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Neural And Psychological Bases Of Health News Sharing

Abstract

Mass media content often propagates through social channels, for instance through shares on social media. In these social spaces, message effects interact with social forces like social influence to impact behavior and attitudes which has important implications for large-scale media effects. The abundance of online data about sharing patterns has enabled detailed descriptions of these processes but commonly used methods are less well suited to understand the psychological processes that facilitate sharing decisions. To address this knowledge gap, this dissertation used functional magnetic resonance imaging to study processes occurring in propagation chains where communicators shared New York Times health news articles with receivers through Facebook messages. Results from four empirical studies support a parsimonious framework, suggesting that communicators integrate considerations of the expected self-related and social outcomes of sharing into an overall signal of the value of sharing a piece of content which directly impacts their choices. To this end, Chapter 2 demonstrates the involvement of neural activity in regions associated with self-related, social, and value-related processing in sharing decisions made by individual communicators. Chapter 3 shows that the extent of neural value-related activity in response to these articles is significantly related to population-level sharing behavior of hundreds of thousands of real-world online New York Times readers and that neural valuation mediates the effects of self-related and social processing on choice. Chapter 4 demonstrates that these key processes are relevant across sharing contexts, namely when communicators are faced with different audience sizes. Yet the measures used here still showed insightful context-sensitivity through modulation of signal intensity. Finally, Chapter 5 discusses neural communicator-receiver coupling of activity in key regions of interest associated with valuation, self-related and social processing as a facilitator of information transfer between communications and receivers. Significant coupling suggests that central processes identified in communicators may propagate through social interaction and impact secondary receivers. In sum, this dissertation offers a detailed, parsimonious framework of the neural and psychological bases of sharing decisions and thus constitutes progress in scientific efforts to optimally account for and utilize social forces in the design of large-scale message campaigns and interventions.

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NEURAL AND PSYCHOLOGICAL BASES OF HEALTH NEWS SHARING

Christin Scholz

A DISSERTATION

in

Communication

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2018

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NEURAL AND PSYCHOLOGICAL BASES OF HEALTH NEWS SHARING

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Christin Scholz

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ABSTRACT

NEURAL AND PSYCHOLOGICAL BASES OF HEALTH NEWS SHARING

Christin Scholz

Emily B. Falk

Mass media content often propagates through social channels, for instance through shares on social media. In these social spaces, message effects interact with social forces like social influence to impact behavior and attitudes which has important implications for large-scale media effects. The abundance of online data about sharing patterns has enabled detailed descriptions of these processes but commonly used methods are less well suited to understand the psychological processes that facilitate sharing decisions. To address this knowledge gap, this dissertation used functional magnetic resonance imaging to study processes occurring in propagation chains where communicators shared New York Times health news articles with receivers through Facebook messages. Results from four empirical studies support a parsimonious framework, suggesting that communicators integrate considerations of the expected self-related and social outcomes of sharing into an overall signal of the value of sharing a piece of content which directly impacts their choices. To this end, Chapter 2 demonstrates the involvement of neural activity in regions associated with self-related, social, and value-related processing in sharing decisions made by individual communicators. Chapter 3 shows that the extent of neural value-related activity in response to these articles is significantly related to population-level sharing behavior of hundreds of thousands of real-world online New York Times readers and that neural valuation mediates the effects of self-related and social processing on choice. Chapter 4

demonstrates that these key processes are relevant across sharing contexts, namely when communicators are faced with different audience sizes. Yet the measures used here still showed insightful context-sensitivity through modulation of signal intensity. Finally, Chapter 5 discusses neural communicator-receiver coupling of activity in key regions of interest associated with valuation, self-related and social processing as a facilitator of information transfer between communications and receivers. Significant coupling suggests that central processes identified in communicators may propagate through social interaction and impact secondary receivers. In sum, this dissertation offers a detailed, parsimonious framework of the neural and psychological bases of sharing decisions and thus constitutes progress in scientific efforts to optimally account for and utilize social forces in the design of large-scale message campaigns and interventions.

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Mass media content such as news often propagates through social channels, for instance through shares on social media. In these social spaces, large numbers of additional exposures are generated for some pieces of content, while others are brought up infrequently or not at all. Those pieces of content that are shared, enter a dynamic environment in which receivers' attitudes and behaviors are not only affected by the message itself, but are subject to social forces like social influence and persuasion from communicators who shared the information. Social sharing of media content is thus an important factor when considering media effects on a target population (Hornik & Yanovitzky, 2003; Southwell & Yzer, 2007). The availability of detailed data on sharing behavior in online spaces has made it possible to describe the occurrence of massive sharing events (i.e. content virality) in great detail (Adamic et al., 2016; Chatzopoulou, Sheng, & Faloutsos, 2010; Cheng, Adamic, Kleinberg, & Leskovec, 2016; Goel, Watts, & Goldstein, 2012). However, the basic psychological mechanisms that underlie sharing decisions are less accessible using online logs alone, and hence less well understood. This knowledge gap acts as a barrier to theory-driven message design and evaluation that takes into account and actively targets social sources of exposure and influence. In four empirical studies, this dissertation synthesizes existing work on communicators' motivations to share content, social influence, and persuasion to propose a unifying, parsimonious framework that highlights value-based decision-making as a basis for information sharing behavior.

Functional neuroimaging, more specifically functional magnetic resonance imaging (fMRI), is used here to study value-related neural processes as well as potential sources of value in sharers in the specific context of online health news sharing. Thereby, propagation chains in which a communicator shares a health news article with a receiver through a social media message (Figure 1.1), are used as a simplified, highly controlled model of real-world sharing. This testbed, in connection with real-world data about the virality of actual news articles which are used as stimuli in the lab, allows detailed insights into the psychological and neural correlates of the likelihood of communicators to share media content (Chapter 2), as well as the mechanisms underlying content virality in a real-world population of hundreds to thousands of receivers (Chapter 3). The sensitivity and generalizability of the processes identified in Chapter 2-3 is further examined across different social context characteristics (Chapter 4). Finally, Chapter 5 investigates the relationship of neural and psychological mechanisms in communicators and the mental processes active in their receivers.

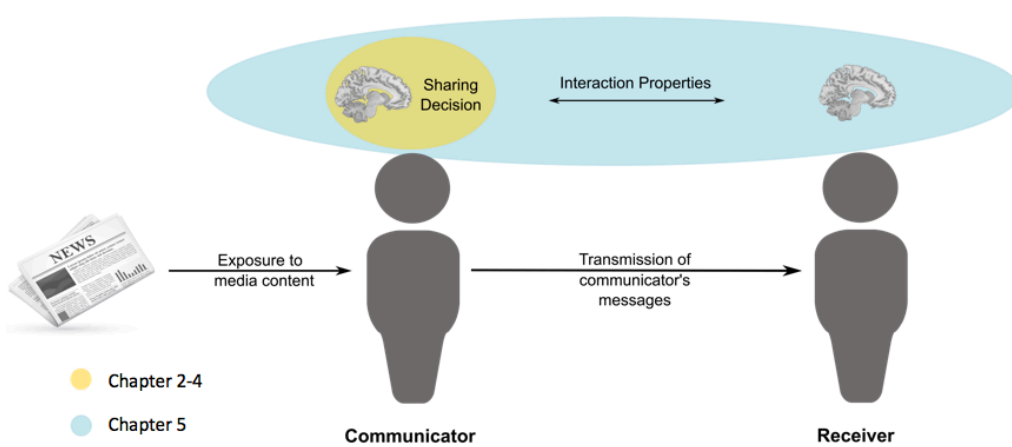

Figure 1.1. Propagation Chain

Existing Knowledge on Media Content Sharing

Two main literatures have examined the occurrence and characteristics of the social diffusion of media content. First, a set of mostly large-scale, survey based studies that is rooted in the diffusion of innovations (Rogers, 2003) and two-step flow (Katz & Lazarsfeld, 1955) traditions, has examined the complex interplay between the effects of mass media and interpersonal communication, both online and offline (Jeong & Bae, 2017; Southwell & Yzer, 2007). Such research has found that interpersonal communication about relevant issues can mediate or moderate the effects of large-scale media campaigns (e.g. Hornik & Yanovitzky, 2003; Jeong & Bae, 2017; Jeong, Tan, Brennan, Gibson, & Hornik, 2015; Valente, 1996; Valente & Fosados, 2006; van den Putte, Yzer, Southwell, de Bruijn, & Willemsen, 2011). This field, which is mostly driven by scholars in communication science and public health, has been dominated by large-scale survey approaches and correspondingly short-form measures of interpersonal communication such as a dichotomous measure of whether communication occurred during a certain period of time (Cho et al., 2009; Frank et al., 2012; Hardy & Scheufele, 2009; C. J. Lee, 2009; Mohammed, 2001; Saba & Valente, 2001; van den Putte et al., 2011). A related set of studies primarily conducted by researchers in fields such as marketing and computer science has applied big data approaches, scraping social networks such as Twitter to estimate the extent to which a piece of content was shared or went viral (Adamic et al., 2016; Chatzopoulou, Sheng, & Faloutsos, 2010; Cheng, Adamic, Kleinberg, & Leskovec, 2016; Goel, Watts, & Goldstein, 2012). These studies have addressed the question of whether social diffusion plays a role in the reach of media messages. However, the methodologies employed are less well suited to making inferences about the psychological and neural processes that facilitate these effects.

A second, smaller set of studies has begun to examine the psychological mechanisms driving the occurrence of interpersonal communication about media, often focusing on the special case of sharing media content through social media. Among the approaches employed here are laboratory experiments using self-report measures to understand sharing motivations (e.g. Barasch & Berger, 2014) and examinations of the message characteristics of content which can provide indirect insights into potential psychological motivations in relation to the occurrence of sharing behavior at a large scale (i.e. virality; (Berger & Milkman, 2012; Cappella, Kim, & Albarracín, 2015; Kim, 2015). This work has identified a large number of specific candidate processes such as self-enhancement and self-presentation which might motivate sharing behavior in specific situations (Berger, 2014; Cappella et al., 2015). Although valuable insights have been gained from these studies, some have focused on post-hoc participant responses related to sharing experiences and motivations, whereas others have focused primarily on the effects of message characteristics, leaving open questions regarding the motivations underlying sharing behavior in communicators (although, cf. Berger, 2011 for a direct manipulation of a candidate mechanism). In addition, the resulting large number of different processes that have been identified across many studies precludes overarching conclusions about the basic building blocks of sharing motivations that drive sharing choices across contexts.

Understanding Sharing Decisions through Neuroimaging

To address this knowledge gap, the studies presented in this dissertation rely on additional literatures in social psychology as well as social and cognitive neuroscience to develop a neuroimaging-based approach to the study of the psychological mechanisms of media content sharing. This broader review of the scientific literature allows a greater focus on unifying (i.e. less context-specific) processes and novel hypotheses in the context of sharing. Additionally, the use of neuroimaging, in particular fMRI, affords several specific methodological advantages. Among these is the ability to access a wide array of cognitions underlying decision-making in the context of sharing, simultaneously and in real-time as people initially process content. This bypasses the potentially biasing influence of conscious, retrospective introspection by study participants (Nisbett & Wilson, 1977; Wilson & Nisbett, 1978; Wilson & Schooler, 1991). fMRI can further capture both consciously perceived and unconscious processes (Lieberman, 2007). In other words, fMRI is sensitive to both conscious attempts of persuasion where a communicator may try to convince a receiver of a certain attitude or opinion, and more implicit social influence processes between communicators and receivers where certain behaviors or norms are being modeled covertly.

Furthermore, prior work has shown the utility of neuroimaging when linking rich individual-level data about psychological mechanisms and population-level, real-world outcomes. Traditionally, detailed psychological processes have been studied in relatively small, unrepresentative groups of individuals in highly controlled environments (e.g. Henrich, Heine, & Norenzayan, 2010). However, to gauge the external validity of these data in the context of media content sharing, large-scale real-world message effects and behaviors need to be considered as well. Neuroscience and, more specifically, studies employing the brain-as-predictor approach (Berkman & Falk, 2013) have the potential to link these two levels of analysis. Brain-as-predictor studies use neural activity in response to a stimulus to predict subsequent attitudes or behavior in small samples or entire populations. Several existing studies have shown that data representing the neural processes active during information processing in small samples of study participants explain significant variance in population-level outcomes such as calls to smoking quit lines (Falk, Berkman, & Lieberman, 2012), music popularity (Berns & Moore, 2010), market-level micro-lending (Genevsky & Knutson, 2015), movie (Boksem & Smidts, 2014), and TV show popularity (Dmochowski et al., 2014). Often, these neural measures predict population-level variance over and above what is explained by self-report measures (e.g. Venkatraman et al., 2014). Consequently, brain-as-predictor studies can expand on existing descriptive work in neuroscience and the limited evidence about the psychological processes underlying sharing decisions by linking real-time data about the neural processes occurring during decision-making in individual communicators to the population-level occurrence of content sharing.

Candidate Mechanisms of Sharing Decisions

By sharing a mass media message with others, a communicator can introduce the content to their conversation partner(s). The way in which this initial social action is carried out routinely leads to the involvement of other social forces such as social influence and persuasion. When sharing media content, communicators often share the original content, comments about the content, or both with their receiver(s) (Singer, 2014). As interpersonal interaction is taking place, both parties might express opinions, evaluate, ask questions, or relate the content to other experiences or concepts. Thereby, communicators and receivers might intentionally attempt to convince, that is persuade, each other of a certain viewpoint, or exert social influence, that is inadvertently influence one another, by modeling certain behaviors or social norms (e.g. Berger, 2014; Falk, Morelli, Welborn, Dambacher, & Lieberman, 2013). When making sharing decisions, communicators likely consider the potential positive and negative outcomes of their behavior, including the extent to which sharing may allow them to persuade or influence others according to their goals and motivations. Consequently, this dissertation builds on the assumption that existing knowledge about the psychological mechanisms of social influence and persuasion may be informative about the psychology that underlies information sharing decisions in communicators.

Several relevant literatures have contributed to our understanding of the interconnected psychological processes underlying information sharing and the social influence, persuasion, and general decision-making processes that follow. Specifically, these topics have been studied across disciplines including communication science, social psychology, economics, as well as social and cognitive neuroscience. Based on a review of this work, we have recently argued (Falk & Scholz, 2018) that decisions across these diverse processes may be supported through a common underlying mechanism, namely subjective value maximization. Subjective value maximization is the tendency of decision makers to make choices based on a weighted sum of positive and negative value signals assigned to the expected outcomes of an option (Neumann & Morgenstern, 2007; Samuelson, 1937). The following sections review existing knowledge on the role of value-based decision-making processes in the context of sharing, as well as evidence for potential sources of or inputs to the value-calculation in communicators who are making decisions about sharing.

Value-Maximization as a Central Pathway of Decision-Making Processes

Research on decision-making processes across domains highlights value maximization as a basic strategy that drives human decisions, although it has not always been made explicit in individual fields (Falk & Scholz, 2018). Neuroscientific studies have identified neural activity in the brain's value-system, consisting of clusters of voxels in ventral striatum (VS) and ventromedial prefrontal cortex (VMPFC), as a reliable predictor of human choice that scales with the subjective value of a stimulus (Bartra, McGuire, & Kable, 2013). These relationships are observed across a large number of domains including primary (e.g. food) and secondary rewards (e.g. money and social approval) (Bartra et al., 2013). Signals produced within this neural value system as well as various behavioral indicators of value are also associated with choice behavior in communicators who engage in persuasion or social influence (Falk & Scholz, 2018). In addition, evidence presented in this dissertation demonstrates the role of valuation in the decision-making of communicators who share information with others.

Prior work shows that study participants tend to assign more monetary value to sharing information with others than to answering knowledge questions, and sharing information with others is related to neural activity in the brain's value system (Tamir &

Mitchell, 2012; Tamir, Zaki, & Mitchell, 2015). Value, in this context, is likely derived from opportunities to fulfill certain goals and motives by selectively sharing certain types of content with specific others (Bazarova & Choi, 2014; Berger, 2014; Cappella et al., 2015).

Neuroscientific evidence further suggests that valuation is not simply one among many processes that predict choice, but acts as a final common pathway through which other types of cognition impact decision-making (Levy & Glimcher, 2011, 2012). Specifically, as mentioned above, neural signals in the brain's value-system have been found to be domain-general. That is, valuation processes are involved in decision-making across a wide range of contexts. Extending these findings, neuroeconomists have argued that the neural value-signal can be described as a 'common currency' of choice which translates various inputs, that is elements that are being considered with regards to a decision, into a common scale for ease of comparison. In this space, a range of aspects can be compared and integrated into a single signal indexing the value of a choice, which is directly linked to behavior. In the context of sharing, this account of value-based decision-making offers a parsimonious framework in which opportunities to fulfill certain sharing motives can be quantified and compared to arrive at a final sharing decision (Falk & Scholz, 2018). This process may be supported by the same neural structures responsible for value-based decision-making in other domains (K. M. Cox & Kable, 2014).

Sources of Value

Assuming value maximization as a central driver of sharing decisions naturally leads to the question what is being valued highly by communicators. In other words, what are the inputs to the calculation of an overall value signal in the context of media content sharing. The answer to this would provide a strong basis for the development of socially focused message strategies.

Berger (2014) proposed five central sharing motivations for communicators, namely emotion regulation, information acquisition, social bonding, impression management, and persuasion of receivers. Others have further proposed five rather similar goals and functions of self-disclosure, or information sharing about the self, including social validation, self-expression, relational development, identity clarification, and social control (Derlega & Grzelak, 1979). We have recently argued that these sharing motivations all constitute sources of value a communicator can gain by selectively sharing content with others (Falk & Scholz, 2018). In part, this is because these concepts map on to basic human motivations of maintaining a positive self-image (Mezulis, Abramson, Hyde, & Hankin, 2004; Taylor & Brown, 1994) and positive relationships with other people (Baumeister & Leary, 1995). Empirical evidence, indeed, suggests that communicators who share media content with others may do so because they expect that it is useful (i.e. valuable) to the receiver (Barasch & Berger, 2014; Berger & Milkman, 2012; Kim, 2015), or because they expect it to be valuable to themselves, for instance by making themselves look good. That is, information about consequences of a choice for the self (e.g., in terms of the presentation of one's self-image) and for social relationships or interactions are particularly relevant in the computation of the overall value of a choice.

Holding a positive image of oneself (Mezulis et al., 2004) and relating positively to others (Baumeister & Leary, 1995) are central human motives that are valuable to actors and drive behavior across contexts. For instance, tailored information, which is generally more self-relevant, tends to be more influential in changing the attitudes and behaviors of those who consume it (Chua et al., 2011; Chua, Liberzon, Welsh, & Strecher, 2009; Cooper, Tompson, O'Donnell, & Falk, 2015; Kreuter, Strecher, & Glassman, 1999), suggesting that it resonates more strongly with receivers. In addition, self-relevant information tends to be discussed more often in daily life (Dunbar, Marriott, & Duncan, 1997; Emler, 1990; Landis & Burtt, 1924; Naaman, Boase, & Lai, 2010) which demonstrates its propensity to start conversations and, potentially, encourage sharing.

In parallel, to effectively and positively relate to others, communicators need to consider potential reactions, opinions, and knowledge of their receivers, that is, engage in social thought processes. Existing evidence from both psychology (Traxler & Gernsbacher, 1993) and neuroscience (Dietvorst et al., 2009; Falk et al., 2013) suggests that considering the perspective of others enhances both the effectiveness of communication and the success of communicators who are attempting to persuade their receivers. In one study, communicators who showed more neural activity in brain regions related to social processing during initial exposure to information were more successful in socially influencing their receivers with whom they shared the original content, so that receivers were more likely to adopt the communicator's opinion about the message (Falk et al., 2013). There is further self-report evidence that communicators routinely consider audience characteristics in order to choose which content to share and how to frame it (Barasch & Berger, 2014; Clark & Murphy, 1982; Marwick & boyd, 2011).

There is further evidence that the opportunity to fulfill self-related and social motives is valuable to decision makers, highlighting these considerations as inputs to a final calculation of the value of a choice and valuation as the common pathway of decision-making. In the case of self-related processing, evidence from neuroscience (D'Argembeau et al., 2012; Enzi, de Greck, Prösch, Tempelmann, & Northoff, 2009; Northoff & Hayes, 2011) as well as psychology and communication science (Darke & Chaiken, 2005; Mezulis et al., 2004) suggests that considerations of self-relevance and value are not independent predictors of choice, but two strongly interdependent processes. Robust psychological findings concerning cognitive biases such as positive illusions, positivity biases and self-serving attributions demonstrate that those entities which are self-relevant are often perceived to be of disproportionally high value and those concepts or objects which are thought to be of high value are generally more likely to be closely attributed to the self (Mezulis et al., 2004; Taylor & Brown, 1994). In addition, whether arguments are viewed positively or negatively is partially impacted by the expected consequences to the self (Darke & Chaiken, 2005) and the extent to which arguments are processed centrally partially depends on their self-relevance (Botha & Reyneke, 2013; Cappella et al., 2015; Johnson & Eagly, 1989). Further, the neural structures supporting self-related (Denny, Kober, Wager, & Ochsner, 2012; Falk, Berkman, Mann, Harrison, & Lieberman, 2010; Murray, Schaer, & Debbané, 2012; Northoff et al., 2006) and value processing (Bartra et al., 2013; Levy & Glimcher, 2012) are partially overlapping. With respect to information sharing, it has been argued that, similar to informing others more generally (Tamir et al., 2015), sharing information about the self might be inherently rewarding (Tamir & Mitchell, 2012). In sum, self-related considerations might be a key element of decision-making in contexts such as persuasion and social influence because of their strong connection to valuation (Falk & Scholz, 2018).

In the context of sharing decisions, it has been argued that content that reflects positively on the self allows communicators to further their self-enhancement and self-presentational motives (Angelis, Bonezzi, Peluso, Rucker, & Costabile, 2012; C. S. Lee & Ma, 2012; Wien & Olsen, 2014). Here, I argue that to the extent that expected outcomes of sharing self-relevant media content are in line with the desired image of the self which is to be presented to others, the value of sharing this information with receivers will increase.

Similar to self-related processing, social considerations are likely to affect decision-making by contributing to the perceived value of choices available to communicators. Choices that are expected to enhance an agent's social standing or a particular relationship are highly valued by human decision makers (Baumeister & Leary, 1995) and engage neural regions which are strongly associated with other, non-social types of rewards and punishments (Bhanji & Delgado, 2014; Fareri & Delgado, 2014; Lieberman & Eisenberger, 2009). Consequently, I argue here that the extent to which sharing media content with other people can be expected to enhance a communicator's social goals, the value of that choice and, ultimately, the likelihood of sharing, should increase.

In sum, self-related and social processing are strong candidates in the search for basic processes that serve as inputs to value-based decision-making about sharing behavior across contexts. The categories of self-related and social processing include many of the more specific processes that have been put forward as sharing motivations in the existing literature (Berger, 2014; Cappella et al., 2015; Derlega & Grzelak, 1979). For instance, among the sharing motivations presented by Berger (2014) and Derlega and Grzelak (1979), impression management, self-expression, identity clarification, and social validation can be described as specific forms of self-related processing, and social bonding, persuasion of receivers, relational development, and social control as forms of social cognition. Following this logic, a focus on basic underlying processes can reduce the high dimensionality of sharing motivation which has emerged from existing work, partly due to the diversity of contexts and methods used to study this phenomenon. Identifying basic principles of sharing decisions may lead to a more generalizable and parsimonious model of the psychology underlying sharing. Functional neuroimaging methods are ideal candidates to contribute to this dimensionality reduction by identifying the greatest common denominators of a multitude of several specific processes, that is basic underlying mechanisms, driving sharing decisions at a neural level and across various contexts. Research presented in this dissertation uses functional neuroimaging to test the involvement of brain regions known to be associated with these types of cognitions in sharing decisions in communicators. Chapter 2 and 3 identify basic psychological building blocks and their interactions in driving sharing decisions in individuals and a large, real-world population, and Chapter 4 examines differences and parallels in the role played by these processes in different communication contexts.

Context as a Moderator of the Mechanisms Driving Sharing Decisions

Communicators make decisions about sharing media content in a multitude of social contexts which vary by the characteristics of the communicator, the receiver, the content that may be discussed, the communication channel used for the interaction, and/or the cultural context in which the interaction occurs (Scholz & Falk, in press). So far, I have argued that similar basic processes underlie broad classes of decision-making including communicator's decisions in the realm of social influence, persuasion and, potentially, sharing. However, it is possible that different contexts impact the specific pieces of information considered by communicators to determine the self- and social relevance of a piece of content and, ultimately the relative impact of these consideration on the content's perceived value of sharing (Scholz & Falk, in press). Communicators may rely on different types of self-related (e.g. self-enhancement or self-presentation) and/or social processing (e.g. relationship management or creation of social capital) depending on the context. In addition, it is possible that the context influences the overall extent of self-related and social processing.

Although any of the factors that make up the communication context may shape the process of value maximization in communicators, it is impossible to examine them all simultaneously. This dissertation focuses on receiver characteristics in particular as a first step towards a better understanding of context characteristics in general. Sharing is an inherently social process that is determined to a large extent by the social actors that are partaking in it. A communicator's psychological experience and decision-making about introducing media content into a conversation should thus be influenced by who the potential receiver is. For instance, audience characteristics such as the number of receivers, pre-existing opinions or previous behavior may impact the expected self-related and social consequences of starting a conversation about a certain piece of media content for communicators.

Studying the variability of the neural processes of decisions to initiate interpersonal communication about media content may allow insights into the generalizability and flexibility of the value-maximization framework that is being proposed here. Chapter 4 examines the example of audience size as a receiver characteristic that changes the context of communication decisions in communicators.

Sharer-Receiver Coupling

The research reviewed above provides evidence for the involvement of self-related, social, and value-related processing in diverse decision-making processes in communicators. Research on decision-making in the receivers of that influence has reported findings suggesting strikingly similar underlying processes (Falk & Scholz, 2018). There are two plausible explanations for this conceptual overlap between the psychological processes driving decisions in communicators and receivers. On the one hand, similarities might be independent manifestations of the influence of basic, domain-general human motives to belong socially (Baumeister & Leary, 1995), perceive oneself positively (Mezulis et al., 2004), and act in a way that maximizes value. On the other hand, these similarities might instead indicate a meaningful transfer of cognitions from communicator to receiver. Chapter 5 tests these two alternative hypotheses in the context of interpersonal communication about media content.

Evidence for Parallel Processes in Communicators and Receivers

The processes that lead receivers to be socially influenced or persuaded are similar to those that underlie decision-making about sharing in communicators (Falk & Scholz, 2018). These parallel patterns have emerged in largely independent literatures which considered receivers and communicators in isolation.

First, theories as well as empirical data highlight valuation as a central driver of susceptibility to persuasion and social influence in receivers. That is, receivers are more likely to align their behaviors and/or attitudes with those of communicators if, through social influence and persuasive processes, the perceived value of these attitudes or behaviors are altered (Falk & Scholz, 2018). This is reflected in traditional theories of attitude and behavior change which highlight strong effects of outcome expectations and the perceived valence of behavior change (Fishbein & Ajzen, 2010; Johnson, Smith-McLallen, Killeya, & Levin, 2004; O'Keefe, 2012), as well as basic expected utility models put forward by economists (Neumann & Morgenstern, 2007; Samuelson, 1937) and neuroeconomists (Camerer et al. 2005, Levy & Glimcher 2012). Neuroscientists have further demonstrated that content which engages neural regions associated with valuation in receivers more strongly is more likely to be persuasive, for instance in the context of health-related messaging (Falk et al., 2010; Falk, Berkman, Whalen, & Lieberman, 2011;

Falk, O'Donnell, et al., 2015; Vezich, Katzman, Ames, Falk, & Lieberman, 2017), music sales (Berns & Moore, 2010), responses to marketing (Venkatraman et al., 2014), box office sales for movie tickets (Boksem & Smidts, 2014) and micro-lending (Genevsky & Knutson, 2015). Furthermore, the social influence literature suggests that the receiver's neural value system tracks the extent to which the receiver's attitudes or behaviors diverge from those expressed by a group or communicator. Higher similarity between communicator and receiver often leads to increased value-related neural activity in receivers, for instance in the contexts of recommendations of mobile game applications, or opinions about music (Campbell-Meiklejohn, Bach, Roepstorff, Dolan, & Frith, 2010; Campbell-Meiklejohn et al., 2012; Cascio, O'Donnell, Bayer, Tinney, & Falk, 2015; Cascio, Scholz, & Falk, 2015; Nook & Zaki, 2015). In other words, social influence may occur in part, because social harmony, or higher social similarity, is valued and dissimilarity is devalued. These effects on the value system are particularly strong in social compared to other non-social learning contexts (e.g., in which feedback is provided by a human vs. computer; (Klucharev, Hytönen, Rijpkema, Smidts, & Fernández, 2009).

Second, similar to value-related thought, self-related processing has been linked to the susceptibility of message receivers to persuasion and social influence across literatures and contexts. Self-relevance and self-interest are key elements in several major theories of persuasion, social influence and behavior change. For example, both the Elaboration Likelihood Model of Persuasion (Petty & Cacioppo 1986) and Heuristic Systematic Model (Chaiken, 1980) hypothesize greater message elaboration and impact depending on the extent of self-relevance, and other models such as Protection

Motivation Theory (Maddux & Rogers, 1983) and the Health Belief Model (Rosenstock, 1990; Rosenstock, Strecher, & Becker, 1988) include concepts of personal vulnerability or the extent to which a receiver believes a threat applies to themselves personally. Further, the Reasoned Action Approach (Fishbein & Ajzen, 2010) and Social Cognitive Theory (Bandura, 2001) highlight self-efficacy or beliefs regarding whether or not the receiver has the ability and opportunity to perform a given behavior. Reviews suggest that more self-related information is more likely to be influential than information that is not self-relevant (Kreuter et al., 1999; Strecher et al., 2005). Finally, neuroscientific studies have confirmed the importance of self-related processing to persuasion in receivers (Chua et al., 2011, 2009; Cooper et al., 2015; Vezich et al., 2017).

Third, social processing has been linked to susceptibility to influence in receivers, who need to take the perspective of their communicators into account to evaluate communicator characteristics such as their expertise and motives (E. J. Wilson & Sherrell, 1993) as well as implications of persuasive attempts and social influence for their future relationship with the communicator (DeWall, 2010). On the basis of these considerations, receivers can make decisions. This claim receives strong support from the literature on social influence and conformity. In a review of the existing work, Cialdini and Goldstein (2004) argue that receivers seek social approval and bonding with those they interact with and thus prioritize conformity or harmony with communicator behaviors and attitudes over non-conformity to promote positive interactions and relationships. Such conformity has been demonstrated empirically across many studies (Asch, 1955; DeWall, 2010; Lakin & Chartrand, 2003). Further support comes from neuroscientific studies which show that when receivers who learn that they are misaligned with a communicator or group show stronger activity in neural regions engaged by considerations of the thoughts and intentions of others, they are more likely to make socially conform changes in their preferences (Cascio, O'Donnell, et al., 2015; Welborn et al., 2016). In sum, value-based decision-making, self-related as well as social considerations are central to the delivery as well as reception of social influence and persuasion.

Neural Communicator-Receiver Coupling as an Indicator of Information Transfer

The research reviewed above allows the conclusion that central processes involved in the decision-making of communicators who engage in sharing parallel those in receivers who are affected by this influence. The sources of these similarities are unclear. One potential explanation is that these associations are due to a third variable that triggers the involvement of self-related, social, and value-related processes independently in communicators and receivers. Given the domain-general nature of value-based decision-making and the centrality of self-enhancement and social bonding motives in humans, it could be plausible that communicators and receivers base their decisions on similar considerations stemming from consideration of the same (e.g., media) content. A second potential explanation for parallel processes in communicators and receivers is a transfer of information from communicators to receivers through interpersonal communication. The presence of this transfer process may be indicated by specific coupling of communicators and their receivers in their expression of key processes known to underlie decision-making.

Communicator-receiver coupling occurs when various psychological and biological processes in communicators and their receivers co-vary or ‘synchronize’ during social interactions. This could include coupling of non-verbal signals (Cappella, 1996; Lakin & Chartrand, 2003; Richardson & Dale, 2005), language use (Branigan, Pickering, & Cleland, 2000; Gonzales, Hancock, & Pennebaker, 2009; Niederhoffer & Pennebaker, 2002), brain activity (Hasson, Ghazanfar, Galantucci, Garrod, & Keysers, 2012; Silbert, Honey, Simony, Poeppel, & Hasson, 2014; Stephens, Silbert, & Hasson, 2010) basic biological processes such as heart rate, or behaviors, among others. In addition to these basic processes, neural coupling has also been shown to occur in higher level neural systems associated with self-relevance, social processing and valuation, among others (Stephens et al., 2010).

Empirical evidence suggests that communicator-receiver coupling might have positive effects on the success of communication between the two parties. A recent meta-analysis revealed robust, small to medium sized, positive effects of such coupling on prosocial behavior, perceived social bonding, social cognition, as well as positive affect (Mogan, Fischer, & Bulbulia, 2017). Further, it has been argued that coupling might enhance successful communication, social learning, and general relationship maintenance (Burgoon, Stern, & Dillman, 2007; Cacioppo & Cacioppo, 2012; Cappella, 1996, 1997a). Stephens and colleagues (2010) also found a relationship between the degree of coupling and the extent to which receivers recalled a story told by a communicator. Interestingly, in a second set of findings, these authors also demonstrated the occurrence of anticipatory coupling. Specifically, receivers showed enhanced activity within brain regions associated with value and self-related processing (MPFC, striatum) and cognitive control (DLPFC) before parallel activation was detected in communicators. That is, receivers anticipated cognitions which would occur shortly thereafter within communicators. Again, the extent of anticipatory coupling was related to the success of the communication encounter. These findings suggest that similarities in the neural processes found in communicators and receivers are not arbitrary but support mutual understanding and coordination in communication encounters. One potential reason for the positive effects of communicator-receiver coupling is that it allows communication partners to learn from (Bandura, 2001; Iacoboni, 2009) and understand (Hatfield, Cacioppo, & Rapson, 1993; Semin & Cacioppo, 2008) one another which allows interaction partners to promote and coordinate joint action (Semin & Cacioppo, 2008) and bonding (Cacioppo & Cacioppo, 2012).

In sum, communicator-receiver coupling occurs routinely between communication partners and might occur in neural regions known to be associated with successful persuasion in communicators and susceptibility to influence in receivers. Further, communicator-receiver coupling might be a useful indicator of successful communication in the context of interpersonal communication about shared mass media content. If coupling enhances social interactions and social learning, it might also facilitate the transfer of information and evaluations of that information, thereby enhancing the impact of original mass media messages on secondary receivers. Chapter 5 of this dissertation examines whether there is evidence for communicator-receiver coupling in the neurocognitive processes found to be crucial for sharing decisions in communicators.

Chapter Overview

In sum, this dissertation seeks to enhance our understanding of neural and psychological bases of communicators' decisions to share media content with others, by studying simple propagation chains in which communicators share health news articles with receivers through social media messages (Figure 1.1). Chapter 2 examines neural and psychological processes involved in the decision to share media content in individual communicators. Chapter 3 investigates whether valuation serves as a final common pathway for considerations of the self-related and social outcomes of a choice and whether these processes in individuals can account for population-level sharing behavior. Chapter 4 tests for contextual effects on the involvement of these processes. Finally, Chapter 5 examines competing hypotheses regarding the underlying reason for similarities in the processes that drive decision-making in communicators and their receivers.

CHAPTER 2. THE VALUE OF SHARING INFORMATION: A NEURAL ACCOUNT OF INFORMATION TRANSMISSION

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Abstract

Humans routinely share information with one another. What drives this behavior? We used neuroimaging to test an account of information selection and sharing that emphasizes inherent reward in self-reflection and connecting with other people. Participants underwent functional MRI while they considered personally reading and sharing *New York Times* articles. Activity in neural regions involved in positive valuation, self-related processing, and taking the perspective of others was significantly associated with decisions to select and share articles, and scaled with preferences to do so. Activity in all three sets of regions was greater when participants considered sharing articles with other people rather than selecting articles to read themselves. The findings suggest that people may consider value not only to themselves but also to others even when selecting news articles to consume personally. Further, sharing heightens activity in these pathways, in line with our proposal that humans derive value from self-reflection and connecting to others via sharing.

Introduction

Humans routinely share information with one another. What drives this behavior? One account suggests that humans have evolved disproportionately large brains, in part to coordinate socially (Dunbar, 2008; Schoenemann, 2006). People learn better when they anticipate opportunities to share with others (Lieberman, 2012), and the brain's so-called default mode facilitates efficient social judgments (Spunt, Meyer, & Lieberman, 2013). Thus, sharing may be inherently promoted by human biology (Tamir & Mitchell, 2012). Social-network platforms, on which users share billions of messages daily (Facebook, 2015; Twitter, 2012), also reflect the motivation to share. In the current study, we tested the notion that the human biology may have evolved to support the motivation to share, or coordinate socially, and obtained novel evidence that connecting with others through sharing activates brain systems implicated in reward, social relevance, and self-relevance. We focused on online news as one form of sharing that has the potential for widespread impact (Pew Research Center, 2010).

Neural Precursors of Sharing

Studies of information selection and sharing have relied primarily on characteristics of the content or on self-reported responses (Berger & Milkman, 2012; Botha & Reyneke, 2013; Kim, 2015; Lee & Ma, 2012). However, people may not have the ability or desire to objectively reflect on their thoughts and emotions to explain their behavior (Dijksterhuis, 2004; Schmitz & Johnson, 2007). Furthermore, self-reports do not allow assessment of cognitive processes in real time, at the moment that individuals consider selecting or sharing information, which limits understanding of the cognitive underpinnings of selection and sharing. To address these limitations, we used neuroimaging (functional MRI, or fMRI) of activity in regions of interest (ROIs) as participants considered whether they wanted to read (select) or share New York Times articles. We focused on three sets of neural ROIs implicated in subjective value, self-related processing, and social cognition, respectively (Figure 2.1).

Subjective value. We tested the idea that selecting and sharing information may carry inherent value. A meta-analysis of 206 fMRI studies (Bartra, McGuire, & Kable, 2013) found that activity in regions of the ventral striatum (VS) and ventromedial prefrontal cortex (VMPFC) is associated with positive valuation. We examined whether these meta-analytically defined regions were preferentially activated as participants considered selecting and sharing news articles. We also tested whether activity in these regions scaled with preference to select and share articles. The perceived utility of content influences people's choice of content (Botha & Reyneke, 2013; Kim, 2015), and greater activity in neural regions implicated in processing subjective value is associated with higher enthusiasm for sharing messages (Falk, O'Donnell, & Lieberman, 2012) and disclosing information about oneself (Tamir & Mitchell, 2012).

Self-related processing. We also tested whether brain regions implicated in self-relevance are associated with selecting and sharing information. A meta-analysis of 25 studies (Murray, Schaer, & Debbané, 2012) found that regions of the medial prefrontal cortex (MPFC) and posterior cingulate cortex (PCC) were engaged when participants made judgments about self-relevance. We tested whether these regions were engaged while participants considered selecting articles to read themselves. Individuals consider personal relevance when deciding to engage with content (Botha & Reyneke, 2013), and are biased toward content consistent with their preexisting beliefs (Cappella, Kim, & Albarracín, 2015). We also examined whether these ROIs were activated while participants considered sharing articles. Self-enhancement is a key motivation for sharing information, and people find value in sharing self-relevant messages (Berger, 2014; De Angelis, Bonezzi, Peluso, Rucker, & Costabile, 2012; Lee & Ma, 2012; Wien & Olsen, 2014). In addition, we tested whether activity in these regions scaled positively with preference to select and share articles. Greater activity in neural regions implicated in self-related processing is associated with higher enthusiasm to spread ideas (Falk et al., 2012), and articles that resonate more personally are more likely to be selected and shared (Berger, 2014).

Social cognition. Finally, we examined brain activity associated with considering the mental states of other people (social cognition). Our social-cognition ROIs consisted of portions of the VMPFC, middle medial prefrontal cortex (MMPFC), dorsal medial prefrontal cortex (DMPFC), precuneus (PC), bilateral temporoparietal junction (TPJ), and right superior temporal sulcus (rSTS). In a study with a large sample (N = 462), Dufour et al. (2013) found that these regions were engaged when participants considered other people's beliefs. We tested whether these regions were engaged when participants considered selecting information to read themselves. People regularly incorporate others' recommendations when making decisions, and this process is reflected in the activation of brain regions similar to the ROIs we examined (Cascio, O'Donnell, Bayer, Tinney, & Falk, 2015). Furthermore, social-cognitive components within the brain's default-mode network prime people's minds for social judgments even at rest (Spunt et al., 2013), and anticipation of sharing may be a key motive for reading content. In addition, given that sharing information is inherently social and social interaction is a key driver of news sharing (De Angelis et al., 2012; Berger, 2014; Lee, Ma, & Goh, 2011), we examined whether these regions were actively engaged while participants considered sharing articles. We also tested whether activity in these social cognition regions scaled positively with preferences to select and share articles. Anticipation of interpersonal interaction is a key motivation behind sharing (Lee et al., 2011), and sharing information may lead to social reward, such as interpersonal bonding (Berger, 2014). Thus, we tested the notion that people prefer to select and share articles that evoke social thoughts.

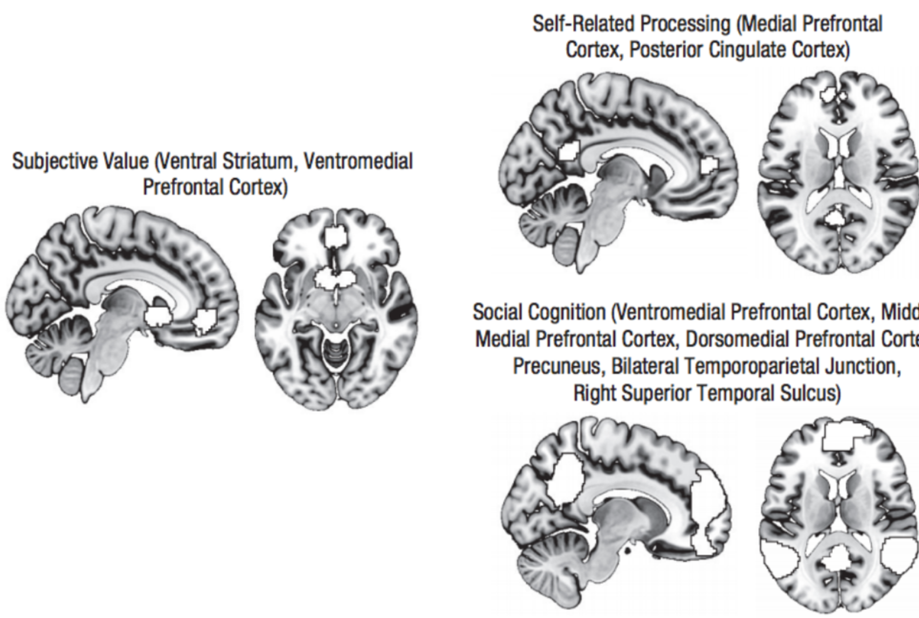

Figure 2.1. The functionally defined regions of interest (ROIs) used in the ROI analysis. The ROIs are the white areas outlined in black.

Summary

Our approach allowed us to measure brain activity within ROIs associated with subjective value, self-related processing, and social cognition (Figure 2.1) while participants made judgments about selecting and sharing news articles, in real time. We used these data to test our proposal that people's decisions to select and share information are based, in part, on the inherent reward associated with connecting with other people, as well as on considerations of self- and social relevance.

Method

Participants

Forty-three participants (30 female) between the ages of 18 and 24 (M = 20.5, SD = 2.1) took part in this study. Our target sample size of 40 participants was predetermined on the basis of funding, but because of concerns with data quality, we collected data from 3 additional participants before any statistical analysis was performed. Data collection stopped when we reached the enrollment goal. Two participants were excluded from analysis because of data corruption. This left 41 participants for our analyses. All participants gave informed consent in accordance with the procedures of the institutional review board of the University of Pennsylvania. Participants also met standard fMRI eligibility criteria; for example, potential participants were excluded if they had metal in their body, were currently taking any psychiatric medications, had a history of psychiatric or neurological disorders, were currently pregnant, or had claustrophobia. Participants were also required to be right-handed.

Procedure

Participants completed a baseline screening, as well as a neuroimaging appointment. During the neuroimaging appointment, they completed a series of self-report surveys and were scanned using blood-oxygen-level-dependent (BOLD) fMRI while they completed two tasks. In the task of interest to the present investigation, participants read 80 news headlines and abstracts that were published online in the health section of the New York Times between July 2012 and February 2013; these stimuli were divided into two runs of 40 news headlines and abstracts each. To control for reading speed, we had participants listen to recordings of the headlines and abstracts ($M = 10.2$ s, range = 8–12 s, $SD = 1.41$ s) while they read them. Each headline and abstract was randomly assigned to one of four conditions, within a randomization scheme that treated article length as a blocking factor (i.e., to balance the length of articles across conditions): In the broadcast-sharing condition, participants were asked, "How likely would you be to share this article on your Facebook wall?" In the narrowcast-sharing condition, they were asked, "How likely would you be to share this article with Facebook Friend _____?" (the name of a specific friend was inserted in the blank). In the select-to-read condition, they were asked, "How likely would you be to read the article yourself?" Finally, in the content recall (control) condition, they were asked to indicate their certainty of the article's topic ("How sure are you that [age/nutrition/fitness/science/laws/well-being/cancer] is the topic of this article?"). Participants responded to the questions on Likert scales from 1 (very unlikely) to 5 (very likely; in the content-recall condition, 1 = certainly not and 5 = certainly yes), thereby indicating their preferences to select or share the articles or their certainty regarding the topics of the articles. Each trial began with a 1.5-s orientation screen that indicated the trial's condition. The participants then saw (and heard via headphones) an article headline and abstract for 8 to 12 s. This display was followed by a fixation screen with a randomly jittered duration (M = 1.5 s, range = 0.5–4.7 s, SD = 0.97 s). Participants then had 3 s to record their response on a 5-point rating scale. A fixation screen was then presented for an intertrial interval, also of jittered duration (M = 2.0 s, range = 1.0–4.7 s, SD = 0.96 s). In order to avoid issues of collinearity between trials, we used Optseq2 software (Optseq2, 2006) to maximize design efficiency. We ran 100,000 Optseq simulations, twice per run, to determine the optimal jitter times between trials and between the reading and rating screens within trials. Figure 2.2 illustrates the task design.

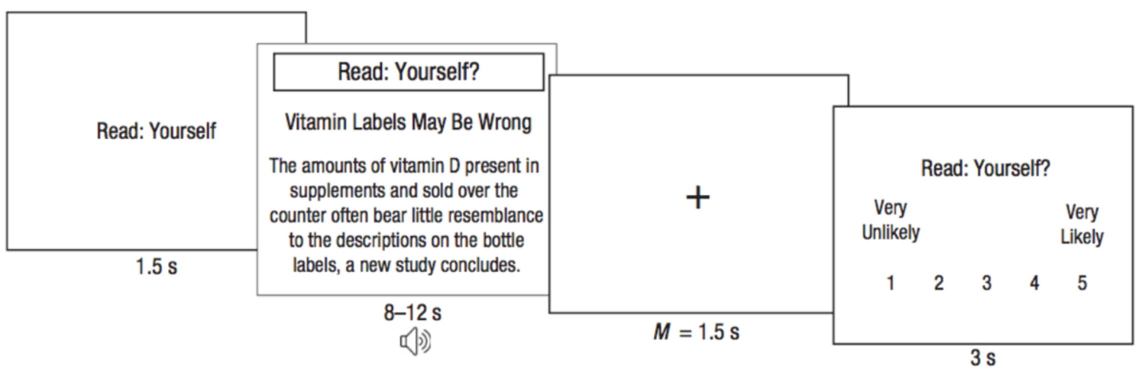

Figure 2.2. Illustration of the trial sequence in the article task. Participants were first reminded of the condition of the trial (a trial in the select-to-read condition is shown here). Then they saw (and heard an audio recording of) an article headline and abstract. This was followed by a jittered intratrial interval (M = 1.5 s). Finally, they were given 3 s to respond to a question, which was determined by the condition of the trial.

fMRI Image Acquisition

Neuroimaging data were acquired using 3-T Siemens scanners.[1] Two functional runs were acquired for each participant (500 volumes per run). Functional images were recorded using a reverse spiral sequence (repetition time = 1,500 ms, echo time = 25 ms, flip angle = 70°, −30° tilt relative to the anterior commissure–posterior commissure line, 54 axial slices[2], field of view = 200 mm, slice thickness = 3 mm; voxel size = 3.0 × 3.0 × 3.0 mm). High-resolution T1-weighted images (magnetization-prepared rapid-acquisition gradient echo, 160 slices, slice thickness = 0.9 × 0.9 × 1 mm) and T2-weighted images were used in place with the BOLD images for coregistration and normalization.

Imaging Data Analysis

Functional data were preprocessed and analyzed using Statistical Parametric Mapping (SPM) software (Version 8, Wellcome Department of Cognitive Neurology, Institute of Neurology, London, United Kingdom). To allow for the stabilization of the BOLD signal, we did not collect data from the first five volumes (7.5 s) of each run. Functional images were despiked using the 3dDespike program as implemented in the AFNI toolbox (Cox, 1996). Next, data were corrected for differences in the time of slice

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[1] Because of technical issues, not all participants could be scanned using a TIM Trio scanner; 2 of the 43 were scanned using a Prisma scanner.

[2] For the 2 participants scanned on the Prisma scanner, 52 axial slices were acquired.

acquisition using sinc interpolation; the first slice served as the reference slice. Data were then spatially realigned to the first functional image. We then coregistered the functional and structural images using a two-stage procedure; a 6-parameter affine transformation was used in each stage. First, in-plane T1 images were registered to the mean functional image. Next, high-resolution T1 images were registered to the in-plane image. After co-registration, high-resolution structural images were segmented into gray matter, white matter, and cerebrospinal fluid to create a whole-brain mask for use in modeling. T1 images were normalized to the skull-stripped Montreal Neurological Institute (MNI) template (MNI152_T1_1mm_brain.nii) provided by the FMRIB Software Library (FSL, 2012). Finally, functional images were smoothed using a Gaussian kernel (8 mm full width at half maximum).

Task Analysis

Data were modeled using the general linear model as implemented in SPM8. Three conditions were modeled. The first condition (share) combined the two types of sharing trials, broadcast sharing (share on Facebook wall) and narrowcast sharing (share with a friend). The second condition (select) consisted of trials on which participants considered whether to select the full articles to read themselves. The third condition (content) included the trials on which participants were asked to recall the content of the article and served as a control condition. Low-frequency noise was removed using a high-pass filter (128 s). The following contrasts were created: share > content, share > select, and select > content. Percentage-signal-change scores were extracted from each contrast for each participant using the MarsBar toolkit for SPM (Brett, Anton, Valabregue, &

Poline, 2002). Next, a random-effects model was computed for each contrast, averaging across participants. Two sets of additional, parallel models were run: a model controlling for reaction time (RT) on each trial and a model using only a subset of trials that were matched on RT across conditions. In addition, we examined the relationship between brain activity and participants' preference ratings in the select and share conditions. These fixed-effects models, implemented in SPM8, used the preference rating as a parametric modulator of neural activity during each trial, for each participant. Next, a random-effects model was computed for each analysis at the group level, averaging across participants.

ROI Analysis

To investigate neural response during the consideration of selecting and sharing news articles, we conducted a series of analyses using neural activity extracted from the three sets of a priori ROIs described earlier: VS and VMPFC for subjective value processing (Bartra et al., 2013), MPFC and PCC for self-related processing (Murray et al., 2012), and VMPFC, MMPFC, DMPFC, PC, bilateral TPJ, and rSTS for social-cognitive processing (Dufour et al., 2013; see Figure 2.1 for brain maps showing these regions). Parameter estimates representing percentage signal change for each of the contrasts were extracted and averaged across participants.

Whole-Brain Analysis

In addition, following our planned ROI analyses, we examined the results of exploratory whole-brain analyses to determine whether neural regions outside of our ROIs were associated with the main contrasts of interest (select > content, share >

content, share > select), as well as whether activity in these regions in the select and share conditions was modulated by the subsequent ratings. For all whole-brain analyses reported, we used a threshold of $p < .05$, $k > 20$, corrected for family-wise error using SPM8.

Results

Neural Correlates of Selecting and Sharing Articles

Decisions to select. We first examined whether making decisions to select articles was associated with brain activity in our a priori sets of ROIs (select > content contrast). All three sets of ROIs were more strongly activated when participants were thinking about selecting an article for themselves than when they were asked to recall the main content of the article Table 2.1, Figure 2.3)[3].

Decisions to share. Next, we examined whether making decisions to share articles was associated with brain activity in our a priori sets of ROIs (share > content). All three sets of ROIs were more strongly activated when participants were thinking about sharing an article with other people than when they were focusing on the content of the article (Table 2.1, Figure 2.3).

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[3] Additional analyses were performed after removal of the social-cognition regions that overlapped with the subjective valuation and self-related-processing ROIs. We report these results in Tables A1 and A2 in the Supplemental Material. All results remained robust in these analyses.

Effects of sharing versus selecting. Although both decisions to select and decisions to share articles were associated with activity in our subjective-value, self-related-processing, and social-cognition ROIs, when activity was measured relative to activity in the control condition, we next directly compared activity in the select and share conditions (share > select) to determine whether activation was stronger in one condition than in the other. We observed greater activation in all three sets of ROIs during the share condition than during the select condition (Table 2.1).

RT robustness analyses. We compared differences in RT between all conditions of interest. Although participants were slower to make decisions during the content trials than during the select and share trials, all ROI results remained robust in analyses controlling for RT and in analyses of a subset of trials that were matched on RT across conditions (see Tables A5, A6, A7, and A8 in the Supplemental Material available online and in Appendix A). These robustness analyses suggest that our results were not driven by differences in difficulty across the conditions.

Table 2.1. Results of the Three Contrasts in the Three Sets of Regions of Interest (ROIs)

ROIs	Select > content			Share > content			Share > select		
	t(40)	*p*	Mean parameter estimate	*t*(40)	*p*	Mean parameter estimate	*t*(40)	*p*	Mean parameter estimate
Subjective valuation	7.22	< .001	0.118 [0.085, 0.151]	12.69	< .001	0.158 [0.133, 0.184]	3.09	.004	0.040 [0.014, 0.067]
Self-related processing	7.26	< .001	0.143 [0.103, 0.183]	15.25	< .001	0.225 [0.195, 0.255]	5.02	< .001	0.082 [0.049, 0.115]
Social cognition	4.99	< .001	0.067 [0.040, 0.095]	9.41	< .001	0.104 [0.082, 0.127]	5.12	.003	0.037 [0.013, 0.061]

Note: Values in parentheses are 95% confidence intervals. Table A3 in the Appendix presents the activations in subregions of each set of ROIs.

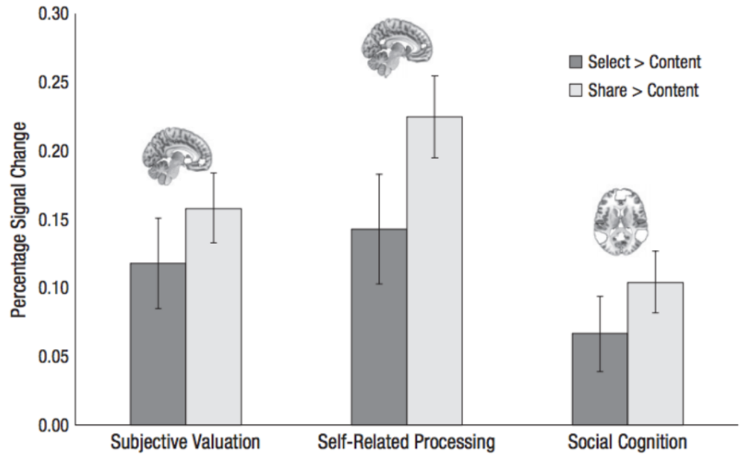

Figure 2.3. Estimates of percent signal change in the subjective-valuation, self-related-processing, and social cognition regions of interest, separately for select and share conditions. Activation in each of these conditions was measured in contrast to activation in the content condition. The sagittal and axial cuts of the brain represent the regions of interest (white areas outlined in black). Error bars represent 95% confidence intervals.

Whole-brain analyses. The whole-brain analyses examined whether regions outside of our a priori ROIs were more active during the select and share trials than during the content trials (select > content, share > content) or were more active during the share trials than during the select trials (share > select). The results of these analyses confirmed the results of our ROI analyses (see Table 2.2 and Figure 2.4).

Table 2.2. Results of the Three Contrasts in the Whole-Brain Analysis

Contrast and region	MNI coordinates			Number of voxels (k)	$t(41)$
	x	y	z		
Select > content					
Medial and ventromedial prefrontal cortex (bilateral)	-9	59	4	1,363	9.63
Dorsomedial prefrontal cortex	-18	38	43	92	6.75
Temporoparietal junction (left)	-51	-64	34	180	7.69
Precuneus (left)	-9	-55	19	82	6.65
Inferior temporal gyrus	66	-10	-14	52	6.30
Middle temporal gyrus	-60	-10	-17	141	7.48
Share > content					
Medial prefrontal cortex (bilateral)	-6	53	10	3,263	15.58
Precuneus (right)	-6	-55	25	935	12.56
Temporoparietal junction (right)	51	-61	25	233	8.52
Temporoparietal junction (left)	-54	-67	43	336	8.20
Middle temporal gyrus	-63	-7	-14	202	8.47
Insula (left)	-30	-17	-14	34	7.74
Inferior temporal gyrus	63	-7	-17	129	7.61
Hippocampus	-27	-34	-11	23	6.10
Share > select					
Precuneus (bilateral)	9	-61	28	385	8.50

Note. The table reports significant activations ($p < .05$, corrected for family-wise error; minimum cluster size = 20 voxels). The t tests were conducted at peak coordinates. MNI = Montreal Neurological Institute.

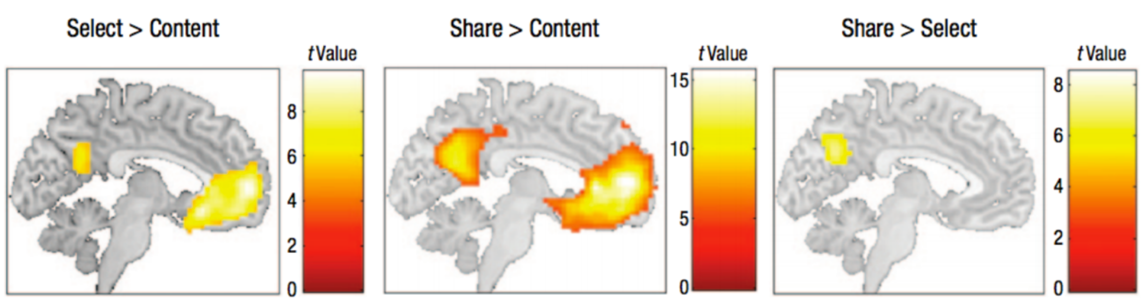

Figure 2.4. Results of the whole-brain analysis. The color coding indicates regions where, from left to right, the select > content, share > content, and share > select contrasts

revealed significant activations ($p < .05$, corrected for family-wise error; minimum cluster size = 20 voxels). See Table 2.2 for a detailed breakdown of the clusters, and see Figures A1 through A3 in the Supplemental Material for complete sets of sagittal slices illustrating these results.

Neural Correlates of Preference to Select and Share Articles

Next, we examined whether activity in the neural regions in question scaled with participants' degree of preference to select and share articles, respectively.

Preference ratings. On average, participants indicated that they had a higher likelihood to select articles ($M = 3.17$, $SD = 1.40$) than to share them ($M = 2.12$, $SD = 1.26$). Intraclass correlation (ICC) analyses revealed higher within-participants than between-participants variance in the preference ratings; individuals' likelihood of selecting and sharing varied across articles, ICC1s = .18 and .20, respectively. In other words, individual participants expressed a range of preferences, rather than tending to rate all articles positively or negatively. Likewise, higher within-articles than between-articles variance in the preference ratings indicated that, across participants, the articles varied in their likelihood of being selected and shared, ICC1s = .11 and .07, respectively; thus, different participants preferred different articles, which suggests that the neural effects observed were not merely a function of article-specific features or due to some articles being universally preferred.

Neural correlates of likelihood to select and share. Activity in all three sets of ROIs was positively associated with higher preference ratings in both the select and the share conditions (see Table 2.3). We also conducted whole brain analyses to more precisely identify neural subregions within and outside of our ROIs whose activation was associated with higher preference to select and share articles (see Table 2.4). The results of these whole-brain analyses supported the ROI analyses and suggested that the effects were relatively specific to our ROIs (i.e., we did not observe widespread activity outside of our main ROIs). Our whole-brain search did suggest, however, that a sub-portion of the VMPFC that is largely associated with self-related processing was associated with greater preference for selecting, but not sharing, articles. In contrast, sub-portions of the DMPFC and TPJ that are largely associated with social cognition were found to be associated with greater preference for sharing, but not selecting, articles (see Figure 2.5).

Table 2.3. Results of the Region-of-Interest (ROI) Analysis Testing Modulation of Neural Activity by Preference Ratings

	Condition					
	Select			Share		
ROIs	*t*(40)	*p*	Mean parameter estimate	*t*(40)	*p*	Mean parameter estimate
Subjective valuation	6.01	< .001	0.046 [0.030, 0.061]	3.66	< .001	0.039 [0.017, 0.061]
Self-related processing	5.28	< .001	0.053 [0.033, 0.073]	3.36	.002	0.058 [0.023, 0.093]
Social cognition	3.47	.001	0.027 [0.011, 0.043]	3.20	.003	0.036 [0.013, 0.059]

Note: Values in brackets are 95% confidence intervals. Table A4 in the Appendix presents the activations in the subregions of each ROI.

Table 2.4. Results of the Whole-Brain Analysis Testing Modulation of Neural Activity by Preference Rating

Contrast and region	MNI coordinates x	y	z	Number of voxels (*k*)	*t*(41)
Select					
Ventromedial prefrontal cortex (bilateral)	-6	38	-8	417	7.50
Cerebellum (right)	36	-61	-41	24	6.54
Middle temporal gyrus	-54	2	-23	47	6.54
Middle temporal gyrus	-63	-22	-14	50	6.31
Inferior frontal gyrus	-42	29	-2	41	6.07
Share					
Dorsomedial prefrontal cortex	-12	53	34	48	6.31
Temporoparietal junction (left)	-48	-64	34	35	6.03
Middle frontal gyrus	-45	8	52	55	6.36
Caudate (right)	9	8	4	24	6.27
Caudate (left)	-9	14	7	27	5.91

Note: The table reports significant activations ($p < .05$, corrected for family-wise error; minimum cluster size = 20 voxels). The *t* tests were conducted at peak coordinates. MNI = Montreal Neurological Institute.

Discussion

We propose that positive valuation, self-relevance, and social relevance drive people's decisions to select and share information. Neural activity within subjective valuation, self-related-processing, and social-cognition ROIs was associated with deciding to select and share news articles, and scaled with preferences to do so. We observed substantial overlap in the processes underpinning selection and sharing decisions, though activity was heightened during sharing relative to selection. Scholars have previously suggested that similar psychological processes may underpin the selection and sharing of information (Cappella et al., 2015; Kim, 2015) and that representations of the self and other often overlap (Brewer, 1991; Platek, Keenan, Gallup, & Mohamed, 2004). Our data support these ideas by demonstrating neural overlap in the processes engaged.

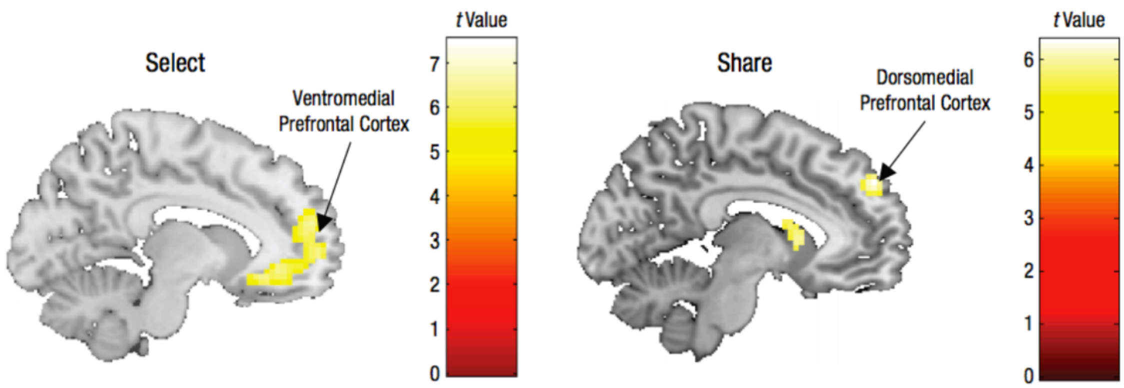

Figure 2.5. Brain images showing regions where the whole-brain analysis indicated that neural activity in the select (left) and share (right) conditions was modulated by preference ratings

Information Selection

Our data are consistent with a value-based account of information selection; the VS and VMPFC are robustly associated with computing subjective values of stimuli (Bartra et al., 2013). One source of value for personal consumption of information may be an article's self-relevance, and we observed greater activity within self-related processing ROIs (MPFC and PCC) during decisions to select articles, relative to recalling the content. A second source of value may be an article's social implications, and we observed greater activity within social-cognition ROIs (VMPFC, MMPFC, DMPFC, TPJ, PC, and rSTS) during decisions to select articles, relative to recalling the content. Activity in all three sets of ROIs was further associated with the degree of preference to select the article for oneself. These findings are consistent with previous literature on persuasion and influence (Cascio et al., 2015; Falk et al., 2012), which suggests that self-related processing may be a key factor in being influenced to act in accordance with a message (in this case, to select the article). These data are also consistent with the idea that even when selecting information for personal consumption, people may consider broader social factors (Cialdini & Trost, 1998). This finding converges with evidence that the default-mode network in the brain primes people to readily consider other people's mental states (Spunt et al., 2013). Thus, social considerations may be important in selecting information, as the knowledge gained can translate into social value.

Information Sharing

We also observed greater activity within all three sets of ROIs during decisions to share, both relative to decisions to select and relative to recall of content. Activity in all three sets of ROIs also scaled with the degree of preference to share the articles. These data are consistent with a value-based account of information sharing, in accordance with evidence that informing other people (Tamir, Zaki, & Mitchell, 2015) and sharing about oneself (Tamir & Mitchell, 2012) activates reward pathways. We extended these findings to the domain of sharing more broadly, and also examined two possible additional sources of value: self-relevance and social relevance. Indeed, activity in meta-analytically defined self-related processing regions of the MPFC and PCC was greater during sharing even when compared with making selections for oneself. These findings align with previous research demonstrating that MPFC activity scales with intentions to recommend ideas (Falk, Morelli, Welborn, Dambacher, & Lieberman, 2013). We extended these findings to show that merely considering sharing information activates this ROI, and the activity scales with preference. These findings also highlight how the social act of sharing may be self-reflective, converging with accounts of self-presentation motives in sharing (Barasch & Berger, 2014). It has been suggested that desires to enhance one's reputation and social status are key motivators behind news sharing (De Angelis et al., 2012; Berger, 2014; Lee & Ma, 2012; Wien & Olsen, 2014). Further, people are particularly likely to engage with messages that promote their values (Berger, 2014; Botha & Reyneke, 2013). Critically, our findings provide neural evidence that self-related processing is engaged not only when people consider selecting messages for themselves to read, but also when they consider sharing those messages with other people. We also observed greater activity in our social-cognition ROIs in the share condition than in the select condition and the content condition. Also, this activity scaled with preferences to share. Humans have an inherent motivation to socialize through sharing information (Baumeister & Leary, 1995; Berger, 2014; Tamir & Mitchell, 2012). Prior research has shown that activity within subregions of the social-cognition ROIs is associated with successful retransmission of information (Falk et al., 2013) and enthusiastic recommendations (Falk et al., 2012).

Neural Differences between Selecting and Sharing Information

Although there was substantial overlap in neural activity when participants considered selecting and sharing information, the activity in all three sets of ROIs was strongest during decisions to share. In addition, we found preliminary support for some spatial distinctions in the areas engaged by preferences to select information to read oneself and preferences to share with other people. Specifically, our whole-brain results showed that a more ventral sub-portion of MPFC previously implicated in self-related processing and value to self was robustly associated with greater preference for selecting, but not sharing, articles. In contrast, DMPFC and TPJ areas previously implicated in social cognition were associated with greater preference for sharing, but not selecting, articles. These results support the proposed ventral-dorsal gradient of self- and other-related processing in the MPFC (Denny, Kober, Wager, & Ochsner, 2012) and suggest that although there is overlap of self-related and social-cognition activity in the selection and sharing of information, some specificity may also be involved when people consider how much they would like to read information as opposed to how much they would like to share it with other people. In summary, we have proposed a novel account of the neurocognitive mechanisms behind selection and retransmission processes as participants actively consider selecting and sharing news. Increased activity in hypothesized subjective value, self-related-processing, and social-cognition ROIs was associated with decisions to select and share information, as well as with preferences to do so. These results suggest fundamental dimensions of the motivation to communicate and highlight more generally the overlap in processes involved in considering information for personal and social purposes.

CHAPTER 3: A NEURAL MODEL OF VALUATION AND INFORMATION VIRALITY

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Abstract

Information sharing is an integral part of human interaction that serves to build social relationships and affects attitudes and behaviors in individuals and large groups. We present a unifying neurocognitive framework of mechanisms underlying information sharing at scale (virality). We argue that expectations regarding self-related and social consequences of sharing (e.g., in the form of potential for self-enhancement or social approval) are integrated into a domain-general value signal that encodes the value of sharing a piece of information. This value signal translates into population-level virality. In two studies (n = 41 and 39 participants), we tested these hypotheses using functional neuroimaging. Neural activity in response to 80 New York Times articles was observed in theory-driven regions of interest associated with value, self, and social cognitions. This activity then was linked to objectively logged population-level data encompassing n = 117,611 internet shares of the articles. In both studies, activity in neural regions associated with self-related and social cognition was indirectly related to population-level sharing through increased neural activation in the brain's value system. Neural activity

further predicted population-level outcomes over and above the variance explained by article characteristics and commonly used self-report measures of sharing intentions. This parsimonious framework may help advance theory, improve predictive models, and inform new approaches to effective intervention. More broadly, these data shed light on the core functions of sharing—to express ourselves in positive ways and to strengthen our social bonds.

Introduction

Human social interaction is centered on sharing information with others (Csibra & Gergely, 2011), and this sharing critically affects the reach and impact of news, ideas, and knowledge over time (Berger, 2014; Cappella et al., 2015; Rogers, 2003; Southwell & Yzer, 2007). The more than 4 billion Facebook messages, 500 million tweets (Krikorian, 2013), and 200 billion e-mails (Radicati Group, 2015) shared daily highlight this phenomenon. However, not all information is equally likely to be shared (Bandari, Asur, & Huberman, 2012; Southwell, 2013). Although a growing body of research describes large-scale patterns of sharing (Goel, Anderson, Hofman, & Watts, 2016; Kim, 2015; Suh, Hong, Pirolli, & Chi, 2010), the types of data that are used to describe such patterns cannot speak to the underlying psychological and neurocognitive antecedents of sharing. Furthermore, extant empirical research on the psychological mechanisms of sharing (Berger, 2014; Cappella et al., 2015) is limited by social desirability bias, memory gaps, and the inaccessibility of unconscious, basic processes inherent in self-report and other commonly used measures (Krumpal, 2011; T. D. Wilson & Nisbett, 1978; T. D. Wilson & Schooler, 1991).

To this end, we assess the neurocognitive processes in individuals that translate into population-level sharing of health news articles (i.e., virality, defined as the mass popularity of a piece of information among those with direct access to that information). Real-time measurement of brain activity offers a mechanistic window into the processes underlying sharing decisions, is less biased by the factors noted above (Falk, Cascio, & Coronel, 2015; Plassmann, Venkatraman, Huettel, & Yoon, 2015), and hence may offer a new way to understand and predict virality.

Value-Based Virality

We tested a parsimonious model of virality centered around the value of sharing. Value-based virality posits that (i) two types of inputs—expectations of self-related outcomes and the social impact of sharing—inform an overall computation of the value of sharing a piece of information with others, and (ii) this domain-general value signal translates into population-level information virality. Operationally, we relied on meta-analyses and large-scale studies in social neuroscience and neuroeconomics to define theory-driven brain regions of interest (ROIs) from which to extract neural activity as a proxy for each of the three psychological processes central to value-based virality (Table C1).

Information-Sharing Value

Neuroscientists have identified subregions of the ventromedial prefrontal cortex (VMPFC) and ventral striatum (VS) that compute value in various contexts (Bartra et al., 2013). Importantly, prior work has characterized the domain-general nature of the value signal that is computed in this neural system (Levy & Glimcher, 2011, 2012). That is, if a decision maker is faced with different types of value (e.g., primary and secondary rewards), the brain's value system enables direct comparisons by transforming them onto a common scale during decision-making. Value-based virality argues that this same mechanism enables sharers to compute an overall value of the act of sharing a specific piece of information based on considerations of the self-related and social consequences of sharing. Operationally, the neural valuation system includes VS and VMPFC subclusters which are linked to preference judgments and valuation in decision-making across hundreds of studies (Bartra et al., 2013) and which have been linked to sharing decisions in individuals (Baek, Scholz, O'Donnell, & Falk, 2017; Falk et al., 2013).

Self-Related Outcome Expectations as an Antecedent of Sharing

Value-based virality suggests that expectations of self-related outcomes are one primary antecedent to sharing. In line with work on self-relatedness, this concept assumes thoughts about how sharing information affects "our self-presentation or mental concept" (Murray et al., 2012). This broad definition encompasses various specific thought processes, for instance about the effects of sharing on one's self-presentation or its potential to support self-enhancement, which have been studied separately elsewhere (Berger, 2014; Cappella et al., 2015). Value-based virality suggests that neural activity in the brain's self-related processing system is the greatest common denominator of these broadly self-related processes, allowing us to capture within one measure a set of related cognitions that can vary across people and contexts. Similar to content that enhances such self-related thoughts (Berger, 2014; Cappella et al., 2015), information that engages neural activity in regions related to such processes, especially in medial prefrontal cortex

(MPFC) (Murray et al., 2012; Northoff et al., 2006), has been linked to self-reported intentions to share information (Baek et al., 2017; Falk et al., 2013).

Extant observational evidence further suggests that self-relevant issues are among the most frequent conversation topics (Dunbar et al., 1997; Landis & Burtt, 1924), especially in social media (Naaman et al., 2010), and that disclosing information about the self may be inherently rewarding (Tamir & Mitchell, 2012). Value-based virality suggests that, through this neural mechanism, expectations of positive self-related outcomes of sharing increase the perceived value of information sharing, which in turn increases the likelihood of actual sharing.

Operationally, we focus on a self-related processing ROI consisting of clusters in the MPFC and precuneus/posterior cingulate cortex (PC/PCC), regions commonly activated by the types of self-related judgments detailed above (Falk et al., 2016; Murray et al., 2012).

Social Outcome Expectations as an Antecedent of Sharing

In parallel, value-based virality suggests that expectations of social outcomes of sharing are another primary antecedent of sharing decisions. Sharing is an inherently social process, and social considerations can strongly impact how content is received and acted upon (Cascio, Scholz, et al., 2015; Southwell & Yzer, 2007). In particular, sharers need to consider others' mental states (e.g., knowledge, opinions, and interests) to predict the potential reactions of their audience and to share successfully (Barasch & Berger, 2014; Clark & Murphy, 1982). This type of social cognition is called "mentalizing" and involves cognitions or forecasts about the mental states of others (Frith & Frith, 2006), for instance, predicting what others are likely to think and feel about the shared information and about the sharer. Value-based virality suggests that neural activity in the brain's social cognition system constitutes the greatest common denominator of a range of socially relevant thought processes in sharers, including thoughts about the meaning of the information to receivers and the potential for positive social interactions with others. Neurally, activity in the mentalizing system has been linked to sharing decisions in individuals (Baek et al., 2017), and successful persuaders engage brain regions strongly associated with mentalizing (Dufour et al., 2013) more than unsuccessful persuaders within two-person propagation chains (Falk et al., 2013).

Furthermore, sharing information with others has been found to be rewarding (Tamir et al., 2015). Value-based virality predicts that, by this mechanism, thoughts about potential positive social outcomes of sharing (e.g., having another person know you better or gaining others' approval) increase the perceived value of information sharing. This is reflected by positive associations between neural activity in social cognition and value systems.

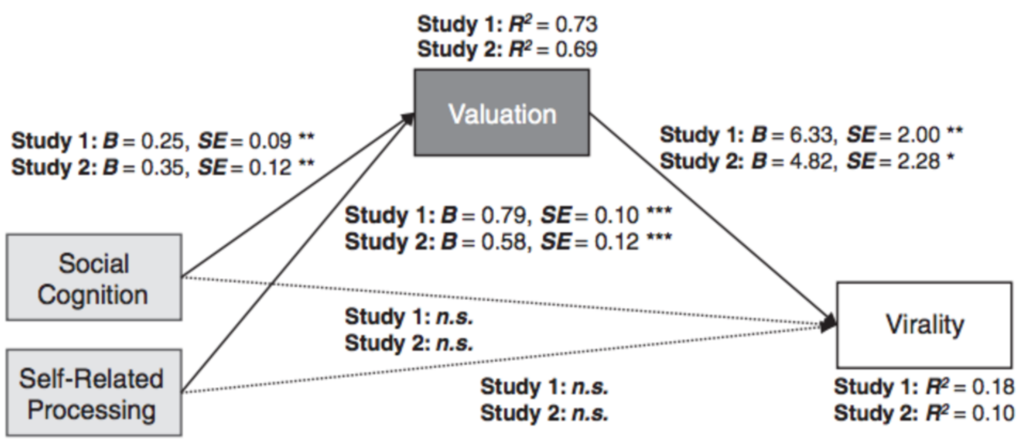
We operationalize social cognition as defined above with an ROI consisting of clusters in the middle and dorsal MPFC, bilateral temporoparietal junction, and right superior temporal sulcus, regions which are robustly activated by tasks involving mentalizing (Dufour et al., 2013) and which specifically overlap with considerations of whether others' mental states are rational and social (Tamir, Thornton, Contreras, & Mitchell, 2016).

Current Study

We tested the value-based virality framework empirically by combining data from two fMRI experiments with objectively logged population-level data on the sharing of New York Times (NYTimes) health news articles that were collected using the NYTimes' Most Popular application programming interface (API) search tool (Kim, 2015). We focused on neural activity in theory-driven ROIs associated with key psychological processes (positive valuation, self-related, and social processing) measured while participants in two samples were exposed to headlines and abstracts of NYTimes health news articles. fMRI participants also provided ratings of the likelihood with which they would share each article with their Facebook friends. To create a more realistic sharing context, participants were informed that they would be asked to act on their self-reported intentions after the fMRI scan by sharing articles they rated positively with actual Facebook friends. Furthermore, several article characteristics, such as positivity and perceived usefulness, were available from a prior content-focused investigation of the articles used here (Kim, 2015). Participants completed similar tasks in the two studies (Figure C1), and parallel analyses were applied to the two datasets to allow the replication of our results linking neural and population-level data. The population-level framework presented here substantially extends orthogonal analyses of individual-level results based on study 1 data showing that decisions about information sharing engage more activity in value, self-related, and social cognition ROIs than do other types of decisions and that this neural activity scales with self-reported, individual-level sharing preferences (Baek et al., 2017).

Results

Based on the predictions made by value-based virality (Figure 3.1), path models were specified to link percent signal change of brain activity measured in the three theory-driven ROIs while our participants read headlines and abstracts to the population-level sharing counts of each article. The 80 NYTimes articles were shared a total of 117,611 times (mean ± SD, 1,470.1 ± 2,304.3 times; range, 34–12,743 times) via Facebook, Twitter, and email by the NYTimes online reader population within 30 d of each item's publishing date.



Independent Variable	Study 1 Indirect Effects	Study 2 Indirect Effects
Social Cognition	*B* = 1.59, CI [0.56 – 3.33]	*B* = 1.67, CI [0.24 – 4.87]
Self-Related Processing	*B* = 4.97, CI [2.47 - 8.15]	*B* = 2.81, CI [0.39 – 6.80]

Figure 3.1. Value-based virality path model. The path diagram shows maximum likelihood estimates (unstandardized coefficients). The table presents indirect effect coefficients and bias-corrected, bootstrapped 95% CIs (1,000 replications). As in prior work predicting population-level message effects from neural data (30), all variables were rank-ordered. $n = 80$ in study 1 and 76 in study 2; $^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$, n.s., not significant.

In both samples, we found robust support for value-based virality (Figure 3.1 and Table C2). First, articles that had high sharing value indicated by stronger neural activity in the valuation ROI in each of our samples were shared more frequently by NYTimes readers. This result is in line with the idea that, in the context of sharing, the brain's valuation system encodes the value of sharing information with others. Further, there are commonalities across people in the extent to which information engages this neural system.

In addition, the effects of neural activity in self- and social-cognition systems on population-level virality were fully mediated through value-related activity in both samples. This finding is consistent with the idea that considerations of self-related and social outcomes of sharing impact the overall perceived value of the act of sharing, which in turn directly affects sharing behavior.

These results were robust when using unranked variables (Appendix C, Figure C2, and Table C3). Further, models specifying value-related neural activity as the mediator of the effects of social and self-related processing on virality showed acceptable model fit and outperformed alternative path models (Appendix C, Table C4). Finally, following our planned ROI analyses, a whole-brain search for regions associated with population-level virality did not reveal widespread activity outside our ROIs (Appendix C, Figure C3, and Table C5).

We further compared the predictive power of neural activity in regions predicted by value-based virality with variance explained by commonly used self-report measures (intentions to share each article on Facebook) and tested the robustness of the framework when controlling for the effects of article characteristics that have been associated with news virality in prior work (Berger & Milkman, 2012; Kim, 2015). For both the study 1 and study 2 samples, self-reported intentions were significant predictors of population-level sharing (explaining 11.3% and 13.8% of its variance, respectively). Neural activity alone explained 17.5% and 9.6% of the variance in the virality outcome in studies 1 and 2, respectively (Figure 3.1). When combined, both self-reported intentions and brain activity remained significant predictors, together explaining 19.2 and 19.1% of the variance in studies 1 and 2, respectively (Figure C4 and Table C2). In addition, all effects reported in Figure 1 were robust, even when controlling for any of nine content characteristics available for the article headlines and abstracts (Appendix C). Thus, brain activity measured with fMRI can significantly improve the prediction of large-scale sharing behavior beyond other commonly used metrics.

Discussion

Information sharing is an integral part of human nature (Csibra & Gergely, 2011) that enables and accelerates innovation and development in modern societies (Pentland, 2014; Rogers, 2003). We iteratively combined neuroimaging data with objectively logged population-level data on hundreds of thousands of shares from the NYTimes API search tool to test a parsimonious, neurocognitive framework of the psychological mechanisms underlying sharing decisions that translate into population-level virality. Specifically, we argue that potential sharers consider a broad range of self-related and social consequences of sharing a piece of information with others. The resulting self-related and social-relevance judgments then serve as inputs to the brain's valuation system, which converts them to a common scale. This overall value of information sharing is directly predictive of largescale sharing dynamics.

Consistent with this framework, we found that brain activity in the valuation system (VS and VMPFC) in two groups of participants was associated with virality in the larger population (117,611 total shares of 80 NYTimes articles). That is, articles associated with higher information-sharing value in the brain when individuals first read the headlines and abstracts were shared more frequently by the population of NYTimes readers. Information-sharing value may be a primary psychological motivator and central theoretical concept that guides sharing behavior at scale. Prior work has shown that neural activity in the brain's valuation system is not only associated robustly with personal preferences (Bartra et al., 2013) but also with the expectation of positive outcomes (Diekhof, Kaps, Falkai, & Gruber, 2012; Rademacher et al., 2010). Brain activity in response to persuasive messages in these regions also is associated with message-consistent behaviors at the individual (Cooper et al., 2015; Falk et al., 2013) and population level (Falk et al., 2012, 2016; Plassmann et al., 2015). Our findings show that the predictive validity of neural valuation activity extends to the realm of information virality and highlights the domain-general nature of this brain signal (Levy & Glimcher, 2011, 2012). In the case of sharing, value-based virality suggests that considerations of self-related and social consequences of sharing are key inputs in the computation of the value of sharing information, even though the specific nature of the self-related and social inputs that inform that value signal may vary depending on qualities of the information sharer, the receiver, or their relationship.

In line with this argument, we found robust, indirect effects of brain activity in regions associated with self-related processing during article exposure on population-level sharing behavior through value-related activity. Prior evidence has linked a range of self-related judgments to sharing. For example, the promotion of a positive self-image (Mezulis et al., 2004; Taylor & Brown, 1994) is an important goal in social interactions, and information that allows potential sharers to appear in a more positive light is more likely to go viral (Barasch & Berger, 2014; Cappella et al., 2015), perhaps because it increases the perceived value of information sharing. Further, self-disclosure increases activity in the brain's valuation system, suggesting that providing information about or reflecting about the self might be inherently rewarding (Tamir & Mitchell, 2012). Value-based virality brings together prior findings, arguing that self-related neural activity is the greatest common denominator for various self-related thought processes, including reflecting self-concept and self-presentational concerns, and constitutes a primary antecedent of sharing value.

Further, our results show an indirect effect of activity in neural regions associated with social cognition, and in particular mentalizing, on population-level article virality through value-related activity. Existing work has shown that the expectation of positive social outcomes such as positive interactions with others engages the brain's valuation system (Fehr & Camerer, 2007; Rademacher et al., 2010), and our ROI overlaps with brain regions supporting considerations of whether others' mental states are rational and whether they are social (Tamir et al., 2016). Social belonging is a basic human need and motivation (Baumeister & Leary, 1995; Lieberman, 2013), and relationship maintenance has been suggested as a motivator of information sharing (Berger, 2014; Cappella et al., 2015). A range of basic social motives focused on understanding others' minds and forecasting their reactions, and expectations about positive social outcomes of sharing information with others may increase the perceived value of information sharing; in turn, the perceived increase in the value of information increases the potential that the information will go viral. Value-based virality brings together prior findings, arguing that neural activity in areas associated with social cognition is the greatest common denominator for various social thought processes and informs sharing value.

Although we removed voxels within the VMPFC and PCC [regions commonly associated with both self-related and social processing (Dufour et al., 2013; Murray et al., 2012; Saxe, Moran, Scholz, & Gabrieli, 2006)] from our social-processing ROI to ensure statistical validity, self-related and social thoughts are conceptually intertwined. Social psychologists have suggested that one's sense of self is defined by simple rules that include or exclude an individual from certain social groups and practices, resulting in a "social self" concept (Bretherton, 1991; Brewer, 1991). In the context of value-based virality, it follows that content that is expected to have positive social outcomes when shared (e.g., because it is helpful to the receiver or results in a positive social interaction) will likely reinforce the perceived positivity of self-related outcomes of sharing (e.g., by making the sharer look charitable and friendly) and vice versa. Nonetheless, our analyses demonstrate that when operationalizations of both self-related and social processing are included in one model, each concept contributes unique variance to the calculation of overall sharing value. In the future, explorations of the relative importance of each cognition and the patterns of their interaction in the calculation of information-sharing value will be valuable.

Finally, in line with prior investigations in other contexts (Berns & Moore, 2010; Falk et al., 2012, 2016; Genevsky & Knutson, 2015; Venkatraman et al., 2014), we show links between brain activity in small groups of individuals and large-scale virality, even though the perception of the sharing value of the same content might vary across people, and the same content might appear valuable to different people for different reasons. Although what is personally relevant to the self and useful to share with others might differ somewhat across individuals, human societies are characterized by a set of basic common values and social norms that drive behavior across individuals (Schwartz, 2006, 2007). Sharing decisions rely on such basic motives, namely, the pursuit of a positive self-image and social belonging (Baumeister & Leary, 1995; Mezulis et al., 2004). Consequently, similar types of information are likely to be perceived to have high sharing value across individuals. Furthermore, expectations of self-related and social outcomes, two core concepts within value-based virality, are defined broadly as the greatest common denominators of various self-related and social thought processes, respectively. In other words, population-level prediction of virality from neuroimaging of small groups is likely facilitated by broad societal values, the inclusiveness of our theoretical conceptualizations, and the unique information afforded by neuroimaging. Specifically, neuroimaging is optimally situated to identify such high-level, hard-to-articulate cognitions, allowing us to capture relevant cognitions in a parsimonious way despite the variability in the thought processes that different individuals might associate with the same content. Along with this strength, however, we relied on functionally defined ROIs to take optimal advantage of neuroimaging to operationalize these constructs, which are inherently subject to the limitations of reverse inference (Poldrack, 2011).

The results summarized in this article were robust across several methods of analysis, and the hypothesized model outperformed alternative path structures, although causal inferences are limited by the cross-sectional nature of our data. Additionally, a whole-brain analysis did not provide strong evidence for the involvement of neural regions outside our ROIs in population-level virality. Nevertheless, future work might reveal other basic processes that could complement the theory, for instance as additional inputs to the value signal or its antecedents. Further, our effects were robust, even when controlling for self-reported sharing intentions and various article characteristics. In sum, our data highlight the value of including neural variables in the conceptualization of virality in the context of health news and offer a testable and parsimonious framework that could be extended to virality in other contexts. This mechanistic account of sharing decisions complements insights from previous studies using self-report measures or big data approaches (e.g., Goel et al., 2016; Suh et al., 2010).

Conclusion

Information that elicits greater brain response in self-, social-, and in turn value-related systems is more likely to be shared. These processes may reflect thoughts about the potential outcomes of sharing to the self and to one’s social relationships. If so, self-related and social processes could serve as targets for content designers aiming to increase the virality potential of their messages. Taken together, our data support a parsimonious neurocognitive model of virality, one of the most prominent social phenomena in the 21st century, and shed light on the core functions of sharing— to express aspects of ourselves and to strengthen our social bonds.

Methods

Neural activity was examined while two samples of participants (study 1 and study 2) completed the article task (Figure C1) in which participants were exposed to headlines and abstracts of news items taken from the NYTimes website (https://www.nytimes.com/). We then tested for associations between activity within functionally defined, theory-driven ROIs associated with self-relatedness, social processing, and valuation and the number of article retransmissions performed online by NYTimes readers as a population-level indicator of virality.

Similar protocols were administered in both studies, and each group of participants was presented with the same news items. Differences in data collection and processing between the two studies are detailed below. All models and results reported here were derived using parallel statistical approaches across studies. All participants provided informed consent, and all procedures were approved by the Institutional Review Board at the University of Pennsylvania.

Hypothesis Pre-Registration

At the onset of study 1, we preregistered our study design (Scholz, Baek, O'Donnell, & Falk, 2015), and upon completion of data collection we explored the relationship between neural data and population-level article retransmission. Based on the results in study 1, hypotheses specifying the effects of self- and social-processing on value-related neural activity and of activity in the value-related ROI on population-level virality were preregistered before the analysis of study 2 data (Scholz, Baek, O'Donnell, & Falk, 2016).[4]

Sample NYTimes articles

During the article task, participants in both samples were exposed to the original headline and abstract of 80 articles from the Health section of the NYTimes website (https://www.nytimes.com/). The articles were chosen from a complete census (excluding certain article categories to preserve homogeneity in article format; see Kim, 2015 for details) of articles (n = 760) published online in the 7.7 mo between 11 July 2012 and 28 February 2013. Population-level data about the number of retransmissions of each article through email, Twitter, and Facebook were collected via the NYTimes API. The 80 articles were chosen to maximize comparability regarding topic (healthy living and physical activity) and length (for the word count of title and abstract, see Appendix C). The 80 articles selected into the final sample were of comparable lengths, i.e., a word count (mean ± SD) of 29.43 ± 3.87 words (range, 21–35 words). To control for reading speed in study 1, we produced audio files in which a female voice read each of the article headlines and abstracts. Depending on word count, each audio file was produced to last 8, 10, or 12 s. Coded characteristics of each article's headline and abstract were available as described by Kim (2015).

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[4] See Appendix B for a more detailed comment on efforts made to implement open science practices in this dissertation.

Population-Level Retransmission

An article's population-level retransmission count was measured through the NYTimes' Most Popular API and defined as the sum of retransmissions via Facebook, Twitter, and email using sharing tools available on the NYTimes website within 30 d of the article's first appearance on the website (mean ± SD, 1,470.14 ± 2,304.32 retransmissions; range, 34–12,743 retransmissions). Retransmission counts for social media (Twitter and Facebook) and email were highly correlated ($r = 0.917$) and thus are not presented separately, although results remain substantively identical when each type of sharing is considered separately.

Study 1 Participants

From a larger sample of respondents who participated in a project examining the neural correlates of retransmission and social influence by filling out a short online survey, we selected 43 participants. These 43 participants completed an online screening process and an in-person appointment including a 60-min fMRI scan. To be eligible for the fMRI portion, screened participants had to meet standard fMRI eligibility criteria including no metal in the body, no history of psychiatric or neurological disorders, not currently pregnant or breast-feeding, and not currently taking psychiatric or illicit drugs. All participants were right-handed.

Two participants were excluded from analysis because of data corruption. One participant saw only three of the four conditions during the article task, and one participant showed poor normalization to the template brain. Additionally, for four participants a smaller number of trials was available for analysis because of the loss of data from one run of the article task (n = 1), excessive head motion in one run of the task (n = 2), and technical difficulties in which 23 articles were shown twice, resulting in only 57 trials that qualified as initial exposures to an article (n = 1). The partial data from these participants were included in the analyses. The age of the final sample of 41 participants (29 females) was 20.6 ± 2.1 y (mean ± SD) (range, 18–24 y).

Study 2 Participants

Forty participants were selected from the pool of respondents used to select the study 1 sample using inclusion criteria that paralleled those in study 1. These participants underwent an fMRI session. Because of excess head movement during the article task, one participant was removed from all analyses, and one run of the article task was discarded for a second participant. The remaining 39 participants (28 female) were 18–24 y old (mean ± SD, 21.0 ± 2.02 y).

Study 1 Article Task

Inside the fMRI scanner, study 1 participants completed two runs of the article task consisting of 40 trials each (Figure C1A). Each trial lasted an average of 14.7 s without fixation. At the beginning of each trial a cue screen indicating the current condition was presented for 1.5 s. Then participants read the article’s title and abstract while considering a condition-specific question. In the four conditions participants were asked to consider (i) whether to read the full text of the article themselves, (ii) whether to share the article via a post on their Facebook wall; (iii) whether to share the article via a private Facebook message to one friend (5-point Likert-type scales from very unlikely to very likely), and (iv) whether age/nutrition/fitness/science/ laws/well-being/cancer was the topic of this article (5-point Likert-type scale from certainly not to certainly yes). Conditions were presented in a pseudorandom order based on a Latin-square. To control for reading speed, headlines and abstracts were also presented in auditory format through scanner-compatible headphones while the text was presented on the screen. Article abstracts were categorized in three groups depending on the length of the text. Consequently, the reading screen was presented for 8 (n = 16), 10 (n = 40), or 12 (n = 24) s. Article length was counterbalanced across conditions and task runs. The reading screen was followed by a randomly jittered fixation screen that lasted 1.5 s on average (range, 0.5–4.7 s). Participants then used a button box to indicate their answer to the condition-specific question (3 s). Finally, there was a randomly jittered inter-trial interval with an average length of 2 s (range, 1–4.7 s).

In this analysis, we focused on reading trials in which participants viewed the article headlines and abstracts to decide whether they wanted to read the full text of the article (see Appendix C for results in other conditions). Furthermore, we only included reading screens within each trial (i.e., periods in which article headlines and abstracts were visible). This task condition closely mimics natural situations in which readers are initially exposed to articles online.

Study 2 Article Task

Study 2 participants completed two runs (21 trials each) of a modified version of the article task (Figure C1B). First, each article's headline and a description of the article were presented on the reading screen for 10 s, and participants were instructed to read the text on the screen. Articles were not presented in auditory format in study 2. Three types of article descriptions were used: Participants saw the original article headline and abstract that also was seen by study 1 participants (i) or saw the original article headline and a Tweetlength message written by a participant in study 1 to be shared either with one Facebook friend (ii) or on the participants' Facebook wall (iii). The reading screen was followed by a randomly jittered fixation period (mean, 1.5 s; range, 0.3–4.8 s). Afterward, participants provided two ratings per trial: (i) the likelihood they would share the article on their Facebook wall and (ii) the likelihood (on 5-point Likert-type scales paralleling those used in study 1) that they would share the article via a private Facebook message with one friend. Each rating screen was available for 3 s. Rating screens were separated by a short, jittered fixation period (mean, 1.5 s; range, 0.4–4.3 s). Finally, there was a randomly jittered intertrial interval (mean, 2.9 s; range, 0.5–11.5 s). To parallel study 1 analyses closely, only reading screen periods within each trial (i.e., when article headlines and descriptions were visible) and only abstract trials that presented original NYTimes abstracts were analyzed here. The 80 articles used in study 1 were pseudo-randomly assigned to experimental conditions for each participant in study 2; however, because of randomization, only 76 articles were presented in the relevant abstract condition across all study 2 participants.

A Priori ROIs

Three neural masks were constructed as functional ROIs based on extensive prior work in each of the respective subject areas (Table C1). The self-relatedness ROI was defined based on a prior study (Falk et al., 2016) that collected neural data using a well-validated self-localizer task (Schmitz & Johnson, 2007) in which participants judge whether personality traits describe them or not (the self-condition) or whether the adjective shown is positive or negative (the valence condition). Blocks of self-judgments are contrasted with blocks of valence judgments to isolate neural activity associated with self-relatedness.

The social-processing ROI was defined based on a large-scale study that used the well-validated false-belief localizer during which participants engage in mentalizing. Trials during which participants judged whether beliefs held by others were true or false were contrasted to trials in which they judged whether physical representations were true or false to retrieve the mask used here. To avoid inflated correlations among activity in the three neural systems, we created a reduced version of the social cognition mask, excluding the clusters in VMPFC and PCC that overlap with the self and value ROIs. This mask is used in all analyses presented here. Models using the full social-cognition ROI instead of the reduced social-cognition ROI yielded very similar results and support identical conclusions.

Finally, the valuation ROI was defined based on a quantitative meta-analysis of 206 studies that reported neural correlates of subjective valuation during decision-making. This mask represents the conjunction of several valuation-relevant contrasts, all of which required some form of value-based decision-making (figure 9 in Bartra et al., 2013).

MRI Image Acquisition

Neuroimaging data were collected using a 3-T Siemens Magnetom Tim Trio scanner equipped with a 32-channel head coil was used for 40 participants in study 1 and

33 participants in study 2, and a Siemens Prisma 3T whole-body MRI with a 64-channel head/neck array was used for one participant in study 1 and six participants in study 2. Identical specifications were used on both scanners, except for the number of slices acquired for T2*-weighted images (54 at the Tim Trio and 52 at the Prisma scanner). This difference was accounted for in the slice-time correction step during preprocessing. Standard parameters used to acquire T2*- (two runs of 500 volumes in study 1 and two runs of 311 volumes in study 2), T2-, and T1-weighted anatomical image sequences are described in detail in Appendix C.

Imaging Data Pre-Processing

For the analysis of data from both studies, we used SPM8 (Wellcome Department of Cognitive Neurology, Institute of Neurology, the University of London), incorporating tools from AFNI (Analysis of Functional NeuroImages) (R. W. Cox, 1996) and FSL (FMRIB Software Library) (S. M. Smith et al., 2004) during data preprocessing. The first five volumes of each run were not collected to allow stabilization of the blood oxygenation level-dependent (BOLD) signal. Functional images were despiked using 3dDespike as implemented in AFNI. Slice time correction was performed using Sinc (Stanford University ideal bandlimited) interpolation in FSL. Data then were spatially realigned to the first image and were co-registered in two six-parameter affine stages. First, mean functional images were registered to in-plane T2-weighted images. Next, high-resolution T1 images were registered to the in-plane image. After co-registration, high-resolution structural images were segmented into gray matter, white matter, and cerebral spinal fluid to create a brain mask used to determine the voxels to be included in first- and second-level models. The masked structural images then were normalized to the skull-stripped Montreal Neurological Institute (MNI) template provided by FSL (MNI152_T1_1mm_brain.nii). Finally, functional images were smoothed using a Gaussian kernel (8 mm FWHM). The fMRI data were modeled for each participant using fixed-effects models within the general linear model as implemented in SPM8, using SPM's canonical difference of gamma hemodynamic response function (HRF). The six rigid-body translation and rotation parameters derived from spatial realignment were also included as nuisance regressors in all first-level models. Data were high-pass filtered with a cutoff of 128 s. Random effects models for the article task were also implemented in SPM8.

Analysis of Study 1 Imaging Data

We took an item-wise approach to modeling the article task using procedures similar to those used elsewhere (Falk et al., 2016). Specifically, using a single boxcar function for each trial (i.e., each of the 80 articles) encompassing the 8- to 12-s reading screen, we extracted neural activity in each ROI during each trial compared with the implicit baseline resting state. Activity related to cue and all rating screens was pooled into a separate regressor of no interest each. In addition, the model for one participant who accidentally saw several articles twice included an additional regressor of no interest for each second occurrence of an article. Fixation periods were pooled into the implicit baseline rest.

Analysis of Study 2 Imaging Data

Study 2 data were analyzed using methods parallel to those applied to study 1 data to yield comparable models. Specifically, using a single boxcar function for each of the 42 trials per participant, encompassing the 10-s reading screen, we extracted neural activity observed during each trial compared with the implicit baseline resting state. A regressor of no interest was included for each of the two rating screens. Fixation periods were pooled into the implicit baseline rest.

Path Models

For each a priori ROI, average parameter estimates of activity across all voxels within the region were extracted for each participant and each article using Marsbar (Brett, Anton, & Valabregue, 2002). Each set of parameter estimates was divided by the grand mean to derive estimates of the percent signal change. Percent signal change vectors for each participant were reduced to those trials shown in the reading condition for study 1 and in the abstract condition for study 2. For each participant, these reduced vectors were then z-scored and ranked across articles. As in prior work (Falk et al., 2016), we then computed the mean ranks of each article across participants and linked these data with the ranked population-level data from the NYTimes API separately. Specifically, we conducted path analyses using maximum likelihood estimation in lavaan (Rosseel, 2012) to yield the results presented in Figure 3.1. Nonparametric, bias-corrected 95% confidence intervals (CIs) for indirect effects using 1,000 bootstrap samples were further estimated using the mediation package for R (Tingley, Yamamoto, Kentaro, Keele, & Imai, 2014) to test for indirect effects of self-related processing and social processing on population-level retransmission through valuation (see Table C2 for relevant correlation matrices).

Robustness Checks

To check the robustness of our results, we fit (i) models using unranked variables in which population-level retransmission counts were log-transformed because of the positively skewed distribution (Figure C2 and Table C3), (ii) models excluding the insignificant direct effects of the exogenous variables shown in Figure 3.1 to obtain model fit statistics (Appendix C), and (iii) alternative structural models to those estimated in step ii to compare model fit (Appendix C and Table C4).

Whole-Brain Analysis

We conducted exploratory whole-brain searches for regions associated with population-level retransmission ranks in study 1 and study 2 to verify the specificity of our results to our ROIs and to explore whether additional activity outside these ROIs is associated with population-level virality (Appendix C).

Models Including Self-Reported Sharing Intentions and Article Characteristics

We further tested whether the predictions of value-based virality held above and beyond the variance explained by self-reported sharing intentions (Figure C4 and Table C2) and article characteristics (Appendix C). Study 1 participants provided one rating (intention either to broadcast or narrowcast) for 40 articles. For each article, we computed a mean sharing intention across participants including all available narrowcast and broadcasting ratings. Study 2 participants provided both narrowcast and broadcasting ratings for all 42 articles shown to them. For trials shown in the abstract condition, we first calculated a mean sharing intention across the two ratings for each article within participants and then computed a mean sharing intention for each article across participants. First, ranked population-level retransmission was regressed onto sharing intentions to estimate the effect of intentions on virality in each sample. Second, we re-estimated the models shown in Figure 3.1 with self-reported intentions specified as an additional exogenous variable with a direct effect on population-level retransmission. This step was further repeated for each available article characteristic (Appendix C).

CHAPTER 4: MOTIVATIONS OF BROAD- AND NARROWCASTING: A NEUROSCIENTIFIC PERSPECTIVE

Abstract

What differentiates sharing with few, well-defined others (narrowcasting) from sharing with loosely defined crowds (broadcasting)? One account suggests a trade-off where broadcasting is self-focused and self-serving, and narrowcasting is based on other-oriented, altruistic motives. We present neuroimaging data consistent with a second, parallel-processes perspective. According to this account, both narrow- and broadcasting simultaneously involve self-related and social motives since these concepts are strongly intertwined both on a psychological and neural level. Instead, narrow- and broadcasting may be differentiated by the intensity of these parallel processes. We recorded brain activity within regions that are meta-analytically associated with self-related and social cognition while participants made decisions to narrow- or broadcast New York Times articles on social media. Results show increased involvement of regions associated with both self-related and social processing in narrow- and broadcasting compared to a control condition. However, both processes were involved with higher intensity during narrow- compared to broadcasting. These data help to disambiguate a theoretical discussion in communication science and clarify the neuropsychological mechanisms that drive sharing decisions in different contexts. Specifically, we highlight that narrow- and broadcasting afford differing intensities of two psychological processes that are crucial to persuasion and population-level content virality.

Introduction

Information sharing is an inherently social process. As such, communicators who share information with others must consider the characteristics, preferences, and goals of their audience to effectively create messages that will resonate with receivers (Barasch & Berger, 2014; Bargh & Williams, 2006; Clark & Murphy, 1982; Magnifico, 2010). This effort allows the communicator to fulfill central self-related and social motivations such as to shape and present their own identity and to manage social relationships (Berger, 2014; Cappella et al., 2015; Cunningham, 2012; Meshi, Tamir, & Heekeren, 2015; Rosenberg & Egbert, 2011). Communicators regularly transmit information to one or few well-characterized others, for instance through private chat messages (narrowcasting), or large, often loosely defined audiences, for instance through social media status updates (broadcasting). The size of an audience may modify the motivations that lead to information sharing and, consequently, sharing behavior (Barasch & Berger, 2014; Bazarova & Choi, 2014; Derlega & Grzelak, 1979; Omarzu, 2000) and downstream outcomes such as persuasion and information diffusion (Falk & Scholz, 2018). Whether and how audience size changes the role played by self-related and social concerns during sharing remains a matter of active discussion. Here, we test two competing accounts of this relationship. The trade-off perspective, suggests a trade-off between self-related and social concerns wherein broadcasting is mainly motivated by self-focused considerations, and narrowcasting is driven by audience-directed, social thought processes. An alternative account, the parallel-processes perspective, implies that narrow- and broadcasting simultaneously engage both self-related and social thinking and are, instead, differentiated by the intensity of these parallel processes. We derive falsifiable hypotheses from each account of the motivational bases of narrow- and broadcasting and present empirical tests based on a neuroimaging experiment.

Characteristics of Broad- and Narrowcasting

Broadcasting involves sharing with large, often ill-defined audiences. Shared content is usually not private and messages composed by information sharers tend to be undirected, that is, not addressed towards a particular individual or group (Bazarova & Choi, 2014). Broadcasting allows sharers to address self-presentation and social affiliation motivations efficiently by reaching many and diverse receivers through a single message. For instance, a Facebook status update might reach about 200 potential receivers for the median adult Facebook user (Smith, 2014). At the same time, broadcasters face significant risks and uncertainty regarding the appropriateness of the content they share due to the diversity of potential audience members. Broadcast audiences are often characterized by context collapse, that is a conglomeration of people from different contexts within a person's life (e.g. work and a sports team; Marwick & boyd, 2011) and broadcasters tend to hold biased representations of the size and characteristics of their audience (Bernstein, Bakshy, Burke, & Karrer, 2013; Marwick & boyd, 2011). The limited information available to accurately predict attitudes, preferences and potential reactions to shared content (Krämer & Haferkamp, 2011; Marwick & boyd, 2011) might have implications for the extent to which sharers pursue self-related and social motivations.

In contrast, narrowcasting, or sharing with one or few, well-defined others, affords more privacy and more often leads to messages which are directed at specific individuals or groups (Bazarova & Choi, 2014; Nguyen, Bin, & Campbell, 2012; Walther, 1996). Sharers retain greater control over who may receive their messages and can thus rely on more specific person or group-specific knowledge as the basis for their sharing decisions. Dyadic interactions, especially in online contexts (Nguyen et al., 2012; Walther, 1996), have been shown to increase the intimacy of shared content (Bazarova & Choi, 2014). In what follows, we will discuss two competing accounts of the effects of these audience characteristics in narrow- and broadcasting situations on central sharing motivations, namely self-related and social considerations.

The Trade-Off Perspective

Arguing for a trade-off between self-related and social processing in broad- and narrowcasting, Barasch and Berger (2014) suggest that default egocentrism, a sharer's default focus on the self, motivates individuals to primarily share content that is related to their self-concept (e.g. by sharing content that reflects positively on themselves) when faced with loosely defined broadcasting audiences. Narrowcasting, on the other hand, is described as a special case of sharing where sharers are confronted with more prominent and concrete representations of their audience and thus motivated to abandon their egocentrism for a more sociocentric approach to sharing (e.g. by choosing content useful to the audience). In this view, ego- and socio-centrism are conceptualized and operationalized as extremes on a bipolar scale, suggesting that sharers focus primarily on one at a time and that increasing the focus on one, will decrease attention to the other.

The idea of an egocentric default is grounded in psychological research which suggests a central role of self-perceptions when interacting with others. Holding a positive self-image is a central human motive that drives behavior across contexts (Leary, 1996; Mezulis et al., 2004). Research has demonstrated that sharing information about the self is intrinsically rewarding (Tamir & Mitchell, 2012), and that most conversations include self-related information (Dunbar et al., 1997; Emler, 1990; Landis & Burtt, 1924), particularly on social media (Naaman et al., 2010). Reviews of the existing work on word-of-mouth and virality have confirmed the prominent role of self-presentational and self-enhancement concerns in the context of information sharing (Berger, 2014; Cappella et al., 2015). Even in social contexts, people tend to rely disproportionately on their own perspectives to predict those of their interaction partners (Dunning, Boven, & Loewenstein, 2001), perhaps because self-related information is more easily accessible (Ross & Sicoly, 1979). The trade-off perspective argues that egocentrism is particularly prominent in broadcasting situations where audiences tend to be ill-defined and reactions to shared content are hard to predict (Bazarova & Choi, 2014; Krämer & Haferkamp, 2011; Marwick & boyd, 2011). In other words, when broadcasting, sharers might focus on themselves as the primary known variable in a complex social equation.

Nevertheless, next to the desire to hold a positive image of oneself, humans are also inherently social and motivated to associate positively with others in social groups (Baumeister & Leary, 1995; Lieberman, 2013). When narrowcasting, a clearer definition of audience make-up and more reliable predictions about potential audience preferences and reactions might make it more feasible to address such social motivations through information sharing.

There is some empirical evidence for the trade-off perspective in the literatures on information sharing and self-disclosure. In a study by Barasch and Berger (2014), broadcasters were more likely than narrowcasters to share information that made them look good and to report a stronger self- rather than other-focus. In contrast, participants reported stronger other- than self-focus during narrowcasting compared to broadcasting and tended to share information considered helpful to the audience. In a study reported by Bazarova and Choi (2014), one part of the empirical data showed that participants identified self-related motivations, namely self-expression and social validation of self-related aspects, as the most common motivations for information sharing in broadcasting situations like Facebook status updates. Social motivations like the development of positive relationships were reported for a greater proportion of narrowcasted than broadcasted Facebook messages. Interestingly, other findings reported in this study are more supportive of hypotheses within the parallel processes account which will be discussed shortly.

An additional, important aspect of the trade-off account is the idea that ego- and sociocentric states are negatively related to each other, so that a self-focus in sharers decreases attention to the audience and an other-focus decreases attention to the self (Barasch & Berger, 2014). A similar notion can be found in the self-disclosure literature, which describes an intrapersonal-interpersonal orientation continuum (Archer & Earle, 1983; Miller & Read, 1987). Characteristics of the self-disclosure context such as one's audience are thought to impact a sharer's position on this bipolar scale.

Existing evidence for the trade-off account is derived primarily from self-report scales, which operationalize pre-existing assumptions about a competing relationship between self- and other-focus during sharing. In addition, existing measures have typically required the measurement of these concepts to occur post-hoc, sequentially, and using pre-defined categories and descriptions of cognitions.

The Parallel-Processes Perspective

Evidence from economics, social psychology, communication science and social neuroscience supports a set of competing hypotheses to the trade-off account. Specifically, the parallel-processes perspective suggests that: 1) Self-related and social processing do not have a trade-off relationship where one process suppresses the other, but often co-occur and might interact; 2) Both narrow- and broadcasting are based on both self-related and social considerations; 3) Differences between narrow- and broadcasting are likely due to differences in intensities of both self-related and social processing.

Neuroscientists who observe the brain's resting state, that is, spontaneous activity when study participants are not given specific instructions, routinely observe activity in the brain's so-called default mode network which substantially overlaps with neural systems related to both self-related and social processing (Mars et al., 2012; Schilbach, Eickhoff, Rotarska-Jagiela, Fink, & Vogeley, 2008; Spreng, Mar, & Kim, 2008). These data provide a first hint at a default mode that may consider the self and others simultaneously. In further support of this idea, game theorists and economists frequently observe social behavior in study participants, even when selfish behavior is more rational and explicitly anonymous (Nowak, Page, & Sigmund, 2000) which is inconsistent with a purely egocentric default. In line with these findings, psychologists have advocated the 'social self', arguing that a definition of self is itself developed based on the inclusion and distinction from social groups and practices (Bretherton, 1991; Brewer, 1991).

Extending this argument to the realm of information sharing leads to the prediction that self-related and social sharing motives occur in parallel and interact with one another during narrow- and broadcasting. For instance, even though sharers motivated to present themselves in a positive light are labeled as self-focused in the trade-off account, they likely consider aspects of their audience in order to determine what a given individual or group may perceive as a positive characteristic. Similarly, when trying to understand others, for instance, to help somebody, information sharers might reference their own experiences and preferences (Dunning et al., 2001).

Some existing data supports this view. For instance, some empirical work has shown effects of broadcasts about characteristics of the self on social relationships and enhanced relationship management both online and offline (Greene, Derlega, & Mathews, 2006; Valkenburg & Peter, 2009). For instance, in one study (Steijn & Schouten, 2013) participants were most likely to identify public status updates (i.e. broadcasts) as the most common causes for changes in their social relationships (e.g. uptake of new relationships or changes in trust), compared to other types of narrow- and broadcasting. Similarly, Utz (2015) found a positive relationship between certain characteristics of broadcasted self-disclosures on Facebook and the perceived connection to the communicator experienced by message receivers.

Although these findings call into question whether broadcasting is primarily egocentric, they merely speak to the outcomes of sharing, not the motivations driving it in different contexts. Addressing motivational underpinnings, other researchers have suggested that information sharers use heuristics to engage in social processing by making predictions about the preferences and characteristics even of large, ill-defined broadcasting audiences (Bernstein, Bakshy, Burke, & Karrer, 2013; Litt, 2012; Marwick & boyd, 2011). For instance, in a largest common denominator approach, communicators might attempt to identify content believed to be suitable for all possible audience members. Alternatively, according to the strongest audience effect, a sharer might focus more on a concrete subset of audience members than the entire group (Hogan, 2010; Litt, 2012; Marder, Joinson, Shankar, & Thirlaway, 2016; Vitak, 2012).

With regards to narrowcasting, information about the self also remains a prominent topic for sharers, even in dyads, the most extreme form of narrowcasting (Nguyen et al., 2012). One important way of enhancing the intimacy of a social relationship is to disclose increasingly intimate information about the self (Collins & Miller, 1994; Jiang, Bazarova, & Hancock, 2011; Kashian, Jang, Shin, Dai, & Walther, 2017) and this self-disclosure intimacy is both more expected (Bazarova, 2012) and practiced (Bazarova & Choi, 2014) in sharing situations that are more private. Privacy, in turn, is higher during narrowcasting compared to broadcasting (Bazarova & Choi, 2014). In this way, self-disclosure, which requires a self-focus, might help to achieve relationship maintenance goals and might occur more frequently in narrowcasting. This stands in contrast to the trade-off hypothesis that narrowcasting is inherently sociocentric, and not self-focused.

Although the parallel-processes account suggests that narrow- and broadcasting involve similar types of cognitions, differences are hypothesized in the intensity of both types of thought processes. Compared to narrowcasters, broadcasters' thoughts are guided by a more abstract, and loosely defined conception of audience (e.g. the entire Facebook network or a general interest group) than when sharing with specific others. Cognitions driving broadcasting are thus likely to be based on heuristics such as the ones described above rather than person-specific knowledge. As a result, social and self-related cognitions might be more vivid and intensive during narrowcasting.

Table 4.1. Hypotheses (H) derived from Trade-Off and Parallel-Processes Accounts of Narrow- and Broadcasting

Trade-Off		Parallel-Processes	Data Supports
H1: Broadcasting involves more self-related, but not more social cognitions than the control condition.	*vs.*	*H5:* Broadcasting involves more self-related and more social cognitions than the control condition.	*H5 Parallel Processes*
H2: Narrowcasting involves more social, but not more self-related cognitions than the control condition.	*vs.*	*H6:* Narrowcasting involves more social and more self-related cognitions than the control condition.	*H6 Parallel Processes*
H3: Narrowcasting engages more social cognitions than broadcasting. *H4:* Broadcasting engages more self-	*vs.*	*H7:* Self-related and social cognitions are stronger during narrowcasting than during broadcasting.	*H3 (Trade-Off **and** Parallel Processes) & H7 (Parallel Processes)*

related cognitions than narrowcasting.	

Measuring Self-Related and Social processes with Neuroimaging

The hypotheses outlined in Table 4.1 require the measurement of basic psychological processes, namely self-related and social processing. This implies several measurement issues. First, these broad categories of thought processes may be expressed as a number of different motivations depending on the context (Berger, 2014; Cappella et al., 2015; Scholz et al., 2017). For instance, self-related processing may manifest as self-presentational concern or self-enhancement. Social processing might be associated with the wish to help somebody or to start a funny, relationship-building conversation. Second, each of these motivations might impact sharing within or outside of conscious awareness. Third, given the possibility of the co-occurrence and interactions between self-related and social processes, sequential, post-hoc measurement might be vulnerable to memory bias and introduce unintended order effects. Consequently, well-known consequences of self-report measures (e.g. Nisbett & Wilson, 1977; Wilson & Nisbett, 1978) limit our ability to distinguish between the trade-off and parallel-processes accounts of narrow- and broadcasting through this method alone.

Neuroimaging methods such as functional magnetic resonance imaging (fMRI) can provide additional, unique information about sharing decisions that can ultimately help to triangulate the underlying mechanisms of sharing (Baek et al., 2017; Meshi et al., 2015; Scholz et al., 2017; Tamir & Mitchell, 2012). Specifically, fMRI provides an estimate of neural activity in real-time and across the entire brain while participants consider sharing content with others. This allows simultaneous measurement of a multitude of potential processes as they unfold in an unobtrusive manner.

We rely on large existing literatures of hundreds of brain mapping studies which have identified neural substrates of self-related and social thought. The results of these studies are meta-analytically summarized on the open-access database Neurosynth (Yarkoni, Poldrack, Nichols, Van Essen, & Wager, 2011). Using this database, we identified region of interest (ROI) masks consisting of voxels implicated in self-related and social processing. We then analyzed the intensity of neural activity during narrow- and broadcasting within each ROI (compared to a control condition and compared to each other) as a proxy for the extent to which participants engage in social- and self-related processing. The self-related processing mask consists of clusters of brain voxels located mainly within medial prefrontal cortex (MPFC) and precuneus/posterior cingulate cortex (PC/PCC) and thus converges with other meta-analyses of the neural correlates of various types of self-related processing (Murray et al., 2012). In addition to clusters within ventral and dorsal MPFC, social processing regions include the temporal poles bilaterally as well as bilateral temporo-parietal junction (TPJ). These regions conform to other large-scale studies of social processing (Dufour et al., 2013). Given the diversity of self-related and social tasks that have been found to activate similar underlying neural regions, neural activity in these brain areas might constitute the greatest common denominator of various specific motivations relevant to sharing (Scholz et al., 2017).

Methods

To distinguish between the trade-off and parallel-processes perspectives (Table 4.1), we conducted a within-subject experiment in which participants were exposed to 80 News York Times (NYTimes) articles in different conditions in the Article task while we monitored their neural activity using fMRI. We have reported on orthogonal analyses of the same neural data elsewhere to understand the neural correlates of individual (authors redacted) and population-level sharing (authors redacted), averaging across (and thereby ignoring differences between) narrow- and broadcasting situations. Here, for the first time, we distinguish between narrow- and broadcasting.

Article Task

Inside the fMRI scanner, participants completed two task runs of the Article Task which consisted of 40 trials each (Figure 4.1). In the current analysis, we focus on three within-subject conditions (20 trials each) in which participants were asked to consider: (1) whether to share each article with a specific, close friend via a private Facebook message (narrowcasting), (2) whether to use a Facebook status update to post the article (broadcasting), or (3) whether a word shown on the screen (cancer/age/laws/fitness/science/nutrition/well-being) represented the article's main topic (control condition). In a fourth condition that is not analyzed here, participants decided whether they wanted to read the full text of the article after the scan. In an online survey prior to scanning, participants identified six Facebook friends who they had interacted with recently, and who they thought were interested in the general subject matter of the articles used here (physical activity and healthy living). In each narrowcasting trial, participants were asked to consider sharing with one randomly chosen individual from this list. The control condition was designed to subtract neural processes associated with exposure to the visual stimuli, reading NYTimes articles about health, and being in the fMRI experiment environment. Comparing each sharing condition to the control condition thus isolates neural activity associated with the specific processes of interest. Each trial lasted an average of 14.7 s, excluding fixation periods. The first screen informed participants about the trial condition and was visible for 1.5 s. Next, participants read the article's title and abstract, while considering a question corresponding to the current condition (e.g. whether to narrowcast the article). Reading speed was controlled through additional auditory presentation of the articles by a female voice through MRI compatible headphones. The reading screens were presented for 8 (N = 16 trials), 10 (N = 40 trials) or 12 (N = 24 trials) seconds, depending on the word count of the text and the length of the corresponding audio file. For each participant, article length was counterbalanced across task runs and conditions. An, on average, 1.5 s (range 0.5 – 4.7 s) fixation period followed the reading screen. Afterwards, depending on the trial condition, participants had 3 s to rate their likelihood to narrowcast, broadcast, to read the article's full text, or their certainty that the word presented on the screen represented the article's main topic (control trials). Ratings were made on 5-point Likert-type scales and followed by a second fixation period with an average length of 2 s (range 1 - 4.7 s). Optimized fixation time distributions were obtained using Optseq2 (Dale, Greve, & Burock, 1999). All analyses are based on neural activity extracted from task screens which presented article headlines and abstracts, only.

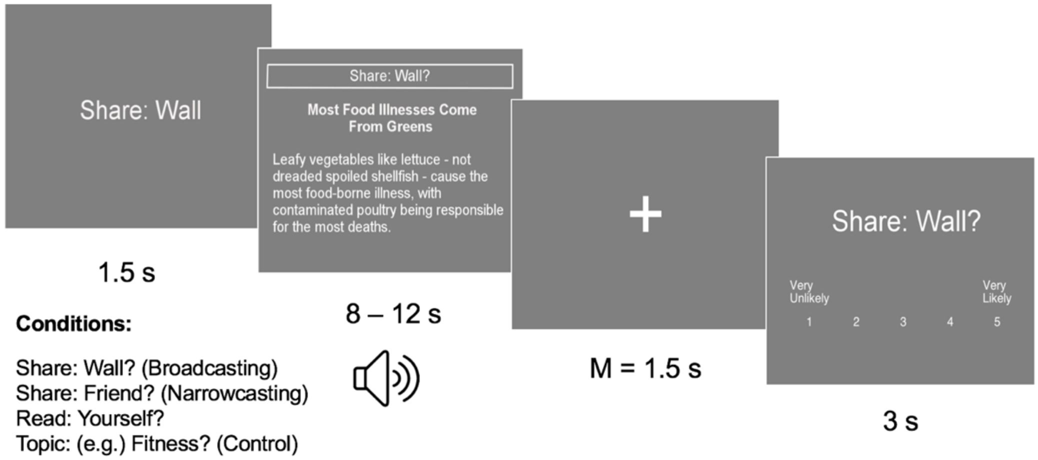

Figure 4.1. Article sharing task (example trial in broadcasting condition)

New York Times Article Sample

The 80 headlines and abstracts used in the Article Task were originally published in the health section of the NYTimes website (www.nytimes.com). All articles were sampled from a census (excluding certain article categories to preserve homogeneity in article format) of articles (N = 760) published between 11 July 2012 and 28 February 2013 and described in detail by Kim (2015). Inclusion criteria were comparability regarding word count and topic. To this end, we conducted a keyword search to identify articles that discuss healthy living and exercise. Keywords included: physical activity, exercise, running, fitness, swimming, soccer, skiing, food (excluding "Food and Drug Administration"), walking, eating, nutrient, nutrition, diet, gluten, calcium, vitamin, caffeine, carbohydrates, obesity, cholesterol, and weight. Four irrelevant articles were excluded before we sub-selected 80 articles from the resulting sample (N = 139) to meet fMRI time constraints. This final selection was made based on word count comparability (range: 21 and 35 words).

Participants

Forty-three participants were sampled from respondents of an online survey which was part of a project about social influence and information diffusion[5]. In addition to completing this online screening survey, selected participants attended a lab session which included a 60-min fMRI scan. Screening criteria included conventional fMRI eligibility criteria, namely no history of neurological or psychiatric disorders, being right-handed, having no metal in their body, no current pregnancy or breast-feeding, and currently not taking psychiatric medication or illicit drugs.

Two participants were excluded from all analyses. One of them was only presented with three out of four conditions of the Article Task and the second showed poor normalization to the template brain. For four additional participants we only analyze a sub-set of trials due to data loss affecting one task run ($N = 1$), excessive head movement affecting one task run ($N = 2$), and technical issues leading to 23 articles being shown to one participant twice. For this latter person, 57 trials represent initial article exposures and are thus included in the analyses. The final sample of 41 participants (29

[5] Note that a larger sample of participants was screened for participation in this study. Forty-three participants were chosen based on the ego-betweenness centrality of their Facebook networks in order to answer a research question that is orthogonal to the analyses discussed here (see the online pre-registration document for details; authors redacted, 2015).

female) was aged between 18 and 24 ($\bar{M}$ = 20.6, SD = 2.1). The Institutional Review Board at our institution reviewed and approved all study procedures.

MRI Image Acquisition

Thirty-nine participants underwent fMRI scanning using a 3-Tesla Siemens Magnetom TrioTim scanner (32-channel head coil). Two participants were scanned using a Siemens Prisma 3 Tesla whole-body MRI (64-channel head/neck array). Both scanners were operated using identical specifications (described below), except for slice numbers acquired for functional T2*-weighted images (54 at the TrioTim and 52 at the Prisma scanner) which we took into account during slicetime correction.

T1-weighted anatomical images were acquired using an MPRAGE (magnetization-prepared rapid-acquisition gradient echo) sequence (160 axial slices, slice thickness = 1 mm, TI = 1110 ms, FOV = 240 mm, voxel size = 0.9 x 0.9 x 1). A structural, in plane, T2-weighted image (176 axial slices, slice thickness = 1 mm, voxel size = 1 x 1 x 1) was collected for the purpose of two-stage co-registration. While participants completed the Article Task, we collected five-hundred volumes of functional images per run using a T2*-weighted reverse spiral sequence (TR = 1.5 s, - 30 degree tilt relative to AC-PC line, flip angle = 70°, TE = 25 ms, voxel size = 3 x 3 x 3 mm, slice thickness = 3 mm, FOV = 200 mm, multiband acceleration factor = 2, interleaved slice order).

A Priori Regions of Interest (ROIs)

Two region of interest (ROI) masks were extracted from the Neurosynth "reverse inference"[6] meta-analysis tool: a self-related processing ROI based on 903 studies using the search term "self", and a social processing ROI based on 104 studies using the search term "mentalizing". Mentalizing refers to thoughts about others' mental states (Frith & Frith, 2006), a highly relevant type of social processing for information sharing and social interactions (Baek et al., 2017; Dietvorst et al., 2009; Falk et al., 2013; Meshi et al., 2015; Scholz et al., 2017). We further intersected these ROIs to create two additional masks representing regions sensitive to self-related, but not social processing and vice versa (see Figure 4.2A).

Imaging Data Analysis

Statistical Parametric Mapping (SPM8, Wellcome Department of Cognitive Neurology, Institute of Neurology, London, UK) was used for all data-preprocessing steps described below except those which are explicitly identified as using tools from AFNI (R. W. Cox, 1996) or FSL (S. M. Smith et al., 2004). The initial five volumes of each functional run were not recorded to allow the BOLD signal to stabilize. AFNI's 3dDespike tool was used to despike functional images. Subsequently, FSL sinc interpolation was used for slice time correction, before images were realigned spatially to the first image in SPM8 and co-registered to structural and functional images in two

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[6] As noted on neurosynth.org: "Reverse inference map: z-scores corresponding to the likelihood that a term is used in a study given the presence of reported activation (i.e., P(Term|Activation))", in other words reverse inference maps illustrate brain regions where activation is associated with the specified function.

stages, each of which was six-parameter affine. Thereby, the in-plane T2-weighted image was registered to the mean functional image before the high-resolution T1 image was registered to the in-plane image. To select voxels to be included in statistical modeling, high-resolution structural images were then segmented into cerebral spinal fluid, white and gray matter. These masked structural images were normalized in SPM8 to the skull-stripped Montreal Neurological Institute (MNI) template available in FSL ("MNI152_T1_1mm_brain.nii"). Functional images were finally smoothed using a Gaussian kernel (8mm FWHM). For each participant, we modeled functional neuroimaging data using fixed effects models within the general linear model in SPM8, using SPM's canonical difference of gammas HRF. Six rigid-body translation and rotation parameters derived from spatial realignment were included in first-level models as nuisance regressors. Data were further high-pass filtered with a 128 s cutoff. Finally, random effects models were implemented in SPM8.

Neural Model of the Article Task

We modeled the Article Task using the following boxcar functions: one function describing all condition screen periods, four functions describing reading screen periods pooled by task condition, eight functions describing each rating screen type separately pooled by task condition, a function describing entire trials in which participants failed to provide a rating. Fixation periods were pooled into a baseline rest regressor. For the participant who was exposed to several articles twice, repeated exposure trials were pooled into a separate regressor of no interest. The contrasts of interest for the current analysis are: (1) reading screens during narrowcasting vs. control trials, (2) reading screens during broadcasting vs. control trials, and (3) reading screens during narrowcasting vs. broadcasting trials.

On average, reaction times for providing ratings in control trials ($\bar{M}$ = 0.94 s, *SD* = 0.26) were significantly slower than reaction times in narrowcasting ($\bar{M}$ = 0.74 s, *SD* = 0.18, $T(40) = 7.09$, $p < .001$) and broadcasting trials ($\bar{M}$ = 0.82, *SD* = 0.23, $T(40) = 2.88$, p = .006). Reaction times in broadcasting trials were further significantly slower than those in narrowcasting trials ($T(40) = 3.23$, p = .002). This may indicate differing demands on processing resources. Consequently, a second model was constructed to test the robustness of the results. In this model, four additional regressors were added to represent reading screen periods for all four task conditions modulated by a parametric modulator of reaction time (i.e., allowing us to control for reaction time).

ROI and Whole Brain Analyses

Average parameter estimates of neural activity across all voxels were extracted for each participant, contrast, and ROI using MarsBaR (Brett et al., 2002). These values were then divided by the constant to convert them to percent signal change. One-sample t-tests were computed in R to test for significant percent signal change in each contrast (R Team, 2015). All tests were two tailed to account for competing hypotheses. As a robustness check, we further tested the effects of individual differences in Facebook friend counts, and hence size of each participant's potential broadcast audience, on these results by computing bivariate correlations between percent signal change in each of the contrasts and each of the regions and friend count. None of these correlations was significant.

Whole brain analyses combined contrast images using random effects models in SPM8. FDR correction at $p < .05$ assured multiple comparison correction.

Results

First, we separately examined the role played by self-related and social processing in narrow- and broadcasting by comparing each sharing condition to control. Figure 4.2B shows increased activity within both hypothesized self-related and social cognition ROIs during both types of sharing relative to control judgments. Parallel results were obtained using the *self exclusive of social* (narrowcasting>control: $\overline{M} = 0.18$, $T(40) = 11.81$, $p < .001$, broadcasting>control: $\overline{M} = 0.14$, $T(40) = 10.73$, $p < .001$) and *social exclusive of self* (narrowcasting>control: $\overline{M} = 0.09$, $T(40) = 6.64$, $p < .001$, broadcasting>control: $\overline{M} = 0.07$, $T(40) = 5.57$, $p < .001$) ROIs and all results remained highly significant when controlling for reaction time. In sum, we find direct overlap between the neural processes involved in the two sharing contexts, which is consistent with the parallel-processes (H5 and 6), but not trade-off perspective (H1 and 2; Table 4.1).

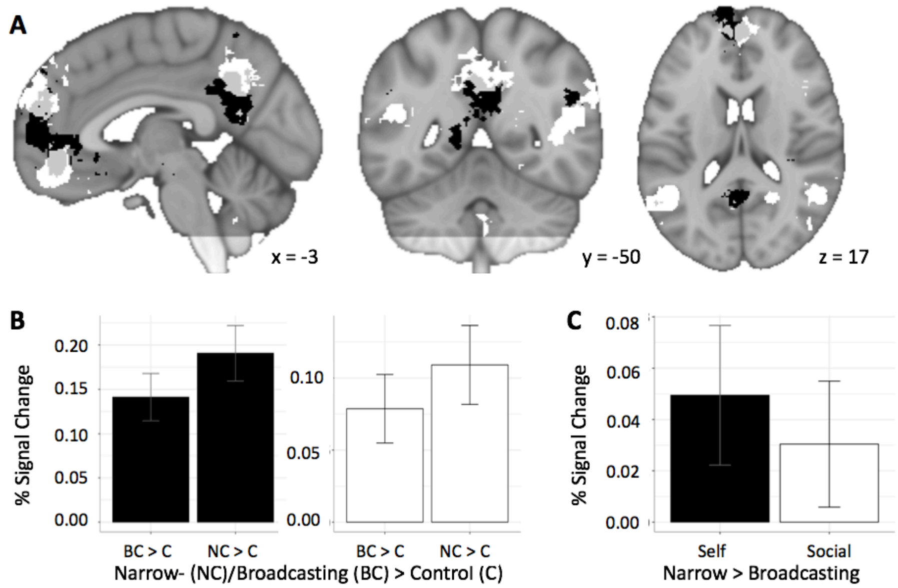

Figure 4.2. (A) Regions of interest (ROIs) based on reverse inference maps calculated using neurosynth.org. Black: Voxels that are exclusively part of the self-related processing ROI, White: Voxels that are exclusively part of the social processing ROI, Grey: Overlap; Coordinates correspond to the Montreal Neurological Institute (MNI) standard space.; (B) Percent signal change in self- and social-processing ROIs for the broadcasting (BC) > control (C), and the narrowcasting (NC) > control contrasts.; (C) Percent signal change in self- and social processing ROIs for the narrowcasting > broadcasting contrast.; Error bars represent 95% confidence intervals; N = 41

Figure 4.2C shows the results of a one sample, two-sided t-test assessing percent signal change during narrow- compared to broadcasting trials. Results show significantly stronger activation in both the self-related ($\bar{M} = 0.05$, $T(40) = 3.56$, $p < .001$) and social cognition ($\bar{M} = 0.03$, $T(40) = 2.43$, $p = .02$) ROIs during narrowcasting trials, supporting H3 which is implicated in both the trade-off and parallel processes accounts but not trade-off H4. In contrast, parallel processes H7 is supported (see Table 4.1). These results are replicated in the *self exclusive of social* ($\bar{M}$ = 0.04, *T(40)* = 3.16, p = .003) and the *social exclusive of self* ($\bar{M}$ = 0.02, *T(40)* = 2.02, p = .05) ROIs and all results remain significant in the neural model that controls for reaction time, except the test for percent signal change in the *social exclusive of self* ROI which becomes marginal ($\bar{M}$ = 0.02, *T(40)* = 1.65, p = .10). Again, our data lend stronger support to an account of differences between broad- and narrowcasting that focuses on the intensity of parallel-processes rather than the type of process.

After completing our planned ROI analyses, we conducted exploratory whole-brain analyses to identify clusters of significant activity outside of the ROI masks differentiating narrow- and broadcasting from the control condition, respectively, and clusters of significant activity differentiating narrow- from broadcasting (Figure 4.3, Table 4.2). Whole brain results show large clusters overlapping with regions within both the self-related and social ROIs that are more involved in both narrow- and broadcasting, compared to control. In addition, consistent with the finding of longer reaction times during the control condition, control trials compared to narrow- and broadcasting trials showed stronger involvement in areas such as the dorsolateral prefrontal cortex which is thought to be involved in effortful processing, among others. Analyses comparing narrow- to broadcasting confirm the heightened intensity of neural activity in regions associated with self-related and social processing during narrowcasting which was shown in the ROI analyses. In addition, we identified several regions outside of our a priori

ROIs which showed heightened activity during broadcasting compared to narrowcasting, including the lateral prefrontal cortex and anterior cingulate cortex.

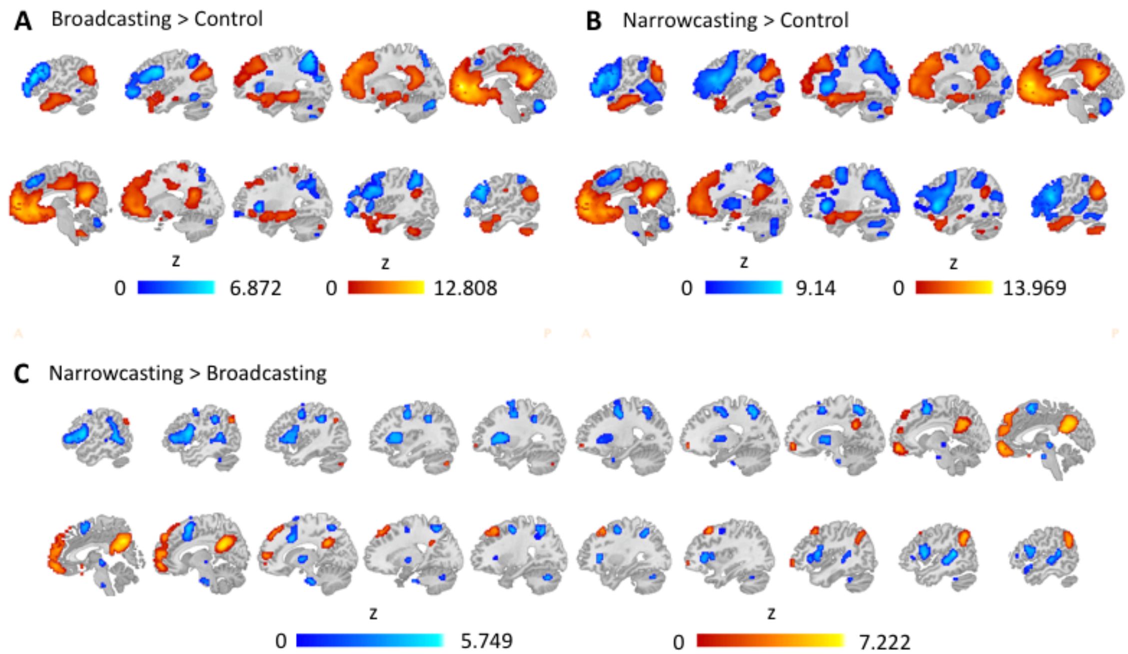

Figure 4.3. Exploratory whole brain results showing voxels positively (warm colors) or negatively (cold colors) associated with the following contrasts: (A) narrowcasting greater than control, (B) broadcasting greater than control, and (C) narrowcasting greater than broadcasting; Whole brain maps are FDR corrected at $p < .05$. Coordinates refer to the Montreal Neurological Institute (MNI) standard space. In each sequence, the first slice of the first row is located at $x = -52.5$, and the first slice of the second row at $x = 5$ (2.5 in panel C).

Table 4.2. Whole brain analysis comparing narrow- and broadcasting to the control condition, and narrow- to broadcasting

Regions	R/L	X	Y	Z	T	K
Narrow- > Broadcasting						
Precuneus	R	3	-52	25	7.22	579
Precuneus	R	3	-61	34	7.11	
Ventro-medial prefrontal cortex	R	3	59	-8	5.93	943
Middle medial prefrontal cortex	R	6	56	13	4.73	
Dorso-medial prefrontal cortex	R	6	53	40	4.19	
Right temporo-parietal junction	R	48	-61	43	5.48	195
Left temporo-parietal junction	L	-51	-70	40	4.10	52
Left temporal lobe	L	-69	-22	-14	4.90	99
Right temporal lobe	R	63	-7	-20	4.38	39
Narrow- < Broadcasting						
Right temporal lobe	R	48	-40	13	5.75	141
Lateral frontal cortex	L	-51	8	16	5.26	700
Lateral frontal cortex	L	-51	35	7	4.74	
Insula	L	-30	20	7	4.27	
Lateral frontal cortex	R	45	11	13	5.00	267
Insula	R	33	29	10	3.84	
Supplemental motor area	R	6	8	58	4.76	514
Anterior cingulate cortex	R	12	11	43	4.41	
Superior frontal cortex	L	-24	-10	49	4.14	
Parietal lobe	L	-18	-61	55	4.67	129
Supra marginal gyrus	L	-57	-43	28	3.72	
Parietal lobe	R	24	-58	55	4.57	112
Inferior parietal lobe	L	-42	-40	40	4.52	292
Temporal lobe	L	-51	-46	10	4.49	
Precentral gyrus	R	27	-4	55	4.23	52
Brain stem	R	12	-19	-35	4.16	62
Brain stem	M	0	-25	-2	4.09	24

Note. BA = Brodmann area, R = right, L = Left, M = Medial, K = number of voxels within cluster, X, Y, and Z coordinates correspond to the Montreal Neurological Institute (MNI) standard brain. Clusters are separated by horizontal lines. The first row within each cluster shows the peak voxel. Whole brain maps were FDR corrected at $p < .05$, K > 20. All coordinates (except peaks) were chosen to represent cluster extends.

Discussion

Information sharers confronted with an audience of few, well-defined others (narrowcasting), or a large, loosely defined crowd (broadcasting) may arrive at their sharing decisions through different psychological processes. Research has shown strong links between such thought processes underlying sharing decisions and important downstream outcomes such as persuasion and virality (Falk & Scholz, 2018). We have outlined two competing accounts of psychological antecedents of broad- and narrowcasting. The trade-off perspective suggests that, when broadcasting, sharers are primarily focused on presenting themselves in a positive light, while smaller, well-defined audiences in narrowcasting situations demand greater attention and lead to greater other-focus (e.g. Barasch & Berger, 2014). The parallel-processes perspective, on the other hand, suggests that both self-related and social processing are key to sharing with small and large audiences, and that narrow- and broadcasting are differentiated instead by the intensity of these processes. We used fMRI to test competing hypotheses generated by these two accounts of differences in the psychological drivers of broad- and narrowcasting.

Our data are consistent with a parallel-processes account showing higher activity in both brain regions associated with self-related and social cognition when participants were considering either narrow- or broadcasting relative to a control condition. In addition, neural activity during narrow- and broadcasting differed in intensity, such that both processes showed stronger involvement during narrow- compared to broadcasting.

These results are consistent with the idea that sharing decisions are made on the basis of both social and self-related considerations irrespective of audience size and that the two types of thought processes are not necessarily mutually exclusive or negatively correlated. Neural activity within self-related and social processing systems in the brain might originate in sharers' considerations of the consequences of sharing for themselves and their self-image and for their social interactions and relationships (Scholz et al., 2017). Holding a positive self-image and social belonging are two central human motives which are relevant to behaviors and cognitions across domains (Baumeister & Leary, 1995; Mezulis et al., 2004) and these core motives are strongly interconnected. For instance, psychologists have argued that a person's self-concept is often defined in terms of inclusion and exclusion from certain social groups and practices (Bretherton, 1991; Brewer, 1991). In the context of sharing information with others, researchers have demonstrated relationships between self-focused actions (e.g., disclosure of self-related information) and social motivations and outcomes (e.g., relationship management and changes in trust) (Steijn & Schouten, 2013; Utz, 2015). Adding to these insights about sharing outcomes, our data suggest that self-related and social sharing motivations tend to co-occur during sharing decisions in both narrow- and broadcasting situations.

Although self-related and social processes both played some role in narrow- and broadcasting, both types of neural activity were significantly stronger during narrow- compared to broadcasting. This finding further supports the parallel-processes account which posits that narrow- and broadcasting are differentiated by the intensity rather than the involvement of two parallel-processes. Again, this difference might be due to the affordances of each sharing mode. Small, well-defined narrowcasting audiences might be associated with higher certainty regarding the knowledge, opinions or past behavior of one's audience. Increased neural activity during narrowcasting might thus reflect the greater tendency to integrate and translate this knowledge into expectations regarding the self-related and social consequences of sharing.

Finally, expanding on both the trade-off and parallel processes accounts, our exploratory whole brain analysis identified clusters within lateral prefrontal cortex and anterior cingulate cortex which were activated more strongly during broadcasting compared to narrowcasting. Similar regions have been implicated in cognitive control, effortful processing, and emotion regulation (Buhle et al., 2014, www. neurosynth.org). For instance, these areas are active when participants reappraise their reactions to emotionally evocative stimuli by imagining that the depicted events are not relevant to them or happened a long time ago (i.e. through psychological distancing). In the context of broadcasting, these processes might indicate the greater psychological distance between broadcasters and their audience which may be due to uncertainty about the composition and potential reactions of ill-defined broadcasting audiences (Krämer & Haferkamp, 2011; Marwick & boyd, 2011). The cognitive control network is also involved in broader effortful processes to adapt and react appropriately in situations which are not highly automatized (Wager, Jonides, & Reading, 2004). Thus, another possible interpretation is that broadcasting is more effortful or deliberate, possibly because shared content is judged and seen by more individuals and sharing might thus be perceived as more consequential. Future research aimed at exploring psychological differences between narrow- and broadcasting next to those identified with regards to self-related and social processing will complement the theoretical account presented here.

Additionally, it will be important to understand the effects of differences in psychological antecedents of sharing decisions on downstream behaviors. Barasch and Berger (2014) found that participants were more likely to share information deemed useful to the audience when narrowcasting and more likely to share information which made the sharer look good during broadcasting. Prior work shows associations between variation in sharing behavior and thought processes measured while sharing decisions are being made (Baek et al., 2017; Scholz et al., 2017). To better understand these effects, it will be crucial to examine whether differences in the intensity of social and self-related processing in narrow- and broadcasters are related to these differences in sharing behavior. Next, identifying the source of these motivational differences will be informative for interventional approaches. Another relevant future direction concerns the effects of communication context on self-related and social processing in narrow- and broadcasters. The parallel-processes account does not posit that all instances of narrow- and broadcasting are necessarily governed to an equal extent by social and self-related considerations. Instead, the relative contributions can vary across contexts (e.g. different media).

Finally, it is important to note inherent limitations of inferences about psychological processes based on observations made using fMRI (Poldrack, 2006), for instance, because more than one type of process may engage activity in the same brain region. In this project, we strengthened these reverse inferences by examining activity in regions in which activity is regularly observed when study participants engage in self-related and social processing according to consensus across hundreds of neuroimaging studies. In addition, the involvement of these specific processes was hypothesized a priori based on a strong theoretical background. Finally, the results presented here demonstrate shared processes across narrow and broadcasting, regardless of the specific psychological labels ascribed to the brain activation.

In sum, the size of the audience attending to a communicator who is considering to share information has specific effects on the psychological processes underlying sharing decisions. Our data show that both self-related and social processing occurs when communicators consider sharing via narrow- and broadcasting. However, both types of processing occur more intensively during narrowcasting. That is, narrow- and broadcasting afford different intensities of two processes known to be highly relevant for downstream outcomes concerning the diffusion of information such as persuasion and virality (Falk & Scholz, 2018).

CHAPTER 5: A NEURAL PROPAGATION SYSTEM: NEUROCOGNITIVE AND PREFERENCE COUPLING IN INFORMATION SHARERS AND THEIR RECEIVERS

Abstract

Interpersonal communication shapes and catalyzes the spread of information through populations. We propose that propagation between information sharers and receivers is driven by neural coupling in brain systems associated with valuation, self-reflection, and social cognition. To test this hypothesis, we measured neural activity as well as content-related preferences in communicators who share information while they were exposed to news articles and in receivers exposed to communicator-composed messages about the same articles. We observed significant neurocognitive synchrony between communicators and receivers within the hypothesized regions of interest, but not within other areas of the brain associated with saliency and attention. This effect held irrespective of the news article content, sharer, and receiver characteristics, suggesting that it is a characteristic of human communication rather than a by-product of the situation. Next, we tested whether the observed coupling could be explained by exposure to shared content; Here, we observed coupling only for communication partners, not randomly paired individuals who were exposed to the same content without interacting, suggesting that neurocognitive coupling is driven by the interpersonal communication instead. Finally, the extent of neurocognitive coupling covaried with the successful propagation of content-related preferences. Together, our findings suggest that sharer-receiver coupling, especially in a neural propagation system consisting of regions

associated with valuation, self-reflection, and social cognition, supports the interpersonal transmission of information and preferences across contexts. These findings highlight not only core neurocognitive processes relevant to social influence and the spread of ideas, but also more fundamental elements of human communication.

Introduction

Interpersonal communication shapes and catalyzes the spread of information through populations as is evident across multiple fields including the work on the diffusion of innovations, word of mouth, and interactions between mass and interpersonal communication (Berger, 2014; Cappella et al., 2015; Katz & Lazarsfeld, 1955; Rogers, 2003; Southwell & Yzer, 2007). What happens in the minds of communicators who share information with others and their receivers that facilitates this type of propagation? Beyond the processes that unfold in either party alone, we argue that successful propagation may be facilitated by synchronized or coupled activity across biological and behavioral systems (Mogan et al., 2017), including certain brain regions (Stephens et al., 2010). More specifically, given strong evidence of their involvement in both the processes that facilitate sharing decisions and persuasiveness in communicators (Baek et al., 2017; Falk et al., 2013; Scholz et al., 2017) and susceptibility to social influence in receivers (Cascio, Scholz, et al., 2015), we propose that brain regions associated with subjective valuation, self-reflection, and social cognition are central elements of this neural propagation system. The successful spread of information can bring communicators' and receivers' views and preferences into alignment (Falk et al., 2013). Here, we use neuroimaging to test whether coupling of brain activity within specific regions of interest also supports the transmission of information from communicators to receivers.

Information Propagation through Neurocognitive Sharer-Receiver Coupling

What is the meaning of sharer-receiver coupling? Research has revealed that activity across various biological and behavioral systems couples or synchronizes between interaction partners who engage in interpersonal communication. Coupling between human communicators has been identified in multiple domains, including linguistic patterns exhibited by communicators and their receivers (Branigan et al., 2000; Gonzales et al., 2009; Niederhoffer & Pennebaker, 2002), nonverbal cues (Cappella, 1996; Giles & Smith, 1979; Richardson & Dale, 2005), and brain activity related to the production and decoding of information (Hasson et al., 2012; Stephens et al., 2010). Further, both verbal and nonverbal synchrony of communication partners is advantageous, for instance in the context of learning processes, social relationships, attachment, and mutual understanding (Burgoon et al., 2007; Cappella, 1996, 1997b; Mogan et al., 2017; Semin, 2007). Relatedly, large bodies of research have shown that mirroring others is one of the ways in which people learn and behaviors spread (Bandura, 1986, 2001).

Here, we argue that this natural communicator-receiver coupling during interpersonal communication facilitates successful information propagation as well. Specifically, self-related, social, and value-related considerations are central drivers of both sharing decisions and persuasiveness in communicators (Baek et al., 2017; Falk et al., 2013; Scholz et al., 2017) and susceptibility to persuasion and influence in receivers

(Cascio, Scholz, et al., 2015). We argue that successful transmission of information, that is correspondence in the content-related preferences of communicators and receiver, is driven by communicator-receiver coupling during interpersonal communication. More specifically, coupled neural activity in regions associated with self-reflection, social cognition, and valuation may be particularly important in the facilitation of information propagation.

Components of the Neural Propagation System

Brain structures associated with self-reflection, social cognition, and valuation may be central elements of a neural system that supports information propagation between communicators and receivers. Each of these processes has been shown to be involved when communicators share information with others and when receivers are exposed to the shared information (Falk & Scholz, 2018).

Valuation, or the extent to which individuals value objects and concepts across a large variety of domains (from food, to money, to social encounters) covaries robustly with activity in the ventral striatum (VS) and ventro-medial prefrontal cortex (VMPFC) (Bartra et al., 2013). Recent work linked activity in the brain’s valuation system to the intention of individuals to share a message with others (Baek et al., 2017) and large-scale sharing behavior (Scholz, Baek, O’Donnell, Kim, et al., 2016). In the context of sharing, value-related neural activity might encode the perceived value of the act of sharing a piece of information with others (Scholz, Baek, O’Donnell, Kim, et al., 2016). In prior work, the extent to which sharers showed VS activity during initial information exposure predicted their success in communicating the content to a receiver (Falk et al., 2013). The act of sharing information itself might be a rewarding experience (Tamir et al., 2015). Next to these communicator-centered results, neural valuation signals in the VS and VMPFC co-vary with the susceptibility of receivers to influence by communicators (Cascio, Scholz, et al., 2015). Thus, the brain's value system is implicated in both successful sharing and receiving information. We argue that similarities in neural content valuation in communicators and receivers might originate in the propagation of key cognitions from communicators to receivers via neurocognitive coupling in the brain's value system during interpersonal communication.

Prior theorizing and empirical evidence (Baek et al., 2017; Berger, 2014; Falk & Scholz, 2018; Scholz et al., 2017) suggests that communicators consider the consequences of information propagation for their self-image and social relationships to determine the value of sharing a piece of information. If there is communicator-receiver synchrony in content valuation, communicators may also propagate self-related and social cognitions as contextualizing information and, thereby, further facilitate the propagation of information.

Brain regions most commonly involved in self-reflection include medial prefrontal cortex (MPFC) and posterior cingulate cortex (PCC) (Murray et al., 2012), and the brain's social cognition system encompasses clusters within bilateral temporo-parietal junction (TPJ), right superior temporal lobe, PCC, and MPFC (Dufour et al., 2013). Paralleling results in the valuation system, neural signatures of self-reflection and social cognition play a role in both sharing and receiving information. Activity in MPFC and PCC during initial information exposure (Falk et al., 2013), as well as neural signatures representing the entire self-reflection and social cognition systems (Baek et al., 2017) have been linked to sharing intentions, and large-scale sharing behavior (Scholz, Baek, O'Donnell, Kim, et al., 2016). MPFC activity is associated with being persuaded in information receivers (Chua et al., 2009; Cooper et al., 2015; Falk et al., 2010). Further, activity in TPJ, a key component of the social cognition system, is associated with increased success in communicating ideas with others (Falk et al., 2013) and with being influenced information shared by peers (Cascio, O'Donnell, et al., 2015). Extending this work, we suggest that sharer-receiver synchrony in brain systems of self-reflection and social cognition facilitates successful information propagation, and may constitute a missing link between research focused exclusively on communicators or receivers, respectively.

Alternative Hypotheses

We hypothesize that neural communicator-receiver synchrony is a natural characteristic of communication, and indicates the transmission of neural signals associated with valuation, self-reflection, and social cognition between communicators and their receivers. This process may facilitate information propagation. However, alternative explanations exist for each of these claims.

Although communicator-receiver coupling of activity within hypothesized brain regions may be evidence for a specialized neural propagation system, it is possible that coupling extends across a broader neural network. For instance, neural synchrony might represent general situational attention or saliency that is propagated from sharers to receivers, rather than more specific cognitions of the type we hypothesize. If so, sharer-receiver synchrony would be expected in neural systems encoding these kinds of processes instead of or in addition to synchrony in the hypothesized neural propagation system. Consequently, here we not only examine synchrony in key hypothesized brain regions, but also within areas encoding attention and saliency, namely the ventral and dorsal attention networks and the saliency system (Power et al., 2011)

Second, it is possible that neurocognitive synchrony is a function of the communication context rather than a characteristic of communication itself. That is, synchrony during interpersonal communication might be fully explained by the persuasiveness of sharers, the susceptibility of receivers to influence, or the quality of shared content. Prior work has focused on each of these communication context variables individually and demonstrated variation of propagation success across characteristics of sharers, receivers, as well as content. Specifically, in one study, the success of propagating sharer's preferences about TV show ideas was associated with the extent to which sharers showed neural activity in the TPJ, a region often implicated in social cognition, while they were first exposed to the shared contents (Falk et al., 2013). That is, communicators might differ in their ability to create communicator-receiver synchrony between content-related preferences (i.e. successful propagation). Demonstrating similar results for receivers, other work found that those participants who showed more TPJ activity when receiving the information that others' preferences differed from their own, were more likely to synchronize their preferences with those of their peers (Cascio, O'Donnell, et al., 2015). Finally, it is well documented that different pieces of content can vary substantially in their popularity and the extent to which they are propagated through social interactions (Cappella et al., 2015; Kim, 2015). To test the hypothesis that communicator-receiver synchrony is solely a function of communication context variables, we will control for variation in synchrony attributable to communicators, receivers, and shared content, to observe whether there is an effect of synchrony on information propagation success above and beyond these component parts.

Third, sharers and receivers are often exposed to partially identical content, especially in online environments. For instance, instant messenger services often display content previews when a hyperlink is shared together with a personal message composed by the communicator. Exposure to identical content such as movies (Hasson, Malach, & Heeger, 2010), TV shows and advertisements (Dmochowski et al., 2014; Imhof, Schmälzle, Renner, & Schupp, 2017), and political speeches (Schmälzle, Häcker, Honey, & Hasson, 2015), can lead to cognitive synchrony among audience members. However, this type of synchrony does not capture aspects of human interaction and can, in fact, exist in its absence. Here, we examine the possibility that synchrony is due to exposure to partially identical content (hereinafter called exposure effects) by comparing situations in which communicators and receivers are exposed to identical content and interact, and situations with partially identical content but without interaction.

The Current Study

In sum, we argue that synchrony in a neural propagation system involved in valuation, self-reflection, and social cognition parsimoniously connects separate literatures on propagation from the perspectives of communicators and receivers, and on synchrony in interpersonal communication encounters. We experimentally initiated online interactions between two groups of study participants (called “communicators” and “receivers”). Communicators retransmitted news articles via Facebook to assigned receivers. Results show that neurocognitive coupling selectively occurs in neural regions hypothesized to be part of the neural propagation system and that the strength of this synchrony is related to successful information propagation, expressed as coupling in content preferences.

Methods

Two groups of participants (“communicators” and “receivers”) formed two-step propagation chains (Figure 5.1). Communicators were exposed to headlines and abstracts of New York Times health news articles while performing the Article Task (described below) while we measured their brain activity using functional magnetic resonance imaging (fMRI). After seeing each article, communicators indicated their intentions to share the content with others. After the scan, sharers completed a Writing Task (described below) in which they composed short messages about the articles and further rated each article on the extent to which they perceived sharing it to be beneficial. Receivers were exposed to original article headlines and messages written about each article by assigned sharers while performing a variant of the Article Task inside the fMRI scanner. Receivers further provided sharing intention and perceived benefit ratings paralleling those collected from sharers. All study procedures were approved by the IRB at the University of Pennsylvania.

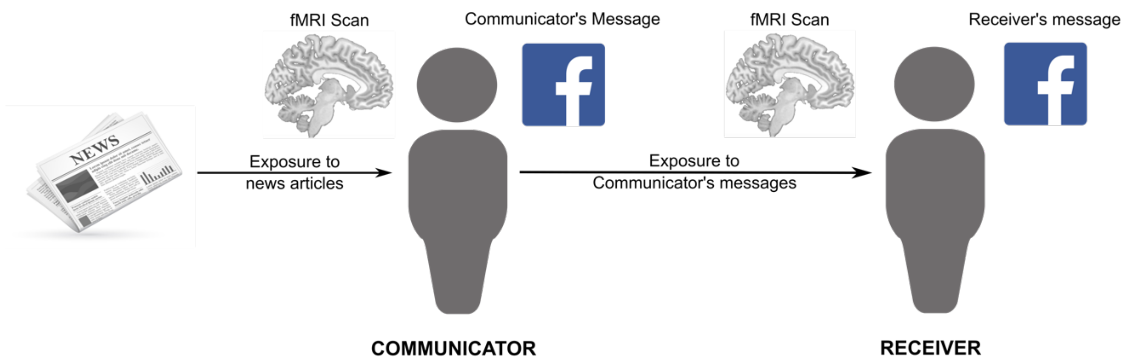

Figure 5.1. Study Design

Communicators

Forty-three "communicators" ($\bar{M}_{Age} = 20.58, SD_{Age} = 2.13$, 30 females) were selected from a larger sample of respondents to an online screening survey and invited to complete a three-hour study appointment including a 60-minute fMRI session. Eligibility requirements included standard fMRI safety criteria, namely having no metal in one's body, no history of psychiatric or neurological disorders, no current pregnancy, breast-feeding, or consumption of psychiatric or illicit drugs. All participants were right-handed. For purposes, orthogonal to the current investigation, respondents were further screened to be high or low in ego-betweenness centrality within their social networks.

Neural data was missing partially[7] (N=4) or completely[8] (N = 2) for some communicators, resulting in a final sample size of 41. Further, due to technical

[7] Partial data loss was due to missing data for one run of the fMRI task ($N = 1$), excessive head motion in one run of the fMRI task ($N = 2$), and errors in stimuli presentation ($N = 1$).

[8] One participant saw only three out of the four conditions during the Article Task, and one participant showed poor normalization to the template brain.

difficulties, sharing intention and benefit ratings (described below) were available for 33 and 34 sharers, respectively.

Receivers

A second group of 40 receivers ($\bar{M}_{Age} = 20.9, SD_{Age} = 2.05$, 28 females) were chosen using the same screening criteria and the same respondent pool utilized to select communicators. Communicators were excluded from participation as receivers. Receivers then completed a study appointment including an fMRI scan.

Neural data was partially excluded for one participant and completely discarded for a second[9], resulting in a final sample of 39 receivers. Additionally, technical difficulties led to reduced sample sizes for the analysis of sharing benefit preferences (N = 34).

New York Times Articles

Headlines and abstracts of 80 New York Times health news articles were propagated between communicators and receivers. The articles were sampled from a census of articles (excluding certain article categories to ensure homogeneity format, see (Kim, 2015) for details; *N* = 760) published online between 11 July 2012 and 28 February 2013 (7 ½ months).

Eighty articles were chosen maximizing comparability in subject matter (healthy living and physical activity), and length (title and abstract word count). A keyword search on the full set of articles included the following terms: exercise, fitness, physical activity,

[9] Exclusions were due to excess head movement, which affected the entire fMRI task for one participants, and one run for a second.

running, swimming, skiing, soccer, walking, food (excluding "Food and Drug Administration"), eating, nutrition, nutrient, diet, vitamin, calcium, carbohydrates, gluten, caffeine, cholesterol, obesity, and weight. This procedure retrieved 143 articles, of which four were removed because the topic was judged irrelevant. Finally, 80 articles of comparable lengths (word count $M = 29.43$, $SD = 3.87$; Range = 21 to 35) were selected to adhere to time restrictions during the fMRI scan.

Neural Regions of Interest

We relied on meta-analyses and large-scale studies in social neuroscience and neuroeconomics to define brain regions of interest (ROIs) related to valuation, self-reflection, and social cognition (Figure 5.2A) which were used to operationalize neural activity within the hypothesized neural propagation system. Specifically, the neural valuation system includes clusters in VS and VMPFC derived from a large meta-analysis of studies in neuroeconomics (Bartra et al., 2013). The self-related processing ROI consists of regions within MPFC and PCC, which are commonly activated by self-reflection (e.g. about one's personality characteristics; Falk et al., 2016). Finally, the social cognition ROI includes clusters in ventral, middle and dorsal MPFC, PCC, bilateral TPJ, and right STS, which are often activated when participants consider the thoughts and mental states of others (called mentalizing; Dufour et al., 2013).

In addition, we selected neural regions implicated in attention and saliency (Figure 5.2B), using a large atlas of 264 brain regions which describe the functional organization of the human brain in healthy adults (Power et al., 2011). Specifically, we defined 8 mm spheres around the nine coordinates that are part of the ventral attention network, eleven coordinates of the dorsal attention network, and 18 coordinates of the salience network. All sub-clusters within the same neural system were combined into a single mask, representing the system as a whole.

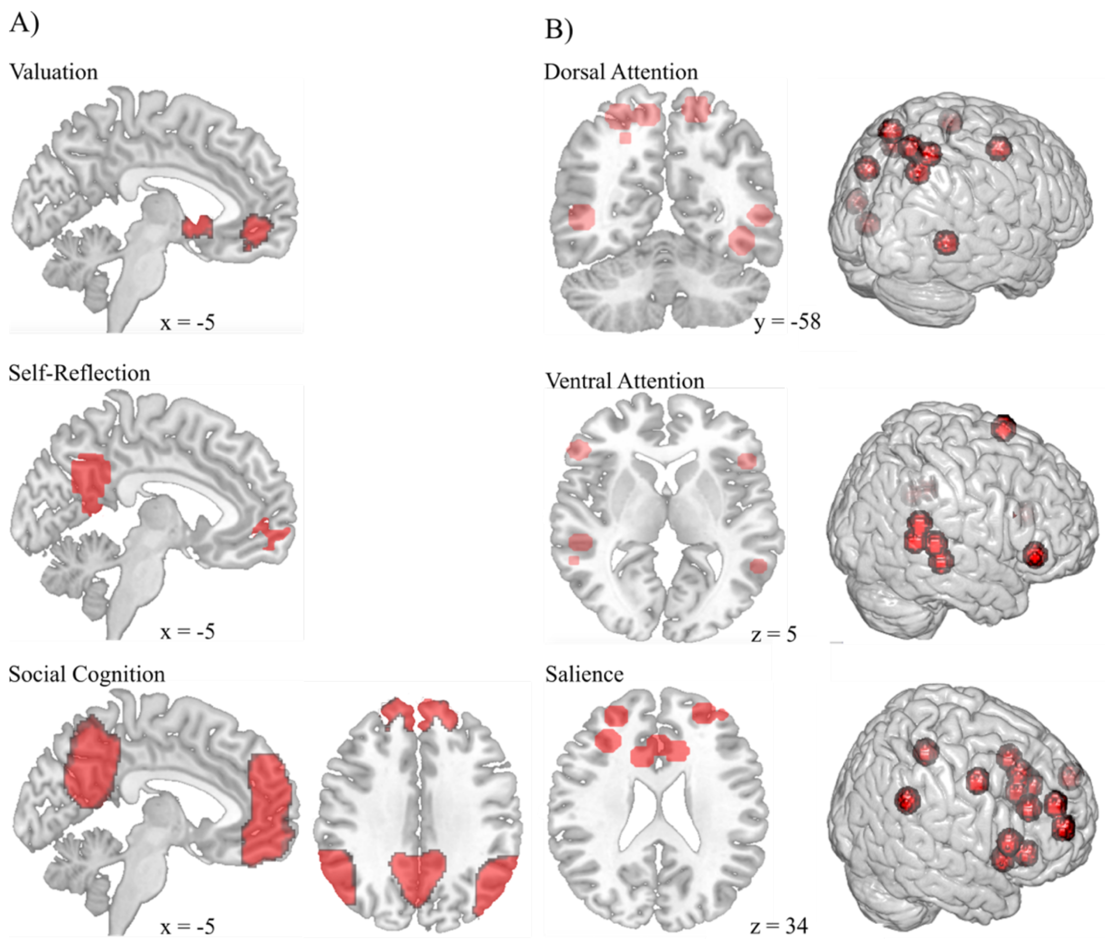

Figure 5.2. Regions of Interest A) Proposed neural propagation system, B) Attention and salience systems, coordinates indicate slice locations within the Montreal Neurological Institute (MNI) space

Article Task - Communicators

During the fMRI session, communicators were exposed to the original headlines and abstracts of the 80 articles[10] described above in four conditions (Figure 5.3A) which are described in detail elsewhere (Baek et al., 2017). In this analysis, we focused on data extracted from 40 trials, in which participants viewed article headlines and abstracts with the goal of deciding whether to share the article via private Facebook messages (narrowcasting condition) or by posting them on their Facebook wall (broadcasting condition). For the purpose of the analyses presented here, trials from these two sharing conditions are combined. After viewing each article, participants used a 5-point Likert-type scale to indicate their sharing intentions.

Writing Task - Communicators

Communicators completed the Writing Task after the fMRI scan. For each article shown in one of the two sharing conditions during the Article Task, they were asked to compose a short message which they might use to share the content on Facebook.

All messages were required to be at least 140 characters long. Before sharer-composed messages were propagated to receivers, we removed excessively used characters which some participants utilized as space fillers (e.g. a large number of dots). The final messages seen by receivers consisted of, on average, 130.7 characters (SD = 34.2).

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[10] To control for reading speed, headlines and abstracts were also presented in auditory format through scanner-compatible headphones while the text was presented on the screen.

Article Task - Receivers

Receivers completed a modified version of the Article Task which consisted of 42 trials due to time restrictions during the fMRI scan (Figure 5.3B). Each article's original headline was presented together with a description of the article and participants were instructed to read the text on the screen. Participants saw two types of article descriptions including either the original headline and abstract that was also seen by communicators (14 trials), or the original article headline and a message written by an assigned communicator during the Writing Task (28 trials). The analyses presented here focus on the latter propagation condition.

After seeing each article headline and description, receivers rated (a) their likelihood to share the article on their Facebook wall, and (b) their likelihood to share the article via a private Facebook message to one friend on 5-point Likert-Type scales (which paralleled those used in the narrowcasting and broadcasting conditions completed by sharers.

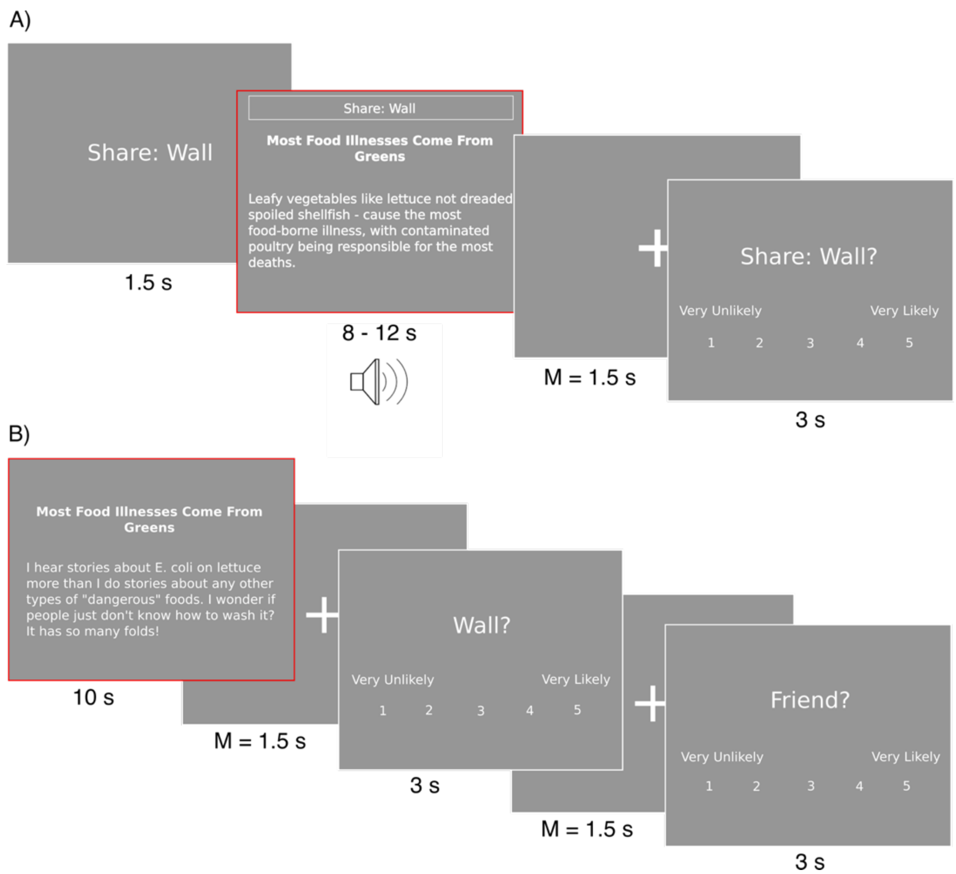

Figure 5.3. Article Task. Succession of screens seen for each trial by sharers (A) and receivers (B). Red frames indicate trial periods used for the analysis of cognitive synchrony. For sharers, article abstracts were categorized in three groups varying by the length of the text. Consequently, the reading screen was presented for 8 (N = 16), 10 (N = 40) or 12 (N = 24) seconds (counterbalanced across conditions). Trials for both sharers and receivers were separated by a randomly jittered inter-trial interval of an average of 2 seconds (range 1 - 4.7 seconds) for sharers and 2.9 seconds (range 0.5 – 11.5) for receivers.

Perceived Benefits of Sharing

After the fMRI scans, communicators and receivers provided a second type of preference rating regarding the articles seen in the Article Task. For each article, participants rated the extent to which they perceived the act of sharing the article in question to be beneficial on 7-point Likert-Type scales. Average sharing benefit ratings in sharers (M = 3.83, SD = 1.99) were slightly lower than those in receivers (M = 4.38, SD = 1.88).

Preference and Neurocognitive Coupling

To estimate preference coupling (i.e. successful propagation) and neurocognitive coupling between communicators and receivers, we regressed each measure collected in receivers on the corresponding variable assessed in assigned communicators within each communication dyad. Preference coupling was operationalized as communicator-receiver correspondence in sharing intention and sharing benefit ratings. With regards to sharing intention ratings, communicators provided one rating (either intention to broadcast or to narrowcast) for 40 articles. Receivers provided both narrow- and broadcasting ratings for all 42 articles shown to them. Intention coupling analyses considered all available trials (both from narrow- and broadcasting conditions). That is, we include whichever rating was provided for a given article by the communicator (*M* = 2.20, *SD* = 1.52), and an average rating across the narrow- and broadcasting rating provided for the same article by the receiver (*M* = 2.30, *SD* = 1.34)[11]. Neurocognitive coupling was assessed by regressing percent signal change in each brain region of interest in receivers on percent signal change in the same brain region in communicators.

Assigned Communicator-Receiver Communication Dyads

Specific communicators were systematically assigned to interact with specific receivers through the content and messages they shared during the Article Task (Figure 5.4). These assigned dyads were used to study communicator-receiver coupling as a result of interpersonal communication. Each receiver was exposed to messages from two pseudo-randomly assigned communicators, so that each pair of communicators was assigned to approximately the same number of receivers[12]. In the Article Task for communicators, articles were pseudo-randomly assigned to conditions so that a pair of communicators was exposed to an opposite set of 40 articles in the sharing (narrow- and broadcasting) and non-sharing (not analyzed here) conditions, respectively. This ensured a full set 80 articles shown in a sharing condition to the pair of communicators from which articles could be selected to be propagated to receivers. For each communicator,

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[11] Note that both communicator's and receivers' sharing intention ratings were strongly left-skewed. Consequently, results obtained from statistical tests including these variables need to be interpreted with caution.

[12] There were 17 usable groupings of two communicators, eleven of which were assigned to two receivers each, and six of which were assigned to three receivers. For the purpose of analyses orthogonal to the results presented here, each communicator pair consisted of a communicator whose social network showed high ego-betweenness centrality and a communicator with low ego-betweenness centrality. Communicator ego-betweenness centrality was counterbalanced across conditions.

14 propagated messages from the post-scan Writing Task were pseudo-randomly chosen to be shown to an assigned receiver.

Random Communicator-Receiver Dyads

To test the alternative hypothesis that coupling between communicators and receivers is due to the fact that both members of a propagation chain saw partly identical content (namely headlines; 'exposure effects') rather than the propagation of relevant cognitions, we created random communicator-receiver dyads who did not communicate with one another but were exposed to identical article headlines (Figure 5.4). For each trial and each receiver, we randomly chose an individual out of a list of communicators who (a) were not paired with this particular receiver for the propagation of any articles in an assigned communicator-receiver dyad, and (b) saw the same article in question in a sharing condition. That is neural activity in the randomly chosen communicator was collected in a situation identical to that experienced by the communicator who was originally assigned to the receiver in question. Both randomly assigned sharers and receivers were exposed to partially similar content (namely, the same headline), but did not communicate with one another through a Facebook message.

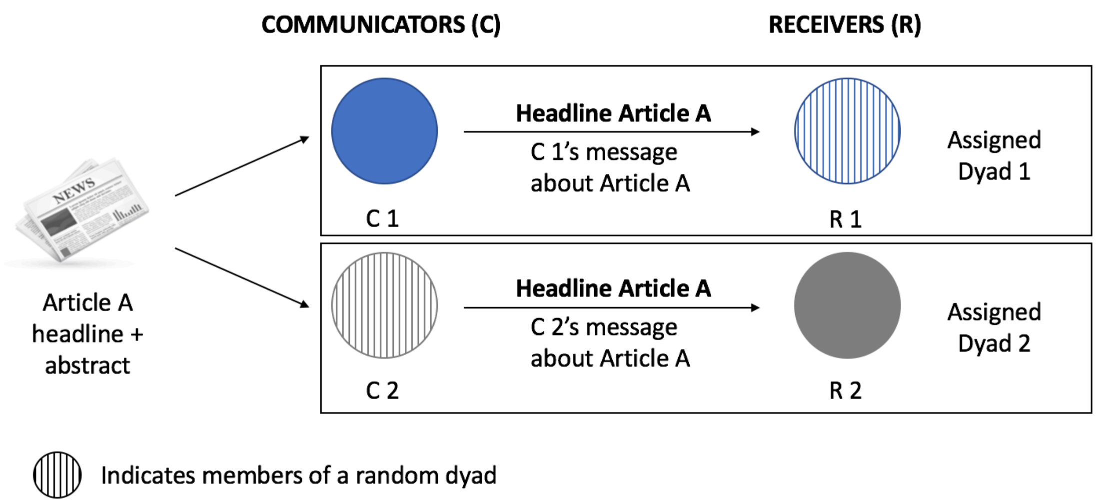

Figure 5.4. Assigned and random communicator-receiver dyads

fMRI Data Acquisition - Communicators

Neuroimaging data from 40 communicators were collected using a 3-Tesla Siemens Magnetom TimTrio scanner and a 32 channel head coil. One communicator was scanned using a Siemens Prisma 3 Tesla whole-body MRI with a 64-channel head/neck array for one sharer. Identical specifications where used on both scanners.

We captured neural activity during two runs of the Article Task (500 volumes each) using a T2*-weighted image sequence (TR = 1.5 s, TE = 25 ms, flip angle = 70°, -30 degree tilt relative to AC-PC line, 54 slices, FOV = 200 mm, slice thickness = 3mm, multiband acceleration factor = 2, voxel size = 3 x 3 x 3 mm). High resolution T1-weighted anatomical images were collected using an MPRAGE sequence (TI = 1110 ms, 160 axial slices, voxel size = 0.9 x 0.9 x 1). Finally, we collected an in plane, structural, T2-weighted image (slice thickness = 1 mm, 176 axial slices, voxel size = 1 x 1 x 1) to implement a two-stage co-registration procedure between functional and anatomical images.

fMRI Data Acquisition - Receivers

Neuroimaging data from 33 receivers were collected using a 3-Tesla Siemens Magnetom TimTrio scanner equipped with a 32 channel head coil. The other six participants were scanned on a Siemens Prisma 3 Tesla whole-body MRI with a 64-channel head/neck array. Receivers completed two runs of the Article Task (311 volumes each). All other MRI acquisition parameters were identical to those described for communicators.

Imaging Data Pre-Processing

For the analysis of data from both communicators and receivers, we used Statistical Parametric Mapping (SPM8, Wellcome Department of Cognitive Neurology, Institute of Neurology, London, UK), incorporating tools from AFNI (R. W. Cox, 1996) and FSL (S. M. Smith et al., 2004) during data pre-processing. The first 5 volumes of each run were not collected to allow for stabilization of the BOLD signal. The 3dDespike program as implemented in the AFNI toolbox was used to despike functional images. We then performed slice time correction using sinc interpolation in FSL. Subsequently, data were spatially realigned to the first image, and co-registered to functional and structural images using two six-parameter affine stages. First, mean functional images were registered to in-plane T2-weighted images. Next, high-resolution T1 images were registered to the in-plane image (total of 12 parameter affine). After co-registration, high-resolution structural images were segmented into gray matter, white matter and cerebral spinal fluid to create a brain mask used to determine voxels to be included in first- and second-level models. The masked structural images were then normalized to the skull-stripped MNI template provided by FSL (“MNI152_T1_1mm_brain.nii”). Finally, functional images were smoothed using a Gaussian kernel (8mm FWHM). The fMRI data were modeled for each participant using fixed effects models within the general linear model as implemented in SPM8, using SPM’s canonical difference of gammas HRF. The six rigid-body translation and rotation parameters derived from spatial realignment were also included as nuisance regressors in all first-level models. Data were high-pass filtered with a cutoff of 128 seconds. Random effects models that aggregate across participants for the Article Task were also implemented in SPM8.

fMRI Data Analysis - Communicators

We took an item-wise approach to modeling the Article Task (Figure 5.3A) using procedures similar to those employed elsewhere (Falk et al., 2012, 2016). Specifically, using a single boxcar function for each trial (i.e. each of the 80 articles), encompassing the 8-12 seconds reading screen of the task, we extracted neural activity in each of the ROIs during each trial as compared to baseline rest. Activity related to all cue and all rating screens was pooled into a separate regressor of no interest each. In addition, the model for one participant who accidentally saw several articles twice included an additional regressor of no interest for each second occurrence of an article. Fixation periods were pooled into a baseline rest regressor. Only data extracted from the 40 sharing trials completed by each participant were utilized in the analyses described below.

fMRI Data Analysis - Receivers

To analyze neural data collected while receivers completed the Article Task (Figure 5.3B), we used methods parallel to those applied to data obtained from communicators to yield comparable models. Specifically, using a single boxcar function for each of the 42 trials per participant, encompassing the 10 seconds reading screen of the task, we extracted neural activity observed during each trial as compared to baseline rest. A regressor of no interest was included for each of the two rating screens. Fixation periods were pooled into a baseline rest regressor. Only data from the 28 propagation trials were used in the analyses described below.

Analysis Steps

First, to identify optimal model structures for the estimation of the various types of cognitive and preference coupling, we fit a series of cross-classified mixed effects models. Specifically, a first set of models ('full models') estimated coupling effects and included random effect terms to allow intercepts and slopes to vary by sharers, receivers, and articles. Using Akaike and Bayesian Information Criteria (AIC, BIC) as well as log-likelihood ratio tests we compared these models to a second set of 'reduced models' which omitted the three random slopes. For the purpose of model comparisons, all models were fit using maximum likelihood (ML) estimation. When full models showed improved model fit compared to a reduced version of the model we further investigated which of the three random slope terms contributed to model fit by adding them individually to the reduced model and repeating the model comparison step. Each random slope which contributed to model fit was retained in the final models.

Second, we re-estimated the final models identified in step one using restricted maximum likelihood estimation (REML) to obtain unbiased estimates of the standard errors for each of the cognitive and preference synchrony effects.

Third, for the models that showed significant neurocognitive coupling effects in step 2, we tested whether there was a relationship between the extent of neurocognitive coupling and communicator-receiver preference coupling. To this end, we fit a set of models using REML, each specifying one of the cognitive or preference coupling effects in question and allowing for variation of intercepts across individual communicators, receivers, and articles. In addition, these models allowed the slopes of each coupling effect to vary across articles. We then used the random slope estimates from each of the cognitive coupling models and correlated them with each of the random slope estimate vectors for preference coupling effects to assess relationships between the extent of cognitive and preference coupling between communicators and receivers across articles.

Fourth, we tested the alternative hypothesis that significant coupling effects identified in step two might represent exposure effects rather than propagation between communicators and receivers. Specifically, we compared 'reduced' models used in step one fit to data from assigned communicators-receiver dyads to identical models fit to data from random dyads (who did not communicate with one another) using REML. These models did not include random slopes and thus did not control for coupling variation across communication context. This results in a broad definition of coupling and, thus, a strong test of differences between random and assigned dyads in several potential types of coupling. We obtained 1,000 bootstrapped estimates for cognitive and preference coupling effects in random communicator-receiver dyads. Subsequently, we computed mean estimates of coupling effects as well as standard deviations, T-values, degrees of freedom and p-values. We then compared coupling estimates derived from random dyads to those derived from corresponding assigned dyads by applying EQ 1 to obtain T-values and EQ 2 to obtain corresponding degrees of freedom.

$$\text{EQ 1}: T = (\beta_{assigned} - \beta_{random}) / \sqrt{se_{assigned}^2 + se_{random}^2}$$

, where $\beta_{assigned}$ and β_{random} are the estimates of coupling in assigned and random communicator-receiver dyads, respectively, and $se_{assigned}$ and se_{random} are the standard error of these estimates.

$$\text{EQ 2}: DF = \frac{(se_{assigned}^2 + se_{random}^2)^2}{\frac{se_{assigned}^4}{df_{assigned}} + \frac{se_{random}^4}{df_{random}}}$$

, where $se_{assigned}$ and se_{random} are the standard errors, and $df_{assigned}$ and df_{random} are the degrees of freedom of the coupling estimates in assigned and random communicator-receiver dyads, respectively. In addition, we provide the percentage of random models in which estimated synchrony effects are larger than in assigned communicator-receiver dyads.

Results

Model Construction

First, we tested whether allowing the slope of each cognitive and preference synchrony effect to vary across communicators, receivers, and articles improved model fit compared to models without random slopes. As shown in Table 5.1, most models did not show improved model fit after inclusion of all three varying slopes with the exception of models estimating coupling in the brain's social cognition, ventral attention, and salience networks.

Table 5.1. Model comparison of "full" models including random slopes for coupling effects across articles, individual sharers and receivers, and "reduced" models without random slopes

Model	AIC_{full}	$AIC_{reduced}$	BIC_{full}	$BIC_{reduced}$	Log-Likelihood Ratio Test (χ^2, p)
Neurocognitive Coupling					
Subjective value	986.1	982.1	1045.7	1012.0	8.113, .230
Self-reflection	1058.8	1050.1	1118.4	1079.8	3.227, .780
Social Cognition	852.0	854.9	911.6	884.7	14.88, .021
Dorsal Attention	706.5	703.9	766.1	733.7	9.432, .157
Ventral Attention	727.6	752.4	787.2	782.2	36.803, <.0001
Salience	742.8	745.3	802.4	775.1	14.485, .025
Preference Coupling					
Sharing intention	2943.5	2937.7	3003.0	2967.4	6.195, .402
Sharing Benefits	3469.1	3461.9	3527.4	3491.1	4.854, .563

Note: Models were estimated using full maximum likelihood estimation to facilitate model comparison.; AIC = Akaike information criterion, BIC = Bayesian information criterion, degrees of freedom for all log-likelihood ratio tests = 6

Examination of the contribution of individual random slope terms showed that the fit of the social cognition coupling model was significantly improved by allowing the coupling effect to vary across articles only (χ^2 (2) = 9.654, p < .01). Model fit for coupling in the ventral attention network was improved by both a random slope for individual receivers (χ^2 (2) = 11.847, p < .01) and articles (χ^2 (2) = 26.296, p < .0001). Finally, the model estimating cognitive salience coupling was improved by a random slope across articles (χ^2 (2) = 10.146, p < .01).

Significant Neurocognitive and Preference Coupling in Assigned Communicator-Receiver Dyads

Table 5.2 presents estimates for both neurocognitive and preference coupling derived from the final, preferred models developed in the model construction step, described above. First, we tested whether there was significant communicator-receiver coupling in neural activity within ROIs hypothesized to be part of the neural propagation system. Indeed, neural activity in regions associated with value-related processing, self-reflection, and social cognition in communicators was significantly related to neural activity in the same regions in receivers with whom they communicated. In contrast, we did not find significant cognitive coupling in any of our attention or salience ROIs, which where thus dropped from further analysis. Additionally, the examination of preference coupling showed significant correspondence between ratings of sharing intentions and benefits provided by assigned communicators and receivers. In sum, we found significant communicator-receiver coupling in areas within the hypothesized neural propagation system, but not in regions associated with attention and salience. Further, hypothesized coupling effects in ROIs related to valuation, self-reflection and social cognition held over and above variance explained by communication context variables (i.e., differences between sharers, receivers, and articles), which were represented by random slopes and intercepts in our models.

Table 5.2. Fixed effects of neurocognitive and preference coupling estimates for assigned communicator-receiver dyads

Model	B	SE	T (df), p
Neurocognitive Coupling			
Subjective Valuation	0.074	0.035	2.096 (677.5), .037
Social Cognition	0.105	0.046	2.265 (69.1), .027
Self-Reflection	0.094	0.034	2.731 (648.6), .007
Ventral Attention	0.079	0.059	1.349 (76.1), .181
Dorsal Attention	0.002	0.039	0.066 (526.6), .947
Salience	0.034	0.048	0.715 (60.63), .477
Preference Coupling			
Sharing Intention	0.070	0.021	3.393 (855.3), .001
Sharing benefits	0.074	0.029	2.584 (532.7), .01

Note: Estimates were obtained using restricted maximum likelihood estimation; B = unstandardized effect estimate, SE = standard error, df = degrees of freedom

Relationship between Neural and Preference Coupling

Next, we tested whether the extent of neural coupling was related to correspondence between communicators' and receivers' self-reported preferences. Estimates of the random slopes of neurocognitive coupling effects for each of the 80 articles did not relate to slope estimates for coupling in sharing intentions in neural regions associated with self-reflection, social cognition or valuation. However, we found significant relationships between the extent of neural coupling in regions associated with self-reflection ($r = .249$, $T(78) = 2.274$, $p = .025$), valuation ($r = .235$, $T(78) = 2.131$, $p = .036$), and social cognition ($r = .253$, $T(78) = 2.313$, $p = .023$), and communicator-receiver correspondence in perceived benefits of sharing.

Sources of Coupling: Propagation vs. Exposure Effects

Finally, we tested whether cognitive and preference coupling effects described above were due to exposure effects or represented the propagation of information between individuals through communication. Table 5.3 presents coupling estimates from models each including a respective synchrony effects and random intercepts for the three communication context variables fitted to data from random (i.e., non-communicating) communicator-receiver dyads. Table 5.4 compares these estimates to estimates from identical models fitted to data from assigned dyads.

Table 5.3. Cognitive and preference coupling estimates for random communicator-receiver dyads

Model	B	SE	T (df), p
Cognitive Coupling			
Subjective Valuation	0.005	0.032	0.139 (1065.3), .499
Social Cognition	-0.009	0.035	-0.257 (1046.1), .459
Self-Reflection	-0.007	0.033	-0.214 (1019.0), .506
Ventral Attention	-0.016	0.034	-0.460 (1061.3), .476
Dorsal Attention	-0.013	0.038	-0.354 (1073.1), .505
Salience	-0.005	0.036	-0.152 (1063.1), .511
Preference Coupling			
Sharing Intention	0.033	0.035	0.948 (676.9), .370
Sharing Benefits	0.009	0.032	0.293 (507.2), .490

Note: Estimates were obtained using restricted maximum likelihood estimation.

We did not find significant neurocognitive or preference coupling in random communicator-receiver dyads. Further, neurocognitive coupling in both the self-reflection and social cognition systems was significantly stronger in communicating (assigned) than in random dyads. This difference was also marginally significant for coupling in the neural valuation system. That is, neurocognitive coupling in the proposed neural propagation system is likely due to the propagation of cognitions between individual communicators rather than exposure effects.

We did not find significant differences in sharing intention correspondence between random and assigned dyads, which might suggest that sharing intention coupling is at least partly due to exposure effects. In contrast, paralleling the observed relationship to brain coupling, coupling estimates for sharing benefit ratings, were (marginally) significantly stronger in assigned than in random communicator-receiver dyads.

Table 5.4. Comparison of cognitive and preference coupling in paired and random communicator-receiver dyads

Model	T (df), p	% superior random models
Neurocognitive Coupling		
Subjective Valuation	1.452 (1582.3), .073	1.2
Social Cognition	1.89 (1598.8), .030	0.2
Self-Reflection	2.125 (1547.9), .017	0.1
Preference Coupling		
Sharing Intentions	0.927 (1132.5), .177	14.8
Sharing Benefits	1.516 (1024.4), .065	1.6

Note: % of superior random models indicates the percentage of the 1,000 bootstrapped estimates derived from models fit to data from random sharer-receiver dyads that indicate stronger coupling effects than corresponding models fit to assigned dyads

Discussion

We used fMRI to observe neural activity in a sample of communicators who shared short messages about New York Times health news articles and in a second sample of receivers who were exposed to these messages. We hypothesized that the propagation of content-related preferences (namely sharing intentions and ratings of perceived benefits of sharing) between communicators and receivers would be facilitated by neural coupling in a propagation system consisting of regions associated with self-reflection, social cognition and valuation. Results show that there is communicator-receiver coupling in the proposed neural propagation system when communicators are exposed to news articles and receivers are exposed to communicator-composed messages about these articles. Further, there was a positive relationship between the extent of neural coupling and successful information propagation operationalized as coupling in perceived benefits of sharing each news item. These findings provide empirical support for the idea that communicator-receiver coupling in key areas of the brain associated with valuation, self-reflection and social cognition, supports the successful propagation of information between individuals. The transmission of such content-related cognitions may facilitate positive social encounters and contribute to the goals of communicators and receivers.

Valuation is a central driver of decision-making across domains (Bartra et al., 2013). When communicators decide whether or not to share content and when receivers determine whether to be persuaded or affected by shared content, the overall value of the expected outcomes of their choice has a direct effect on their decision (Falk & Scholz, 2018). The transfer of this value-signal between communicators and receivers may constitute an opportunity for both parties to fulfill important goals. For instance, knowledge of a communicator's valuation of shared content can help receivers efficiently evaluate the new information. Communicators may influence others or describe their agendas by spreading their valuation for specific stimuli to others. Our data suggest that communicator-receiver coupling in the brain's valuation system might facilitate information transmission in the form of similarity in content evaluations.

In line with prior theorizing on the cognitive processes supporting information sharing decisions (Scholz, Baek, O'Donnell, Kim, et al., 2016; Scholz & Falk, in press), we further argue that the transmission of self-reflective and social cognitions contextualizes this broader content-evaluation. The transmission of content-related self-reflective cognitions can help communicators to fulfill their self-enhancement and self-presentation motives, which often motivate information sharing (Berger, 2014; Cappella et al., 2015). For receivers, self-reflective coupling can help them understand and react to the communicator's viewpoint in the current social context, and provide hints as to how certain contents apply to others (namely the communicator) and, by extension, to themselves. Finally, it can be beneficial for communicators to transmit their social cognitions related to the act of sharing and the content in question to effectively communicate and fulfill relationship management goals which constitute another prominent motivation of sharing behavior (Berger, 2014; Cappella et al., 2015). Understanding the communicator's social motives may also help receivers to react adequately to the current social interaction and potentially plan future interactions about the content. In sum, the propagation of contextual information together with a broader content evaluation might not only facilitate successful information propagation, but benefit both communicators and receivers.

The coupling effects described here may be a product of the broader tendency of communication partners to synchronize cognitions and behaviors to facilitate social learning and the maintenance of positive social relationships (Bandura, 1986; Burgoon et al., 2007; Cappella, 1996). That is, the neural propagation system consisting of neural regions associated with valuation, self-related, and social processing, may originate from the biological evolution of human communication itself. Specifically, humans evolved to be social creatures who seek safety and support in social group membership and relationships (Baumeister & Leary, 1995). A biological system that serves both to learn by mirroring and maintain positive relationships through successful communication and social influence (Cialdini & Goldstein, 2004) could result in correspondence between cognitions, and consequently, preferences of communicators and receivers.

Tests of several alternative hypotheses further supported the idea that cognitive coupling specifically in the proposed neural propagation system is a sign of meaningful and successful information propagation between communicators and receivers. First, we did not find evidence for coupling in neural regions associated with salience and attention. It follows that cognitive coupling during information retransmission does not merely represent the propagation of situational salience. Instead communicators seem to propagate higher-level, contextualized cognitions. Although not directly tested here, one implication of this finding is that the propagation of information through social channels is at least partially dependent on communicator evaluations, which can significantly alter the ways in which the content is received at the next step of a propagation chain.

Second, there was no cognitive or preference coupling in random communicator-receiver dyads who saw identical headlines, but did not communicate with one another. This suggests that in addition to neural synchrony in response to exposure to identical content which has been identified elsewhere (Dmochowski et al., 2014; Hasson et al., 2012; Schmälzle, Häcker, Renner, Honey, & Schupp, 2013; Silbert et al., 2014), the neural propagation system produces synchrony that serves as a vehicle for propagation between communication partners.

Finally, although prior work has shown individual differences in propagation processes from the perspective of communicators, receivers, and content items, we show that coupling in the neural propagation system cannot be fully explained by variation in these context characteristics. This pattern is consistent with the idea that the nature of human communication itself plays a central role in the propagation evaluations and information and suggests that the processes identified here might be operating in any social encounter across contexts.

Limitations and Future Directions

The highly-controlled nature of our data imposes several limitations on the inferences that can be derived from our results. First, because our study population as well as sample of news items is relatively homogeneous, it is possible that we underestimate the role played by variation across communication context variables. Future work will benefit from exploring the extent to which information can spread effectively between individuals, irrespective of variables such as their opinion leadership status or abilities, by including samples that vary more widely on these dimensions.

Second, we studied a specific type of communication, namely a one-way written transmission of a message as it might occur in online contexts. Although the generalizability of our results thus needs to be confirmed in other modes communication, we argue that our study design represents one of the most minimal forms of social interaction. Arguably, coupling effects may be substantially stronger during longer, richer interactions. Finally, although we showed a significant relationship between all three parts of the neural propagation system and coupling in sharing benefit ratings, neurocognitive coupling was not related to the propagation of sharing intention preferences; these results should be interpreted with caution since our intention variable in this investigation was highly skewed. It is possible that the neural propagation system discussed here might selectively facilitate the propagation of certain kinds of preferences while others could be supported by different mechanisms, or that our measure of sharing intentions led to biased statistics and a false null result.

Conclusion

We show that natural synchrony in a neural propagation system between information communicators and their receivers is associated with successful propagation of information. Our results point to the importance of coupling in the brain's valuation, self-relevance and social cognition systems, which are in turn associated with shared perceptions of the benefits of sharing specific information. The fact that, in our data, this finding was robust across communication context variables is encouraging for communication strategists and is consistent with social diffusion as an important complement to mass communication.

CHAPTER 6: DISCUSSION

This dissertation aimed to identify the basic underlying neural and psychological mechanisms driving decisions to share media content. Findings support a mechanistic, and parsimonious account of decision-making about sharing. Specifically, empirical findings from the four studies presented here (Chapters 2-5) suggest a value-based decision-making process in which decision makers attempt to maximize the value of expected outcomes when making choices about sharing information with others. Considerations of the self-related and social outcomes of sharing are highlighted as inputs to this value calculation. That is, valuation may serve as a final common pathway that allows decision makers to integrate diverse inputs into a single value signal that determines choice. This framework parsimoniously integrates prior work on more specific types of sharing motivations (Berger, 2014; Cappella et al., 2015; Derlega & Grzelak, 1979), most of which can be categorized in either social or self-related terms, as well as work on general decision-making processes that are applicable across domains (Falk & Scholz, 2018). In the applied context of the study of interconnected effects of mass media and interpersonal communication on attitude or behavior change, this theoretical account of basic cognitions may further facilitate future hypothesis testing and the development of new strategies to capitalize on social forces when promoting mass media messages at a large scale.

Four empirical studies were conducted to contribute to the development of this framework. These studies systematically examined crucial elements of simple propagation chains (Figure 1.1) in which communicators made decisions about sharing health news articles with receivers through short Facebook messages. Chapters 2-4 focused on the communicator's perspective. Chapter 5 considered cognitive connections between communicators and receivers to understand whether key processes identified as motivating sharing in communicators propagate through the act of communication and affect downstream receivers. Chapter 6 summarizes and interprets the main findings presented here and discusses potential future extensions of this work.

Building Blocks of Communicator Decisions to Share Media Content

Based on a review of research in social psychology, communication science, and social and cognitive neuroscience, this dissertation began with the observation that decision-making, across domains, has been linked to value-maximization processes (Falk & Scholz, 2018). Further, evidence for links between valuation and social (e.g. Rademacher et al., 2010; Tamir et al., 2015) as well as self-related (D'Argembeau et al., 2012; Mezulis et al., 2004; Northoff & Hayes, 2011) outcome considerations in humans suggested that these processes might serve as inputs to the overall calculation of the value of a choice. Chapter 2 presents evidence in support of this idea. Specifically, brain activity collected while communicators in a propagation chain were considering whether to socially share New York Times health news articles on Facebook, revealed the involvement of areas within the brain that, according to meta-analyses and large-scale studies, are associated with self-related, social and value-related processing. Further, activity in these regions was stronger during sharing decisions than when participants considered whether to privately read the full text of each article and when participants made judgments about the main topic of each article. Moreover, activity in all three regions of interest significantly scaled with self-reports of each individual communicator's likelihood to share the article with others. Finally, a whole brain search revealed that increases in brain activity during sharing decisions compared to private reading and content decisions were largely specific to the regions of interest defined here, suggesting the centrality of self-related, social and value-related processes in sharing decisions.

The conclusions that can be drawn based on these results are restricted by the limitations of reverse inference (Poldrack, 2011). That is, given that each of the brain regions of interest studied here has been found to be involved in multiple processes including, but not restricted to the processes discussed so far, interpretations about which of these potential mechanisms is involved in the decisions made by study participants cannot be made with absolute certainty. Attempts were made to reduce the extent of uncertainty by choosing regions of interest in the brain to represent each of the processes of interest based on independent evidence, namely functional data derived from meta-analyses of the brain mapping literature or large-scale studies of each of the processes. In addition, predictions about the involvement of these processes were made a priori (Scholz, Baek, O'Donnell, & Falk, 2016; Scholz et al., 2015) and based on strong empirical evidence. Given these design features, our results are reasonably suggestive towards the involvement of self-related, social, and value-related processing in communicators' sharing decisions about health news. Confidence could further be enhanced in future work by assessing neural activity in conjunction with self-report ratings of the target processes in order to assess whether neural activity is significantly related to the conscious experience of communicators in this particular situation.

Furthermore, self-related, social and value-related processing are defined in very broad terms in this dissertation. Consequently, results provide high-level insights into what communicators were considering when making sharing decisions. Prior work identified various more specific sharing motivations and thought processes that may fall within the broader categories of self-related and social processing (Berger, 2014; Cappella et al., 2015). Assuming this birds-eye view on decision-making processes has both advantages and limitations. A clear limitation is the lack of specificity. Given the proven successfulness of message tailoring and targeting approaches (Davis & Resnicow, 2011; Kreuter et al., 1999; Matz, Kosinski, Nave, & Stillwell, 2017; Noar, Benac, & Harris, 2007), being able to distinguish whether a communicator's decision is likely to be based on self-enhancement rather than self-presentation motives may enhance the effects of messages aiming to encourage sharing behavior.

At the same time, focusing on basic cognitive processes allows us to take optimal advantage of the affordances offered by fMRI, which does not currently have the level of granularity to confidently identify and distinguish between the more specific thought processes such as self-enhancement and self-presentation within the categories of self-related and social thoughts. In contrast, large-scale studies and meta-analyses are available to functionally localize basic thought processes such as valuation (Bartra et al., 2013), social cognition or mentalizing (Dufour et al., 2013), and self-related processing (e.g. Falk et al., 2016). In addition, it is advantageous to understand the basic building blocks of communicator decision-making as it is being processed in the brain. By measuring and targeting a high-level factor rather than individual indicators such as specific types of self-related or social processing, the neuroimaging methodology used here presents a more parsimonious account of decision-making and a more universally usable metric for intervention. Specifically, neural activity in the regions discussed here is sensitive to a range of relevant, related processes, even in slightly varying circumstances. For instance, across sharing situations, an individual is likely to experience multiple types of self-related and social processing, which can all be captured using the same neural indicator. That is, fMRI allows us to parsimoniously capture the greatest common denominators of multiple processes given their functional co-localization in specific brain regions (Lieberman, 2010). In contrast, it is problematic to approach these cognitions through self-report which is restricted by the researcher's foresight regarding which specific processes will be involved and limitations on questionnaire length. Thus, fMRI provides advantages regarding the generalizability and predictive power of the measure and, thus, it's utility for diverse research endeavors. In this manner, the neural data add new information to the existing literature. In sum, data presented in Chapter 2 provide evidence for the involvement of self-related, social and value-related processes in communicators' decisions to share media content.

Value-Based Virality: Mechanisms of Population-Level Communicator Decisions

Data discussed in Chapter 3 add nuance to and extend the findings reviewed so far. This study showed that value-related processing during decision-making about a given message is not only predictive of the communication behaviors of a small group, but also associated with large-scale article sharing behavior in the population of the New York Times' online readership. In line with existing brain-as-predictor work (Falk et al., 2011; Venkatraman et al., 2014), value-related processing explained variance in population-level article virality over and above commonly used self-reports of sharing likelihood in two samples of fMRI participants. Finally, neural value-related activity was identified as a common pathway, or mediator, for the effect of social and self-related considerations on information sharing at scale.

The capability of population-level prediction is crucial in the context of information sharing. Media content such as of the New York Times articles studied here routinely targets large populations and the effects of campaigns and messages are often assessed at the population-level (Hornik, 2002; Snyder et al., 2004). Yet, information sharing represents individual-level decision-making and leads to individual interactions. Unfortunately, available methodologies for the in-depth study of psychological processes, including fMRI, are generally hard to assess in large groups of people. The fact that the neural measures used here in two small groups of study participants are predictive of large-scale sharing behavior thus offers a unique opportunity to gain in-depth understanding of psychological processes that drive choices and behaviors in large groups and to parsimoniously connect the two levels of analysis inherent in the study of sharing of media content.

Our ability to detect relationships between neural activity in a small group and population-level outcomes may be surprising initially. Individual communicators likely vary in which specific pieces of content are self-relevant or socially advantageous.

Nevertheless, human societies are also characterized by a set of basic common values and social norms (Hofstede, Hofstede, & Minkov, 1991; Schwartz, 2006, 2007). Consequently, similar types of content can be expected to have relatively high sharing value across individuals. In other words, those content items which represent a certain societal value more effectively (e.g. health, belonging, positivity, intelligence) will have higher sharing value and be shared more often. A second issue for population-level prediction is that different people might be motivated to share the same article for different reasons, that is based on different types of self-related and/or social processing. As described above, one advantage of focusing on basic, broadly defined constructs rather than more specific instances of these concepts is that variation in the specific manifestations of thought processes (e.g. specific self-presentational concerns) within these greater categories (e.g. broader self-related thought) across participants and contexts can be captured using a single measure. The underlying assumption is that various specific types of self-related and social thought load on the same, basic constructs and contribute to information sharing value in similar ways. This allows us to capture relevant cognitions in a parsimonious way, despite individual variability, and thus predict population-level virality.

It will be important in future work to understand the boundary conditions under which a relationship between population-level sharing and individual-level cognitions can be identified. Some studies within the brain-as-predictor tradition have begun to explore individual differences in the power of brain activity to predict large-scale outcomes (Dore, Scholz, Baek, & Falk, under review; Vezich et al., 2017; Weber, Huskey, Mangus, Westcott-Baker, & Turner, 2015). This work shows, for instance, that those individuals who are not frequent New York Times readers in normal life, show neural activity in the brains' value system that is more predictive of population-level sharing behavior than individuals who are frequent readers (Dore et al., under review). The authors reason that domain expertise in frequent readers may lead to a non-discriminatorily high value-signal in response to all, not just the most enticing, articles, suppressing predictive effects. Continuing this line of work may allow researchers in future studies to further enhance the predictive power of their neural models by strategically selecting samples that are likely to be neurally representative of the target population.

Conceptualizing the diverse processes involved in sharing decisions as a broad class of value-based decision-making offers a parsimonious explanation for similarities in the decision-making processes across previously disconnected empirical literatures and theories. Specifically, similar brain regions have been shown to encode choice value across a large number of domains (Bartra et al., 2013; Rademacher et al., 2010) and value has been implicitly characterized as a driver of behavior in the contexts of persuasion and social influence, for instance in the form concepts such as self-interest and expectations or beliefs about the outcomes of behavior for oneself or one's social relationships (Darke & Chaiken, 2005; Fishbein & Ajzen, 2010; Johnson et al., 2004; O'Keefe, 2012). It has been argued that sharing information with other people might be intrinsically valuable (Tamir et al., 2015), maybe because it allows communicators to fulfill their evolutionarily developed need for social belonging (Baumeister & Leary, 1995). Indeed, prior work in line with findings reported in Chapter 3, identifies value-maximization as a final common pathway of decision-making which allows decision makers to integrate considerations regarding diverse aspects of a decision context to derive a final value signal that affects choice.

In sum, Chapters 2 and 3 support a parsimonious theoretical framework of the mechanisms that drive communicators' decisions to include media content into interpersonal conversations. Specifically, communicators may consider self-related and social outcomes of their choices and integrate them into an overall value signal associated with the choice which is directly related behavior. These processes appear to predict choices at both the individual and population-level.

Context Effects

Chapter 4 demonstrates that this framework is sensitive to yet remains relevant across communication contexts. Specifically, findings reveal that self-related and social processing are important elements of sharing decisions both in the case of narrow- and broadcasting. At the same time, our neural measures showed sensitivity to this context variable in that neural self-related and social activity was found to be stronger during narrow- than during broadcasting.

These findings further support the idea that the broad conceptualization of basic processes in the proposed model is advantageous in that these concepts are generalizable to different contexts in which a communicator may make decisions about sharing. Nevertheless, only one of many potentially influential context effects was tested here and the generalizability of these findings is thus limited to narrow- and broadcasting situations in the context of health news article sharing on Facebook. Prior work suggests that not only the number of receivers, but also their identity may play an important role in interpersonal communication. For instance, one study has shown that conversations about anti-binge drinking PSAs differed depending on whether the communication partner was familiar or unfamiliar (Hendriks, de Bruijn, Meehan, & van den Putte, 2016) and others have found different associations between interpersonal communication and health behavior depending on the relationship between communication partners (e.g. family members, friends, or teacher and student; Dorsey, Scherer, & Real, 1999; Hendriks et al., 2016). Thus, future investigations of the role played by self-related, social and value-related processing in communicator decision-making across contexts differing, for instance, in cultural variables, communicator, receiver, content, or channel characteristics would be highly insightful.

Next to investigations regarding the relative contributions of the three main processes of interest discussed here, it will further be interesting to investigate potential roles played by other types of processes in specific contexts. Chapter 4 provides some exploratory evidence suggesting the stronger involvement of other types of processes including areas of the brain often involved in emotion-regulation and effortful processing when broadcasting rather than narrowcasting.

Neural Propagation

Finally, findings presented in Chapter 5 provide evidence suggesting that neural traces of the three processes of interest discussed here may be transmitted from communicators to receivers. This may suggest downstream effects of the processes identified in communicators (Chapters 2-4) for receivers further down the propagation chain.

Prior work has demonstrated that synchrony across various biological and linguistic systems is a feature of natural human communication and may contribute to communicative success (Mogan et al., 2017; Stephens et al., 2010). Our findings suggest the possibility that next to enhancing the relationship between communicators and receivers and supporting the transfer of content, coupling in specific neural regions of interest may also be involved in the transfer of a communicator's value-based calculations with regards to talking about the content. Potentially, this may influence further downstream interpersonal communication. This suggests that message-based interventions enhancing these central processes in a first set of communicators may affect downstream sharing by their receivers as well.

Future work is needed to further understand the sources, nature, and effects of synchrony in the context of interpersonal communication about media content. Are there message or communicator characteristics that might increase or decrease synchrony? Does synchrony only occur on the aggregate level (i.e. per trial) as demonstrated here or also second by second in longer interactions? Does increased communicator-receiver synchrony lead to downstream effects such as sharing by the original receiver? Future work tackling these questions would strongly contribute to our understanding of the psychology of sharing decisions and their effects in interpersonal contexts.

Future Practical Implications

This dissertation presents studies focused on the specific contexts of sharing health news articles on social media. As briefly discussed before, sharing is a process that introduces media content into a social domain where it is subject to social forces such as persuasion and social influence. The findings presented here are thus of relevance to the literature examining the complex interconnections between mass media effects and the influence of interpersonal communication, both online and offline, on attitudes and behavior (Hornik & Yanovitzky, 2003; Jeong & Bae, 2017; Katz & Lazarsfeld, 1955; Southwell & Yzer, 2007).

Relationships between mass media and interpersonal effects have been widely recognized in communication science, public health, and studies on the diffusion of innovations and word-of-mouth (Berger, 2014; Jeong & Bae, 2017; Rogers, 2003; Southwell & Yzer, 2007). Yet, less is known about the psychology underlying the progression of mediated content into interpersonal conversations. As a result, social factors such as the number and types of conversations that are motivated by media messages are underappreciated in theory-based message design and evaluation within the realm of communication science and public health. In contrast, commercial sectors have whole-heartedly embraced the potential of social routes to persuasion with large, yet seldomly theoretically driven literatures on social media marketing and word-of-mouth in the fields of marketing and business (e.g. Scott, 2015; Tuten & Solomon, 2017). Understanding the psychological processes that lead communicators to share media content from a communication scientific perspective will contribute to theorizing and facilitate hypothesis testing about potential media message-based interventions that could strategically encourage and enhance interpersonal communication about media content.

This dissertation provides evidence that may contribute to one particular part of these process, namely the initiation of sharing, or social interactions about media content.

Existing work on the effects of interpersonal communication on health behavior shows that, next to occurrence, characteristics of interpersonal communication encounters such as the valence of the interaction (David, Cappella, & Fishbein, 2006; Dunlop, Kashima, & Wakefield, 2010; Hendriks, van den Putte, & de Bruijn, 2014; Scholz, Dore, Cooper, & Falk, in prep) and the nature of conversation partners (Dorsey et al., 1999; Hendriks et al., 2016) are crucial in determining whether the effects of these encounters are congruent or incongruent with the intent of the original media message. More work is needed to understand the psychological mechanisms that underlie downstream processes of interpersonal communication about media messages that follow the initial sharing decision discussed here. Nevertheless, Chapter 5 of this dissertation provides initial evidence for the idea that processes known to drive decision-making in communicators may also be central to receiver preferences and behaviors.

Conclusion

In sum, findings presented in this dissertation suggest a central role of neural activity in regions associated with self-related, social, and value-related processing in the decisions of communicators to share media content with others. Support for this claim was found at both the individual and population levels. In addition, valuation is highlighted as a central, common pathway through which other types of processes impact decision-making. These findings were robust across two separate samples and across interpersonal communication with large and small Facebook audiences. Finally, neural communicator-receiver coupling in brain systems of interest was associated with similarities in preferences and may have implications for further downstream effects of messages which are successful in encouraging sharing. Taken together, these findings address the lack of knowledge in the existing literature regarding the psychological mechanisms that encourage sharing decisions about media content and provide a basis for future research and hypothesis testing regarding potential new message strategies which systematically enhance these processes and, thereby, interpersonal communication about media. Thus, this dissertation constitutes scientific progress towards the development of theory-based message strategies which allow persuaders to take adequate advantage of the potential of social forces that are constantly active in their target populations.

APPENDIX

Appendix A: Chapter 2 Supplementary Materials

Supplementary materials, first published in: Baek, E. C.*, Scholz, C.*, O'Donnell, M. B., & Falk, E. B. (2017). Neural correlates of selecting and sharing information. *Psychological Science. 28*(7), p. 851-861. DOI: https://doi.org/10.1177/0956797617695073. Copyright © 2017 (The Authors). Reprinted by permission of SAGE Publications.

* denotes joint first-authors

Tables A1 and A2 below show the neural correlates of selecting and sharing news articles in the social cognition ROI, after removing regions that overlap with the Self-Related Processing and Subjective Valuation ROIs. All results remained robust after removing overlapping regions.

Table A1. Neural Correlates of Selecting and Sharing News Articles, Non-Overlapping Regions

ROIs	Select > Content			Share > Content			Share > Select		
	t(40)	*p*	*Mean parameter estimate [95% CI]*	*t*(40)	*p*	*Mean parameter estimate [95% CI]*	*t*(40)	*p*	*Mean parameter estimate [95% CI]*
Social Cognition, Non-overlapping with Self or Subjective Valuation	4.81	<.001	0.063 [0.036, 0.089]	8.92	<.001	0.096 [0.075, 0.118]	2.96	.005	0.034 [0.011, 0.057]

Table A2. Neural Activity Modulated by Preference Ratings Measuring Likelihood to Select to Read or Share, Non-Overlapping Regions

ROIs	Conditions					
	Select x Rating			Share x Rating		
	t(40)	*p*	*Mean parameter estimate [95% CI]*	*t*(40)	*p*	*Mean parameter estimate [95% CI]*
Social Cognition, Non-overlapping with Self or Subjective Valuation	3.30	.002	0.025 [0.010, 0.041]	3.18	.003	0.035 [0.013, 0.058]

Tables A3 and A4 below show the results of selecting and sharing news articles in the sub-regions of the subjective valuation, self-related processing, and social cognition ROIs.

Table A3. Neural correlates of selecting and sharing news articles

	Conditions								
ROIs	Select > Content			Share > Content			Share > Select		
	t(40)	*p*	*Mean parameter estimate [95% CI]*	*t*(40)	*p*	*Mean parameter estimate [95% CI]*	*t*(40)	*p*	*Mean parameter estimate [95% CI]*
Subjective Valuation	7.22	<.001	0.118 [0.085, 0.151]	12.69	<.001	0.158 [0.133, 0.184]	3.09	.004	0.040 [0.014, 0.067]
VMPFC	7.88	<.001	0.181 [0.134, 0.227]	13.99	<.001	0.248 [0.212, 0.284]	3.92	<.001	0.067 [0.032, 0.101]
Striatum	3.97	<.001	0.040 [0.019, 0.060]	5.54	<.001	0.047 [0.030, 0.064]	0.75	>.250	0.007 [-0.012, 0.027]
Self-Related Processing	7.26	<.001	0.143 [0.103, 0.183]	15.25	<.001	0.225 [0.195, 0.255]	5.02	<.001	0.082 [0.049, 0.115]
MPFC	7.91	<.001	0.153 [0.114, 0.192]	16.04	<.001	0.230 [0.201, 0.260]	4.43	<.001	0.077 [0.042, 0.112]
PCC	4.92	<.001	0.130 [0.077, 0.183]	9.61	<.001	0.223 [0.176, 0.270]	4.92	<.001	0.093 [0.055, 0.132]
Social Cognition	5.00	<.001	0.067 [0.040, 0.095]	9.41	<.001	0.104 [0.082, 0.127]	3.12	.003	0.037 [0.013, 0.061]
VMPFC	8.03	<.001	0.157 [0.118, 0.197]	12.93	<.001	0.223 [0.188, 0.258]	4.19	<.001	0.066 [0.034, 0.097]
MMPFC	7.18	<.001	0.127	14.45	<.001	0.198	4.46	<.001	0.070

			[0.091, 0.163]			[0.170, 0.225]			[0.039, 0.102]
DMPFC	5.23	<.001	0.080 [0.049, 0.111]	8.99	<.001	0.125 [0.097, 0.153]	3.22	.003	0.045 [0.017, 0.073]
PC	2.61	.013	0.053 [0.012, 0.094]	7.21	<.001	0.128 [0.092, 0.163]	5.01	<.001	0.075 [0.044, 0.105]
rTPJ	2.73	.009	0.028 [0.007, 0.049]	4.48	<.001	0.042 [0.023, 0.062]	1.43	.161	0.014 [-0.006, 0.034]
lTPJ	4.26	<.001	0.058 [0.031, 0.086]	5.73	<.001	0.064 [0.042, 0.087]	0.53	>.250	0.006 [-0.017, 0.029]
rSTS	3.34	.002	0.037 [0.015, 0.060]	3.97	<.001	0.038 [0.019, 0.057]	0.07	>.250	0.001 [-0.021, 0.024]

Note: Brain activity within sub regions of the major networks reported in the main body of the paper associated with selecting and sharing articles, compared to a control condition (recalling the article's content), and relative to one another.

Table A4. Neural Activity Modulated by Preference Ratings Measuring Likelihood to Select or Share

ROIs	Conditions					
	Select x Rating			Share x Rating		
	T (40)	*p*	*Mean parameter estimate [95% CI]*	*t*(40)	*p*	*Mean parameter estimate [95% CI]*
Subjective Valuation	6.01	<.001	0.046 [0.030, 0.062]	3.66	<.001	0.039 [0.017, 0.061]
VMPFC	6.04	<.001	0.064 [0.043, 0.086]	3.46	.001	0.048 [0.020, 0.076]

Striatum	3.97	<.001	0.024 [0.012, 0.036]	3.50	.001	0.028 [0.012, 0.044]
Self-Related Processing	5.28	<.001	0.053 [0.033, 0.073]	3.36	.002	0.058 [0.023, 0.093]
MPFC	5.38	<.001	0.057 [0.036, 0.079]	3.56	<.001	0.056 [0.024, 0.087]
PCC	3.29	.002	0.043 [0.017, 0.069]	2.72	.010	0.061 [0.016, 0.107]
Social Cognition	3.47	.001	0.027 [0.011, 0.043]	3.20	.003	0.036 [0.134, 0.059]
VMPFC	5.25	<.001	0.052 [0.032, 0.072]	3.51	.001	0.046 [0.019, 0.072]
MMPFC	5.38	<.001	0.052 [0.032, 0.071]	3.82	<.001	0.057 [0.026, 0.085]
DMPFC	4.62	<.001	0.043 [0.024, 0.062]	4.23	<.001	0.055 [0.029, 0.081]
PC	0.99	>.250	0.011 [-0.012, 0.034]	2.11	.041	0.037 [0.002, 0.072]
rTPJ	0.59	>.250	0.005 [-0.012, 0.022]	1.05	>.250	0.010 [-0.009, 0.030]
lTPJ	3.09	.004	0.022 [0.008, 0.036]	4.42	<.001	0.038 [0.020, 0.055]
rSTS	3.06	.004	0.026 [0.009, 0.042]	2.00	.052	0.021 [0, 0.043]

Note: This table shows brain activity within sub regions of the major networks reported in the main body of the paper associated with ratings of how likely participants would be to select and share the articles, respectively.

Our findings suggest that activity in all three ROIs was greater during selecting and sharing compared to the content condition. One alternative explanation for these differences might be due to the content trials being more cognitively taxing. We found that participants' reaction times were slower during the content trials than during selecting and sharing. However, all results remained robust when we ran the analyses controlling for RT (see Tables A5 and A6 below), and when considering only trials matched on RT (see Tables A7 and A8 below) suggesting that our results were not driven exclusively by difficulty across conditions.

Table A5. Mean Reaction Time (RT) by Condition

Condition	Mean (SD) RT
Content	0.95 (0.59)[a]
Select to Read for Self	0.80 (0.47)[b]
Share with Others	0.79 (0.46)[b]

Note: Content trials (a) differed significantly from Select to Read and Share with Others trials (b), but the latter two were not significantly different from one another

Table A6. Neural Correlates of Selecting and Sharing News Articles, with Reaction Time (RT) as covariate

ROIs	Select > Content			Share > Content			Share > Select		
	t (40)	*p*	*Mean parameter estimate [95% CI]*	*t* (40)	*p*	*Mean parameter estimate [95% CI]*	*t* (40)	*p*	*Mean parameter estimate [95% CI]*
Subjective Valuation	6.65	<.001	0.116 [0.081, 0.151]	13.03	<.001	0.159 [0.134, 0.184]	3.13	.003	0.044 [0.015,0.072]
Self-Related Processing	6.84	<.001	0.164 [0.115, 0.212]	14.54	<.001	0.258 [0.222, 0.294]	4.86	<.001	0.095 [0.055, 0.134]
Social Cognition	4.51	<.001	0.065 [0.036, 0.094]	9.38	<.001	0.105 [0.082, 0.128]	3.23	.002	0.040 [0.015, 0.065]

We extracted the middle 50% of the distribution of trials within the sharing condition, based on RT (0.476-0.952), and subsetted the content and select to read conditions to match this range. This resulted in a subset of all 3 conditions with same range and similar distributions of RT. As Table A7 indicates, the subsetted data no longer had significantly different mean differences on RT. In other words, the subsets of trials are of comparable difficulty across conditions.

Table A7. Mean Reaction Time (RT) by Condition, Before and After Subsetting Data

Condition	Mean RT, before subsetting (range)	Mean Difference from Content	Mean RT, after subsetting (range)	Mean Difference from Content
Content	0.951 (0.008-3.01)	--	0.670 (0.477-0.951)	--
Select to Read for Self	0.803 (0.063-2.99)	-0.148***	0.673 (0.477-0.951)	0.003 (*n.s.*)
Share with Others (combined narrowcasting & broadcasting trials)	0.794 (0.014-2.93)	-0.157***	0.663 (0.477-0.947)	0.007 (*n.s.*)

Table A8. Neural Correlates of Selecting and Sharing News Articles, reduced dataset with comparable RTs

ROIs	Select > Content			Share > Content			Share > Select		
	$t(40)$	p	*Mean parameter estimate [95% CI]*	$t(40)$	p	*Mean parameter estimate [95% CI]*	$t(40)$	p	*Mean parameter estimate [95% CI]*
Subjective Valuation	4.92	<.001	0.131 [0.077, 0.185]	10.01	<.001	0.177 [0.141, 0.212]	2.35	.02	0.046 [0.006, 0.085]
Self-Related Processing	5.18	<.001	0.179 [0.109, 0.249]	14.50	<.001	0.300 [0.258, 0.341]	4.48	<.001	0.121 [0.066, 0.175]
Social Cognition	3.29	.002	0.071 [0.027, 0.114]	8.58	<.001	0.122 [0.094, 0.152]	3.28	.002	0.052 [0.020, 0.085]

Tables A9 and A10 show the sharing conditions separated by narrowcasting and broadcasting.

Table A9. Neural Correlates of Selecting and Sharing News Articles, Narrowcasting

ROIs	Narrowcasting > Content			Narrowcasting > Select		
	t(40)	*p*	*Mean parameter estimate [95% CI]*	*t*(40)	*p*	*Mean parameter estimate [95% CI]*
Subjective Valuation	10.94	<.001	0.178 [0.145, 0.211]	3.46	.001	0.060 [0.025, 0.095]
Self-Related Processing	14.08	<.001	0.269 [0.230, 0.307]	5.93	<.001	0.125 [0.083, 0.168]
Social Cognition	8.90	<.001	0.123 [0.095, 0.150]	3.85	<.001	0.055 [0.026, 0.084]

Table A10. Neural Correlates of Selecting and Sharing News Articles, Broadcasting

ROIs	Broadcasting > Content			Broadcasting > Select		
	t(40)	*p*	*Mean parameter estimate [95% CI]*	*t* (40)	*p*	*Mean parameter estimate [95% CI]*
Subjective Valuation	9.75	<.001	0.139 [0.110, 0.167]	1.47	.149	0.020 [-0.008, 0.049]
Self-Related Processing	11.21	<.001	0.182 [0.149, 0.215]	2.32	.026	0.039 [0.005, 0.072]
Social Cognition	7.09	<.001	0.086 [0.061, 0.110]	1.43	.160	0.018 [-0.008, 0.044]

Figures A1, A2, and A3 show the sagittal cuts of whole brain associations of select to read and share conditions. The numbers in the top left corner indicate x-coordinates, using standard MNI (Montreal Neurological Institute) coordinates.

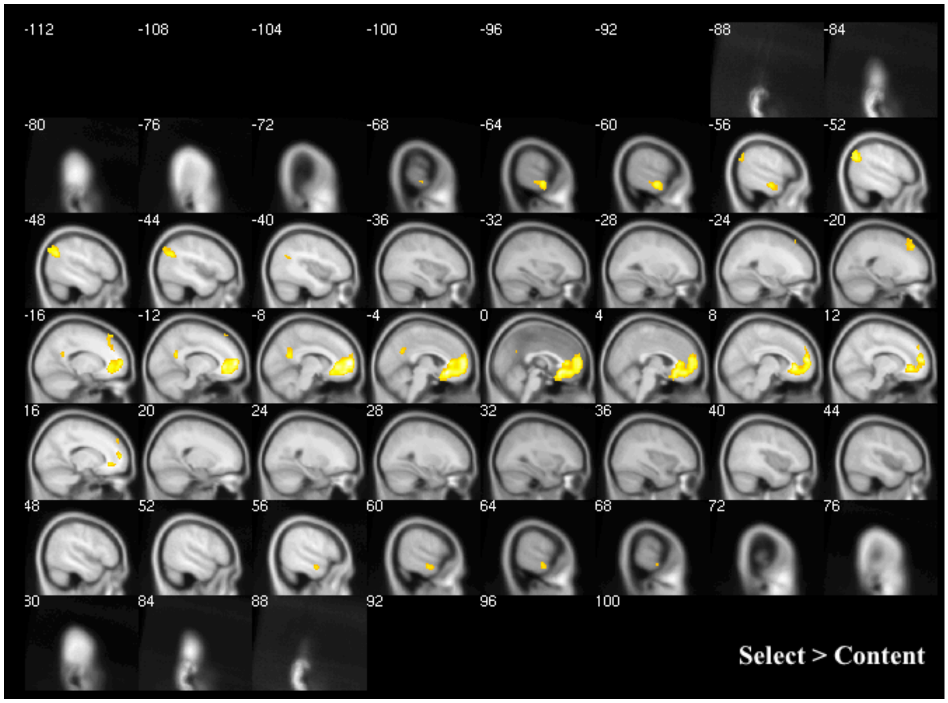

Figure A1. Sagittal cuts of whole brain associations of Select > Content contrast, thresholded at $p < .05$, corrected for family-wise error with a minimum cluster size of 20.

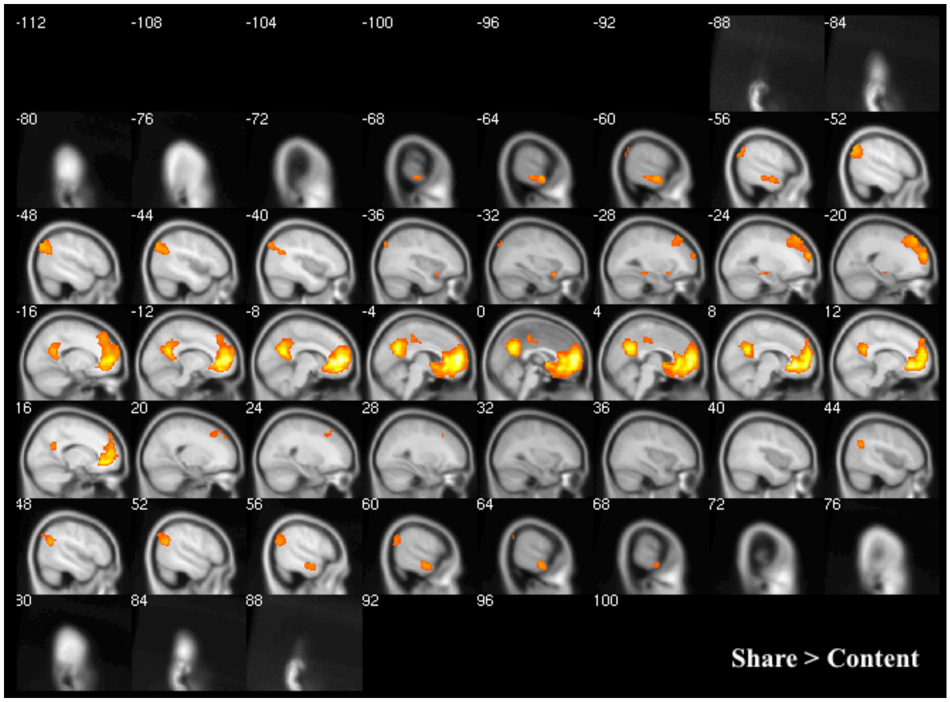

Figure A2. Sagittal cuts of whole brain associations of Share > Content contrast, thresholded at $p < .05$, corrected for family-wise error with a minimum cluster size of 20.

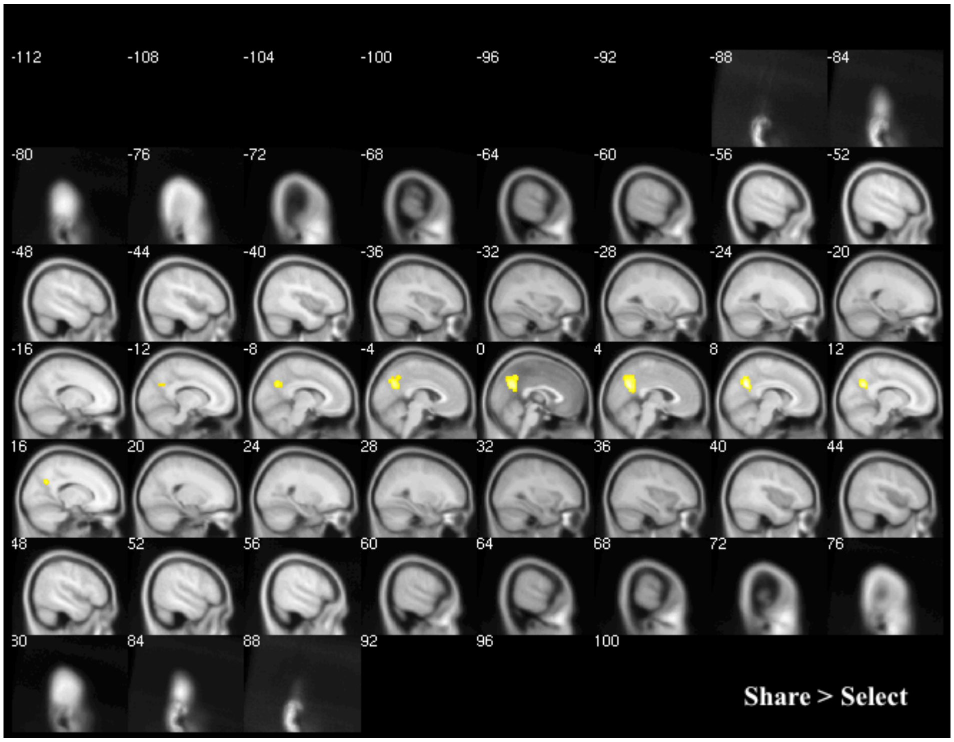

Figure A3. Sagittal cuts of whole brain associations of Share > Select contrast, thresholded at $p < .05$, corrected for family-wise error with a minimum cluster size of 20.

Appendix B: A Comment on Open Science

This dissertation is based on a research program that developed in parallel to dramatic changes in the social science community. Concerns about reproducibility (Open Science Collaboration, 2015) have led to increased calls for rigorous and open scientific practices including, but not limited to, replication studies, hypothesis pre-registrations, and open, inclusive reporting about the scientific process as well as significant and null results. Improvements in the implementation of these elements for an increasing number of projects will enhance transparency of research and may uncover much needed additional information about null results tackling the current file drawer problem.

In an effort to contribute to these steps towards an open and transparent science, the work presented in this dissertation implements several of the recommended elements. The studies reported in Chapters 2, 3, and 4 are fully or partially based on hypothesis pre-registration documents that were registered with the Open Science Foundation before data analysis began (Scholz, Baek, O'Donnell, & Falk, 2016; Scholz et al., 2015). The study in Chapter 3 further offers a replication of reported effects in a second sample. Analysis code and data for the published papers is available to interested readers on a linked GitHub page, and, finally, my co-authors and I have begun to publish null findings related to this project on GitHub.

Making the science presented here open and transparent to other researchers has been a challenge and a learning process, and the documents created to facilitate this process, especially early hypothesis pre-registrations, are flawed in various ways. For instance, the studies presented here were part of a larger research project combining the interests and research questions of several researchers and were thus designed to test a large number of hypotheses. All of these scientific interests were combined into a single document listing a large number of hypotheses for each of the two datasets discussed here. I have since come to the conclusion that a more detailed pre-registration focused on a small set of connected hypotheses and analyses which might be part of one planned publication would be a more sensible format. In that way, readers may be more likely to read the additional, yet concise text and gain a more complete understanding of the original thinking of the scientists. Such a format would also make it easier to report on all related null and significant results obtained throughout the study in a single manuscript. Nevertheless, the efforts made here to contribute to the development of Open Science have achieved at least a minimum level of reproducibility of the published findings and demonstrated the replicability of a subset of the results presented. It is the hope of the author that some of the lessons learned here about the open science process may inform and support others in implementing similar elements into their projects in increasingly efficient and helpful ways.

Appendix C: Chapter 3 Supplementary Materials

Supporting Information: First published in: Scholz, C., Baek, E. C., O'Donnell, M. B., Kim, H. S., Cappella, J. N., & Falk, E. B. (2017). A neural model of valuation and information virality. *Proceedings of the National Academy of Sciences of the United States of America*, DOI: 10.1073/pnas.1615259114

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SI NY Times Article Sample

We selected 80 articles from the full set of 760 articles analyzed in ref. 11 with the goal of maximizing comparability in topic and length. Specifically, we conducted a keyword search of the full set of 760 articles using the following terms: exercise, fitness, physical activity, running, swimming, skiing, soccer, walking, food (excluding "Food and Drug Administration"), eating, nutrition, nutrient, diet, vitamin, calcium, carbohydrates, gluten, caffeine, cholesterol, obesity, and weight. The search retrieved 143 articles. A closer examination revealed that four articles were irrelevant, and these articles were removed. Of the remaining 139 articles, the 80 that were most similar in length were chosen.

SI Scanning Parameters

We captured neural activity during two runs of the article task (500 volumes in each run in study 1 and 311 volumes in each run in study 2) using a T2*-weighted image sequence [repetition time (TR) = 1.5 s, echo time (TE) = 25 ms, flip angle = 70°, −30° tilt relative to the anterior commissure–posterior commissure (AC– PC) line, 54 slices at the Magnetom Tim Trio scanner, 52 slices at the Prisma scanner, field of view (FOV) = 200 mm, slice thickness = 3 mm, multiband acceleration factor = 2, voxel size = 3 × 3 × 3 mm]. High-resolution T1-weighted anatomical images were collected using a magnetization-prepared rapid gradient-echo (MPRAGE) sequence [inversion time (TI) = 1,110 ms, 160 axial slices, voxel size = 0.9 × 0.9 × 1 mm]. Finally, we collected an in-plane, structural, T2-weighted image (slice thickness = 1 mm, 176 axial slices, voxel size = 1 × 1 × 1 mm) to implement a two-stage co-registration procedure between functional and anatomical images.

SI Robustness Checks

To test the robustness of our main results reported in Figure 3.1, we estimated models using unranked variables. These analyses produced results similar to those presented in the main text and supported identical conclusions (Figure C2 and Table C3). Further, models excluding the insignificant direct effects of the two exogenous variables on virality shown in Figure 1 were estimated to obtain model fit statistics. Both models revealed satisfactory model fit for the hypothesized structural model, considering its small degrees of freedom (df) and small sample size (66): $\chi 2$ (2) = 2.36, P = 0.31, comparative fit index (CFI) = 0.997, residual mean square error of approximation (RMSEA) = 0.05, 90% CI (0.00, 0.23) for study 1; $\chi 2$ (2) = 3.26, P = 0.20, CFI = 0.986, RMSEA = 0.09, 90% CI (0.00, 0.26) for study 2. Additional analyses revealed the model fit for the hypothesized path structure was superior to that of alternative structural models

(Table C4), providing additional confidence to our proposal that valuation, taking inputs from self and social considerations, serves as a final common pathway.

SI Study 1 Whole-Brain Analysis

To test the specificity of our results to our theory-driven ROIs, we conducted exploratory whole-brain analyses. We first created first-level models for each participant that included a separate boxcar function for activity across all trials within a certain condition (content, reading, broadcasting, narrowcasting) for the reading screen and the rating screen of the article task, respectively (eight regressors). An additional regressor represented the boxcar function representing the reading screen during reading trials modified by a mean-centered parametric modulator of population-level virality ranks of each article. Population-level virality ranks were derived by ranking all articles presented within the reading condition by their population-level retransmission counts for each participant (range, 1–20). The model also included a boxcar function for activity across all trials within the cue screen and six nuisance regressors to control for motion. Finally, to ensure that only first exposures were modeled in the main regressor of interest, one regressor of no interest was entered to account for trials in which one participant was accidentally presented with an article for a second time. Second, at the group level, neural activity was pooled for all participants to examine the main contrasts of interest: activity during the reading screen in reading trials modulated by population-level retransmission ranks compared with implicit baseline. To balance the risks of false positives and false negatives, we conducted two different kinds of correction for multiple comparisons to derive whole-brain maps and tables of voxels in which neural activity scales with population-level virality (Figure C3 and Table C5). The first whole-brain map was thresholded at $P < 0.005$ and $K \geq 320$, where K is the number of voxels per cluster, to produce a threshold of $P < 0.05$, corrected using 3dClustSim simulation (version AFNI_16.2.02). Although the type 2 error rate can be expected to be lower for this method of analysis, prior work has shown that cluster correction tends to overestimate the number of significant voxels and thus increases the type 1 error rate (Eklund, Nichols, & Knutsson, 2016). Consequently, we also present the results of a more stringent whole-brain correction that controls the number of false positives more efficiently. Specifically, we used nonparametric permutation testing (5,000 iterations) and false-discovery rate (FDR) correction for a voxel-wise P-threshold of $P < 0.05$ and $K \geq 10$ as implemented in the SnPM13 toolbox ("Statistical nonParametric Mapping. A toolbox for SPM," n.d.). (Study 1 results for multiple comparisons correction using nonparametric permutation testing corrected at FDR $P < 0.05$ vary across individual runs of the 5,000 permutations protocol implemented here, because of random elements in this analysis technique. Specifically, although several runs produced maps similar to the map printed in Figure C3, these results border on $P < 0.05$. All runs of the permutation protocol for study 1 produced maps that looked very similar to the one printed here at $P < 0.06$ or $P < 0.07$. Study 2 results are highly robust across several runs of the permutation protocol, $P < 0.05$, FDR corrected.)

SI Study 2 Whole-Brain Analysis

To conduct a parallel whole-brain analysis for study 2 participants, we first created first-level models for each participant that included a separate boxcar function for activity across all trials within a certain condition (abstract, narrowcasting, broadcasting) for the reading screen (three regressors) of the article task. Separate regressors for rating screens were further derived depending on the condition presented on the reading screen (six regressors in total). Crucially, an additional regressor specified the boxcar function representing the reading screen during abstract trials modified by a mean-centered parametric modulator of population-level virality ranks of each article. As for study 1, virality ranks were derived by ranking articles shown within the abstract condition by their population-level retransmission counts for each participant (range, 1–14). The model also included six nuisance regressors to control for motion. Second, at the group level, neural activity during the main task was pooled for all participants to examine the main contrasts of interest: activity during the reading screen in abstract trials modulated by population-level virality ranks compared with the baseline resting state. See Appendix C, Figure C3, and Table C4 for details and results.

In parallel to study 1 analyses, whole-brain maps were thresholded via 3dClustSim simulation at $P < 0.005$ and $K \geq 296$ (version AFNI_16.2.02) and nonparametric permutation testing (5,000 iterations) and FDR correction for a voxel-wise P-threshold of $P < 0.05$ and $K \geq 10$ as implemented in the SnPM13 toolbox ("Statistical nonParametric Mapping. A toolbox for SPM," n.d.). Results are reported in Figure C3 and Table C5.

SI Analysis of Other Article Task Conditions

In the main text, we focus on neural activity extracted from reading trials in the study 1 article task (Figure 3.1) because the reading condition most closely represents real-world experiences of NYTimes readers who are unlikely to visit the website to find an article to share with somebody. Instead, readers are more likely to browse abstracts and consider reading various articles until one article motivates them to share it with somebody else. Nonetheless, an additional question to consider is the extent to which task instructions affect the relationship between neural activity during article exposure and population-level sharing. Therefore, we examined the relationship between value-related neural activity in our value ROI in response to an article's headline and abstract and population-level article retransmission data, focusing separately on narrowcasting trials in which participants were primed before each trial via a cue screen to consider sharing articles with one Facebook friend and broadcasting trials in which participants were primed to consider sharing the article on their Facebook wall. Note that this analysis is not possible for study 2 data, because the other two conditions, not analyzed in the main text, are not comparable to those in study 1 and did not include the presentation of original article abstracts. Results show that value-related neural activity in response to articles shown in a sharing condition is marginally related to population-level virality in the case of narrowcasting trials [$r = 0.184$, $P = 0.10$] and is not significantly related to population-level virality in the case of broadcasting trials [$r = 0.133$, $P = 0.24$]. Individual-level data from study 1 suggest that explicit instructions to share (i.e., the two sharing conditions) increase the overall level of sharing-relevant brain activity compared with instructions to consider reading the full text of an article (i.e., the reading condition analyzed here; Baek et al., 2017). However, we also found that these explicit instructions reduce the variance in value-related activity, which is larger for reading trials ($s2 = 5.10$)

than for narrowcasting (s2 = 4.18) and broadcasting (s2 = 3.24) trials. This ordering of conditions according to variance in information-sharing value corresponds to the condition ordering in terms of the strength of the relationship between value-related activity and population-level virality. If this interpretation is correct, one potential implication could be that sharers are likely to share articles based on "gut" decisions, which are better represented by the reading trials, which did not specifically give participants the goal of sharing in each trial, than by longer elaboration, which is better represented by sharing trials.

SI Article Characteristics

In a content-focused investigation of 760 NYTimes health news articles that included the 80 articles used here, Kim (2015) characterized the article headlines and abstracts by analyzing human (i.e., the presence of efficacy information or the mention of diseases or bad health conditions) and computerized (expressed positivity: the difference between the number of positive and negative words; expressed evocativeness/arousal: the sum of positive and negative words) content and with the help of lay human raters (perceived usefulness, induced positivity, perceived controversiality, induced evocativeness/arousal, and perceived novelty). Here we explore the relationship between these content characteristics and concepts within our value-based virality framework as well as population-level virality.

SI Analysis of Article Characteristics

Prior work has shown that content characteristics can impact virality (Berger, 2014; Cappella et al., 2015), and this argument has been made particularly effectively in the case of news articles (Berger & Milkman, 2012; Kim, 2015). Consequently, we explored the role of content characteristics in value-based virality. Specifically, content characteristics might be involved in three different ways. (i) Article characteristics might affect virality directly and independently of variables included in the value-based virality model. If so, it would be of interest whether neural data explain the variance in population-level sharing over and above that explained by article characteristics. (ii) Article characteristics might affect information-sharing value directly or via some other mechanism not currently included in the value-based virality model. (iii) Article characteristics might be antecedents of thoughts regarding the self-related and social outcomes of sharing. To explore these possibilities, we first checked whether the predictions made by value-based virality (Figure 3.1) hold even when controlling for article characteristics. For this purpose, we estimated models identical to the one in Figure 3.1 but for the sake of parsimony excluded the insignificant direct effects of self-related and social processing on virality. Each model additionally included a direct effect of one article characteristic on population-level virality. Paralleling other analyses presented in this article, all variables were rank-ordered. In both studies, the effects presented in Figure 3.1 were robust when controlling for any of the nine article characteristics considered here. In fact, the only article characteristic that showed a significant effect on population-level virality in these models was the perceived usefulness of an article [B (unstandardized estimate of this parameter) = 0.202, SE = 0.101, P = 0.04] in study 1, but this effect did not replicate in study 2. Second, we examined the relationships between each of the nine content characteristics available to us and average neural activity in regions associated with self-related and social processing in response to each article using t tests and Pearson correlation where appropriate. Paralleling other analyses presented in this article, all variables were rank-ordered. In study 1, we found a positive relationship between induced positivity in an article and neural activity in the self-related processing ROI [$r = 0.231$; $P = 0.04$]. In addition, articles that mentioned diseases or negative health issues (mean, 9.74) were associated with less self-related processing than articles that did not [mean, 10.70; $T(78) = 2.24$; $P = 0.03$] in study 1. However, these effects did not replicate in study 2. Finally, we explored direct effects of article characteristics on information-sharing value (i.e., average neural activity in our value-related processing ROI) using analytical strategies identical to those explained above. Value-related neural activity was positively related to the extent to which articles induced positivity in human raters [$r = 0.309$; $P = 0.005$], and articles that mentioned diseases or bad health conditions (mean, 9.50) engaged less value-related activity than articles that did not [mean, 10.96; $T(78) = 3.04$; $P = 0.003$]. However, these effects did not replicate in study 2. In sum, our results hold, even when controlling for the effects of various article characteristics on virality, suggesting that neural activity contributes information over and above what can be learned from variables commonly used in the literature on virality (Berger & Milkman, 2012; Kim, 2015). In contrast to prior work, most article characteristics did not predict population-level sharing. This dissonance with existing studies might be the result of methodological differences among studies. Most notably, previous reports of effects between article characteristics and population-level sharing showed relatively small effect sizes that were identified only in very large samples (e.g., n > 6,000 in Berger & Milkman, 2012 and n = 760 in Kim, 2015). Because of time restrictions in the fMRI scan, we were not able to replicate these article sample sizes. Nonetheless, our ability to predict virality from neural variables even in this small sample of articles speaks to the strength and utility of fMRI. In addition, we identified selected relationships between individual article characteristics and the extent to which articles engaged neural activity associated with self-related, social, or value-related cognition in study 1. Although these relationships generally did not replicate in study 2, these findings might suggest that content characteristics could be promising candidates in the search for antecedents of the psychological processes that affect sharing. The lack of robustness of these effects might be due to the small sample size and homogeneity of articles. In addition, it is possible that sharing-relevant cognitions are more sensitive to combinations of article characteristics (e.g., the emotional tone in combination with the topic) than to isolated characteristics. However, the specific combination of article characteristics that enhances expectations of positive social or self-related outcomes of sharing might be highly context dependent. An exploration of the large number of potential interaction terms is beyond the scope of this investigation.

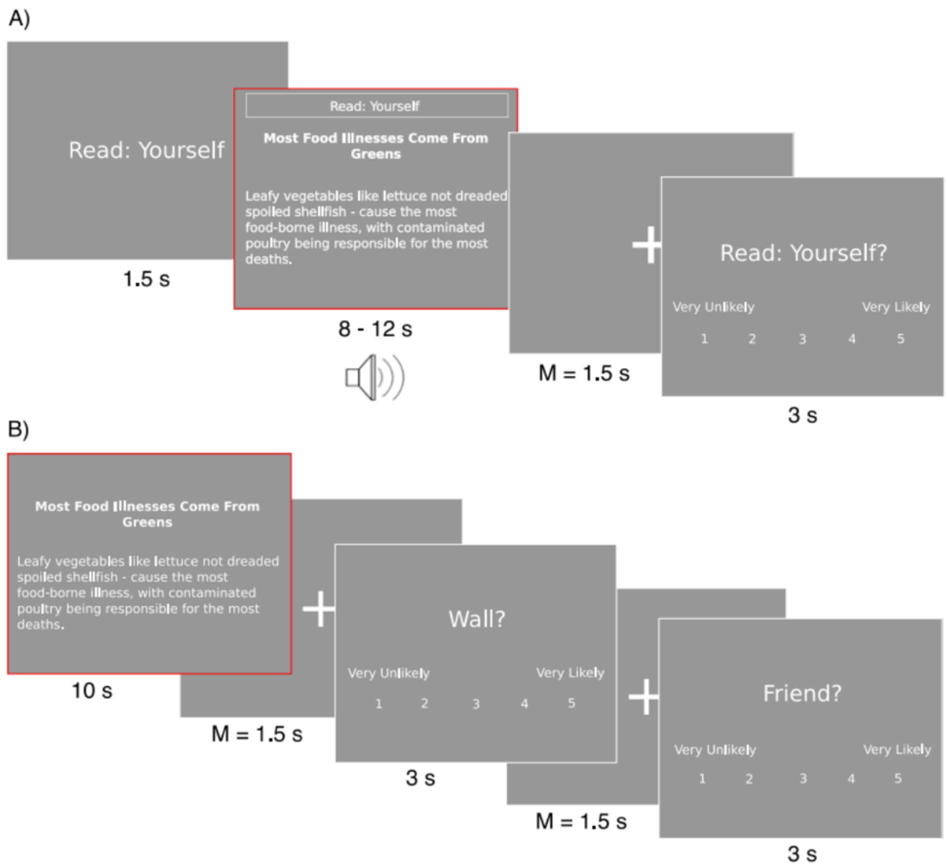
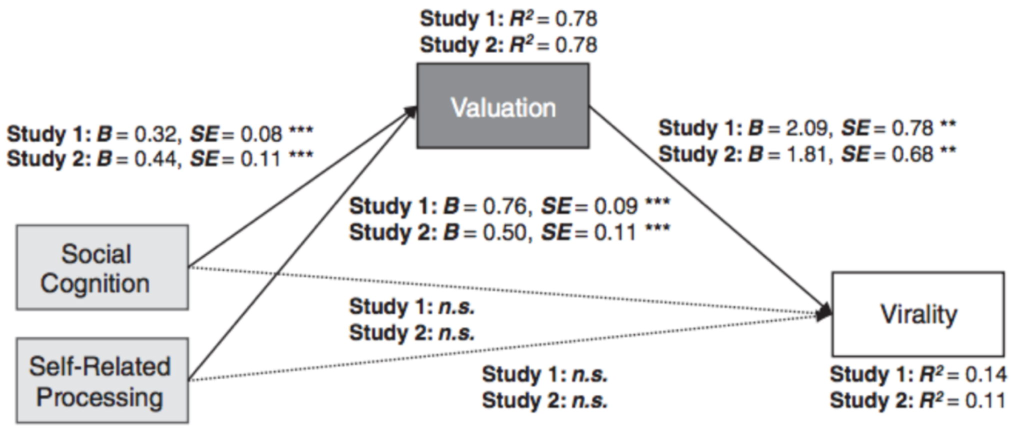


Figure C1. fMRI tasks. (A) Reading trial of the article task (study 1). (B) Abstract trial of the article task (study 2). The trial modeled in main analyses is marked in red.



Independent Variable	Study 1 Indirect Effects	Study 2 Indirect Effects
Social Cognition	*B* = 0.67, CI [0.24 - 1.20]	*B* = 0.80, CI [0.26 – 1.79]
Self-Related Processing	*B* = 1.59, CI [0.62 - 2.68]	*B* = 0.90, CI [0.25 – 1.86]

Figure C2. Value-based virality path model including unranked variables. The path diagram shows maximum likelihood estimates (unstandardized coefficients). The table presents indirect effect coefficients and bias-corrected, bootstrapped 95% CIs (1,000 replications). Population-level virality was log-transformed because of its positively skewed distribution. n = 80 in study 1 and 76 in study 2; *P < 0.05, **P < 0.01, ***P < 0.001, n.s., not significant

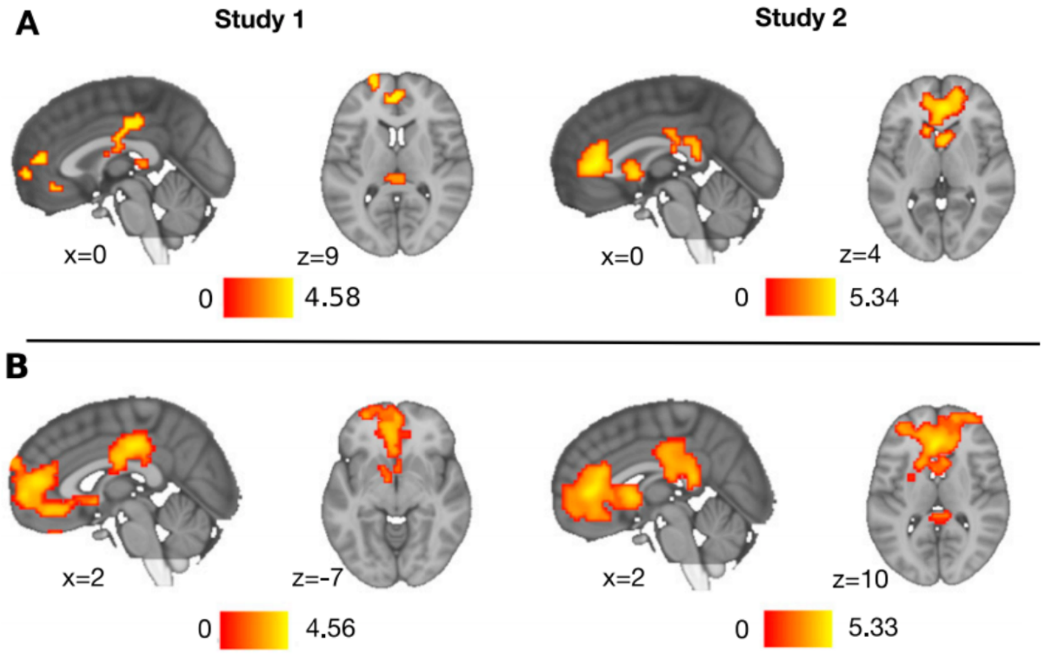


Figure C3.Whole-brain analyses of regions associated with each article's rank of population-level sharing counts in study 1 and study 2. Whole-brain maps were thresholded using (A) a nonparametric permutation analysis corrected at FDR-corrected P < 0.05, K ≥10 and (B) a cluster-based approach thresholded at P < 0.005 uncorrected and K ≥320 in study 1 and K ≥296 in study 2, respectively where K is the number of vowels per cluster on a 3dClustSim simulation together corresponding to P < 0.05 corrected.

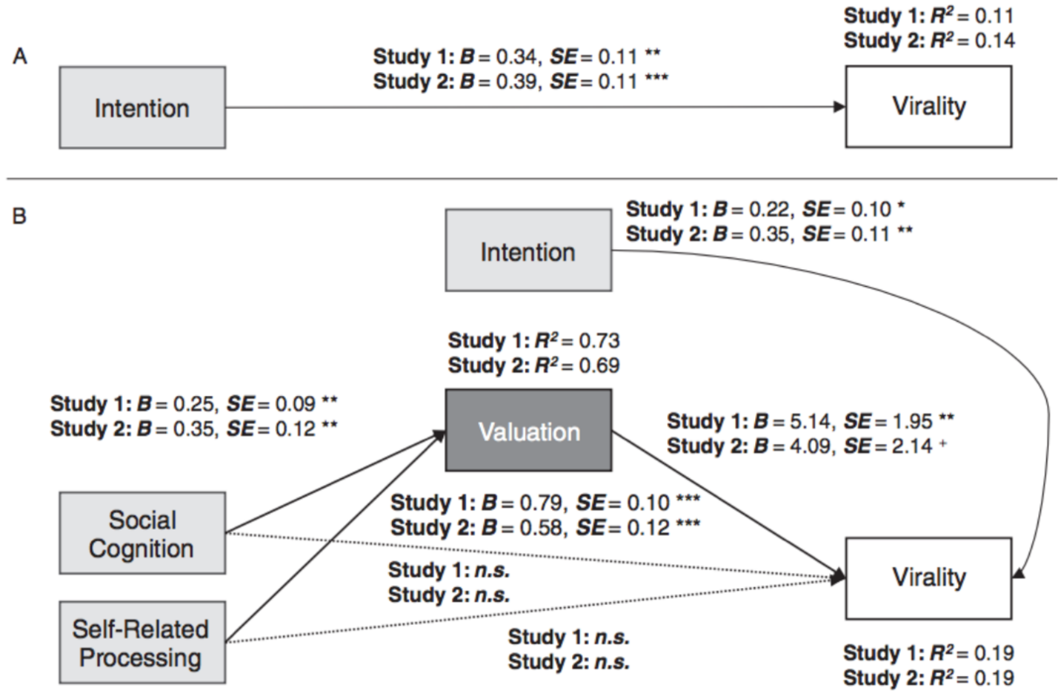


Figure C4. Effects of self-reported intention. (A) Model using intention ratings to predict population-level virality. (B) Model using both intention ratings and value-based virality to predict virality. All variables are rank-ordered; *P < 0.05, **P < 0.01, ***P < 0.001, +P = 0.056, n.s., not significant.

Table C1. ROIs in study 1 and study 2

ROI	Volume, cm^3	Center of mass x	Center of mass y	Center of mass z
Self-related processing				
Ventromedial prefrontal cortex	0.23	-4.26	56.6	-3.92
Precuneus/posterior cingulate cortex	1.93	-6.68	-55	28.2
Valuation				
Ventral striatum	4	-3	10	-4
Ventromedial prefrontal cortex	3.59	1	46	-7
Social processing				
Middle-medial prefrontal cortex	2.4	1.91	55	11.6
Dorsomedial prefrontal cortex	2.61	-0.13	53.7	29.3
Right temporoparietal junction	3.0	54.1	-52.6	23.1

Left temporoparietal junction	3.0	-51.7	-58.3	24.8
Right superior temporal lobe	3.1	54.4	-8.45	-17.3

The *x*, *y*, and *z* coordinates correspond to the MNI standard brain. All neural systems and subclusters are defined based on prior studies as described in *Methods*.

Table C2. Correlation matrices underlying the path models in Figure 3.1 (variables 1-4) and Figure C4 (variables 1-5)

Variable	1	2	3	4	5
Study 1, $n = 80$					
1. Self-related processing ROI	1				
2. Social processing ROI	0.705***	1			
3. Valuation ROI	0.838***	0.702***	1		
4. Population-level virality	0.240*	0.253*	0.387***	1	
5. Self-reported intentions	0.125	0.263*	0.285*	0.337**	1
Study 2, $n = 76$					
1. Self-related processing ROI	1				
2. Social processing ROI	0.822***	1			
3. Valuation ROI	0.814***	0.770***	1		
4. Population-level virality	0.094	0.182	0.237*	1	
5. Self-reported intentions	0.146	0.164	0.191	0.372***	1

Asterisks indicate statistical significance: $*P < .05$, $**P < 0.01$, $***P < 0.001$

Table C3. Correlation matrices underlying the path model in Figure C2 that includes unranked variables

Variable	1	2	3	4
Study 1, $n = 80$				
1. Self-related processing ROI	1			
2. Social processing ROI	0.717***	1		
3. Valuation ROI	0.856***	0.758***	1	
4. Population-level virality	0.236*	0.235*	0.352***	1
Study 2, $n = 76$				
1. Self-related processing ROI	1			

2. Social processing ROI	0.868***	1		
3. Valuation ROI	0.859***	0.851***	1	
4. Population-level virality	0.107	0.163	0.256*	1

Population-level virality showed a positively skewed distribution and thus was log-transformed. Asterisks indicate statistical significance: *P < .05, **P < 0.01, ***P < 0.001

Table C4. Model fit comparison for alternative path structures

Model	χ^2 (df), *P*	CFI	RMSEA (90% CI)	AIC	BIC
Study 1, *n* = 80					
(A) Valuation mediates	2.36 (2), 0.31	0.997	0.05 (0.00-0.23)	1,593.80	1,605.71
(B) Self-related processing mediates	10.63 (2), 0.01	0.925	0.23 (0.11-0.38)	1.602.08	1,613.99
(C) Social cognition mediates	10.08 (2), 0.01	0.888	0.23 (0.10-0.37)	1,601.53	1,613.44
Study 2, *n* = 76			0.09 (0.00-0.26)		
(A) Valuation mediates	3.26 (2), 0.20	0.986	0.18 (0.05-0.34)	1,457.07	1,468.72
(B) Self-related processing mediates	6.98 (2), 0.03	0.955	0.14 (0.00-0.30)	1,460.79	1,472.44
(C) Social cognition mediates	5.09 (2), 0.08	0.968		1,458.90	1,470.56

(A) represents a model resembling the path model in Figure 3.1 excluding the two insignificant effects. (B) represents a version of model A in which the roles of "valuation" and "self-related processing" are switched. (C) represents a version of model A in which the roles of "valuation" and "social cognition" are switched. AIC, Akaike's information criterion; BIC, Bayesian information criterion.

Table C5. Whole-brain tables: Clusters significantly associated with population-level virality ranks of the NYTimes articles shown in each trial during reading screen periods (study 1) or abstract trials (study 2)

					Cluster		Nonparametric	
Region	R/L	x	y	z	T	K	T	K
Study 1								
Medial prefrontal cortex*	L	-3	59	1	4.52	1,495	4.52	90
Anterior cingulate cortex	L	-3	47	10	4.27		4.28	
Caudate†	R	3	8	-5	2.97			
Dorsomedial prefrontal cortex	L	-12	38	31	4.08		4.09	14
Dorsomedial prefrontal cortex†	R	6	68	25	3.22			
Dorsolateral prefrontal cortex/superior frontal gyrus	L	-27	53	31	3.28		3.28	11
Ventromedial prefrontal cortex	L	-3	38	-11	4.23		4.24	11
Lateral orbital frontal cortex	L	-21	62	10	4.08		4.09	48
Mid cingulate cortex*	L	-6	-16	34	4.56	549	4.57	129
Mid cingulate cortex	M	0	-22	40	4.33		4.33	
Precuneus†	L	-18	-49	31	4.09			
Cingulate†	R	12	-28	28	3.84			
Thalamus	L	-4	-28	7	-		3.05	32
Study 2								
Medial prefrontal cortex	R	15	50	1	4.76	2,698	4.77	905
Medial prefrontal cortex	L	-15	50	-2	4.42		4.43	
Ventromedial prefrontal cortex	R	3	38	-8	3.67		3.67	
Anterior cingulate cortex*	L	-3	32	10	5.33		5.34	
Caudate	R	3	8	4	4.73		4.74	
Putamen	R	15	8	-8	3.88		3.89	
Caudate	L	-12	20	1	4.59		4.61	
Caudate	R	12	17	1	3.99		4.01	
Posterior cingulate cortex*	R	3	-40	19	4.48	506	4.50	126
Posterior cingulate cortex	R	6	-22	31	3.99		4.00	
Posterior cingulate cortex	L	-9	-43	19	3.70		3.72	

Clusters significantly associated with population-level virality ranks of the NYTimes articles shown in each trial during reading screen periods of reading (study 1) or abstract trials (study 2). The x, y, and z coordinates correspond to the MNI standard brain. No suprathreshold clusters were observed that were negatively associated with the parametric modulator. Thresholding: For each study, voxels significant under cluster correction and voxels significant under nonparametric correction are shown. Cluster correction thresholding was performed based on 3dClustSim simulation at $P < 0.005$ uncorrected and $K \geq 320$ in study 1 and $K \geq 296$ in study 2; nonparametric thresholding was performed through nonparametric permutation testing and FDR $P < 0.05$, $K > 10$. Separate clusters in the cluster-corrected map are divided by spaces between rows. df = 1, 38; voxel size = 3 × 3 × 3 mm. *K,* number of voxels per cluster. L, left; M, medial; R, right.

*Peak voxel within cluster.

† Peaks that are present only under cluster correction.

BIBLIOGRAPHY

Adamic, L. A., Lento, T. M., Adar, E., & Ng, P. C. (2016). Information evolution in social networks (pp. 473–482). ACM Press. https://doi.org/10.1145/2835776.2835827

Angelis, M. D., Bonezzi, A., Peluso, A. M., Rucker, D. D., & Costabile, M. (2012). On Braggarts and Gossips: A Self-Enhancement Account of Word-of-Mouth Generation and Transmission. *Journal of Marketing Research*, *49*(4), 551–563. https://doi.org/10.1509/jmr.11.0136

Archer, R. L., & Earle, W. B. (1983). The Interpersonal Orientations of Disclosure. In P. B. Paulus (Ed.), *Basic Group Processes* (pp. 289–314). Springer New York. https://doi.org/10.1007/978-1-4612-5578-9_12

Asch, S. (1955). Opinions and social pressure. *Nature*, *176*(4491), 1009.

Baek, E. C., Scholz, C., O'Donnell, M. B., & Falk, E. B. (2017). Neural correlates of selecting and sharing information. *Psychological Science*. https://doi.org/10.1177/0956797617695073

Bandari, R., Asur, S., & Huberman, B. A. (2012). The pulse of news in social media: Forecasting popularity. *ArXiv:1202.0332 [Physics]*. Retrieved from http://arxiv.org/abs/1202.0332

Bandura, A. (1986). *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, N.J: Prentice-Hall.

Bandura, A. (2001). Social Cognitive Theory of Mass Communication. *Media Psychology*, *3*(3), 265–299. https://doi.org/10.1207/S1532785XMEP0303_03

Barasch, A., & Berger, J. (2014). Broadcasting and narrowcasting: How audience size affects what people share. *Journal of Marketing Research*, *51*(3), 286–299. https://doi.org/10.1509/jmr.13.0238

Bargh, J. A., & Williams, E. L. (2006). The Automaticity of Social Life. *Current Directions in Psychological Science*, *15*(1), 1–4. https://doi.org/10.1111/j.0963-7214.2006.00395.x

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. https://doi.org/10.1016/j.neuroimage.2013.02.063

Baumeister, R. F., & Leary, M. R. (1995). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin*, *117*(3), 497–529. https://doi.org/10.1037/0033-2909.117.3.497

Bazarova, N. N. (2012). Public Intimacy: Disclosure Interpretation and Social Judgments on Facebook. *Journal of Communication*, *62*(5), 815–832. https://doi.org/10.1111/j.1460-2466.2012.01664.x

Bazarova, N. N., & Choi, Y. H. (2014). Self-Disclosure in Social Media: Extending the Functional Approach to Disclosure Motivations and Characteristics on Social Network Sites. *Journal of Communication*, *64*(4), 635–657. https://doi.org/10.1111/jcom.12106

Berger, J. (2011). Arousal increases social transmission of information. *Psychological Science*, *22*(7), 891–893.

Berger, J. (2014). Word of mouth and interpersonal communication: A review and directions for future research. *Journal of Consumer Psychology*, *24*(4), 586–607. https://doi.org/10.1016/j.jcps.2014.05.002

Berger, J., & Milkman, K. L. (2012). What makes online content viral? *Journal of Marketing Research*, *49*(2), 192–205. https://doi.org/10.1509/jmr.10.0353

Berkman, E. T., & Falk, E. B. (2013). Beyond brain mapping using neural measures to predict real-world outcomes. *Current Directions in Psychological Science*, *22*(1), 45–50. https://doi.org/10.1177/0963721412469394

Berns, G., & Moore, S. E. (2010). A neural predictor of cultural popularity. *Available at SSRN 1742971*. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1742971

Bernstein, M. S., Bakshy, E., Burke, M., & Karrer, B. (2013). Quantifying the invisible audience in social networks. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 21–30). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2470658

Bhanji, J. P., & Delgado, M. R. (2014). The social brain and reward: social information processing in the human striatum. *Wiley Interdisciplinary Reviews: Cognitive Science*, *5*(1), 61–73. https://doi.org/10.1002/wcs.1266

Boksem, M. A. S., & Smidts, A. (2014). Brain Responses to Movie Trailers Predict Individual Preferences for Movies and Their Population-Wide Commercial Success. *Journal of Marketing Research*, *52*(4), 482–492. https://doi.org/10.1509/jmr.13.0572

Botha, E., & Reyneke, M. (2013). To share or not to share: the role of content and emotion in viral marketing. *Journal of Public Affairs*, *13*(2), 160–171. https://doi.org/10.1002/pa.1471

Branigan, H. P., Pickering, M. J., & Cleland, A. A. (2000). Syntactic co-ordination in dialogue. *Cognition*, *75*(2), B13–B25. https://doi.org/10.1016/S0010-0277(99)00081-5

Bretherton, I. (1991). Pouring new wine into old bottles: The social self as internal working model. In M. R. Gunnar & L. A. Sroufe (Eds.), *Self processes and development* (pp. 1–41). Hillsdale, NJ, England: Lawrence Erlbaum Associates, Inc.

Brett, M., Anton, J.-L., & Valabregue, J.-B. P. (2002). Region of interest analysis using an SPM toolbox. *NeuroImage*, *16*(2).

Brewer, M. B. (1991). The social self: On being the same and different at the same time. *Personality and Social Psychology Bulletin*, *17*(5), 475–482. https://doi.org/10.1177/0146167291175001

Buhle, J. T., Silvers, J. A., Wager, T. D., Lopez, R., Onyemekwu, C., Kober, H., … Ochsner, K. N. (2014). Cognitive Reappraisal of Emotion: A Meta-Analysis of Human Neuroimaging Studies. *Cerebral Cortex*, *24*(11), 2981–2990. https://doi.org/10.1093/cercor/bht154

Burgoon, J. K., Stern, L. A., & Dillman, L. (2007). *Interpersonal adaptation: Dyadic interaction patterns*. New York, NY: Cambridge University Press.

Cacioppo, S., & Cacioppo, J. T. (2012). Decoding the invisible forces of social connections. *Frontiers in Integrative Neuroscience*, *6*(51), 354–360. https://doi.org/10.3389/fnint.2012.00051

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*, *20*(13), 1165–1170. https://doi.org/10.1016/j.cub.2010.04.055

Campbell-Meiklejohn, D. K., Simonsen, A., Jensen, M., Wohlert, V., Gjerløff, T., Scheel-Kruger, J., … Roepstorff, A. (2012). Modulation of Social Influence by Methylphenidate. *Neuropsychopharmacology*, *37*(6), 1517–1525. https://doi.org/10.1038/npp.2011.337

Cappella, J. N. (1996). Dynamic coordination of vocal and kinesic behavior in dyadic interaction: Methods, problems, and interpersonal outcomes. Retrieved from http://psycnet.apa.org/psycinfo/1996-98153-014

Cappella, J. N. (1997a). Behavioral and judged coordination in adult informal social interactions: Vocal and kinesic indicators. *Journal of Personality and Social Psychology*, *72*(1), 119–131. https://doi.org/10.1037/0022-3514.72.1.119

Cappella, J. N. (1997b). The development of theory about automated patterns of face-to-face human interaction. *Developing Communication Theories*, 57–84.

Cappella, J. N., Kim, H. S., & Albarracín, D. (2015). Selection and transmission processes for information in the emerging media environment: Psychological motives and message characteristics. *Media Psychology*, *18*, 396–424. https://doi.org/10.1080/15213269.2014.941112

Cascio, C. N., O'Donnell, M. B., Bayer, J., Tinney, F. J., & Falk, E. B. (2015). Neural correlates of susceptibility to group opinions in online word-of-mouth recommendations. *Journal of Marketing Research*, *52*(4), 559–575. https://doi.org/10.1509/jmr.13.0611

Cascio, C. N., Scholz, C., & Falk, E. B. (2015). Social influence and the brain: persuasion, susceptibility to influence and retransmission. *Current Opinion in Behavioral Sciences*, *3*, 51–57. https://doi.org/10.1016/j.cobeha.2015.01.007

Chaiken, S. (1980). Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *Journal of Personality and Social Psychology*, *39*(5), 752–766. https://doi.org/10.1037/0022-3514.39.5.752

Chatzopoulou, G., Sheng, C., & Faloutsos, M. (2010). A first step towards understanding popularity in YouTube. In *INFOCOM IEEE Conference on Computer Communications Workshops, 2010* (pp. 1–6). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5466701

Cheng, J., Adamic, L. A., Kleinberg, J., & Leskovec, J. (2016). Do Cascades Recur? *ArXiv Preprint ArXiv:1602.01107*. Retrieved from http://arxiv.org/abs/1602.01107

Cho, J., Shah, D. V., McLeod, J. M., McLeod, D. M., Scholl, R. M., & Gotlieb, M. R. (2009). Campaigns, Reflection, and Deliberation: Advancing an O-S-R-O-R Model of Communication Effects. *Communication Theory*, *19*(1), 66–88. https://doi.org/10.1111/j.1468-2885.2008.01333.x

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*, *20*(1), 1.

Chua, H. F., Liberzon, I., Welsh, R. C., & Strecher, V. J. (2009). Neural correlates of message tailoring and self-relatedness in smoking cessation programming. *Biological Psychiatry*, *65*(2), 165–168.

Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annu. Rev. Psychol.*, *55*, 591–621.

Clark, H. H., & Murphy, G. L. (1982). Audience design in meaning and reference. *Advances in Psychology*, *9*, 287–299. https://doi.org/10.1016/S0166-4115(09)60059-5

Collins, N. L., & Miller, L. C. (1994). Self-disclosure and liking: A meta-analytic review. *Psychological Bulletin*, *116*(3), 457–475. https://doi.org/10.1037/0033-2909.116.3.457

Cooper, N., Tompson, S., O'Donnell, M. B., & Falk, E. B. (2015). Brain activity in self- and value-related regions in response to online antismoking messages predicts behavior change. *Journal of Media Psychology*, *27*(3), 93–109.

Cox, K. M., & Kable, J. W. (2014). BOLD Subjective Value Signals Exhibit Robust Range Adaptation. *Journal of Neuroscience*, *34*(49), 16533–16543. https://doi.org/10.1523/JNEUROSCI.3927-14.2014

Cox, R. W. (1996). AFNI: software for analysis and visualization of functional magnetic resonance neuroimages. *Computers and Biomedical Research*, *29*(3), 162–173. https://doi.org/10.1006/cbmr.1996.0014

Csibra, G., & Gergely, G. (2011). Natural pedagogy as evolutionary adaptation. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, *366*(1567), 1149–1157. https://doi.org/10.1098/rstb.2010.0319

Cunningham, C. M. (2012). *Social Networking and Impression Management: Self-Presentation in the Digital Age*. Plymouth, UK: Lexington Books.

Dale, A. M., Greve, D. N., & Burock, M. A. (1999). Optimal stimulus sequences for event-related fMRI. *NeuroImage*, *9*, S33–S33.

D'Argembeau, A., Jedidi, H., Balteau, E., Bahri, M., Phillips, C., & Salmon, E. (2012). Valuing One's Self: Medial Prefrontal Involvement in Epistemic and Emotive Investments in Self-views. *Cerebral Cortex*, *22*(3), 659–667. https://doi.org/10.1093/cercor/bhr144

Darke, P. R., & Chaiken, S. (2005). The pursuit of self-interest: Self-interest bias in attitude judgment and persuasion. *Journal of Personality and Social Psychology*, *89*(6), 864–883. https://doi.org/10.1037/0022-3514.89.6.864

David, C., Cappella, J. N., & Fishbein, M. (2006). The social diffusion of influence among adolescents: Group interaction in a chat room environment about antidrug advertisements. *Communication Theory*, *16*(1), 118–140.

Davis, R. E., & Resnicow, K. (2011). The cultural variance framework for tailoring health messages. In *Health Communication Message Design: Theory and Practice* (pp. 115–136). SAGE.

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*(8), 1742–1752.

Derlega, V. J., & Grzelak, J. (1979). Appropriateness of self-disclosure. In *Self-discloure: Origins, patterns, and implications of openness in interpersonal relationships* (pp. 151–176). San Francisco, CA, US: Jossey-Bass.

DeWall, C. N. (2010). Forming a basis for acceptance: Excluded people form attitudes to agree with potential affiliates. *Social Influence*, *5*(4), 245–260. https://doi.org/10.1080/15534511003783536

Diekhof, E. K., Kaps, L., Falkai, P., & Gruber, O. (2012). The role of the human ventral striatum and the medial orbitofrontal cortex in the representation of reward magnitude – An activation likelihood estimation meta-analysis of neuroimaging studies of passive reward expectancy and outcome processing. *Neuropsychologia*, *50*(7), 1252–1266. https://doi.org/10.1016/j.neuropsychologia.2012.02.007

Dietvorst, R. C., Verbeke, W. J. M. ., Bagozzi, R. P., Yoon, C., Smits, M., & van der Lugt, A. (2009). A sales force–specific theory-of-mind scale: Tests of its validity by classical methods and functional magnetic resonance imaging. *Journal of Marketing Research*, *46*(5), 653–668. https://doi.org/10.1509/jmkr.46.5.653

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*, 4567. https://doi.org/10.1038/ncomms5567

Dore, B. P., Scholz, C. S., Baek, E. C., & Falk, E. B. (under review). Brain activity predicts population information sharing by capturing consensus judgments of value.

Dorsey, A. M., Scherer, C. W., & Real, K. (1999). The College Tradition of "Drink 'Til You Drop": The Relation Between Students' Social Networks and Engaging in Risky Behaviors. *Health Communication*, *11*(4), 313–334. https://doi.org/10.1207/S15327027HC1104_1

Dufour, N., Redcay, E., Young, L., Mavros, P. L., Moran, J. M., Triantafyllou, C., … Saxe, R. (2013). Similar brain activation during false belief tasks in a large sample of adults with and without autism. *PLoS ONE*, *8*(9), e75468. https://doi.org/10.1371/journal.pone.0075468

Dunbar, R. I., Marriott, A., & Duncan, N. D. (1997). Human conversational behavior. *Human Nature*, *8*(3), 231–246. https://doi.org/10.1007/BF02912493

Dunlop, S. M., Kashima, Y., & Wakefield, M. (2010). Predictors and Consequences of Conversations About Health Promoting Media Messages. *Communication Monographs*, *77*(4), 518–539. https://doi.org/10.1080/03637751.2010.502537

Dunning, D., Boven, L. V., & Loewenstein, G. F. (2001). Egocentric empathy gaps in social interaction and exchange. In *Advances in Group Processes* (Vol. 18, pp. 65–97). Emerald Group Publishing Limited. Retrieved from http://www.emeraldinsight.com/doi/abs/10.1016/S0882-6145(01)18004-5

Eklund, A., Nichols, T. E., & Knutsson, H. (2016). Cluster failure: Why fMRI inferences for spatial extent have inflated false-positive rates. *Proceedings of the National Academy of Sciences*, *113*(28), 7900–7905. https://doi.org/10.1073/pnas.1602413113

Emler, N. (1990). A Social Psychology of Reputation. *European Review of Social Psychology*, *1*(1), 171–193. https://doi.org/10.1080/14792779108401861

Enzi, B., de Greck, M., Prösch, U., Tempelmann, C., & Northoff, G. (2009). Is Our Self Nothing but Reward? Neuronal Overlap and Distinction between Reward and Personal Relevance and Its Relation to Human Personality. *PLoS ONE*, *4*(12), e8429. https://doi.org/10.1371/journal.pone.0008429

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. https://doi.org/10.1177/0956797611434964

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*(25), 8421–8424. https://doi.org/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*(2), 177–185. https://doi.org/10.1037/a0022259

Falk, E. B., Cascio, C. N., & Coronel, J. C. (2015). Neural prediction of communication-relevant outcomes. *Communication Methods and Measures*, *9*(1–2), 30–54. https://doi.org/10.1080/19312458.2014.999750

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. https://doi.org/10.1177/0956797612474670

Falk, E. B., O'Donnell, M. B., Cascio, C. N., Tinney, F., Kang, Y., Lieberman, M. D., … Strecher, V. J. (2015). Self-affirmation alters the brain's response to health messages and subsequent behavior change. *Proceedings of the National Academy of Sciences*, *112*(7), 1977–1982. https://doi.org/10.1073/pnas.1500247112

Falk, E. B., O'Donnell, M. B., Tompson, S., Gonzalez, R., Cin, S. D., Strecher, V., … An, L. (2016). Functional brain imaging predicts public health campaign success. *Social Cognitive and Affective Neuroscience*, *11*(2), 204–214. https://doi.org/10.1093/scan/nsv108

Falk, E. B., & Scholz, C. (2018). Persuasion, Influence, and Value: Perspectives from Communication and Social Neuroscience. *Annual Review of Psychology*, *69*(1), 329–356. https://doi.org/10.1146/annurev-psych-122216-011821

Fareri, D. S., & Delgado, M. R. (2014). Social Rewards and Social Networks in the Human Brain. *The Neuroscientist*, *20*(4), 387–402. https://doi.org/10.1177/1073858414521869

Fehr, E., & Camerer, C. F. (2007). Social neuroeconomics: the neural circuitry of social preferences. *Trends in Cognitive Sciences*, *11*(10), 419–427. https://doi.org/10.1016/j.tics.2007.09.002

Fishbein, M., & Ajzen, I. (2010). *Predicting and Changing Behavior: The Reasoned Action Approach*. New York: Psychology Press.

Frank, L. B., Chatterjee, J. S., Chaudhuri, S. T., Lapsansky, C., Bhanot, A., & Murphy, S. T. (2012). Conversation and Compliance: Role of Interpersonal Discussion and Social Norms in Public Communication Campaigns. *Journal of Health Communication*, *17*(9), 1050–1067. https://doi.org/10.1080/10810730.2012.665426

Frith, C. D., & Frith, U. (2006). The neural basis of mentalizing. *Neuron*, *50*(4), 531–534. https://doi.org/10.1016/j.neuron.2006.05.001

Genevsky, A., & Knutson, B. (2015). Neural affective mechanisms predict market-level microlending. *Psychological Science*, 0956797615588467. https://doi.org/10.1177/0956797615588467

Giles, H., & Smith, P. (1979). Accommodation Theory: Optimal Levels of Convergence‖ in Giles, H. and St. Clair, R. *Language and Social Psychology*.

Goel, S., Anderson, A., Hofman, J., & Watts, D. J. (2016). The structural virality of online diffusion. *Management Science*, *62*(1), 180–196. https://doi.org/10.1287/mnsc.2015.2158

Goel, S., Watts, D. J., & Goldstein, D. G. (2012). The structure of online diffusion networks. In *Proceedings of the 13th ACM conference on electronic commerce* (pp. 623–638). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2229058

Gonzales, A. L., Hancock, J. T., & Pennebaker, J. W. (2009). Language Style Matching as a Predictor of Social Dynamics in Small Groups. *Communication Research*. https://doi.org/10.1177/0093650209351468

Greene, K., Derlega, V. J., & Mathews, A. (2006). Self disclsoure in personal relationships. In A. Vangelisiti & D. Perlmans (Eds.), *Cambridge Handbook of Personal Relationships* (pp. 409–427). Cambridge: Cambridge University Press. Retrieved from http://himaforstaunair.url.ph/soal/Self%20Disclsoure%20in%20Personal%20Relationships%20copy.pdf

Hardy, B. W., & Scheufele, D. A. (2009). Presidential Campaign Dynamics and the Ebb and Flow of Talk as a Moderator: Media Exposure, Knowledge, and Political Discussion. *Communication Theory*, *19*(1), 89–101. https://doi.org/10.1111/j.1468-2885.2008.01334.x

Hasson, U., Ghazanfar, A. A., Galantucci, B., Garrod, S., & Keysers, C. (2012). Brain-to-brain coupling: a mechanism for creating and sharing a social world. *Trends in Cognitive Sciences*, *16*(2), 114–121. https://doi.org/10.1016/j.tics.2011.12.007

Hasson, U., Malach, R., & Heeger, D. J. (2010). Reliability of cortical activity during natural stimulation. *Trends in Cognitive Sciences*, *14*(1), 40–48. https://doi.org/10.1016/j.tics.2009.10.011

Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1993). Emotional contagion. *Current Directions in Psychological Science*, *2*(3), 96–99.

Hendriks, H., de Bruijn, G.-J., Meehan, O., & van den Putte, B. (2016). Online and Offline Conversations About Alcohol: Comparing the Effects of Familiar and Unfamiliar Discussion Partners. *Journal of Health Communication*, 1–9. https://doi.org/10.1080/10810730.2016.1153766

Hendriks, H., van den Putte, B., & de Bruijn, G.-J. (2014). Changing the Conversation: The Influence of Emotions on Conversational Valence and Alcohol Consumption. *Prevention Science*, *15*. https://doi.org/10.1007/s11121-013-0418-2

Henrich, J., Heine, S. J., & Norenzayan, A. (2010, June 30). Most people are not WEIRD [Comments and Opinion]. https://doi.org/10.1038/466029a

Hofstede, G., Hofstede, G. J., & Minkov, M. (1991). *Cultures and organizations: Software of the mind* (Vol. 2). Citeseer. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.446.3598&rep=rep1&type=pdf

Hogan, B. (2010). The Presentation of Self in the Age of Social Media: Distinguishing Performances and Exhibitions Online. *Bulletin of Science, Technology & Society*, 0270467610385893. https://doi.org/10.1177/0270467610385893

Hornik, R. (2002). *Public Health Communication: Evidence for Behavior Change*. Routledge.

Hornik, R., & Yanovitzky, I. (2003). Using theory to design evaluations of communication campaigns: The case of the National Youth Anti-Drug Media Campaign. *Communication Theory*, *13*(2), 204–224.

Iacoboni, M. (2009). Imitation, Empathy, and Mirror Neurons. *Annual Review of Psychology*, *60*(1), 653–670. https://doi.org/10.1146/annurev.psych.60.110707.163604

Imhof, M. A., Schmälzle, R., Renner, B., & Schupp, H. T. (2017). How real-life health messages engage our brains: Shared processing of effective anti-alcohol videos. *Social Cognitive and Affective Neuroscience*, *12*(7), 1188–1196. https://doi.org/10.1093/scan/nsx044

Jeong, M., & Bae, R. E. (2017). The Effect of Campaign-Generated Interpersonal Communication on Campaign-Targeted Health Outcomes: A Meta-Analysis. *Health Communication*, *0*(0), 1–16. https://doi.org/10.1080/10410236.2017.1331184

Jeong, M., Tan, A. S. L., Brennan, E., Gibson, L., & Hornik, R. C. (2015). Talking about quitting: Interpersonal communication as a mediator of campaign effects on smokers' quit behaviors. *Journal of Health Communication*, *20*(10), 1196–1205.

Jiang, L. C., Bazarova, N. N., & Hancock, J. T. (2011). The Disclosure–Intimacy Link in Computer-Mediated Communication: An Attributional Extension of the

Hyperpersonal Model. *Human Communication Research*, *37*(1), 58–77. https://doi.org/10.1111/j.1468-2958.2010.01393.x

Johnson, B. T., & Eagly, A. H. (1989). Effects of involvement on persuasion: A meta-analysis. *Psychological Bulletin*, *106*(2), 290–314. https://doi.org/10.1037/0033-2909.106.2.290

Johnson, B. T., Smith-McLallen, A., Killeya, L. A., & Levin, K. D. (2004). Truth or consequences: Overcoming resistance to persuasion with positive thinking. *CHIP Documents*, *14*. Retrieved from http://digitalcommons.uconn.edu/cgi/viewcontent.cgi?article=1013&context=chip_docs

Kashian, N., Jang, J., Shin, S. Y., Dai, Y., & Walther, J. B. (2017). Self-disclosure and liking in computer-mediated communication. *Computers in Human Behavior*, *71*, 275–283. https://doi.org/10.1016/j.chb.2017.01.041

Katz, E., & Lazarsfeld, P. F. (1955). *Personal Influence, The part played by people in the flow of mass communications*. Glencoe: Free Press.

Kim, H. S. (2015). Attracting views and going viral: How message features and news-sharing channels affect health news diffusion. *Journal of Communication*, *65*(3), 512–534. https://doi.org/10.1111/jcom.12160

Klucharev, V., Hytönen, K., Rijpkema, M., Smidts, A., & Fernández, G. (2009). Reinforcement Learning Signal Predicts Social Conformity. *Neuron*, *61*(1), 140–151. https://doi.org/10.1016/j.neuron.2008.11.027

Krämer, N. C., & Haferkamp, N. (2011). Online Self-Presentation: Balancing Privacy Concerns and Impression Construction on Social Networking Sites. In *Privacy Online* (pp. 127–141). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-21521-6_10

Kreuter, M. W., Strecher, V. J., & Glassman, B. (1999). One size does not fit all: The case for tailoring print materials. *Annals of Behavioral Medicine*, *21*(4), 276–283. https://doi.org/10.1007/BF02895958

Krikorian, R. (2013, August 16). New Tweets per second record, and how! Twitter Official Blog. Retrieved from https://blog.twitter.com/2013/new-tweets-per-second-record-and-how

Krumpal, I. (2011). Determinants of social desirability bias in sensitive surveys: a literature review. *Quality & Quantity*, *47*(4), 2025–2047. https://doi.org/10.1007/s11135-011-9640-9

Lakin, J. L., & Chartrand, T. L. (2003). Using Nonconscious Behavioral Mimicry to Create Affiliation and Rapport. *Psychological Science*, *14*(4), 334–339. https://doi.org/10.1111/1467-9280.14481

Landis, M. H., & Burtt, H. E. (1924). A study of conversations. *Journal of Comparative Psychology*, *4*(1), 81–89.

Leary, M. R. (1996). *Self-presentation: Impression management and interpersonal behavior* (Vol. 15). Boulder, CO, US: Westview.

Lee, C. J. (2009). The Interplay Between Media Use and Interpersonal Communication in the Context of Healthy Lifestyle Behaviors: Reinforcing or Substituting? *Mass*

Communication and Society, *13*(1), 48–66. https://doi.org/10.1080/15205430802694869

Lee, C. S., & Ma, L. (2012). News sharing in social media: The effect of gratifications and prior experience. *Computers in Human Behavior*, *28*(2), 331–339. https://doi.org/10.1016/j.chb.2011.10.002

Levy, D. J., & Glimcher, P. W. (2011). Comparing apples and oranges: Using reward-specific and reward-general subjective value representation in the brain. *Journal of Neuroscience*, *31*(41), 14693–14707. https://doi.org/10.1523/JNEUROSCI.2218-11.2011

Levy, D. J., & Glimcher, P. W. (2012). The root of all value: a neural common currency for choice. *Current Opinion in Neurobiology*, *22*(6), 1027–1038. https://doi.org/10.1016/j.conb.2012.06.001

Lieberman, M. D. (2007). Social Cognitive Neuroscience: A Review of Core Processes. *Annual Review of Psychology*, *58*(1), 259–289. https://doi.org/10.1146/annurev.psych.58.110405.085654

Lieberman, M. D. (2010). Social cognitive neuroscience. In S. T. Fiske, D. T. Gilbert, & G. Lindzey (Eds.), *Handbook of Social Psychology* (5th ed., pp. 143–193). New York, NY: McGraw-Hill.

Lieberman, M. D. (2013). *Social: Why Our Brains Are Wired to Connect* (1st ed.). New York, NY: Crown.

Lieberman, M. D., & Eisenberger, N. I. (2009). Pains and Pleasures of Social Life. *Science*, *323*(5916), 890–891. https://doi.org/10.1126/science.1170008

Litt, E. (2012). Knock, Knock. Who's There? The Imagined Audience. *Journal of Broadcasting & Electronic Media*, *56*(3), 330–345. https://doi.org/10.1080/08838151.2012.705195

Maddux, J. E., & Rogers, R. W. (1983). Protection motivation and self-efficacy: A revised theory of fear appeals and attitude change. *Journal of Experimental Social Psychology*, *19*(5), 469–479. https://doi.org/10.1016/0022-1031(83)90023-9

Magnifico, A. M. (2010). Writing for Whom? Cognition, Motivation, and a Writer's Audience. *Educational Psychologist*, *45*(3), 167–184. https://doi.org/10.1080/00461520.2010.493470

Marder, B., Joinson, A., Shankar, A., & Thirlaway, K. (2016). Strength matters: Self-presentation to the strongest audience rather than lowest common denominator when faced with multiple audiences in social network sites. *Computers in Human Behavior*, *61*, 56–62. https://doi.org/10.1016/j.chb.2016.03.005

Mars, R. B., Neubert, F.-X., Noonan, M. P., Sallet, J., Toni, I., & Rushworth, M. F. S. (2012). On the relationship between the "default mode network" and the "social brain." *Frontiers in Human Neuroscience*, *6*. https://doi.org/10.3389/fnhum.2012.00189

Marwick, A. E., & boyd, D. (2011). I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New Media & Society*, *13*(1), 114–133. https://doi.org/10.1177/1461444810365313

Matz, S. C., Kosinski, M., Nave, G., & Stillwell, D. J. (2017). Psychological targeting as an effective approach to digital mass persuasion. *Proceedings of the National Academy of Sciences*, 201710966. https://doi.org/10.1073/pnas.1710966114

Meshi, D., Tamir, D. I., & Heekeren, H. R. (2015). The emerging neuroscience of social media. *Trends in Cognitive Sciences*, *19*(12), 771–782. https://doi.org/10.1016/j.tics.2015.09.004

Mezulis, A. H., Abramson, L. Y., Hyde, J. S., & Hankin, B. L. (2004). Is there a universal positivity bias in attributions? A meta-analytic review of individual, developmental, and cultural differences in the self-serving attributional bias. *Psychological Bulletin*, *130*(5), 711–747. https://doi.org/10.1037/0033-2909.130.5.711

Miller, L. C., & Read, S. J. (1987). Why am I telling you this? Self-disclosure in a goal-based model of personality. In V. J. Derlega & J. H. Berg (Eds.), *Self-Disclosure: Theory, Research, and Therapy*. New York, NY, USA: Plenum Press.

Mogan, R., Fischer, R., & Bulbulia, J. A. (2017). To be in synchrony or not? A meta-analysis of synchrony's effects on behavior, perception, cognition and affect. *Journal of Experimental Social Psychology*, *72*, 13–20. https://doi.org/10.1016/j.jesp.2017.03.009

Mohammed, S. (2001). Personal Communication Networks and the Effects of an Entertainment-Education Radio Soap Opera in Tanzania. *Journal of Health Communication*, *6*(2), 137–154. https://doi.org/10.1080/10810730117219

Murray, R. J., Schaer, M., & Debbané, M. (2012). Degrees of separation: A quantitative neuroimaging meta-analysis investigating self-specificity and shared neural activation between self- and other-reflection. *Neuroscience & Biobehavioral Reviews*, *36*(3), 1043–1059. https://doi.org/10.1016/j.neubiorev.2011.12.013

Naaman, M., Boase, J., & Lai, C.-H. (2010). Is it really about me?: message content in social awareness streams. In *Proceedings of the 2010 ACM conference on Computer supported cooperative work* (pp. 189–192). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1718953

Neumann, J. von, & Morgenstern, O. (2007). *Theory of Games and Economic Behavior*. Princeton University Press.

Nguyen, M., Bin, Y. S., & Campbell, A. (2012). Comparing Online and Offline Self-Disclosure: A Systematic Review. *Cyberpsychology, Behavior, and Social Networking*, *15*(2), 103–111. https://doi.org/10.1089/cyber.2011.0277

Niederhoffer, K. G., & Pennebaker, J. W. (2002). Linguistic Style Matching in Social Interaction. *Journal of Language and Social Psychology*, *21*(4), 337–360. https://doi.org/10.1177/026192702237953

Nisbett, R. E., & Wilson, T. D. (1977). Telling more than we can know: Verbal reports on mental processes. *Psychological Review*, *84*(3), 231–259. https://doi.org/10.1037/0033-295X.84.3.231

Noar, S. M., Benac, C. N., & Harris, M. S. (2007). Does tailoring matter? Meta-analytic review of tailored print health behavior change interventions. *Psychological Bulletin*, *133*(4), 673.

Nook, E. C., & Zaki, J. (2015). Social Norms Shift Behavioral and Neural Responses to Foods. *Journal of Cognitive Neuroscience*, *27*(7), 1412–1426. https://doi.org/10.1162/jocn_a_00795

Northoff, G., & Hayes, D. J. (2011). Is Our Self Nothing but Reward? *Biological Psychiatry*, *69*(11), 1019–1025. https://doi.org/10.1016/j.biopsych.2010.12.014

Northoff, G., Heinzel, A., de Greck, M., Bermpohl, F., Dobrowolny, H., & Panksepp, J. (2006). Self-referential processing in our brain—A meta-analysis of imaging studies on the self. *NeuroImage*, *31*(1), 440–457. https://doi.org/10.1016/j.neuroimage.2005.12.002

Nowak, M. A., Page, K. M., & Sigmund, K. (2000). Fairness Versus Reason in the Ultimatum Game. *Science*, *289*(5485), 1773–1775. https://doi.org/10.1126/science.289.5485.1773

O'Keefe, D. J. (2012). The relative persuasiveness of different forms of arguments-from-consequences. In *Communication Yearbook* (Vol. 36, pp. 109–135). Routledge.

Omarzu, J. (2000). A Disclosure Decision Model: Determining How and When Individuals Will Self-Disclose. *Personality and Social Psychology Review*, *4*(2), 174–185. https://doi.org/10.1207/S15327957PSPR0402_05

Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251), aac4716–aac4716. https://doi.org/10.1126/science.aac4716

Pentland, A. (2014). *Social physics: How good ideas spread-the lessons from a new science*. New York, NY: The Penguin Press.

Plassmann, H., Venkatraman, V., Huettel, S., & Yoon, C. (2015). Consumer neuroscience: Applications, challenges, and possible solutions. *Journal of Marketing Research*, *52*(4), 427–435. https://doi.org/10.1509/jmr.14.0048

Poldrack, R. A. (2006). Can cognitive processes be inferred from neuroimaging data? *Trends in Cognitive Sciences*, *10*(2), 59–63.

Poldrack, R. A. (2011). Inferring mental states from neuroimaging data: from reverse inference to large-scale decoding. *Neuron*, *72*(5), 692–697.

Power, J. D., Cohen, A. L., Nelson, S. M., Wig, G. S., Barnes, K. A., Church, J. A., … Petersen, S. E. (2011). Functional network organization of the human brain. *Neuron*, *72*(4), 665–678. https://doi.org/10.1016/j.neuron.2011.09.006

R Core Team. (2015). R: A language and environment for statistical computing. Vienna, Austria; 2014. *Http://Www.R-Project.Org*.

Rademacher, L., Krach, S., Kohls, G., Irmak, A., Gründer, G., & Spreckelmeyer, K. N. (2010). Dissociation of neural networks for anticipation and consumption of monetary and social rewards. *NeuroImage*, *49*(4), 3276–3285. https://doi.org/10.1016/j.neuroimage.2009.10.089

Radicati Group. (2015, February). Email statistics report 2015-2019, executive summary. Retrieved from http://www.radicati.com/wp/wp-content/uploads/2015/02/Email-Statistics-Report-2015-2019-Executive-Summary.pdf

Richardson, D. C., & Dale, R. (2005). Looking to understand: The coupling between speakers’ and listeners’ eye movements and its relationship to discourse comprehension. *Cognitive Science*, *29*(6), 1045–1060.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York, NY: Free Press.

Rosenberg, J., & Egbert, N. (2011). Online Impression Management: Personality Traits and Concerns for Secondary Goals as Predictors of Self-Presentation Tactics on Facebook. *Journal of Computer-Mediated Communication*, *17*(1), 1–18. https://doi.org/10.1111/j.1083-6101.2011.01560.x

Rosenstock, I. M. (1990). The health belief model: Explaining health behavior through expectancies. In K. Glanz, F. M. Lewis, & B. K. Rimer (Eds.), *Health behavior and health education: Theory, research, and practice* (pp. 39–62). San Francisco, CA, US: Jossey-Bass.

Rosenstock, I. M., Strecher, V. J., & Becker, M. H. (1988). Social Learning Theory and the Health Belief Model. *Health Education & Behavior*, *15*(2), 175–183. https://doi.org/10.1177/109019818801500203

Ross, M., & Sicoly, F. (1979). Egocentric biases in availability and attribution. *Journal of Personality and Social Psychology*, *37*(3), 322–336. https://doi.org/10.1037/0022-3514.37.3.322

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36.

Saba, W. P., & Valente, T. W. (2001). Campaign Exposure and Interpersonal Communication as Factors in Contraceptive Use in Bolivia. *Journal of Health Communication*, *6*(4), 303–322. https://doi.org/10.1080/108107301317140805

Samuelson, P. A. (1937). A Note on Measurement of Utility. *The Review of Economic Studies*, *4*(2), 155–161. https://doi.org/10.2307/2967612

Saxe, R., Moran, J. M., Scholz, J., & Gabrieli, J. (2006). Overlapping and non-overlapping brain regions for theory of mind and self reflection in individual subjects. *Social Cognitive and Affective Neuroscience*. https://doi.org/10.1093/scan/nsl034

Schilbach, L., Eickhoff, S. B., Rotarska-Jagiela, A., Fink, G. R., & Vogeley, K. (2008). Minds at rest? Social cognition as the default mode of cognizing and its putative relationship to the "default system" of the brain. *Consciousness and Cognition*, *17*(2), 457–467. https://doi.org/10.1016/j.concog.2008.03.013

Schmälzle, R., Häcker, F. E., Honey, C. J., & Hasson, U. (2015). Engaged listeners: shared neural processing of powerful political speeches. *Social Cognitive and Affective Neuroscience*, nsu168.

Schmälzle, R., Häcker, F., Renner, B., Honey, C. J., & Schupp, H. T. (2013). Neural Correlates of Risk Perception during Real-Life Risk Communication. *The Journal of Neuroscience*, *33*(25), 10340–10347. https://doi.org/10.1523/JNEUROSCI.5323-12.2013

Schmitz, T. W., & Johnson, S. C. (2007). Relevance to self: A brief review and framework of neural systems underlying appraisal. *Neuroscience &*

Biobehavioral Reviews, *31*(4), 585–596. https://doi.org/10.1016/j.neubiorev.2006.12.003

Scholz, C., Baek, E. C., O'Donnell, M. B., & Falk, E. B. (2015). Social networks and neural mechanisms of communication. Open Science Framework. Retrieved from https://osf.io/a8xme

Scholz, C., Baek, E. C., O'Donnell, M. B., & Falk, E. B. (2016). Neural mechanisms of influence and message propagation. Open Science Framework. Retrieved from https://osf.io/hzg5b/

Scholz, C., Baek, E. C., O'Donnell, M. B., Kim, H. S., Cappella, J. N., & Falk, E. B. (2016). Value-based virality: A neurocognitive model of information sharing. Presented at the International Communication Association, Fukuoka, Japan.

Scholz, C., Baek, E. C., O'Donnell, M. B., Kim, H. S., Cappella, J. N., & Falk, E. B. (2017). A neural model of valuation and information virality. *Proceedings of the National Academy of Sciences*, *114*(11), 2881–2886. https://doi.org/10.1073/pnas.1615259114

Scholz, C., Dore, B. P., Cooper, N., & Falk, E. B. (in prep). Neural Message Engagement Predicts Susceptibility to Conversational Influence on Drinking Behavior.

Scholz, C., & Falk, E. B. (in press). The neuroscience of viral ideas. In S. González-Bailón & B. Foucault Welles (Eds.), *Handbook of Communication in the Networked Age*. Oxford University Press.

Schwartz, S. H. (2006). A theory of cultural value orientations: Explication and applications. *Comparative Sociology*, *5*(2), 137–182.

Schwartz, S. H. (2007). Value orientations: Measurement, antecedents and consequences across nations. *Measuring Attitudes Cross-Nationally: Lessons from the European Social Survey*, 161–193.

Scott, D. M. (2015). *The new rules of marketing and PR: How to use social media, online video, mobile applications, blogs, news releases, and viral marketing to reach buyers directly*. John Wiley & Sons.

Semin, G. R. (2007). Grounding communication: Synchrony. In A. Kruglanski & E. T. Higgins (Eds.), *Social Psychology: Handbook of Basic Principles* (2nd ed., pp. 630–649). Guilford Publications.

Semin, G. R., & Cacioppo, J. T. (2008). Grounding social cognition: Synchronization, entrainment, and coordination. In G. R. Semin & E. R. Smith (Eds.), *Embodied Grounding: Social, Cognitive, Affective, and Neuroscientific Approaches*. New York: Cambridge University Press.

Silbert, L. J., Honey, C. J., Simony, E., Poeppel, D., & Hasson, U. (2014). Coupled neural systems underlie the production and comprehension of naturalistic narrative speech. *Proceedings of the National Academy of Sciences*, *111*(43), E4687–E4696.

Singer, J. B. (2014). User-generated visibility: Secondary gatekeeping in a shared media space. *New Media & Society*, *16*(1), 55–73.

Smith, A. (2014, February 3). 6 new facts about Facebook. Retrieved July 12, 2017, from http://www.pewresearch.org/fact-tank/2014/02/03/6-new-facts-about-facebook/

Smith, S. M., Jenkinson, M., Woolrich, M. W., Beckmann, C. F., Behrens, T. E., Johansen-Berg, H., … others. (2004). Advances in functional and structural MR image analysis and implementation as FSL. *Neuroimage*, *23*, S208–S219. https://doi.org/10.1016/j.neuroimage.2004.07.051

Snyder, L. B., Hamilton, M. A., Mitchell, E. W., Kiwanuka-Tondo, J., Fleming-Milici, F., & Proctor, D. (2004). A Meta-Analysis of the Effect of Mediated Health Communication Campaigns on Behavior Change in the United States. *Journal of Health Communication*, *9*(sup1), 71–96. https://doi.org/10.1080/10810730490271548

Southwell, B. G. (2013). *Social networks and popular understanding of science and health: Sharing disparities*. Baltimore, MD: Johns Hopkins University Press.

Southwell, B. G., & Yzer, M. C. (2007). The roles of interpersonal communication in mass media campaigns. *Communication Yearbook*, *31*(1), 420–462. https://doi.org/10.1080/23808985.2007.11679072

Spreng, R. N., Mar, R. A., & Kim, A. S. N. (2008). The Common Neural Basis of Autobiographical Memory, Prospection, Navigation, Theory of Mind, and the Default Mode: A Quantitative Meta-analysis. *Journal of Cognitive Neuroscience*, *21*(3), 489–510. https://doi.org/10.1162/jocn.2008.21029

Statistical nonParametric Mapping. A toolbox for SPM. (n.d.). Retrieved from http://warwick.ac.uk/snpm

Steijn, W. M. P., & Schouten, A. P. (2013). Information Sharing and Relationships on Social Networking Sites. *Cyberpsychology, Behavior, and Social Networking*, *16*(8), 582–587. https://doi.org/10.1089/cyber.2012.0392

Stephens, G. J., Silbert, L. J., & Hasson, U. (2010). Speaker–listener neural coupling underlies successful communication. *Proceedings of the National Academy of Sciences*, *107*(32), 14425–14430.

Strecher, V. J., Marcus, A., Bishop, K., Fleisher, L., Stengle, W., Levinson, A., … Nowak, M. (2005). A Randomized Controlled Trial of Multiple Tailored Messages for Smoking Cessation Among Callers to the Cancer Information Service. *Journal of Health Communication*, *10*(sup1), 105–118. https://doi.org/10.1080/10810730500263810

Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). Want to be retweeted? Large scale analytics on factors impacting retweet in Twitter network. In *2010 IEEE Second International Conference on Social Computing (SocialCom)* (pp. 177–184). https://doi.org/10.1109/SocialCom.2010.33

Tamir, D. I., & Mitchell, J. P. (2012). Disclosing information about the self is intrinsically rewarding. *Proceedings of the National Academy of Sciences*, *109*(21), 8038–8043. https://doi.org/10.1073/pnas.1202129109

Tamir, D. I., Thornton, M. A., Contreras, J. M., & Mitchell, J. P. (2016). Neural evidence that three dimensions organize mental state representation: Rationality, social impact, and valence. *Proceedings of the National Academy of Sciences*, *113*(1), 194–199. https://doi.org/10.1073/pnas.1511905112

Tamir, D. I., Zaki, J., & Mitchell, J. P. (2015). Informing others is associated with behavioral and neural signatures of value. *Journal of Experimental Psychology: General*, *144*(6), 1114–1123. https://doi.org/10.1037/xge0000122

Taylor, S. E., & Brown, J. D. (1994). Positive illusions and well-being revisited: Separating fact from fiction. *Psychological Bulletin*, *116*(1), 21–27. https://doi.org/10.1037/0033-2909.116.1.21

Tingley, D., Yamamoto, T., Kentaro, H., Keele, L., & Imai, K. (2014). mediation: R package for causal mediation analysis. *Journal of Statistical Software*, *59*(5), 1–38.

Traxler, M. J., & Gernsbacher, M. A. (1993). Improving written communication through perspective-taking. *Language and Cognitive Processes*, *8*(3), 311–334.

Tuten, T. L., & Solomon, M. R. (2017). *Social media marketing*. Sage.

Utz, S. (2015). The function of self-disclosure on social network sites: Not only intimate, but also positive and entertaining self-disclosures increase the feeling of connection. *Computers in Human Behavior*, *45*, 1–10. https://doi.org/10.1016/j.chb.2014.11.076

Valente, T. W. (1996). Mass-Media-Generated Interpersonal Communication as Sources of Information About Family Planning. *Journal of Health Communication*, *1*(3), 247–266. https://doi.org/10.1080/108107396128040

Valente, T. W., & Fosados, R. (2006). Diffusion of Innovations and Network Segmentation: The Part Played by People in Promoting Health: *Sexually Transmitted Diseases*, *33*(Supplement), S23–S31. https://doi.org/10.1097/01.olq.0000221018.32533.6d

Valkenburg, P. M., & Peter, J. (2009). Social Consequences of the Internet for Adolescents: A Decade of Research. *Current Directions in Psychological Science*, *18*(1), 1–5. https://doi.org/10.1111/j.1467-8721.2009.01595.x

van den Putte, B., Yzer, M., Southwell, B. G., de Bruijn, G.-J., & Willemsen, M. C. (2011). Interpersonal Communication as an Indirect Pathway for the Effect of Antismoking Media Content on Smoking Cessation. *Journal of Health Communication*, *16*(5), 470–485. https://doi.org/10.1080/10810730.2010.546487

Venkatraman, V., Dimoka, A., Pavlou, P. A., Vo, K., Hampton, W., Bollinger, B., … Winer, R. S. (2014). Predicting Advertising Success Beyond Traditional Measures: New Insights from Neurophysiological Methods and Market Response Modeling. *Journal of Marketing Research*, *52*(4), 436–452. https://doi.org/10.1509/jmr.13.0593

Vezich, I. S., Katzman, P. L., Ames, D. L., Falk, E. B., & Lieberman, M. D. (2017). Modulating the neural bases of persuasion: Why/How, Gain/Loss, and Users/Non-users. *Social Cognitive and Affective Neuroscience*, *12*(2), 283–297.

Vitak, J. (2012). The Impact of Context Collapse and Privacy on Social Network Site Disclosures. *Journal of Broadcasting & Electronic Media*, *56*(4), 451–470. https://doi.org/10.1080/08838151.2012.732140

Wager, T. D., Jonides, J., & Reading, S. (2004). Neuroimaging studies of shifting attention: a meta-analysis. *NeuroImage*, *22*(4), 1679–1693. https://doi.org/10.1016/j.neuroimage.2004.03.052

Walther, J. B. (1996). Computer-mediated communciation research: Impersonal, interpersonal, and hyperpersonal interaction. *Communication Research*, *23*(1), 3–43.

Weber, R., Huskey, R., Mangus, J. M., Westcott-Baker, A., & Turner, B. O. (2015). Neural Predictors of Message Effectiveness during Counterarguing in Antidrug Campaigns. *Communication Monographs*, *82*(1), 4–30. https://doi.org/10.1080/03637751.2014.971414

Welborn, B. L., Lieberman, M. D., Goldenberg, D., Fuligni, A. J., Galván, A., & Telzer, E. H. (2016). Neural mechanisms of social influence in adolescence. *Social Cognitive and Affective Neuroscience*, *11*(1), 100–109. https://doi.org/10.1093/scan/nsv095

Wien, A. H., & Olsen, S. O. (2014). Understanding the Relationship between Individualism and Word of Mouth: A Self-Enhancement Explanation. *Psychology & Marketing*, *31*(6), 416–425. https://doi.org/10.1002/mar.20704

Wilson, E. J., & Sherrell, D. L. (1993). Source effects in communication and persuasion research: A meta-analysis of effect size. *Journal of the Academy of Marketing Science*, *21*(2), 101–112.

Wilson, T. D., & Nisbett, R. E. (1978). The accuracy of verbal reports about the effects of stimuli on evaluations and behavior. *Social Psychology*, *41*(2), 118–131. https://doi.org/10.2307/3033572

Wilson, T. D., & Schooler, J. W. (1991). Thinking too much: Introspection can reduce the quality of preferences and decisions. *Journal of Personality and Social Psychology*, *60*(2), 181–192. https://doi.org/10.1037/0022-3514.60.2.181

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. *Nature Methods*, *8*(8), 665–670. https://doi.org/10.1038/nmeth.1635