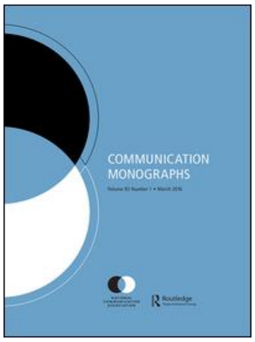

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Taking messages into the magnet: Method–theory synergy in communication neuroscience

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ABSTRACT
Brain imaging techniques within communication research have rapidly expanded in popularity in recent years, driven by an increase in access to functional magnetic resonance imaging (fMRI) technology and by theoretical developments within the field. In this manuscript, we present an overview of research from within communication and cognate disciplines that has leveraged insights from fMRI research to "push the envelope," demonstrating a synergy between methodological and theoretical progress. In addition, we provide a review of fMRI technology, methodology, and theoretical considerations, focusing on recent developments in the cognitive and brain sciences that are of special relevance to communication scholars. Finally, we provide a series of practical recommendations and resources for communication scholars interested in conducting fMRI studies.

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Brain imaging; functional magnetic resonance imaging; media neuroscience; communication neuroscience; method–theory synergy

Researchers within communication science and cognate disciplines have recently developed an increasing number of research programs incorporating functional magnetic resonance imaging (fMRI), a methodological tool that allows researchers to investigate brain activation during the course of message processing. This is driven, in part, by communication researchers' increasing access to brain imaging technology, but also by a concerted shift in focus within media and communication effects research toward processing approaches that prioritize the central role of the brain in encoding, processing, and storing messages (Lang, 2013; Lang & Ewoldsen, 2013; Weber, 2015). Rather than considering the human processing system as a "black box" impenetrable to investigation, the processing approach incorporates analysis of physiological and neurological responses in order to build models of communication processes and message effects with unprecedented levels of accuracy and explanatory power. These approaches are examples of a new form of method–theory synergy in communication research that embraces current scientific epistemology and ontology with the goal of providing prediction and explanation from the individual neuron level to population-level dynamics. This synergy between methods and theory allows researchers to build more rigorous models and select "fewer and more powerful theories and variables" (Weber, Sherry, & Mathiak, 2009, p. 42).

There are many approaches that are well suited to measure the ways in which the brain encodes and decodes messages. For example, communication scholarship benefits from a

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long and productive history of research using psychophysiological measures, such as skin conductance, electrocardiography, and electromyography to index affect and cognition during the communication process (Potter & Bolls, 2011; Ravaja, 2004). Since the first fMRI study that was published 25 years ago (Kwong et al., 1992), brain imaging measures have exploded in popularity. Now thousands of studies are published using fMRI each year (Smith, 2012). Many psychology departments have developed in-house brain imaging centers rather than relying on the after-hours rental of MRI time from hospitals and university medical centers, further increasing access to brain imaging (Raichle & Mintun, 2006). This increasing access to brain imaging resources has allowed communication researchers the opportunity to investigate many topics of interest, including persuasion (e.g., Falk, Berkman, Mann, Harrison, & Lieberman, 2010; Weber, Huskey, Mangus, Westcott-Baker, & Turner, 2015), attention to media content (e.g., Huskey, Craighead, Miller , & Weber, 2017; Weber, Alicea, Huskey, & Mathiak, 2017), narrative engagement (Cohen, Henin, & Parra, 2017; Schmälzle, Häcker, Honey, & Hasson, 2015), flow experiences (Klasen, Weber, Kircher, Mathiak, & Mathiak, 2012), moral narratives (Amir et al., 2017), virality of messages (Scholz et al., 2017), speaker–listener coupling during conversation (Dikker, Silbert, Hasson, & Zevin, 2014; Stephens, Silbert, & Hasson, 2010), affectionate communication in close relationships (Hesse et al., 2013), and many more questions of interest.

As is evidenced in this broad range of research areas, data gathered from brain imaging hold particular promise for building and improving models of human behavior in ways not possible with behavioral data alone (Gabrieli, Ghosh, & Whitfield-Gabrieli, 2015). As Greenwald (2012) emphasized, novel methodologies provide unprecedented forms of new data which, when considered in the light of precise, falsifiable models, lead to theory refinements, theory rejection, and new theories/models. This synergistic relationship between theory and method facilitates additive scientific progress (Kuhn, 1962). Within communication research, several promising research areas have emerged in recent years, catalyzed by an approach emphasizing the synergy among content analysis, behavioral and self-report measures, and brain imaging. By leveraging brain imaging tools, as well as data analysis methods from network science, computational social science, machine learning, and other fields, communication scholars have contributed significantly to knowledge of the human processing system, the understanding of message effects, and the theoretical and methodological toolkit used to investigate these questions.

With the above information in mind, in this manuscript we highlight recent methodological advancements in communication research that exemplify method–theory synergy, focusing on the interconnected relationships among content analysis (both manual and computational), brain imaging research, and behavioral data. We also illuminate several key ways this approach leverages communication scholars' unique expertise to develop stimuli and tasks suitable for brain imaging research which, in turn, provide a clear benefit for scholars in cognitive neuroscience and cognate disciplines. In addition, we provide a review of fMRI technology, methodology, and theoretical considerations (e.g., which research questions can be reasonably addressed with brain imaging methodology), focusing on recent developments in the cognitive and brain sciences that are of special relevance to communication scholars. Finally, we provide a series of practical recommendations and resources for scholars interested in conducting brain imaging studies.

While this journal article cannot deliver a comprehensive introduction into fMRI research, it can serve as a crucial "jump start" for scholars in communication and related disciplines. For more advanced overviews of study design and data preprocessing in fMRI research, please see Weber, Eden, Huskey, Mangus, and Falk (2015) and Huettel, Song, and McCarthy (2014). For those interested in advanced data analysis, Ashby (2011) and Poldrack, Mumford, and Nichols (2011) provide a helpful introduction. Readers interested in the quickly growing research area dedicated to the study of dynamic networks of the brain via fMRI data are encouraged to consult Bassett and Sporns (2017) or Sporns (2010).

Communication neuroscience and method–theory synergy

A central goal within communication theory is the development and explication of empirically testable, falsifiable theory regarding the causal processes underlying human communication (Slater & Gleason, 2012). Importantly, theories within communication should have the ability to predict and explain observed relationships between variables (Weber, Sherry, et al., 2009). Brain imaging, although undeniably useful for the prediction of outcomes, finds unique value in its utility for explanation (Mather, Cacioppo, & Kanwisher, 2013). Several research areas within communication scholarship have greatly benefited from the explanatory power afforded by a synergistic approach incorporating content analytic methods, brain imaging, and behavioral measures. Recent advancements in fMRI data analysis informed by network science, machine learning, and novel statistical techniques have further enabled researchers in these areas to "push the envelope" of communication theory and methodology. In this section, we outline three examples of such research within the communication discipline.

Brain-as-predictor

Communication scholars have paid great attention to extending their understanding of how certain message features evoke attitudinal and behavioral changes in particular target audiences. This research has culminated in several theoretical advancements. For example, the elaboration-likelihood model (ELM; Petty & Cacioppo, 1986), the extended-elaboration-likelihood model (E-ELM; Slater, 2002), the activation model of information exposure (Donohew, Palmgreen, & Duncan, 1980), and the limited capacity model of motivated mediated message processing (LC4MP; Lang, 2009) have all arisen from an increasing focus on message processing. Despite these important developments, several challenges remain in understanding how and under what circumstances messages result in persuasive outcomes.

Many studies in communication have drawn on self-report measures to assess how likely individuals – usually after being exposed to a certain media stimulus – are to change their attitude/behavior in favor of the presented content. While self-reports provide an important supplement, for example, to measure perceived message effectiveness, they fall short on extracting information about dynamic subconscious processes throughout the message. Although certain measures (e.g., continuous response measurement) provide dynamic feedback, they still fail to provide a more nuanced, multidimensional approach to message processing. In addition, many theories of message persuasion have led to incompatible predictions in the past with rather low accuracies when predicting actual behavior change, especially in high-risk populations (Weber, Westcott-Baker, & Anderson, 2013).

Recently, great gains have been made in improving the predictive accuracy of persuasion measures in communication by adding a novel predictor – the brain – to prediction models. This *brain-as-predictor* approach (Berkman & Falk, 2013) draws on "brain systems that previously have been linked to specific psychological processes to predict meaningful outcomes beyond the confines of the laboratory" (p. 46). Falk and colleagues (Falk, Berkman, Whalen, & Lieberman, 2011; Falk, Berkman, et al., 2010; O'Donnell & Falk, 2015), recorded neural signals of brain regions associated with self-related processing, valuation of external stimuli, and spontaneous motor behavior (present in a subregion of the medial prefrontal cortex, and the precuneus[1]; Falk, Berkman, et al., 2010), while individuals were being exposed to certain persuasive messages. After the fMRI scanning session, participants were asked to report perceived message effectiveness and the likelihood of changing their future behavior. In a final regression model, neural activation pattern and individuals' self-reports were then merged as predictors for real-world behavior change both in research participants and in independent, larger populations exposed to the same messages. Adding neural activation into persuasion likelihood models also improved the predictive accuracy of these models by over 20% (Falk, Berkman, et al., 2010). Furthermore, brain activation observed in these small groups of participants predicted population-level media effects where self-report data did not (Falk, Berkman, & Lieberman, 2012; Falk et al., 2016).

Focusing more strongly on refining the perspective on message content and persuasion theory, O'Donnell and Falk (2015) further extended the *brain-as-predictor* approach by merging fMRI with an automated content analysis to investigate the underlying neural correlates that precede message-sharing behavior. While undergoing fMRI scanning, subjects were exposed to ideas for potential new TV shows and afterward were asked to report how likely they would be to recommend each show. These recommendations were then transcribed and analyzed using a sentiment analysis classifier that was trained on other movie ratings to identify evaluative/descriptive and positive/negative language. In a sentiment analysis, a computer algorithm is used to count the presence of positive or negative words in a document based on a specific list of such words (Günther & Quandt, 2016). Another common approach to sentiment analysis is the use of supervised learning techniques, extracting a set of determinative features, such as individual words or *n*-grams from training texts. Documents can then be classified into groups based on their overall positivity or negativity. Recorded neural activity from the brain scanning session was then merged with the text data to examine which brain regions were associated with the use of positive evaluative language and overall positive language. The results confirmed that neural activity in brain regions associated with self-referential processes was related to higher overall positivity scores of show descriptions. Accordingly, activation in a region associated with mentalizing (the temporoparietal junction) was associated with higher positive evaluations of these shows. This suggests that individuals tend to use more overall positive language to describe ideas that they deem as self-relevant, and more positive evaluative language for ideas that they perceive to have social value.

In a similar vein, Scholz and colleagues (2017) examined whether neural activation in certain brain areas while reading an online newspaper article can be predictive of message virality. In this study, participants read the headline and short summary of articles from the *New York Times* while undergoing fMRI scanning. Researchers recorded neural activation in brain regions associated with interpreting information-sharing value (ventromedial prefrontal cortex, VMPFC; ventral striatum, VS), as well as regions related to the expectations of self-referential (MPFC; PC) and social outcomes (middle and dorsal MPFC) of message sharing. Data on logged sharing counts of these articles were then retrieved using the NYTimes' Most Popular application programing interface (API). The findings using these combined methodologies revealed that those online newspaper articles that were associated with higher brain activation in regions of interest were also shared more frequently by the entire population of NYTimes readers. Taken together, O'Donnell and Falk (2015) and Scholz et al. (2017) demonstrate how the methodological fusion of brain imaging data with the automated content analysis of self-reports and logged sharing counts of newspaper articles can be a promising approach for uncovering how novel ideas are evaluated and subsequently may spread through social networks.

So far, the described studies that draw upon the underlying method–theory synergy logic of the brain-as-predictor approach have combined human and automated content analytical procedures with brain imaging, self-report, and behavioral measures to gain a more complete picture of the circumstances in which message content successfully impacts and spreads among individual audiences. A final variable complementing this synergy – the social network of a message receiver – was introduced by O'Donnell and Falk (O'Donnell, Bayer, Cascio, & Falk, 2017; O'Donnell & Falk, 2015) who combined neural and "ego network" data (i.e., information on the social network surrounding a particular individual) of smokers to examine why certain socially framed anti-smoking messages are effective in reducing the intention to smoke in some smokers, but not in others. Their findings indicate that a higher number of smokers within the social network of an individual smoker results in greater neural activity in brain regions associated with mentalizing (i.e., thinking about the mental states, perceptions, and thoughts of others). Interestingly, although mentalizing had previously been linked to an increased intention to stop smoking (e.g., Cialdini & Goldstein, 2004), mentalizing processes were not tied to decreases in intent to smoke for smokers who had had a higher concentration of other smokers in their ego network. This finding helped identify the boundary conditions associated with previous work regarding the effectiveness of mentalizing as a potential persuasive device for anti-smoking messages. Recent research by Schmälzle and colleagues has further revealed the utility of investigating brain network dynamics for investigating an individual's social network structure (Schmälzle et al., 2017). The inclusion of this social network structure highlights the contextual importance of a message receiver and provides helpful preliminary insights into the possible socio-environmental inhibitors of successful health campaigns. Research integrating understanding of social networks with understanding of structural and functional brain networks promises a wealth of new insights into the role(s) of both networks in processes relevant to scholars in a broad range of disciplines (Falk & Bassett, 2017).

In sum, the brain-as-predictor approach has been a flagship paradigm of synergizing communication theory, brain imaging, self-report, (automated) content analytic, and behavioral data to uncover insights into the linkages among individuals' behavior on the micro-level, their socio-environmental context on meso-levels, and macro-level trends of shifting population-based outcomes. Importantly, traditional self-report and cross-sectional research designs require large, carefully sampled subject pools to minimize sampling and standard errors for achieving satisfactory predictive accuracy. Given the predictive power of this *brain-as-predictor* approach, researchers have not only gained new theoretical insights into the concepts under study, but have been able to project laboratory findings with unprecedented predictive accuracy onto large, independent samples. By investigating neural processing of messages in small populations, researchers can improve understanding of the "how" and the "why" of persuasion in ways that seemed to be impossible using traditional social science techniques.

Finally, the latest innovations in this area suggest that realizing the true potential of the *brain-as-predictor* approach depends on thoughtfully considering the role of individual differences in neural activation during message processing, thus answering the question "whose brain is best for prediction?" This approach, given the moniker *population neuroscience*, leverages expertise across disciplinary lines to improve sampling mechanisms through clear definition of relevant populations based on understanding of statistical and neural mechanisms relevant for the study at hand (Falk et al., 2013). Additionally, further improvements in prediction accuracy will require accounting for the human brain's complex network structure. In addressing these innovations, scholars in communication and cognitive neuroscience have embarked to study individual differences in the neural processing of persuasive messages (neural message tailoring) and to incorporate new measures of network connectivity in (brain) prediction models (e.g., Cooper, Bassett, & Falk, 2017; Huskey, Mangus, & Weber, 2016; Weber, Turner, Huskey, & Mangus, 2015).

Neurocinematics and "mind reading"

Many communication scholars also develop and test theories involving complex, real-world stimuli like entertainment media. For instance, movie viewing is an experience that takes viewers through many cognitive states that evolve over time in a stochastic manner. Sequences of audiovisual stimuli trigger neural processes that contribute to viewer enjoyment and memory (Hasson et al., 2008). Brain imaging research utilizing naturalistic stimuli, such as movies and video games, are vital to understanding the richness, complexity, and dynamics of neural processing over time. For communication researchers, these approaches also necessitate research that exhibits a deep understanding of the role of message features in processing, requiring rigorous content analysis as well as behavioral measures.

Two key methodological developments in fMRI research have facilitated the rapid rise of this research area: intersubject correlations (ISCs; Hasson, Nir, Levy, Fuhrmann, & Malach, 2004) and multivoxel pattern analysis (MVPA; Haxby et al., 2001; Mur, Bandettini, & Kriegeskorte, 2009; Norman, Polyn, Detre, & Haxby, 2006). These innovative approaches allow researchers much more freedom in experimental design and stimulus selection than would be afforded under more traditional hypothesis-driven fMRI paradigms. For instance, ISCs (see definition below), due to their demonstrated ability to use dynamic, low-controlled stimuli such as entire movies or advertisements, gave rise to an entirely new research field deemed *Neurocinematics* (Hasson et al., 2008). Furthermore, brain imaging, for much of the history of the discipline, has been largely based on a paradigm of *encoding*. In this paradigm, aspects of the environment are experimentally manipulated and brain responses are measured, creating an understanding of how brain activation changes as experimental stimuli are altered. Recent fMRI paradigms using MVPA now also adopt a *decoding* perspective, in which researchers attempt to ascertain how much can be learned about external states and stimuli from activation patterns in the brain (Naselaris, Kay, Nishimoto, & Gallant, 2011). MVPA and other decoding methods have been used with success to roughly reconstruct internal and external states from brain activation, and are thus often referred to as a "mind reading" approach (Norman et al., 2006).

Intersubject correlation (ISC) – synchronization across brains

Differences in brain activation between subjects have been demonstrated in countless experiments using fMRI, but these activation patterns are largely based on highly controlled environments and simplistic stimuli. Traditional fMRI analyses do a poor job finding differences between the brains of individuals viewing more natural, free-flowing experimental stimuli that are of interest to communication scholars. This is due to many factors, including the multidimensionality and complexity of the data and the relative lack of any clear division between experimental conditions in naturalistic paradigms. Intersubject correlations modify the classical approach to fMRI analysis in which one stimulus condition is contrasted with another and differences in brain activity are observed. Rather than using a collection of preselected stimulus condition and contrasting them, the ISC approach uses complex, dynamic, naturalistic stimuli such as film and measures how individuals' brain responses are similar (i.e., pairwise correlated) during stimulus exposure (Hasson et al., 2004). The ISC approach replaces the traditional subtraction or contrast perspective of fMRI analyses with a covariance perspective. A basic premise of this approach is that pairwise average correlations (also called similarity, synchrony, or temporal reliability) of individuals' brain responses between stimulus conditions are meaningful and possess predictive value for behavior.

Evidence for this premise has been presented in numerous studies in communication and cognate disciplines. Recent research has used movies (Chen et al., 2016; Cohen et al., 2017; Hasson et al., 2008), narrated short stories (Brennan et al., 2012; Wilson, Molnar-Szakacs, & Iacoboni, 2008; Yeshurun et al., 2017), political speeches (Schmälzle et al., 2015), speaker–listener interpersonal interactions (Dikker et al., 2014; Stephens et al., 2010), and health communication messages (Schmälzle, Häcker, Renner, Honey, & Schupp, 2013) in intersubject correlation analyses. Observed correlations between key areas in participants' brains have been validated as indices of shared visual perception (Hasson et al., 2004), narrative engagement (Cohen et al., 2017; Weber, Eden, & Mathiak, 2011), variation in narrative perception based on pre-existing views (Yeshurun et al., 2017), perception of moral violations in political liberals and conservatives (Amir et al., 2017), convincingness of oral rhetoric (Schmälzle et al., 2015), interpersonal communication success (Hasson & Frith, 2016; Stephens et al., 2010), shared memories (Chen et al., 2016), and shared risk perception (Schmälzle et al., 2013). While ISC approaches possess great potential for the communication discipline, it is important to note that in this type of fMRI research, brain areas for correlation analysis should be defined based on in-depth theoretical knowledge of the structure and function of particular brain areas, as well as on the types of processing that are expected to be induced by the stimulus. For maximum precision and meaning, stimuli should be analyzed using a rigorous and theory-based content analysis that can reveal why specific brain regions fall into and out of synchrony with one another during the course of dynamic stimuli.

Multivoxel pattern analysis

MVPA is a natural fit for investigating many extant questions within communication and media neuroscience, and as such has been used in several recent research areas. One of the best-known instances of MVPA is in reconstruction (decoding) of visual scenes from brain data collected during movie viewing (e.g., Nishimoto et al., 2011). MVPA has been used to analyze moral judgment and intuition in the processing of political attack ads (Amir et al., 2017). MVPA has also been used in clinical applications relevant to communication scholars, creating communication interfaces for those in "locked-in" states (Naci et al., 2012), and illuminating neural correlates of social anxiety disorder (Frick et al., 2014). Another potential application of MVPA in interpersonal communication research, albeit still in its inception, is deception detection. Recent work has shown that it is possible to decode the veracity of thoughts independent of intent to conceal (Yang et al., 2014), but much progress is still needed to ascertain whether fMRI is a worthwhile tool for detection or prediction of deception (Rusconi & Mitchener-Nissen, 2013).

Traditional whole-brain fMRI analyses model the response of each voxel[2] in the brain as a function of stimulus conditions (encoding). That is, for about 1.4 million voxels in a high-resolution (1 mm^3 voxels) scan of a human brain, 1.4 million univariate general linear models need to be fitted. MVPAs, in contrast, model a limited number of voxels all together in a multivariate approach. Typically, distinct patterns of a set number of voxels in specific brain regions of interest are used as "features" or training samples in a classification procedure with the goal to predict the stimulus conditions an individual was exposed to with high accuracy (decoding, Norman et al., 2006).

In more detail, MVPA uses observed voxel response patterns with stimulus events to create a "training set," which is analyzed for similarity between and within stimulus conditions. This training set is used to create a "classifier" or a criterion for the differentiation of observed activation patterns into discrete categories. There are many classifiers that have been successfully used in fMRI research, but one of the most common is known as a least squares support vector machine (SVM; Suykens & Vandewalle, 1999). Once the algorithm is trained to classify stimuli into discrete categories based on voxel response patterns collected via fMRI, it can be used to classify stimulus categories in a "test set": a subset of the data that was not used for training. If the classification accuracy in the test set is both beyond chance and not significantly worse than in the training set, researchers assume that the classification was successful, or that the classifier can successfully decode brain responses into real-world information.

MVPA is computationally expensive, and can take a long time to run on even small brain regions of interest. In addition to this, MVPA analyses can quickly become prone to the "curse of dimensionality" (Friedman, 1997), wherein the number of feature combinations (different voxel response patterns) is far greater than the number of available training and test events in the data. For this reason, it is important that communication researchers interested in applying brain imaging methodology maintain a certain set of best practices when using MVPA in their research. First of all, stimuli should be as tightly controlled as possible. In the presence of relatively simple stimuli, this is rather uncomplicated, but for complex, naturalistic media stimuli or interpersonal communication paradigms cognitive states at any point in time are much less predictable. In addition, it is important that researchers analyze theoretically informed regions of interest or utilize other methods, such as searchlight analysis (Etzel, Zacks, & Braver, 2013) or recursive feature elimination procedures (De Martino et al., 2008), for reducing dimensionality and complexity of the data. Implementation of dynamic content analytic measures informed by communication theory can also assist brain imaging researchers in better understanding how message structure and content contributes to neural processing, facilitating the creation of more precise models of neural activity during these low control experimental protocols. For example, recent research has revealed robust intersubject correlations of brain activation when viewing and also *recalling* media stimuli (Chen et al., 2016). While this finding provides promising future directions for research, communication researchers and neuroscientists are left wondering *why* and *what features of* messages seem to elicit these shared patterns in viewing and recall. Research designs that combine rigorous content analysis of both the stimulus itself and of participants' reported recall with intersubject correlation data can provide communication scholars and neuroscientists with a path forward to answering these questions. This optimally positions media neuroscientists to leverage their unique methodological skillsets to contribute to a rapidly growing field.

Flow theory – synchronization within brains

Our third and final example of theoretical advancement driven by method–theory synergy in communication research is Synchronization (Sync) Theory of Flow (Weber, Tamborini, Westcott-Baker, & Kantor, 2009). Communication scholars have long sought research-driven, practical recommendations for media forms and content features that facilitate enjoyment and optimal experiences during media exposure (Sherry, 2004). Much of the notion of optimal experience stems from literature on flow (Csikszentmihalyi, 1990), a state which is characterized by (a) optimal balance of difficulty and ability, (b) intense concentration (c) the disappearance of self-consciousness, (d) the loss of temporal awareness, (e) pleasantness of the experience, and (f) gratification. Flow states are such that individuals would perform the given activity "for its own sake, with little concern for what they will get out of it, even when it is difficult, or dangerous" (Csikszentmihalyi, 1990, p. 71).

Despite a substantial literature around flow, there is still considerable conceptual ambiguity about what exactly constitutes flow and how flow, as an unconscious experience, can be measured with high reliability and predictive validity. Sync Theory was motivated by these ambiguities, contributing specific neuropsychological processes that likely give rise to flow experiences. The theory comprises five central premises based on empirical evidence that is widely accepted in the neuroscientific community. In brief, (1) brains are oscillating systems, (2) synchronized (brain) systems are energy efficient, (3) brain states are discrete, (4) brains are functionally organized, and (5) brains are hierarchically organized (for an in-depth description, see Weber, Huskey, & Craighead, 2017). Combining these central premises with the phenomenological characteristics of flow experiences resulted in a reconceptualization of flow experiences as the cognitive synchronization of attentional and reward networks in the brain (Weber, Tamborini, et al., 2009). In this conceptualization of flow, synchronization reflects a state in the human brain in which specified neural networks oscillate at the same frequency, with the notion that the effect of these shared oscillations is greater than the sum of the individual parts so that a higher-order experience such as flow can emerge from information processing in lower-order brain systems.

Researchers have long utilized a diverse set of methodological approaches to measure flow, primarily focusing on experience sampling (Csikszentmihalyi & Larson, 2014) and post hoc behavioral measures (Webster, Trevino, & Ryan, 1993). In contrast, Sync Theory allows for the derivation of specific novel hypotheses about the various components of flow that can then be tested with more precise measures in brain imaging studies. A first test of these premises regarding media use was conducted by Klasen et al. (2012), who had participants play a video game while undergoing fMRI scanning. Initial findings demonstrated that participants' self-reported flow experiences were associated with neural activation in brain regions associated with attention (visual cortex), reward (thalamus), error monitoring (anterior cingulate cortex; AAC), and motor stimulation (somatosensory and premotor cortices). The incorporation of neural measures of flow allow for these processes to be analyzed in real time without "breaking" the flow experience through solicitation of self-reported flow or enjoyment.

To acquire further evidence on the synchronization of attentional and reward systems during flow experiences, researchers have started to implement secondary task reaction times (STRTs; Lang, Bradley, Park, Shin, & Chung, 2006) – a commonly used index of attentional resource allocation in media psychology. Focusing on the attentional components of flow, Weber and Huskey (2013) used STRTs as an unobtrusive measure of available attentional resources in flow experiences, demonstrating that longer response times were observable during heightened flow states, suggesting high cognitive resource allocation to the stimulus. Combining the two previous approaches, another fMRI study had participants free-play a first-person-shooter game while responding to a secondary distractor task (Weber et al., 2017), demonstrating Sync Theory's prediction of non-linear increase in functional connectivity (i.e., the synchronization in activation among two or more anatomically distant brain regions over a time period) among executive attention structures (e.g., superior frontal gyrus, middle frontal gyrus) and subcortical structures (e.g., thalamus). This functional connectivity increased as distraction decreased. Lastly, a recent study by Huskey et al. (2017) had subjects play a video game with flexible difficulty levels, illustrating that under conditions of balanced task difficulty and individual ability, feelings of high intrinsic reward corresponded to increased functional connectivity between cognitive control and reward networks, thus providing additional evidence for the assumption that attentional and reward networks synchronize during flow experiences.

While the previously illustrated studies have been highly influential in refining the methodological approaches to study flow experiences, we argue that an even greater emphasis on the synergy among theoretical innovations, brain imaging methods, self-report data, and precisely content analyzed media stimuli is required. As theoretical knowledge of the neural substrates of flow increases, methods can be refined that more accurately index these substrates. It is also likely that the above-outlined brain-as-predictor perspective, as well as ISC and MVPA, will be combined with Sync Theory's arguments to improve predictions. For example, temporal event-coded content analyses of the dynamical structure between rewards and punishments in video games (e.g., Craighead & Weber, 2016), coupled with neural activation during the on- and offset of these events, can provide even more fine-grained insights into the characteristics of media content that elicit flow experiences.

Each of the examples outlined in this section significantly advances existing communication theory by adopting a solution-oriented approach and taking advantage of method–theory synergy. It is often argued (e.g., Coltheart, 2013) that brain imaging measures can only contribute to theories that make explicit statements about brain activation. We disagree. As the above examples demonstrate, brain imaging research can be used to re-frame and even settle theoretical debates regarding the nature of human information processing (Mather et al., 2013), making it useful in many applications for communication researchers. At the same time, communication researchers have much to offer to the broader neuroscientific community, especially in contributing expertise in the methodical analysis and understanding of message *content*, which often falls short in neuroscientific studies.

Understanding the basics of fMRI

Despite the growing popularity of brain imaging measures, the mechanics behind fMRI are still arcane and intimidating for many scholars. In addition, new fMRI technologies and statistical analysis techniques are rapidly developing, and it can be difficult to remain abreast of the latest advancements. In order to evaluate the utility of fMRI for any chosen research program, one first must develop a thorough understanding of what fMRI actually *measures*. This process involves understanding the technology or software upon which the method depends, examining the latent constructs that are purportedly indexed by the measure, and investigating the reliability and (predictive) validity of the measure for relevant research questions.

A beginning step for researchers interested in conducting fMRI is to develop a working understanding of the various parts of the brain and how they contribute to the communication process. This requires a general understanding of the basic architecture of the brain, as well as fundamental processing networks such as the somatosensory and motor systems. For communication researchers, it is also beneficial to develop an understanding of the functional architecture of networks responsible for language processing and speech creation, executive control and distraction inhibition, emotional processing, social cognition, and memory, as knowledge of each of these networks can inform communication and media theory. As an overview of neuroanatomy is beyond the scope of this manuscript, readers interested in further expanding their understanding are encouraged to consult Vanderah and Gould (2015) or Bear, Connors, and Paradiso (2015) for accessible, yet thorough treatments of functional neuroanatomy and the broad field of behavioral neuroscience.

For communication researchers interested in using fMRI in their area of interest, it is worth pausing for a moment and considering types of questions fMRI is well suited to answer. Often, researchers look to neural measures as a “porthole into the brain,” allowing for an easy index of complex, multilayered phenomena that are present in communication. These approaches often apply a complex communication theory (e.g., presence theory; Lee, 2004) to an overly simplistic model of the brain (e.g., identifying the “presence spot” in the brain). On the other hand, in the psychological and brain sciences, many research programs are entirely devoted to the understanding of very granular phenomena. These approaches use very small-scale theoretical understandings, and take a much more detailed view of the brain. Communication researches would do well to identify "Goldilocks problems" in their area of interest (Watts, 2017). These problems are not too big and complex as to be unusable in brain imaging, but not too small as to be irrelevant for communication theory in general.

An additional point to highlight is that neural activation is not bijective, often leading to reverse inference errors. Cognitive processes do not map onto brain regions in a one-to-one manner. Just because a researcher observes that an area of interest in the brain "lights up" during an experimental protocol does not necessarily mean that a particular type of processing has taken place, or that the particular processing had anything to do with the stimulus. In fact, so-called resting-state scans, where participants are meant to lay still and think of nothing, will still reveal specific neural activation patterns (Raichle et al., 2001). Researchers can build support for their hypotheses regarding neural activation in two primary ways (Poldrack, 2006). The first method is to combine brain imaging approaches with traditional behavioral or self-report data. These measures can help triangulate data gathered from brain imaging and provide support for the occurrence of the process of interest during the experimental protocol. This is well within the scope of an individual experiment, and does not add much complication. The second method requires convergent evidence from many studies in support of the *selectivity* of the area of interest – demonstrating that the region is activated in certain types of processes but not in others. In relating evidence from multiple studies which propose activation in a brain area of interest, researchers can develop more certainty of the role of brain regions of interest in processes or states.

How do we measure activation in the brain with fMRI?

Activation in the brain is measured in an MRI scanner. MRI scanners create a structural image of the brain by taking advantage of the various physical and chemical properties of bodily tissue, specifically spinning protons of the hydrogen atom (Edelman & Warach, 1993). Two primary types of brain scans occur in a typical fMRI study. The first of these is a high-resolution anatomical image, which is used to standardize human brains of different sizes and shapes, as well as assist researchers in determining the precise location of neural activity in research participants' brains. These high-resolution anatomical scans are important for the second type of images recorded in an fMRI study: functional images.

Functional MRI (fMRI) creates an image by measuring the differences in paramagnetic properties of fluids and tissues in the brain. Hemoglobin, a protein responsible for transporting oxygen in the blood of vertebrates, exhibits slightly different magnetic properties depending on its state of oxygenation (i.e., how much oxygen is attached to blood cells; Ogawa et al., 1992). The differences in oxygenated and deoxygenated hemoglobin have been shown to be tightly correlated with neural processing, and thus can be used as a close proxy for measurement of neural firing. As neurons fire, they require an immediate influx of oxygenated hemoglobin and glucose in order to maintain function. This increase in blood flow into regions of heightened neural firing follows a more or less consistent pattern known as the hemodynamic response function (HRF). For an excellent treatment of the hemodynamic response function, see Raichle and Mintun (2006) and Logothetis, Pauls, Augath, Trinath, and Oeltermann (2001). Critically, for the purposes of functional imaging, the amount of oxygen flow into areas of neural firing is greater than the amount of oxygen that is consumed. This means that an increase in neural firing is associated with an increase in oxygenated hemoglobin (Logothetis, 2008; Logothetis et al., 2001). The dynamic contrast between oxygenated and deoxygenated hemoglobin is known as the BOLD contrast. In newer fMRI scanners, this contrast can be measured at a spatial resolution of less than 1 mm^3 and a temporal resolution of less than 1 second. In this way, it opens a spatio-temporal window into neural processing and brain function (Kwong et al., 1992).

The BOLD response carries with it a very low signal and very high noise. Because of this, functional imaging data must undergo in-depth preprocessing before it can be analyzed further. For an overview of preprocessing steps with special application to communication scholars, see Weber, Mangus, and Huskey (2015). Strother (2006) and Ashby (2011) also provide helpful, thorough overviews of the preprocessing "pipeline" for fMRI data. This preprocessing pipeline is necessary for filtering out various forms of noise in collected data, including scanner "drift" and high frequency noise resulting from scanner heat-up, electrical equipment within the scanner, participant physiology, and other sources. In the preprocessing pipeline, the researcher must also pay attention to smoothing out motion artifacts from subjects moving around in the scanner, matching functional images to the anatomical scans, and registering images from each subject to a standardized brain atlas. These steps help ensure that data are as clean and usable as possible, while simplifying additional analyses.

In addition to cleaning, denoising, and matching functional images to anatomical scans, brain imaging researchers increasingly employ a technique known as "functional localization" to define regions of interest (ROIs) for further analysis (Poldrack, 2007). This can be especially helpful in that the exact location of brain regions of interest in a particular experimental paradigm can differ from subject to subject and between groups (Saxe, Brett, & Kanwisher, 2006). In designing a localizer, a researcher first makes a theoretically derived assumption as to the brain region(s) that should be involved in a particular task. After this, a task is chosen that is known to activate these regions of interest. Each participant is asked to complete the task while in the scanner. Activation patterns recorded during this task can then be used to identify functional regions of interest at the group level or at the individual level. These functional localizers have the advantage of increasing statistical power of analyses by reducing the number of voxelwise comparisons to voxels that are not thought to be involved in the task. Any data treatment done in preprocessing should be independent of any hypotheses, and should not vary greatly from study to study. Therefore, most preprocessing steps are largely standardized and available in fMRI data analysis software packages (e.g., FSL, see below). It is important to note that all preprocessing steps should be diligently recorded and fully reported in any manuscript that is submitted from the data. Increasingly, publications of high academic merit require researchers conducting brain imaging studies to "pre-register" preprocessing steps alongside other aspects of study design and data analysis.

A practical roadmap to fMRI research

So far, this paper has provided examples of method–theory synergy in communication research as well as a primer in understanding the basics of fMRI. We speculate that by now some of this article's readers may be entertaining the idea of engaging in brain imaging research using fMRI. For communication researchers interested in taking advantage of fMRI in their own research, further concrete steps must be taken to become familiar with many of the more nuanced terms, concepts, and assumptions of fMRI. To this end, in this section, we provide researchers with a roadmap to fMRI research based on our own experiences as communication scholars and neuroscientists.

Get informed

Entire sub-disciplines within the psychological and brain sciences are devoted to the understanding of comparatively narrow concepts, such as attention, memory, motivation, reward, emotion, and learning. Communication research, by comparison, is often integrative in nature, requiring thoughtful consideration of several of these concepts at once (Fisher, Huskey, Keene, & Weber, 2017). Familiarizing oneself with what has already been done in these areas can provide a solid methodological and theoretical foundation while simultaneously avoiding redundant research. Many of these areas have also been subjected to thorough meta-analyses, providing interested researchers quick overviews of relevant questions and developments within the research area.[3]

Communication researchers interested in fMRI are also encouraged to consult psychological and brain sciences departments at their university for lists of classes related to neuroanatomy, behavioral and cognitive neuroscience, experimental design, data analysis for fMRI, and additional courses that may be useful. Many of the techniques that are used in fMRI data analysis require statistical training. For this reason, training in multilevel modeling, matrix algebra, and advanced applications of the general linear model can be helpful, although it is not strictly required. For researchers who do not have the time to audit entire classes, useful summaries of statistical procedures used in fMRI are available in Poldrack et al. (2011), Ashby (2011), and in several helpful video channels online.[4]

In addition to statistical and theoretical training, it is beneficial to devote time to becoming familiar with a computer programing language such as Python (www.python.org) or R (https://www.r-project.org). Freely available fMRI data analysis programs, such as FSL (www.fmrib.ox.ac.uk/fsl), SPM (http://www.fil.ion.ucl.ac.uk/spm), and AFNI (https://afni.nimh.nih.gov), as well as commercially available software packages such as BrainVoyager (http://www.brainvoyager.com) offer graphical user interfaces (GUIs) for most basic analytic procedures, but scripting is often more efficient for more advanced analyses. Luckily, packages are offered in Python for many fMRI needs, including stimulus presentation (PsychoPy; http://www.psychopy.org), flow control (NiPype; http://nipype.readthedocs.io/en/latest), statistical analysis (NiStats; https://github.com/nistats/nistats); MVPA and other machine learning techniques (PyMVPA; http://www.pymvpa.org, NiLearn; nilearn.github.io), ISCs (https:// www.nitrc.org/projects/isc-toolbox), and many others.

Get together

One of the most striking things for many scholars upon familiarizing themselves with the fMRI literature is the collaborative spirit that underlies much of fMRI research. Any brain imaging study requires the effort of an entire team of researchers and technicians in order to be successful. For this reason, communication researchers seeking to familiarize themselves with fMRI methodology are encouraged to develop interdepartmental collaborations with researchers in the psychological and brain sciences. Familiarize yourself with the work of researchers who are involved in your campus' brain imaging center and with the steps one must take to utilize fMRI equipment. Most centers offer training courses and certify researchers as "fMRI trained."

This also underscores the need for training programs in fMRI that are either underdeveloped or altogether missing from our field. This might include focused training sessions at the annual meetings of the National and International Communication Associations. Other opportunities include graduate or early-career level training at multi-week seminars (e.g., see http://sicn.cmb.ucdavis.edu; http://www.martinos.org/training/fmri). Excellent methodological training opportunities also exist. FSL, one of the premier fMRI data analysis platforms, offers yearly brain imaging courses (https://fsl.fmrib.ox.ac.uk/fslcourse) covering the theory and practice of fMRI.

Get going

For communication researchers interested in conducting fMRI research, the only remaining step is to start. While it is true that fMRI research is often complex and expensive, interested researchers can "get their hands dirty" with fMRI data that are publically available online. We recommend the OpenfMRI (https://openfmri.org) and NeuroVault (http://neurovault.org) repositories as excellent starting places. Often, these data repositories also provide detailed information about experimental protocol, subject demographics, and other variables of interest. Re-analysis of these datasets is common, and it has contributed to many interesting and innovative findings. Those interested in questions pertaining to social scientific phenomena will find extant data that provide relevant insight in their area of interest.

Conclusion

Brain imaging methods have served to advance understanding of many issues relevant to scholars across an array of disciplines. Although the use of brain imaging in communication research is still in its beginning stages, great theoretical and methodological advancements have already been made. Three important examples of theoretical and methodological innovations for communication scholars have been highlighted in this manuscript. Research that utilizes the *brain-as-predictor* for understanding message effects and persuasion has contributed to greater gains in model prediction accuracy in its brief 7 years than had been seen in the past 70 years – even with smaller sample sizes (Falk et al., 2012). Furthermore, these studies make great strides in understanding the role of individual differences in network topology (both of brain networks and of social networks) in predicting persuasion outcomes. The recent introduction of computational and machine learning techniques to the communication neuroscientist's statistical toolkit has resulted in a wealth of rich data, catalyzing theoretical advancements in the areas of morality, narrative engagement, and risk communication. Brain imaging data have also served to advance our understanding of the neural dynamics of attention, cognitive control, and flow in dynamic multimedia environments.

The use of brain imaging in communication research has contributed to rapid development of innovative, solution-oriented research approaches that would not be possible using only behavioral and self-report data – highlighting the unique role of neuroscience for enhancing prediction, elaboration, and explanation in the social sciences (Gabrieli et al., 2015). Communication scholars are optimally situated for success in this rapidly advancing area, as rigorous, methodical content analysis is paramount for understanding message effects and other communication phenomena, especially when considering the immense complexity of brain imaging data.

The first studies that merged a content analytic approach with modern brain imaging were conducted as collaborative efforts involving both psychiatrists and communication scholars (Mathiak & Weber, 2006; Spiers & Maguire, 2007; Weber, Ritterfeld, & Mathiak, 2006). Interestingly, this approach was initially rejected by the broader neuroscience community for its seeming lack of experimental control. Despite these initial misgivings, the viability of this method has been continually supported through the collaborative efforts of forward-thinking researchers and the development of more refined statistical techniques leveraging the latest advancements in machine learning, networks science, and statistical modeling.

The development and refinement of dynamic content analytic measures, informed by an understanding of how the brain attends to, processes, remembers, and otherwise acts upon message content, will continue to push the envelope in this area and lead to new data and advancement in relevant theories. The brain is the central operator in all communication phenomena, and has relevance even for theories that do not (in their current state) make direct statements about brain activity. Brain imaging within communication research has direct practical utility for the improvement of predictive models, leading to a deeper understanding of message processing and outcomes. These advancements contribute to more reliable and valid recommendations for the creation of messaging which facilitates positive societal outcomes such as smoking cessation (Falk et al., 2011), healthier eating habits (Murdaugh, Cox, Cook, & Weller, 2012), reductions in drug use (Weber, Huskey, et al., 2015), and many more. Furthermore, brain imaging technology has never been more accessible for communication researchers. With all this in mind, we invite our fellow communication researchers to embark on the exciting journey to conducting neuroscientific research.

Notes

1. For a helpful, interactive brain atlas illuminating the location of each of these and other brain regions, we recommend the Harvard Scalable Brain Atlas (https://scalablebrainatlas.incf.org/human).
2. "Voxel" is shorthand for "volume pixel" or "3D pixel." Voxels are a basic unit of resolution in brain imaging. A typical voxel in a modern scanner is around 1 mm^3 and contains about 100.000 neurons.
3. As a service to fellow communication and media neuroscientists, we maintain a constantly updated list of helpful meta-analyses, websites, and resources at www.medianeuroscience.org/resources. We also provide a more detailed, step-by-step roadmap to fMRI research at www.medianeuroscience.org/roadmap.
4. We recommend several freely available channels on YouTube, namely "Mumford Brain Stats," "Principles of fMRI by Tor and Martin," and "Andy's Brain Blog."

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No potential conflict of interest was reported by the authors.

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