paulhus, 1986). A growing body of research suggests that processes that precede behavior change are nonetheless represented in the brain. As such, some of these processes may be captured using neuroimaging methods, and used to predict behavioral outcomes (Berkman & Falk, 2013). This *brain-as-predictor approach* encompasses studies that treat measures of brain activity in response to message exposure or other communication relevant tasks as: 1) mediators between communication relevant stimuli and outcomes, 2) moderators of the relationship between communication relevant stimuli and outcomes, or 3) direct predictors of communication relevant outcomes. As will be described in greater detail below, the brain-as-predictor approach is a relatively new approach with growing bodies of research underway. Below, we will describe initial evidence for its value and how the approach can provide both

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added predictive capacity in parallel with other measurement tools, as well as insights regarding the mechanisms underpinning behavior change. We will provide an overview of what is currently known and where the field is going.

The approach builds on advances in neuroimaging technology that have made it possible to examine mental processes that unfold throughout the brain as participants complete a wide range of tasks. Neuroimaging methodologies (e.g., fMRI, EEG/ERPs, fNIRS) allow researchers to examine responses to relevant stimuli (e.g., messages, cognitive tasks) in real time during stimulus exposure or task execution. Furthermore, neuroimaging technologies collect data without the need for conscious introspection (as would be required of self-report instruments). Finally neuroimaging can measure implicit processing without the need to impose competing cognitive tasks to remove the ability for conscious reflection among participants (e.g., through time pressure or other cognitive load, as would be desired for many implicit measures, but would then fundamentally change the nature of the task being completed). Using neuroimaging technology, scientists have identified constellations of neural activity that are associated with many basic social, affective and cognitive functions (Ariely & Berns, 2010; Cabeza & Nyberg, 2000; Lieberman, 2010; Loewenstein, Rick, & Cohen, 2008; Sanfey, Loewenstein, & Mcclure, 2006). In combination with other research at the intersection of communication and biology (Beatty, McCroskey, & Pence, 2009; Boren & Veksler, 2011) these insights can serve as a foundation for hypothesis generation and testing.

We argue that communication scholars can leverage this critical mass of studies in social and cognitive neuroscience and neuroeconomics to test relationships between communication, the brain, and behavior, and that this in turn can inform both theory and practice. We focus largely on examples from fMRI, but ultimately the brain-as-predictor approach can leverage a wide range of neuroimaging techniques (e.g., fMRI, structural MRI, DTI, EEG/EPRs, fNIRS) and can also be applied in parallel with other biological paradigms employed by communication scholars.[1] The combination of multiple imaging modalities and psychophysiological data promises to provide a more comprehensive account of communication effects and processes. In what follows, we review the brain-as-predictor approach (Berkman & Falk, 2013), provide a step-by-step guide to the approach and then offer selected case examples illustrating practical and theoretical advances made possible by the approach.

WHAT IS THE BRAIN-AS-PREDICTOR APPROACH?

In contrast to neuroimaging studies that manipulate psychological processes and observe neural activity as an outcome, the brain-as-predictor approach specifies neural variables (e.g., brain activity, connectivity, structure) as mediators, moderators or direct predictors of key psychological, psychophysiological or behavioral outcomes (Berkman & Falk, 2013; Figure 1). In other words, whereas past research has mapped the location and time course of neural activity supporting specific psychological processes, the brain-as-predictor approach leverages these insights

[1]Comprehensive review of the mechanics of different neuroimaging technologies is beyond the scope of this review (interested readers are referred to Harmon-Jones & Beer, 2009), as is a broader review of biological metrics in communication science (interested readers are referred to Boren & Veksler, 2011; Potter & Bolls, 2011).

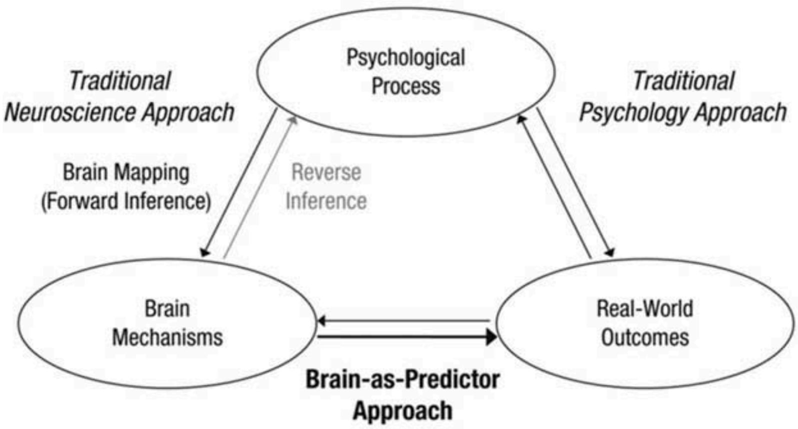

FIGURE 1 The brain-as-predictor approach, reproduced from Berkman and Falk, 2013. Investigations in social, cognitive and affective neuroscience have traditionally manipulated psychological processes and mapped their location in the brain (treating the brain as a dependent measure). Psychologists have also traditionally manipulated psychological processes and observed their cognitive, behavioral and affective consequences. The brain-as-predictor approach combines what has been learned in each of these literatures to hypothesize neural processes as independent variables that directly predict outcomes beyond the neuroimaging lab. Note: arrows in this figure indicate conceptual relationships rather than causation.

to test specific theoretically guided predictions linking neurocognitive processes and subsequent psychological, physiological and behavioral outcomes (see Figure 1 and How to Apply section).

The ability to identify theoretically relevant neural predictors builds on past decades of research conducted in cognitive neuroscience (Cabeza & Nyberg, 2000), social neuroscience (Cacioppo & Berntson, 1992; Cacioppo, 2002; Lieberman, 2010; Ochsner & Lieberman, 2001) and neuroeconomics (Loewenstein et al., 2008; Sanfey et al., 2006). These bodies of research have manipulated psychological variables in the laboratory and mapped the resulting neural activity (see Figure 1). By definition, brain mapping studies treat neural activity as a dependent measure, examining correlations between psychological processes and their neural correlates—in lay terms, reporting what "lights up" (a term that neuroscientists resist).

The brain-as-predictor approach takes a next step by using this accumulated knowledge to make theoretical predictions that link mental processes captured via brain activity (or individual differences inferred from brain structure) and use those data as mediators, moderators, or direct predictors of psychological, physiological, and behavioral outcomes that follow, often beyond the confines of the laboratory (Berkman & Falk, 2013). In the next section, we describe how to implement the brain-as-predictor approach and illustrate some common considerations that researchers employing the approach must grapple with through the use of case examples.

HOW TO APPLY THE BRAIN-AS-PREDICTOR APPROACH TO COMMUNICATION SCIENCE

Berkman and Falk (2013) outlined three steps to implement the brain-as-predictor approach. Here, we review the three proposed steps, with additional notes of particular relevance to applications in communication science (Figure 2).

Step One: Specification of Hypotheses and Identification of Neural Variables

The first step in the brain-as-predictor approach requires specification of hypotheses and identification of neural variables (e.g., functional regions of interest, structural regions of interest, connectivity patterns between regions) that are most relevant to each hypothesis. This further requires defining the specific hypothesized role of the neural variable (as a trait or a state measure; as an independent predictor, mediator, or moderator). The neural variables selected represent the operationalization of mental processes or individual differences. As noted by Berkman and Falk (2013), "careful selection [of neural variables] 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" (p. 48). Neuroimaging data can have high test-retest reliability (Miller et al., 2009), depending on a number of factors (for a review, see Berkman, Cunningham, & Lieberman, in press). As with any measure, however, consideration should be given to the specific measurements being employed and assumptions pertaining to reliability and validity should be verified.

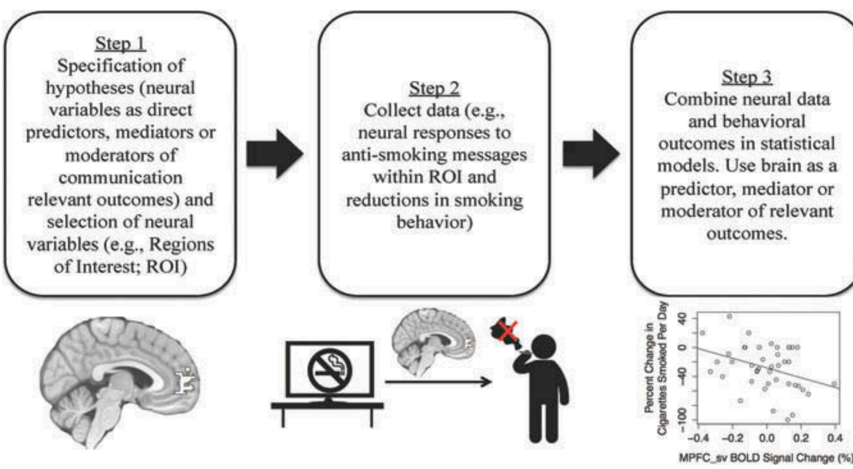

FIGURE 2 Overview of how to apply the brain-as-predictor approach to communication science.

Neural Variables as Moderators

As one example of how neural variables can be selected to operationalize specific cognitive processes, recent work in our laboratory examined how cognitive control and interpersonal communication variables interact to produce risk-taking in a driving context among adolescent males (Cascio et al., 2014). Our primary neural variable was activity within brain regions that have been demonstrated in many cognitive neuroscience studies to support a specific form of cognitive control—response inhibition. Response inhibition involves overriding an otherwise prepotent habit or impulse, and individuals vary in the extent to which they recruit the core set of brain regions that facilitate successful response inhibition (Cascio et al., 2014). We collected information about such individual differences during a baseline neuroimaging session in which participants engaged in a cognitive control task that requires response inhibition. We collected our primary communication variables and behavioral outcome data in a driving simulator session that occurred a week following the neuroimaging session. During that session, each participant drove alone and with a peer (confederate) passenger who subtly communicated risky or cautious norms before the drive.

We examined how peer norms expressed by confederate passengers (cautious versus risky) interacted with individual differences in response inhibition activity during the baseline fMRI cognitive control task to predict risk-taking in the driving context. We found that adolescents showing stronger activation in brain regions linked to response inhibition demonstrated safer driving behaviors in the presence of a peer who communicated cautious norms (compared with solo driving) but not in the presence of a risky peer (compared with solo driving). These data emphasize the importance of subtly communicated social cues in shaping the use of potentially protective cognitive control resources during decision-making in adolescents (or the role of neural resources in responding to different types of social situations). Furthermore, from a practical standpoint, neural activity predicted an additional 10.9–22.8% of the variance in risk taking behavior in the presence of cautious peers, beyond what was explained by participants' solo driving behavior, self-reported susceptibility to peer influence, and a number of other covariates. More broadly, this example illustrates how neural variables can be selected to tap a specific cognitive construct (variation in cognitive control resources), as well as how such a construct can be treated as a moderator of the relationship between situational/ environmental factors (in this case the implicit communication of risk versus cautious preferences) and behavioral outcomes.

Neural Variables as Mediators

Neural data can also be treated as a mediator of the relationship between a communication manipulation and behavioral outcomes at the level of individual behavior and population level responses to campaigns. For example, although they did not formally test mediation, Chua and colleagues (2011) hypothesized that tailoring health messages to specific individuals might increase the extent to which messages were processed as self-relevant, which in turn might predict message-consistent behavior change. To test this hypothesis, they first identified neural regions, including medial prefrontal cortex (MPFC), associated with self-related processing using a well-validated task that compares neural activity during judgments that do or do not require self-related thought (a "self-related processing localizer task"). Next, they examined neural activity within the "self regions" as participants were exposed to tailored and untailored health messages. Their data suggest that one way in which tailoring messages drives behavior change is by increasing the degree of self-related processing (which was greater in response to tailored messages, compared to untailored messages), which in turn predicts behavior change; in this case, though mediation was not formally tested, brain activity is conceptually treated as a mediating variable between the manipulation and outcome.

Likewise, our lab has observed that neural activity in regions of MPFC selected to operationalize a similar form of "self-related processing" in response to anti-smoking messages predicts up to 20% of the variance in participants' behavior change, beyond that predicted by combinations of participants' self-reports of intentions to quit, self-efficacy to quit, ability to relate to the messages, and risk beliefs, among other measures (Falk et al., 2010, 2011; Cooper et al., in press); we have argued that increasing neural activity in brain regions implicated in self-related processing might serve as a mechanism driving behavior change in response to health messages.

These data are suggestive of one mechanism (self-related processing) that might link communication exposure and behavior change. Existing research in this area, however, has largely been restricted to observational studies that cannot rule out the possibility that communication exposure is not necessarily *causing* behavior change. This limitation stems largely from the high cost of fMRI research, which has limited researchers' ability to collect between subjects control groups. In other words, it is possible that the putative self-related processing observed in response to anti-smoking messages is a proxy for receptivity to the idea of quitting more broadly and that those smokers who show the greatest response to the anti-smoking messages presented would have quit or reduced their smoking, even in the absence of intervention. In our lab, we have attempted to address this threat to validity in several ways; for example, Falk et al. (2011; introduced above) selected smokers who all had a similar and strong intention to quit smoking; hence, variability in neural response is not accounted for by different levels of quit intentions. Cooper et al. (in press) took an additional step by demonstrating that activity within the sub-region of MPFC localized to be engaged in "self-related processing" was only predictive of behavior change in response to exposure to anti-smoking media—neural activity in the same brain region during a task that involved self-reflection outside of the smoking context did not predict behavior change. Thus, although the data remain correlational and this analysis does not resolve all concerns, Cooper's results demonstrate that the predictive MPFC response is specific to the target media stimulus. Finally, in recent work, we have randomly assigned participants to conditions designed to increase or decrease levels of self-related processing and consequent MPFC activity during exposure to health messages. This activity, in turn, predicts message consistent behavior change (Falk et al., in press). Beyond work in our lab, funding agencies and research groups are increasingly prioritizing sample sizes and study designs that allow for stronger inferences.

Traversing different levels of analysis, research teams have also examined effects of different message types on neural responses of small groups of participants as predictors of the behavior of larger groups of people. For example, neural responses within MPFC in relatively small groups of participants have been shown to forecast the population level success of different anti-smoking messages in driving calls to smoking quit lines (Falk et al., 2012) and generating email traffic to a quit website (Falk et al., under review). In these studies, neural activity within MPFC assessed in relatively small groups of people in response to anti-tobacco messages was aggregated to predict population response to those ads. In comparison to the self-report ratings of the individuals from the smaller groups, neural activity in MPFC added significant predictive value in both studies. Similar methods have been used to predict population level sales data for songs (Berns & Moore, 2012), perceived effectiveness of anti-drug messages (Weber, Huskey, Mangus, Westcott-Baker, & Turner, in press), and social media response to television content (Dmochowski et al., 2014). These studies differ markedly from those described above in that they treat the message (or other communication content) as the unit of analysis, and compare aggregated neural activity across multiple individuals as predictors of population level behaviors that presumably result from campaign exposure. This approach suffers from the common limitation described by communication scholars that "isolation of the independent effects of mass media campaigns is difficult" (Wakefield, Loken & Hornik, 2010, p. 1268); however, the use of randomized field experiments and increased ability to tightly track behaviors in the context of digital campaigns can help alleviate some of these limits (for one example, see Falk et al., under review).

Neural Variables as Direct Predictors of Communication Outcomes

In addition to specifying neural variables as moderators of the effects of communication variables or mediators of the effects of communication variables on behavioral outcomes, neural activity can also be conceptualized as direct predictor of communication behaviors. In these cases, neural activity is often operationalized in terms of individual differences that affect communication outcomes. For example, in recent work Falk, Morelli and colleagues (2013) hypothesized that the tendency to engage brain systems associated with considering the mental states of others might predict more effective retransmission of ideas, which they termed the "idea salesperson effect." They found that individual variation in their hypothesized "perspective taking regions" during exposure to a set of novel ideas was positively associated with the degree to which each participant was later successful in communicating and recreating his or her own preferences in another group of participants.

O'Donnell and colleagues (in press) followed up on this work using a brain-as-predictor framework, treating neural activity within the putative perspective taking regions during exposure to a different set of ideas as a predictor of the extent to which participants used social language in subsequently retransmitting ideas. The team argues that "our brains are sensitized to social cues, such as those carried by language, and to promoting social communication." They suggest that neural activity in perspective taking regions provides a way to conceptually bridge findings from communication science, sociolinguistics and neuroscience about how individuals process incoming ideas and subsequently retransmit them to others. As may be clear from this example, even studies that treat neural activity as direct predictors of communication behavior often rely on an incoming stimulus to elicit the target neural activity, hence blurring the line between treating the brain as a mediator or direct predictor.

Specifying Region(s) of Interest

The utility of each of the model types described above hinges on appropriate operationalization of constructs, often through selection of neural regions of interest (ROIs). Depending on the research question and hypotheses it may be most appropriate to select regions of interest in a number of different ways. As with several of the examples described above (e.g., Cascio et al., 2014;

Falk, Morelli et al., 2013), one common approach is to select neural regions anatomically based on a review of prior literature on the construct(s) of interest. This approach promotes standardization across studies to the extent that anatomical regions are well defined. An anatomical atlas can be employed to define the region of interest. Some major limitations of this approach include that some regions of interest may not be well defined anatomically and/or may cover large swaths of cortex that are less specific than would be desired for the brain-as-predictor approach. Related to the latter point, individual anatomical regions of interest are likely to be relatively unselective for specific mental processes (i.e., a large anatomical ROI is likely to support multiple mental processes). Hence, when using anatomical ROIs, it may be desirable to consider networks of regions that are known to collectively support specific mental processes (Poldrack, 2006).

A second common approach that addresses some of the limitations noted above is to select neural regions functionally, identifying neural regions that are associated with a manipulated psychological process of interest in past work, or within an independent task collected in the same study. Functional ROIs do not necessarily conform to specific anatomical boundaries (i.e., they may cross anatomical boundaries or be restricted to subregions of an anatomically defined region).

Functional ROIs can be identified using neural regions identified in a prior group of participants—termed a "test/validate" approach. This is the approach taken by Falk and colleagues (2011; described above) to predict smoking behavior change in response to anti-smoking messages. In a prior study, the team had identified neural regions associated with behavior change in the context of exposure to messages promoting sunscreen use (Falk et al., 2010). Neural activity within these same brain regions was then examined as a new group of smokers were exposed to anti-tobacco messages, and that activity was used to predict changes in individual smoking behavior in the month following exposure (Falk et al., 2011) as well as population level responses to subgroups of the ads (Falk et al., 2012). A major advantage of the test-validate approach is that, as the name implies, is provides validation of previously observed brain-behavior relationships. The approach requires resources to conduct multiple studies or collaboration across research teams.

Another way to identify functional ROIs is to use researcher curated (e.g., Salimi-Khorshidi, Smith, Keltner, Wager, & Nichols, 2009; Wager, Lindquist, Nichols, Kober, & Van Snellenberg, 2009) or automated (e.g., Yarkoni, Poldrack, Nichols, Van Essen, & Wager, 2011) meta-analytic results that combine results from multiple studies of the psychological process of interest to identify regions of interest. This is the approach taken by Cooper and colleagues (in press). In addition to the team's goal to link self-related processing with behavior change (described above), Cooper and colleagues were also interested in the economic notion of positive valuation in understanding how people process health messages (Figure 2). They noted that "many studies in the nascent field of neuroeconomics have demonstrated that an area of the ventral MPFC plays a key role in representing the personal, or subjective, value of many types of stimuli during decision making." They hypothesized that a similar common value signal might also respond to the value of ideas in health messages, and hence predict behavioral responses to those health messages. To test this hypothesis, the team built on a meta-analysis of studies that identified brain regions implicated in computing the value of stimuli ranging from money to material goods to social rewards. They reasoned that positive valuation of ideas contained in a PSA might make use of the same neural systems that compute value more generally, which might in turn predict behavior change. To test this hypothesis, they examined neural activity within a meta-analytically defined valuation region of interest as smokers were exposed to anti-smoking messages. Consistent with their hypothesis, neural activity within this meta-analytically defined value-computation ROI did generalize to predicting health behavior change. These data are consistent with the idea that assessing and acting on health messages may make use of a more general mechanism in the brain that computes value of stimuli with respect to one's current goals and motivations. One limitation of this approach is that it requires a substantial number of prior studies. In cases where such a body of literature exists, however, it can be a very powerful approach allowing researchers not only to define functional ROIs, but also quantitatively assess the likelihood of specific mental functions ascribed to the ROI (Yarkoni et al., 2011; see also section below on reverse inference).

Functional ROIs can also be identified using an independent task within the same group of participants (referred to as a "localizer task"; see Saxe et al., 2006). For example, Chua and colleagues' (2011) study of anti-smoking messages (described above) is a good example of the use of a localizer task to identify regions of interest. The research team first used an independent, well-validated task to identify neural regions that were more active during judgments requiring self-reflection compared to judgments that did not require self-reflection. They next examined neural activity within those functionally defined "self" regions as participants were exposed to quit-smoking messages. Finally, they used the neural activity during the smoking messages in the localized "self" regions as the primary predictor of later smoking outcomes. Major limitations of this approach are the increased costs (in terms of scanner time and participant burden). This approach, however, offers the ability to identify person-specific ROIs that can support somewhat stronger inferences about the function of selected ROIs, and requires less cumulative data than the meta-analytic approaches advocated above.

In the context of communication science, some brain-as-predictor hypotheses will pertain to the relationship between well-mapped cognitive, affective and social processes (e.g., self-related processing) during communication-relevant tasks (e.g., media exposure) and subsequent behavioral outcomes (e.g., health or political behaviors). By contrast, some key questions in communication science will build on specific theories or questions that are not well mapped yet in social and cognitive neuroscience or neuroeconomics. In these cases, brain mapping steps, or the use of well-thought-through localizer tasks, may still be necessary to identify regions of interest.

Step Two: Data Collection

Once hypotheses have been specified, the second step in the brain-as-predictor approach is data collection. In this step, relevant neural data (e.g., functional activity during a task, structure of specific brain regions) are collected within the laboratory and subsequent psychological, physiological, and/or behavioral data are collected, often longitudinally. A review of the resources needed to collect fMRI data and issues that arise and require attention in communication science can be found from Weber and colleagues (this volume); resources describing methods and analysis considerations for three potentially useful types of neuroimaging to communication research (fMRI, ERP, fNIRS) can also be found in the Appendix.

As noted above and covered in more depth elsewhere (e.g., see Harmon-Jones & Beer, 2009), successful acquisition of brain data carries nonnegligible costs, constraints, and expertise requirements that are not specific to the brain-as-predictor approach (see Weber & colleagues, this volume). Beyond the methodological considerations covered in more general resources (that focus on brain variables as dependent measures), the brain-as-predictor framework requires not only acquisition of neural data but also further acquisition of subsequent psychological, physiological, or behavioral outcome data. This is one aspect that makes the approach particularly suited to communication research—communication scholars are adept at identifying, measuring, and connecting individual level and large-scale behaviors. For example, methods developed to indirectly assess exposure to media smoking and drinking (Sargent, Worth, Beach, Gerrard, & Heatherton, 2008) could be combined with neural data specified as either a mediator or moderator of key behavioral outcomes of interest (e.g., smoking initiation). Thoughtful selection of subsets of participants in the context of related larger-scale representative studies can also maximize the value of this type of work (Falk et al., 2013) to both communication science and neuroscience. In parallel with its advantages, however, the brain-as-predictor approach is also often more labor intensive than typical brain mapping (because of the requirement to collect data longitudinally).

Step Three: Using Neural Data as Direct Predictors, Mediators or Moderators

In the third step of the brain-as-predictor approach, neural, physiological, or behavioral data are combined in statistical models that specify the brain as a direct predictor, mediator or moderator of relevant outcomes. Convergent validity between neural data and other measures (e.g., self-report survey results, other biological measures) can help establish links between measures that are theoretically predicted to overlap. In parallel, direct comparison between variance explained by neural data and other data can establish the degree to which the brain adds value by explaining variance in key outcomes that are difficult to predict otherwise.

From a practical standpoint, neural measures can be conceptualized in a similar manner to other manipulated or individual difference predictor variables in the social and behavioral sciences. For example, parameter estimates of neural activity from *a priori* specified regions of interest during a target psychological task can be extracted, resulting in one summary value representing average activity within each specified region, during key task conditions, for each participant. Similar summary measures can be constructed relevant to structural features of the brain (e.g., grey-matter volume in specific regions of interest) thought to reflect longer-term life circumstances and biological factors such as genes, functional, and structural connectivity between different neural regions that may alter the way that cognitive processes unfold and relate to one another and so forth.

USING THE BRAIN-AS-PREDICTOR APPROACH TO TEST THEORIES IN COMMUNICATION SCIENCE

Successful execution of the three steps above allows testing of theoretical relationships between neurocognitive processes and outcomes. Below, we provide selected examples of how the brain-as-predictor approach can help address theoretical debates and potentially build knowledge relevant to long-standing questions in communication science. Of course, these examples are only a few of many possible applications.

What Are The Precursors of Message-Driven Behavior Change?

As described in several examples above, the brain-as-predictor approach has been most widely applied to studies of message-driven health behavior change. Well-established theories of persuasion and behavior change have focused heavily on reasoning and cognitive beliefs as precursors of message-consistent behavior change (Ajzen & Fishbein, 2005; Petty, Priester, & Brinol, 2002). Several recent brain-as-predictor studies extend these theories by highlighting a central role of neural activity within brain regions such as the MPFC, implicated in self-related processing (Denny, Kober, Wager, & Ochsner, 2012; Lieberman, 2010) and subjective value computation (Bartra, McGuire, & Kable, 2013). As introduced above, at the individual level, Falk and colleagues (2010) found that neural responses within MPFC—to sunscreen PSAs predicted 21% of the variance in sunscreen behavior change in the week following exposure to the PSAs, above and beyond changes in participants' self-reports of attitudes toward sunscreen use and intentions to increase their sunscreen use.

In follow up work described above, the team found that neural responses within MPFC explained smokers' reductions in smoking behavior following exposure to anti-smoking PSAs, above and beyond those participants self-reported intentions, self-efficacy, and ability to relate to the PSAs (Falk et al., 2011). Furthermore, as described above, the team specifically localized the effects to sub-regions of MPFC implicated in self-related processing and valuation, and demonstrated that the effects were specific to activity during the PSAs and not individual differences in general reactivity within MPFC (Cooper et al., in press). In addressing how these neural findings can translate to message design, as described above, MPFC activity can be increased by intervention components that increase self-related processing, such as message tailoring (Chua et al., 2011). Recent studies described above also suggest that neural data may be useful in identifying messages that are later most effective in producing population level behavior change, despite not being identified through participant self-reports (e.g., Falk et al., 2012; under review).

Taken together, data linking MPFC responses to real-world outcomes have strengthened our understanding of one pathway through which information from the media may interact with psychological processes to influence behavior– the form of self-related processing and valuation captured by MPFC are peripherally treated by current persuasion theories, but not given central importance. These studies have also begun to demonstrate how MPFC activity can be altered to increase the effectiveness of interventions. These data highlight two benefits to the brain-as-predictor approach in the study of media effects—the ability to predict variance beyond what is explained by certain self-report measures and evidence supporting links between key psychological mechanisms stimulated by message exposure (e.g., self-related processing and valuation) and prediction of key behavioral outcomes.

Extending the brain-as-predictor approach to further integrate with theories of persuasion, Weber and colleagues (in press) examined neural responses to anti-drug messages in high and low drug-risk individuals. Combining insights from the elaboration likelihood model (ELM; Petty & Cacioppo, 1986), the activation model of information exposure (AMIE; Donohew, Palmgreen, & Duncan, 1980), and the limited capacity model of motivated mediated message processing (LC4MP; Lang 2009), Weber and colleagues manipulated the argument strength and message sensation value (MSV) of anti-drug messages. They observed an interaction between argument strength and message sensation value in predicting low-risk participants' effectiveness ratings; however, high-risk participants consistently rated messages as ineffective regardless of content (consistent with counterarguing). Despite the lack of variability (and hence predictive capacity) in the high risk participants' self-reports, the team did observe variability in neural processes likely associated with executive function and social cognition (among other functions) that were not apparent from the high-risk participants' self-reports. These neural data went on to predict the effectiveness ratings for the target PSAs in new independent samples. Thus, although defensive processes seem to have diminished the signal apparent in high risk-participants' self-reports of message effectiveness, their neural data provided insight into processes that were not captured by self-reports of effectiveness. These insights can complement existing persuasion theories by indirectly revealing ways that MSV and argument strength affect high and low risk participants' processing of anti-drug messages.

How Do Voters Process Political Information During a Campaign?

Although most widely applied to date in studies of health behavior change, the brain-as-predictor approach could also help address a number of different questions related to political communication research. As one example, during the course of a political campaign, voters are exposed to different types of issue information about the candidates running for office. Historically, public opinion researchers generally found that many citizens cannot recall the issue positions of candidates and that issue positions rarely shaped votes or judgments (Lazarsfeld, Berelson, & Hazel, 1944; Berelson, Lazarsfeld, & McPhee, 1954; Campbell et al., 1964; Converse, 1964). These findings generated the conclusions that citizens do relatively poorly when choosing candidates whose issue positions best reflect their own beliefs and that campaigns exert "minimal effects" on voting behavior. In recent years, however, researchers have begun to consider whether citizens must remember and use previously learned issue position information from media and other sources in order to vote for the candidates whose policy stances best reflect their beliefs. According to one particularly influential claim, advanced by Lodge and colleagues via their theory of online processing, they do not. Their account theorized that voters can extract affective/emotional information about candidates as they learn about them and incorporate this information into an accumulated affective tally—a form of running average specific to that candidate. By the time ballots are cast, voters might have forgotten the candidates' specific issue positions; yet earlier affective responses to actual issue information can still influence their candidate selections through the cumulative affective/emotional tally (Lodge, McGraw, & Stroh, 1989; Lodge, Steenbergen, & Brau 1995; also see Hastie & Park, 1986).

One study (Coronel et al., 2012) conducted a unique and powerful test of this claim using a different brain-based method, the use of brain-damaged patients to identify causal pathways between brain-function in response to communication inputs and voter behavior. More specifically, they tested whether explicit recall of information following exposure to messages about candidate issue positions was necessary by comparing individuals with profound amnesia caused by specific brain damage (i.e., to the hippocampus), whose severe memory impairments prevent them from remembering specific issue information associated with any particular candidate (but who can still form emotional memories), and healthy control participants. If individuals can consistently vote for the candidates with political views most like their own, despite not explicitly remembering specific issue information, this implies that citizens can store information (e.g., from the media environment) in ways that are not reflected by self-report instruments (i.e., overt measures of recall), but nonetheless may have profound effects on political decisions.

The team experimentally manipulated exposure to relevant information through messages about fictitious political candidates, and then assessed whether amnesic patients and healthy controls could vote for candidates whose issue positions come closest to their own political views after (Coronel et al., 2012). The researchers found that the amnesic patients did vote for candidates whose issues positions were closest at high levels commensurate with healthy controls, suggesting that sound voting decisions do not require recall or recognition of previously learned associations between candidates and their issue positions.

Normal voters, of course, are likely to use a combination of issue information and emotional memories. Indeed, one line of inquiry in the fields of political communication and public opinion attempt to determine the conditions under which memories for specific issue information or the affective tally are more likely to influence voting decisions (Kim & Garrett, 2012; Mitchell, 2012; Redlawsk, 2001). Follow-up research employing neuroimaging methods in healthy populations could contribute to this line of work by examining the extent to which neural activity from regions associated with these different forms of learning and memory processes (e.g., hippocampus, amygdala) are a better predictor of political attitudes or behaviors during candidate evaluation under different circumstances.

What Psychological Processes Underlie the Effects Of Media Violence on Aggression?

Given that the brain-as-predictor approach as currently conceptualized is relatively new, there are myriad areas that have not yet been examined, but might be fruitfully explored in the broader landscape of communication research. For example, the brain-as-predictor approach might be used to address questions such as: Are effects of media violence on aggression driven more by differences in threat reactivity or emotion regulation in response to violent media (i.e., are media-violence induced aggression and/or stress responses driven more by alteration in bottom up or top down processing)? Preliminary research has mapped neural regions associated with exposure to media violence (Weber, Ritterfeld, & Mathiak, 2006) and noted that exposure to violent video games is associated with decreased activity in prefrontal cognitive control regions during response inhibition (Hummer et al., 2010), but have not yet linked neural activity within these regions to subsequent aggressive behavior or violence outside of the scanner.

One way to approach this question would be to specify neural activity in brain systems associated with fast emotional responses to threats (e.g., the amygdala) and emotion regulation (e.g., LPFC) as mediators of the relationship between exposure to media violence and subsequent aggressive behavior (measured through behavioral observation) and/or stress responses (measured physiologically). In such a study, participants could be randomly assigned to exposure to violent and non-violent media as their neural activity is recorded. Following the scanner session, participants could encounter an opportunity to engage in aggression. If the relationship between media violence and aggression (and/or stress) were mediated solely by bottom up processes versus additional top down regulation, this might suggest different interventions to mitigate negative effects of media violence. Such an approach could also inform our understanding of pathways to desensitization (i.e., is desensitization a product of diminished threat reactivity or of augmented ability to regulate automatic threat responses).

Neural activity within regions of interest implicated in top-down or bottom-up processing could also be hypothesized as individual difference moderators of the effects of media violence on later aggressive behavior. For example, it might be of interest to test whether individual differences in sensitivity of the brain's reward system, cognitive control system, or connectivity between the two, in response to violent media moderate the relationship between exposure to the violent media and individual differences in real-world aggression, stress responses, etc., following the scan.

NEURAL ACTIVITY AS A COMPLEMENT TO OTHER MEASURES

The examples above illustrate a range of ways in which neural data can complement and extend what is learned from explicit self-reports (e.g., of reactions to health messages, of recall following exposure to political communications). More generally, the brain-as-predictor approach builds on a foundation of behavioral research that has relied not only on self-report surveys and experimental outcomes but also implicit measures to understand a wide range of communication processes. Implicit and indirect behavioral measures (e.g., response times), however, usually require interrupting or changing the natural flow of cognition—such measures typically apply time pressure or otherwise constrain deliberative thought (Fazio & Olson, 2003; Greenwald, Poehlman, Uhlmann, & Banaji, 2009). Hence, though implicit measures are well-suited to assess concept accessibility and evaluations (Hefner, Rothmund, Klimmt, & Gollwitzer, 2011), they do not reveal the underlying mechanisms through which concepts and evaluations are formed and change. By contrast, neural measures can record both explicit and implicit processes throughout the brain as they unfold. Thus, although neuroimaging methods can be more costly to administer in comparison to other measures (e.g., reaction time measures, surveys), neural data can also provide complementary information that would be difficult to obtain otherwise.

The brain-as-predictor approach also builds on a rich history in communication science and psychology of using biological measurement tools such as peripheral physiology, facial coding and other measures to operationalize psychological processes such as attention and arousal. This work has made substantial advances in characterizing media attributes and qualities of interpersonal communication that produce such physiological reactions, but do not capture fine-grained cognitive processes responsible for these reactions (for a review, see Lang, Potter, & Bolls, 2009; Cacioppo, Tassinary, & Berntson, 2007). Neural measures can complement these measurement tools. With some caveats (discussed below), neural data can distinguish between a wide range of underlying cognitive and affective processes, and hence can complement other biological measures (which are related to, but not synonymous with brain function and may offer less specificity in underlying neurocognitive processes as they unfold). Integrating physiological variables as proximal outcomes or additional mediators or moderators in models employing a brain-as-predictor framework will further help to open the black box of mechanisms underlying communication processes.

STRENGTHS, LIMITATIONS AND PRACTICAL NOTES

The brain-as-predictor approach is a relatively new and promising approach to theoretical and practical questions in communication science. As with any method and associated measurement model, however, the brain-as-predictor approach has strengths and limitations. Below, we outline theoretical and practical issues that research teams will need to consider when employing this approach (additional considerations, and a brief checklist for authors, reviewers and editors, can be found in the Appendix and throughout the manuscript above).

Reverse Inference

The issue of reverse inference in fMRI research is explained in detail by Weber and colleagues (this issue). In brief, there is typically a one-to-many relationship between activity in any given neural region and the psychological functions it implements. As such, inferring specific psychological processes from observed brain activity must be qualified with the caveats outlined by Weber and colleagues. Importantly for the brain-as-predictor approach, however, researchers have some control over the strength of inferences that are possible in the choices made during design. As noted by Poldrack (2006), two ways to improve confidence in reverse inference are to "increase the selectivity of response in the brain region of interest, or increase the prior probability of the cognitive process in question" (p. 5). Although the experimenter cannot typically alter the physiological selectivity of a brain region (i.e., the range of stimuli that a brain region responds to/ range of psychological processes that it supports; c.f., Jackson-Hanen, Tompary, deBettencourt, & Turke-Brown, 2013), selectivity in the model can be increased by choosing more targeted brain regions spatially (i.e., smaller regions of interest; see section on functional ROIs), and by examining networks of regions that together may be more selective for a given psychological process than a single region. As discussed above, regions of interest can also be made more selective by using independent functional localizer tasks to identify regions of interest that are associated with specific psychological processes and then examining how these regions respond during a target task. Especially in brain regions that cover large anatomical bounds, functional localizers often identify more targeted sub-regions. Likewise, meta-analyses of specific neurocognitive processes can similarly produce more targeted regions of interest. In addition, the use of databases such as the BrainMap database and Neurosynth can allow researchers to estimate selectivity, and hence provide information about the strength of the inference.

Costs

Neuroimaging methods, such as fMRI, are more financially costly to administer per participant than other measures (e.g., self-report questionnaires, implicit reaction time measures). However, the total cost of acquiring a neuroimaging dataset may be similar to some methods that are familiar to communication scientists (e.g., running a large-scale, longitudinal or nationally representative survey, collecting data in clinics), which likewise require considerable overhead for data acquisition and specialized training for analysis. Also common to methods across the discipline, substantial investment of time and energy are needed to gain the requisite expertise to use the measures intelligently. Both types of cost issues (financial and expertise) can be mitigated through collaborations across disciplines. For example, drawing relatively small sub-samples of participants from larger-scale survey samples which have been specifically designed for representativeness in relation to a target larger-scale population has considerable benefits for both generalizability of the neuroscience findings and for the ability to gain a deeper understanding of mechanisms that may contribute to processes observed in the larger population (for a more complete review of methods and considerations for linking smaller neuroimaging samples and larger-scale population outcomes, see: Falk, Hyde, Mitchell, et al., 2013).

Practical Notes

Choice of Imaging Modality

Although many recent examples of the brain-as-predictor approach have relied on fMRI as a primary method for acquiring brain data, many different neuroimaging technologies are amenable to the brain-as-predictor approach, depending on what is called for by the research question; for example, fMRI offers excellent, uniform spatial resolution of the human brain (i.e., allows one to ask where in the brain cognitive processes are occurring) whereas other brain imaging techniques (e.g., event related potentials; ERPs) offer excellent temporal resolution (i.e., one can ask when or in what order do specific cognitive processes unfold). Ultimately, combined use of neural measures with other tools in the communication research toolbox, such as self-report instruments, implicit behavioral measures, and other psychophysiological and broader biological approaches to understanding human thoughts, feelings and behaviors promises to provide a more comprehensive account of communication processes given the different strengths provided by each method.

Statistical Methods Beyond the GLM

It should also be noted that although many of the examples reviewed specified neural predictors in regression models, the brain-as-predictor framework can also be used outside the confines of the general linear model (GLM). In particular, prediction of outcomes from mean levels of activity in single brain regions of interest may ignore substantial amounts of information about the interplay of networks of regions and spatial and temporal patterns of activity within those regions. Techniques beyond the GLM may be particularly well suited to circumventing these limitations.

For example, Bayesian inference may be preferable when mental processes are best operationalized through brain *networks* of interest (versus individual regions of interest). Linear regression models that use multiple neural regions as independent variables to predict behavioral outcomes often suffer from multicollinearity. Thus, under the GLM framework, the researcher must examine each neural region in a separate regression model or collapse them into a single variable by averaging over activity across the network (with both approaches losing information about their joint contributions, and in the former case, needing to account for multiple comparisons). However, Bayesian statisticians have developed clustering techniques that can allow researchers to explore multiple independent regions of interest in a brain-as-predictor model without imposing *a priori* constraints as to which regions cluster together to form a network (Curtis & Ghosh, 2011). Thus, a Bayesian approach can allow researchers using a brain-as-predictor framework to examine multiple neural regions or networks within the same predictive model, allowing for greater accuracy when examining the underlying processes that drive behavior. Finally, an additional benefit of using Bayesian inference over traditional GLM approaches within a brain-as-predictor framework is the ability to make true probability statements about the relationship between neural predictors and outcomes of interest (Gelman, Carlin, Stern, & Rubin, 2003).

Similarly, the past decade has seen substantial advances in machine learning and multivariate techniques for further exploring patterns of neural activity, especially fMRI data, that go beyond simple averages over an entire region of interest as typically done in the GLM (Bandettini, 2009; Mur, Bandettini, & Kriegeskorte, 2009; Norman, Polyn, Detre, & Haxby, 2006), as well as examining shared patterns across individuals in response to more naturalistic stimuli (Hasson et al., 2012). More detail on these multivariate pattern analysis and intersubject correlation methods is explored by Weber and colleagues (this volume). Such approaches could be used even more extensively in combination with communication-relevant behaviors and theories.

Substantial gains have also been made with respect to cutting edge techniques that now allow for real time feedback based on neural activity (Sulzer et al., 2013). Such techniques could be used to tailor communication interventions, for example by providing researchers feedback about neural responses to mediated communications; in response, researchers could alter the course of the narrative, production elements, or other key features based on an individual's neural responses. In aggregate, such information might also reveal unexpected combinations/permutations of communication features that are powerful across individuals, but not predicted by existing theories. Likewise, provision of real time feedback to patients in response to different types of inputs (e.g., smokers' responses to smoking imagery) could suggest new clinical treatments. This type of feedback could be complemented by stimulation of specific brain regions to increase or temporarily block neural function (Antal, Nitsche, & Paulus, 2006; Camus et al., 2009; Fregni et al., 2005; Lang et al., 2005; Ruff, Driver, & Bestmann, 2009). Methods that allow temporary up and down regulation of targeted neural activity will also boost confidence in the causal pathways hypothesized, as well as real-world impact of these technologies for communication questions.

Finally, computational models of cognition may also help expand the brain-as-predictor framework. Computational models of cognition broadly refer to a set of computationally driven models of human mental processes that attempt to represent or act like cognitive systems. These systems can then be used to model behavior based on the structural properties of the neural system. For example, cognitive architectures that describe basic cognitive and perceptual processes and their links to neural function can be used to test hypotheses about more basic neural components involved in processing complex tasks, such as exposure to mass media messages (for reviews of one set of cognitive architectures, see Borst, Taatgen, & Anderson, in press; Borst, Taatgen, & Rijn, in press; Lehman, Laird, & Rosenbloom, 2006). Cognitive architectures and other computational models of cognition can be used to model communication or psychological theories to predict behavioral outcomes, to the extent that such relationships have been previously established (Borst, Taatgen, & Anderson, in press; Borst, Taatgen, & Rijn, in press; Lehman, Laird, & Rosenbloom, 2006). The use of cognitive models to link neural processes and behavioral outcomes is one particularly promising, but still underdeveloped, avenue that should be pursued to optimally leverage the brain-as-predictor approach in communication science.

CONCLUSION

Communication scholars can leverage advances in neuroscientific measurement tools and the accumulated knowledge on the neural correlates of many basic social, cognitive and affective processes to predict psychological and behavioral outcomes in response to communication within and beyond the laboratory. This approach has considerable potential for testing existing theories or generating new ones. Neuroimaging technologies offer the ability to monitor activity associated with multiple mental processes, in real time as they unfold, without the need to interrupt the target task to request self-reports or to constrain controlled processing. A small but growing body of research in communication and psychology demonstrates that neural variables can predict additional variance in both individual and population level outcomes. This article outlines steps through which a broader range of key questions in communication science might be informed using models that specify neural predictors and relevant psychological or behavioral outcomes. As with any set of methods, the neuroscience methods highlighted here carry significant strengths and limitations; thus, collaborations between neuroscientists and those with other complementary training within communication science will result in advances that are not possible for either discipline alone.

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REFERENCES

Ajzen, I., & Fishbein, M. (2005). The influence of attitudes on behavior. In D. Albarracìn, B. T. Johnson, & M. P. Zanna (Eds.), *The handbook of attitudes* (pp. 173–221). Mahwah, NJ: Erlbaum.

Amodio, D. (2010). Can neuroscience advance social psychological theory? Social neuroscience for the behavioral social psychologist. *Social Cognition*, *28*, 695–716.

Antal, A., Nitsche, M. A., & Paulus, W. (2006). Transcranial direct current stimulation and the visual cortex. *Brain Research Bulletin*, *68*, 459–463. doi:10.1016/j.brainresbull.2005.10.006

Ariely, D., & Berns, G. S. (2010). Neuromarketing: The hope and hype of neuroimaging in business. *National Review Neuroscience*, *11*, 284–292. doi:10.1038/nrn2795

Bandettini, P. (2009). What's new in neuroimaging methods? *Annals of the New York Academy of Science*, *1156*, 260–293.

Bartra, O., McGuire, J. T., & Kable, J. W. (2013). The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. *Neuroimage*, *76*, 412–427. doi:10.1016/j.neuroimage.2013.02.063

Beatty, M. J., McCroskey, J. C., & Pence, M. E. (2009). Communibiological paradigm. In M. J. Beatty, J. C. McCroskey, & K. Floyd (Eds.), *Biological dimensions of communication: Perspectives, methods, and research* (pp. 3–16). Cresskill, NJ: Hampton Press.

Berelson, B. R., Lazarsfeld, P. F., & McPhee, W. N. (1954). *Voting: A study of opinion formation in a presidential campaign*. Chicago, IL: University of Chicago Press.

Berkman, E. T., Cunningham, W. A., & Lieberman, M. D. (in press). Social and affective neuroscience methods. In H. T. Reis & C. M. Judd (Eds.), *Handbook of research methods in social and personality psychology* (2nd ed.). New York, NY: Cambridge University Press.

Berkman, E. T., & Falk, E. B. (2013). Beyond brain mapping: Using the brain to predict real-world outcomes. *Current Directions in Psychological Science*, *22*, 45–55.
Berns, G. S., & Moore, S. E. (2012). A neural predictor of cultural popularity. *Journal of Consumer Psychology*, *22*, 154–160.
Bond, B. J., & Drogos, K. L. (2014). Sex on the shore: Wishful identification and parasocial relationships as mediators in the relationship between *Jersey Shore* exposure and emerging adults' sexual attitudes and behaviors. *Media Psychology*, *17*(1), 102–126.
Boren, J. P., & Veksler, A. E. (2011). A decade of research exploring biology and communication. *Communication Research Trends*, *30*(4), 2–43.
Borst, J. P., Taatgen, N. A., & Anderson, J. R. (in press). Using the ACT-R cognitive architecture in combination with fMRI data. In B. U. Forstmann & E.-J. Wagenmakers (Eds.), *An introduction to model-based cognitive neuroscience*. New York, NY: Springer.
Borst, J. P., Taatgen, N. A., & Van Rijn, H. (2013). Validating models of complex, real-life tasks using fMRI. In A. Johnson & R. W. Proctor (Eds.), *Neuroergonomics: A cognitive neuroscience approach to human factors and ergonomics*. New York, NY: Palgrave MacMillan.
Cabeza, R., & Nyberg, L. (2000). Imaging cognition II: An empirical review of 275 PET and fMRI studies. *Journal of Cognitive Neuroscience*, *12*, 1–47.
Cacioppo, J. T. (2002). Social neuroscience: Understanding the pieces fosters understanding the whole and vice versa. *American Psychologist*, *57*, 819–831.
Cacioppo, J. T., & Berntson, G. (1992). Social psychological contributions to the decade of the brain: Doctrine of multilevel analysis. *American Psychologist*, *47*, 1019–1028.
Cacioppo, J. T., Tassinary, L. G., & Berntson, G. (2007). *Handbook of psychophysiology*. Cambridge, UK: Cambridge University Press.
Campbell, A., Converse, P. E., Miller, W. E., & Stokes, D. E. (1960). *The American voter*. Chicago, IL: University of Chicago Press.
Campbell-Meiklejohn, D. K., Bach, D. R., Roepstorff, A., Dolan, R. J., & Frith, C. D. (2010). How the opinion of others affects our valuation of objects. *Current Biology: CB*, *20*(13), 1165.
Camus, M., Halelamien, N., Plassmann, H., Shimojo, S., O'Doherty, J., Camerer, C., & Rangel, A. (2009). Repetitive transcranial magnetic stimulation over the right dorsolateral prefrontal cortex decreases valuations during food choices. *European Journal of Neuroscience*, *30*, 1980–1988. doi:10.1111/j.1460-9568.2009.06991.x
Cascio, C. N., Carp, J., O'Donnell, M. B., Tinney, F. J., Bingham, C. R., Shope, J. T., . . . Falk, E. B. (2014). Buffering social influence: Neural correlates of response inhibition predict driving safety in the presence of a peer. *Journal of Cognitive Neuroscience*, 1–13. doi:10.1162/jocn_a_00693
Chein, J., Albert, D., O'Brien, L., Uckert, K., & Steinberg, L. (2011). Peers increase adolescent risk taking by enhancing activity in the brain's reward circuitry. *Developmental Science*, *14*(2), F1.
Chua, H. F., Ho, S. S., Jasinska, A. J., Polk, T. A., Welsh, R. C., Liberzon, I., & Strecher, V. J. (2011). Self-related neural response to tailored smoking-cessation messages predicts quitting. *Nature Neuroscience*, *14*, 426–427. doi:10.1038/nn.2761
Converse, P. E. (1964). The nature of belief systems in mass publics. In D. Apter (Ed.), *Ideology and discontent* (pp. 206–261). New York, NY: Free Press.
Cooper, N., Tompson, S., O'Donnell, M. B., & Falk, E. B. (in press). Brain activity in self- and value-related regions in response to online antismoking messages predicts behavior change. *Journal of Media Psychology*.
Coronel, J. C., Duff, M. C., Warren, D. E., Federmeier, K. D., Gonsalves, B. D., Tranel, D., & Cohen, N. J. (2012). Remembering and voting: Theory and evidence from amnesic patients. *American Journal of Political Science*, *56*(4), 837–848.
Cutini, S., & Brigadoi, S. (2014). Unleashing the future potential of functional near-infrared spectroscopy in brain sciences. *Journal of Neuroscience Methods*, *232*, 152–156. doi:10.1016/j.jneumeth.2014.05.024
Curtis, S. M., & Ghosh, S. K. (2011). A Bayesian approach to multicollinearity and the simultaneous selection and clustering of predictors in linear regression. *Journal of Statistical Theory and Practice*, *5*(4), 715–735. doi:10.1080/15598608.2011.10483741
Denny, B. T., Kober, H., Wager, T. D., & Ochsner, K. N. (2012). A meta-analysis of functional neuroimaging studies of self- and other judgments reveals a spatial gradient for mentalizing in medial prefrontal cortex. *Journal of Cognitive Neuroscience*, *24*, 1742–1752. doi:10.1162/jocn_a_00233

Dijksterhuis, A. (2004). Think different: The merits of unconscious thought in preference development and decision making. *Journal of Personality and Social Psychology*, *87*, 586–598.

Dmochowski, J. P., Bezdek, M. A., Abelson, B. P., Johnson, J. S., Schumacher, E. H., & Parra, L. C. (2014). Audience preferences are predicted by temporal reliability of neural processing. *Nature Communications*, *5*. doi:10.1038/ncomms5567

Donohew, L., Palmgreen, P., & Duncan, J. (1980). An activation model of information exposure. *Communication Monographs*, *47*(4), 295–303.

Falk, E. B., Berkman, E. T., & Lieberman, M. D. (2012). From neural responses to population behavior: Neural focus group predicts population level media effects. *Psychological Science*, *23*(5), 439–445.

Falk, E. B., Berkman, E. T., Mann, T., Harrison, B., & Lieberman, M. D. (2010). Predicting persuasion-induced behavior change from the brain. *Journal of Neuroscience*, *30*, 8421–8424. doi:10.1523/JNEUROSCI.0063-10.2010

Falk, E. B., Berkman, E. T., Whalen, D., & Lieberman, M. D. (2011). Neural activity during health messaging predicts reductions in smoking above and beyond self-report. *Health Psychology*, *30*, 177–185. doi:10.1037/a0022259

Falk, E. B., Cascio, C. N., Brook O'Donnell, M., Carp, J., Tinney, F. J., Bingham, C. R., . . . Simons-Morton, B. G. (2014). Neural responses to exclusion predict susceptibility to social influence. *Journal of Adolescent Health*, *54*(5), S22–31. doi:10.1016/j.jadohealth.2013.12.035

Falk, E. B., Hyde, L. W., Mitchell, C., Faul, J., Gonzalez, R., Heitzeg, M. M., . . . Schulenberg, J. (2013). What is a representative brain? Neuroscience meets population science. *Proceedings of the National Academy of Science USA*, *110*, 17615–17622. doi:10.1073/pnas.1310134110

Falk, E. B., Morelli, S. A., Welborn, B. L., Dambacher, K., & Lieberman, M.D. (2013). Creating buzz: The neural correlates of effective message propagation. *Psychological Science*, *24*(7), 1234–1242.

Falk, E. B., O'Donnell, M. B., Cascio, C. N., Tinney, F., Shumaker, K., Kang, Y., . . . Strecher, V. J. (in press). Self affirmation alters the brain's response to health messages and subsequent behavior change. *Proceedings of the National Academy of Sciences*.

Fazio, R. H., & Olson, M. A. (2003). Implicit measures in social cognition research: Their meaning and use. *Annual Review of Psychology*, *54*(1), 297–327. doi:10.1146/annurev.psych.54.101601.145225

Ferrari, M., & Quaresima, V. (2012). A brief review on the history of human functional near-infrared spectroscopy (fNIRS) development and fields of application. *NeuroImage*, *63*(2), 921–935. doi:10.1016/j.neuroimage.2012.03.049

Fregni, F., Boggio, P. S., Nitsche, M., Bermpohl, F., Antal, A., Feredoes, E., . . . Pascual-Leone, A. (2005). Anodal transcranial direct current stimulation of prefrontal cortex enhances working memory. *Experimental Brain Research*, *166*, 23–30. doi:10.1007/s00221-005-2334-6

Gelman, A., Carlin, J. B., Stern, H. S., & Rubin, D. B. (2003). *Bayesian data analysis*. Boca Raton, FL: CRC Press.

Giles, D. C. (2002). Parasocial interaction: A review of the literature and a model for future research. *Media Psychology*, *4*(3), 279–305.

Greenwald, A. G., Poehlman, T. A., Uhlmann, E. L., & Banaji, M. R. (2009). Understanding and using the Implicit Association Test: III. Meta-analysis of predictive validity. *Journal of Personality and Social Psychology*, *97*, 17–41.

Harmon-Jones, E., & Beer, J. (2009). *Methods in social neuroscience*. New York, NY: The Guilford Press.

Hastie, R., & Park, B. (1986). The relationship between memory and judgment depends on whether the judgment task is memory-based or on-line. *Psychological Review*, *93*(3), 258–268.

Hefner, D., Rothmund, T., Klimmt, C., & Gollwitzer, M. (2011). Implicit measures and media effects research: Challenges and opportunities. *Communication Methods and Measures*, *5*(3), 181–202. doi:10.1080/19312458.2011.597006

Horton, D., & Wohl, R. R. (1956). Mass communication and para-social interaction: Observations on intimacy at a distance. *Psychiatry*, *19*(3), 215–229.

Hummer, T. A., Wang, Y., Kronenberger, W. G., Mosier, K. M., Kalnin, A. J., Dunn, D. W., & Mathews, V. P. (2010). Short-term violent video game play by adolescents alters prefrontal activity during cognitive inhibition. *Media Psychology*, *13*(2), 136–154. doi:10.1080/15213261003799854

Jackson-Hanen, V. E., Tompary, A., deBettencourt, M. T., & Turke-Brown, N. (2013, November). *Training of category selectivity through real-time fMRI neurofeedback*. Paper presented at the Society for Neuroscience, San Diego, CA.

Kim, Y. M., & Garrett, K. (2012). On-line and memory-based: Revisiting the relationship between candidate evaluation processing models. *Political Behavior*, *34*(2), 345–368. doi:10.1007/s11109-011-9158-9

Klucharev, V., Hytönen, K., Rijpkema, M., Smidts, A., & Fernández, G. (2009). Reinforcement learning signal predicts social conformity. *Neuron*, *61*(1), 140.

Lang, A. (2009). The limited capacity model of motivated mediated message processing. In R. Nabi & M.Oliver (Eds.), *The Sage handbook of media effects and processes* (pp. 193–204). Thousand Oaks, CA: Sage.
Lang, A., Potter, R. & Bolls, P. (2009). Where psychophysiology meets the media: Taking the effects out of mass media research. In J. Bryant & M. B. Oliver (Eds.), *Media effects: Advances in theory and research* (pp. 185–206). New York, NY: Taylor & Francis.
Lang, N., Siebner, H. R., Ward, N. S., Lee, L., Nitsche, M. A., Paulus, W., . . . Frackowiak, R. S. (2005). How does transcranial DC stimulation of the primary motor cortex alter regional neuronal activity in the human brain? *European Journal of Neuroscience*, *22*, 495–504. doi:10.1111/j.1460-9568.2005.04233.x
Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1944). *The people's choice; how the voter makes up his mind in a presidential campaign*. New York, NY: Duell, Sloan and Pierce.
Lehman, J. F., Laird, J., & Rosenbloom, P. (2006). *A gentle introduction to soar, an architecture for human cognition: 2006 update*. Retrieved from http://ai.eecs.umich.edu/soar/sitemaker/docs/misc/GentleIntroduction-2006.pdf
Lieberman, M. D. (2010). Social cognitive neuroscience. In S. Fiske, D. Gilbert, & G. Lindzey (Eds.), *Handbook of social psychology* (5th ed., pp. 143–193). New York, NY: McGraw-Hill.
Lodge, M., McGraw, K. M., & Stroh, P. (1989). An impression-driven model of candidate evaluation. *The American Political Science Review*, *83*(2), 399.
Lodge, M., Steenbergen, M. R., & Brau, S. (1995). The responsive voter: Campaign information and the dynamics of candidate evaluation. *American Political Science Review*, *89*(02), 309–326.
Loewenstein, G., Rick, S., & Cohen, J. D. (2008). Neuroeconomics. *Annual Review of Psychology*, *59*, 647–72. doi:10.1146/annurev.psych.59.103006.093710
Maltby, J., Giles, D. C., Barber, L., & McCutcheon, L. E. (2005). Intense-personal celebrity worship and body image: Evidence of a link among female adolescents. *British Journal of Health Psychology*, 10(1),17–32.
Miller, M. B., Donovan, C. L., Van Horn, J. D., German, E., Sokol-Hessner, P., & Wolford, G. L. (2009). Unique and persistent individual patterns of brain activity across different memory retrieval tasks. *Neuroimage*, *48*, 625–635. doi:10.1016/j.neuroimage.2009.06.033
Mitchell, D.-G. (2012). It's about time: The lifespan of information effects in a multiweek campaign. *American Journal of Political Science*, *56*(2), 298–311. doi:10.1111/j.1540-5907.2011.00549.x
Mur, M., Bandettini, P. A., & Kriegeskorte, N. (2009). Revealing representational content with pattern-information fMRI—an introductory guide. *Social Cognitive and Affective Neuroscience*, *4*, 101–109. doi:10.1093/scan/nsn044
Nisbett, R., & Wilson, T. (1977). Telling more than we can know: Verbal reports on mental processes. *Psychological Review*, *84*, 231–259.
Norman, K. A., Polyn, S. M., Detre, G. J., & Haxby, J. V. (2006). Beyond mind-reading: Multi-voxel pattern analysis of fMRI data. *Trends Cognitive Science*, *10*, 424–430. doi:10.1016/j.tics.2006.07.005
Ochsner, K., & Lieberman, M. (2001). The emergence of social cognitive neuroscience. *American Psychologist*, *56*(9), 717–734.
O'Donnell, M. B., Falk, E. B., & Lieberman, M. D. (2015). Social in, social out: How the brain responds to social language with more social language. *Communication Monographs*.
Paulhus, D. L. (1986). Self-deception and impression management in test responses. In P. D. A. Angleitner & P. D. J. S. Wiggins (Eds.), *Personality assessment via questionnaires* (pp. 143–165). Berlin, Germany: Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-3-642-70751-3_8
Perse, E. M., & Rubin, R. B. (1989). Attribution in social and parasocial relationships. *Communication Research*, *16*(1), 59–77.
Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. *Advances in Experimental Social Psychology*, 19, 123–205.
Petty, R. E., Priester, J. R., & Brinol, P. (2002). Mass media attitude change: Implications of the elaboration likelihood model of persuasion. In J. Bryant (Ed.), *Media effects: Advances in theory and research* (pp. 99–122). Lawrence Erlbaum.
Picton, T. W., Bentin, S., Berg, P., Donchin, E., Hillyard, S. A., Johnson, R., . . . Taylor, M. J. (2000). Guidelines for using human event-related potentials to study cognition: Recording standards and publication criteria. *Psychophysiology*, *37*(2), 127–152.
Poldrack, R. A. (2006). Can cognitive processes be inferred from neuroimaging data? *Trends Cognitive Science*, *10*, 59–63. doi:10.1016/j.tics.2005.12.004

Poldrack, R. A., Fletcher, P. C., Henson, R. N., Worsley, K. J., Brett, M., & Nichols, T. E. (2008). Guidelines for reporting an fMRI study. *NeuroImage*, *40*(2), 409–414. doi:10.1016/j.neuroimage.2007.11.048

Potter, R. F., & Bolls, P. (2011). *Psychophysiological measurement and meaning: Cognitive and emotional processing of media*. New York, NY: Routledge.

Redlawsk, D. P. (2001). You must remember this: A test of the on-line model of voting. *The Journal of Politics*, *63*(1), 29–58. doi:10.1111/0022-3816.00058

Ruff, C. C., Driver, J., & Bestmann, S. (2009). Combining TMS and fMRI. *Cortex*, *45*(9), 1043–1049. doi:10.1016/j.cortex.2008.10.012

Salimi-Khorshidi, G., Smith, S. M., Keltner, J. R., Wager, T. D., & Nichols, T. E. (2009). Meta-analysis of neuroimaging data: A comparison of image-based and coordinate-based pooling of studies. *Neuroimage*, *45*, 810–823.

Sanfey, A., Loewenstein, G., & Mcclure, S. (2006). Neuroeconomics: Cross-currents in research on decision-making. *Trends in Cognitive Sciences*, *10*, 108–116.

Sargent, J. D., Worth, K. A., Beach, M., Gerrard, M., & Heatherton, T. F. (2008). Population-based assessment of exposure to risk behaviors in motion pictures. *Communication Methods and Measures*, *2*(1-2), 134–151. doi:10.1080/19312450802063404

Saxe, R., Brett, M., & Kanwisher, N. (2006). Divide and conquer: A defense of functional localizers. *Neuroimage*, *30*, 1088–1096; discussion 1097–9. doi:10.1016/j.neuroimage.2005.12.062

Scholkmann, F., Kleiser, S., Metz, A. J., Zimmermann, R., Mata Pavia, J., Wolf, U., & Wolf, M. (2014). A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology. *NeuroImage*, *85*, 6–27. doi:10.1016/j.neuroimage.2013.05.004

Sethuraman, R., Tellis, G. J., & Briesch, R. A. (2011). How well does advertising work? Generalizations from meta-analysis of brand advertising elasticities. *Journal of Marketing Research*, *48*(3), 457–471.

Sulzer, J., Haller, S., Scharnowski, F., Weiskopf, N., Birbaumer, N., Blefari, M. L., . . . Sitaram, R. (2013). Real-time fMRI neurofeedback: Progress and challenges. *NeuroImage*, *76*, 386–399. doi:10.1016/j.neuroimage.2013.03.033

Tak, S., & Ye, J. C. (2014). Statistical analysis of fNIRS data: A comprehensive review. *NeuroImage*, *85*, 72–91. doi:10.1016/j.neuroimage.2013.06.016

Thorson, K. S., & Rodgers, S. (2006). Relationships between blogs as eWOM and interactivity, perceived interactivity, and parasocial interaction. *Journal of Interactive Advertising*, *6*(2), 39–50.

U.S. Total Media Ad Spend Inches Up, Pushed by Digital. (2013). Retrieved from http://www.emarketer.com/Article/US-Total-Media-Ad-Spend-Inches-Up-Pushed-by-Digital/1010154

Wakefield, M. A., Loken, B., & Hornik, R. C. (2010). Use of mass media campaigns to change health behavior. *Lancet*, *376*(9748), 1261–1271.

Wager, T. D., Lindquist, M. A., Nichols, T. E., Kober, H., & Van Snellenberg, J. X. (2009). Evaluating the consistency and specificity of neuroimaging data using meta-analysis. *Neuroimage*, *45*, S210–221.

Weber, R., Huskey, R., Mangus, J. M., Westcott-Baker, A., & Turner, B. (in press). Neural predictors of message effectiveness during counterarguing in antidrug campaigns. *Communication Monographs*.

Weber, R., Ritterfeld, U., & Mathiak, K. (2006). Does playing violent video games induce aggression? Empirical evidence of a functional magnetic resonance imaging study. *Media Psychology*, *8*, 39–60.

Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C., & Wager, T. D. (2011). Large-scale automated synthesis of human functional neuroimaging data. *National Methods*, *8*, 665–670. doi:10.1038/nmeth.1635

APPENDIX: NEURAL PREDICTION OF COMMUNICATION-RELEVANT OUTCOMES— CHECKLIST ITEMS FOR REPORTING BRAIN-AS-PREDICTOR STUDIES

In addition to the considerations that apply to reporting any neuroscience investigation (outlined in resources at the end of this checklist and other manuscripts within this volume), and in addition to the same standards that apply to reporting longitudinally collected behavioral data in communication science (e.g., from surveys, behavioral observation, or whatever means you are using to collect your DV), the following considerations should be noted during the study design phase, and explicitly treated when you report a brain-as-predictor study:

Evaluation Criteria	☑
For any neuroimaging modality	
Conceptualization of position of neural variables within your model (choose at least one from below)	
As primary predictor of a communication behavior or outcome	☐
As mediator of the relationship between communication inputs and behavioral, psychological or physiological outcomes	☐
As moderator of the relationship between communication inputs and behavioral, psychological or physiological outcomes	☐
Conceptualization of psychological role of neural variables (choose at least one from below)	
As a state measure (in relation to manipulated context)	☐
As a trait measure (of stable individual difference)	☐
Treatment of reverse inference in discussion	
Authors are clear/explicit about which relationships between psychological constructs and neural function are directly observed[2]	☐
Authors are clear which are speculative/ based on reverse inference[3]	☐
Statistical and measurement considerations	
Imaging modality chosen is well justified	☐
Authors specify strengths and limits of modality chosen	☐
Statistical methods to link neural predictor with hypothesized outcomes are clearly specified[4]	☐
Statistical assumptions inherent or required for method are detailed	☐
Steps taken (if any) to assess the construct validity of your neural measure (e.g., reliability, convergent validity, discriminant validity, etc.) are specified	☐
For fMRI, fNIRS and other methods that employ spatially defined ROIs	
Method for identifying ROIs is clearly defined (choose one or more from below)	☐
Anatomically based on prior literature	☐
Report how the ROI was constructed	☐
Rationale re: anatomical boundaries	☐
Atlases used (if any)	☐
Functionally	☐
Based on a prior independent dataset	☐

(*Continued*)

[2]As in the case of mediation when neural activity is manipulated using a psychological task and used to predict another specific psychological, psychophysiological or behavioral outcome.

[3]e.g., reverse inferences made about the psychological function of your regions of interest based on past work that has found associations between a psychological process and your region of interest.

[4]e.g., GLM, Non-parametric, Machine learning based classification.

TABLE A1
(Continued)

Based on a meta-analysis	☐
Curated/ Peer reviewed	☐
Automated (e.g., Neurosynth)	☐
ROIs chosen are as selective as possible[5]	☐
For ERP and methods that focus on a combination of spatial and temporal effects	
Authors detail how ERP component focused on is selected and measured[6]	☐
How the ERP waveform was measured (peak amplitude, mean amplitude, etc.)	☐
Why a time window was chosen	☐
Why a given set of electrodes were chosen for analyses.	☐
Authors have accounted for possible effects of the neuroimaging environment (choose one or more below)	☐
Demonstrate that behavioral relationships between psychological manipulations and observed outcomes are not affected by the neuroimaging environment	☐
Demonstrating similar effects between behavioral pilot data collected outside of the neuroimaging context and behavioral data collected in the neuroimaging study	☐
Note limitations of neuroimaging environment	☐

Note: We build on the advice offered by Weber and colleagues (this volume): "This checklist is designed to assist authors, reviewers and editors in the process of reporting and evaluating an fMRI study. No checklist can include an exhaustive list of requirements for every study and not every requirement on this checklist may be necessary for all [brain-as-predictor] fMRI studies. Therefore, we invite fellow researchers to extend or modify our checklist. With this in mind, studies that do not include one or two of the requirements should not necessarily be viewed as invalid or otherwise flawed. Instead, missing requirements should prompt requests for clarification.

Additional Resources for Communication Scholars, Reviewers and Editors

The following resources contain more general guidelines and advice for reporting three potentially useful forms of neuroimaging data. For additional information about data acquisition and methodological notes, readers may also be interested in *Methods in Social Neuroscience* (Harmon-Jones and Beer, 2009).

Guidelines for reporting fMRI data (Poldrack et al., 2008)
This resource provides an excellent overview of methodological choices that go into designing an fMRI study that should be reported in write ups of fMRI studies. An addendum to this checklist

[5]As noted in text, although the experimenter cannot typically alter the physiological selectivity of a brain region (i.e., the range of stimuli that a brain region responds to/ range of psychological processes that it supports), the use of meta-analyses, functional localizer tasks, and focus on networks of regions (instead of single regions) can all help increase selectivity. Databases such as neurosynth.org can also help estimate the selectivity of the brain region in question for the psychological process in question; use this information to adjust the strength of claims made in reporting your findings.

[6]More details in resources specified below.

was proposed by Falk, Hyde, Mitchell and colleagues (2013) to better allow neuroimaging research to link to population level outcomes.

Checklist for reporting ERP data (Picton et al., 2000)
This article presents guidelines for reporting standards advocated by the Society for Psychophysiological Research.

Resources for reporting fNIRS data
An overview of current and future uses of fNIRS (and a short discussion of lack of standard methods) - (Cutini & Brigadoi, 2014)
A review of methods for continuous wave-fNIRS - (Scholkmann et al., 2014)
An overview of statistical analysis of fNIRS data - (Tak & Ye, 2014)
A history and overview of current practices in fNIRS - (Ferrari & Quaresima, 2012)