The Neuroscience of Information Sharing

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Information sharing is a core human activity (Csibra & Gergely, 2011) that catalyzes innovation and development. The frequency with which we share information is evident every day with over 4 billion Facebook messages (Rao, 2010), over 500 million tweets (Krikorian, 2013), and 200 billion e-mails sent to colleagues, acquaintances, friends, family members, and sometimes complete strangers (Radicati Group, 2015) within a single 24-hour cycle. Further the effects of information sharing are powerful and manifold in domains such as advertising (Bughin, Doogan, & Vetvik, 2010), stock prices and returns (Luo, 2007, 2008, e.g. Berger, 2014), and mass media campaigns (Cappella, Kim, & Albarracín, 2015; Southwell & Yzer, 2007). Consequently, extensive research in marketing, health, communication, psychology, political science, sociology and network science, document which information is shared and when. Although immense progress has been realized across these fields, current approaches (e.g., methods from computational social science) have not been as well positioned to uncover the underlying mechanisms that could explain the why and how of sharing decisions and behavior. A better mechanistic understanding is necessary to increase the stability of predictive models across time and contexts, to develop parsimonious theoretical frameworks of interpersonal sharing, and to strategically design interventions based on those theories. Thus, moving beyond the documentation of the importance of interpersonal information sharing and its large-scale patterns and effects, mechanistic approaches to the study of sharing are the logical next step in the development of this exciting field.

In this chapter, we argue that neuroscientific methods offer one approach to generating novel insights about mechanisms underlying sharing between individuals, as well as across larger populations. To this end, we review what is known about the neural mechanisms that support the progression of information through propagation chains such as the one depicted in Figure 1. Specifically, we present recent neuroscientific findings that contribute to our understanding of why and how individuals share information with others (termed interpersonal information sharing), as well as potential mechanisms driving population-level mass sharing events (termed virality).

We focus primarily on functional magnetic resonance imaging (fMRI) studies, which have been used most extensively to study questions related to information sharing and virality. FMRI assesses a blood-oxygen-level dependent (BOLD) signal in the brain as a proxy measure for neural activity with relatively high temporal and spatial resolution. The neuroscience of information sharing uses knowledge from existing neuroscience work to infer psychological states involved in sharing, and to predict sharing-related outcomes, based on observed neural activation patterns. One strength of neuroimaging methods in comparison to many other approaches is a more proximal and less disruptive measurement of psychological processes, across the whole brain (i.e., capturing multiple processes), in real time. This adds crucial information to self-reported, retrospective accounts of thought processes produced post exposure, which are more subject to social desirability, memory errors, or simply the inability or unwillingness of respondents to verbalize specific thoughts or experiences (Krumpal, 2011; Nisbett & Wilson, 1977; Wilson & Nisbett, 1978; Wilson & Schooler, 1991). When sharing information with others, multiple social, emotional, and cognitive factors are integrated in the brain to navigate each social interaction, sometimes outside of conscious awareness. Consequently, adding measures of neural activity to a battery of behavioral measures and computational approaches can help triangulate the underlying mechanisms that drive why and how people share and increase the predictive capacity of our models of what gets shared and when.

We define interpersonal information sharing broadly in terms of facts, ideas, preferences and knowledge that are communicated from a sharer to a receiver in a single interaction. In addition, although multiple external factors influence sharing, this chapter is particularly concerned with the basic psychological and neurocognitive mechanisms that motivate individual sharing decisions. We argue for a set of basic neurocognitive mechanisms, which are likely to be important across diverse sharing contexts, even if the specific inputs to these processes vary. Likewise, in our discussion of virality - a characteristic of information that is massively shared - we will not make a strong distinction between the notions of popularity (i.e. a large number of independent sharing events) and structural virality (i.e. retransmission from person to person through long propagation chains) (see Goel, Anderson, Hofman, & Watts, 2016), but rather focus on neurocognitive mechanisms that are likely common across individual decisions comprising each set of effects. In sum, this chapter offers a review of:

1. How sharing decisions are computed in the brain;
2. The role of neural processing in the creation of downstream outcomes of sharing including information reach, or the numbers of exposures to a unit of information in a population or group, and information impact, or effects of shared information on interactions, behaviors, or attitudes of those who are exposed to it;
3. The effects of contextual factors such as social network structure and individual differences on these processes; and
4. Opportunities and limits for productive interaction between neuroscience and other methodological traditions.

[INSERT FIGURE 1 HERE]

Neural Bases of Sharing Decisions: Value-Based Virality

What happens in a person's brain during initial exposure to information, and what is it about this neural activity that generates the decision to share with others? We recently integrated existing evidence from social, affective, and cognitive neuroscience to propose a model of the processes that lead to the decision to share, called the value-based virality framework (Scholz, Baek, O'Donnell, Kim, et al., 2016). Value-based virality is centered on the sharer's perceived value of sharing information with others, which is represented in the brain's valuation and reward system. The higher the perceived value of sharing a piece of information, the more likely it is that it will in fact be shared with others. In addition, to the extent that this value computation is similar across people, information with higher perceived sharing value in the brain is more likely to gain virality in a larger population. Value-based virality further predicts that sharing value is determined based on two key inputs, namely expectations about self-related and social outcomes of sharing. Neural systems supporting self-related processing, social cognition, and valuation have been identified in extensive prior work (Figure 2).

[INSERT FIGURE 2 HERE]

This model unifies and extends existing knowledge by suggesting a parsimonious theoretical framework that encompasses neural systems and associated psychological processes highlighted in prior empirical and theoretical work on virality (Berger, 2014; Cappella et al., 2015; Falk, Morelli, Welborn, Dambacher, & Lieberman, 2013; Meshi, Tamir, & Heekeren, 2015; Tamir, Zaki, & Mitchell, 2015) and further posits a clear structure detailing how these mechanisms work together to create sharing decisions.

Valuation

The brain's valuation and reward system is the centerpiece of the value-based virality framework, which proposes a direct link between information sharing value and interpersonal sharing and virality. A general psychological principle describes the tendency to seek pleasure or rewards and avoid pain or punishments (Elliot, 2008; Lewin, 1935). When deciding whether or not to share content with others, an individual is likely to consider the potential value and negative outcomes of sharing from various perspectives. This notion of the central role of positive valuation or reward in sharing received first support in a neuroimaging study in which a group of participants (referred to as the "interns" because they were asked to pretend to be interns at a TV studio) were exposed to a set of new TV show ideas and asked which ones they would recommend to a producer. A second set of participants (referred to as the "producers") then saw videos in which the "interns" described the shows. The producers were subsequently asked whether they would further recommend each show (Falk et al., 2013). The shows that were shared most successfully by the "interns" (i.e. those most popular with "producers"), were related to the strongest activations in the value system of the interns' brains when they first learned about the show. Another recent study also suggested that merely sharing information with others produces neural activity in the brain's reward system, and study participants were further willing to forgo monetary rewards for the opportunity to share information with others (Tamir et al., 2015).

How do individuals decide whether information has high sharing value? Value-based virality suggests that people consider combinations of advantages and disadvantages of sharing given the expected self-related and social implications of sharing. For instance, a sharer might wonder whether sharing a piece of information will make them look smart, well informed, or "cool", or whether the shared content will lead to positive or negative interactions or relationships with others. To make a final sharing decision, these different types of considerations need to be consolidated into an overall judgment of whether sharing will have net positive/rewarding or negative/punishing consequences.

Neuroimaging studies suggest that human brains are well suited for such a computation. There is strong evidence showing that different kinds of value (e.g. primary, secondary, self-related, and social values) are integrated within a general valuation system, which includes the ventral striatum (VS) and ventro-medial prefrontal cortex (VMPFC) (for a meta-analysis see Bartra, McGuire, & Kable, 2013). This system is thought to translate the value of different types of inputs onto a common value scale, generating a domain-general value signal that allows for direct comparisons between diverse stimuli (Levy & Glimcher, 2012). Value-based virality suggests that this mechanism also allows those exposed to information to weigh the pros and cons of sharing on different dimensions, such as self-related and social value, and integrate them into a domain-general information sharing value signal which is directly linked to virality.

Self-Related Processing

To achieve a high sharing value, information first needs to resonate with its primary receiver. Indeed, in the study described above, “interns” (i.e., primary receivers) were more likely to self-report a high likelihood to share when their brains were engaged in self-related processing (MPFC and PCC) during initial information exposure (Falk et al., 2013). In functional neuroimaging, neural correlates of self-related thought have been identified by asking participants to think about whether certain stimuli such as personality traits represent them or not (e.g. Murray, Schaer, & Debbané, 2012; Northoff et al., 2006). These studies routinely find that activations within medial prefrontal cortex (MPFC) and posterior cingulate cortex (PCC) increase during self-relevance judgments, relative to judgments that do not require self-related processing.

When making sharing decisions, a range of self-related processes might unfold in a sharer. Information might be perceived as self-relevant, that is, important for the sharer's life, interests, goals, or ideals. Another possibility is that self-related processing is involved in sharing decisions because sharers consider self-enhancement motives. The aim to maintain a positive image in front of others is a key motive of human interaction (Mezulis, Abramson, Hyde, & Hankin, 2004) and thought to be a central driver of interpersonal sharing (Berger, 2014; Cappella et al., 2015). Information that, if shared, would reflect positively on the sharer, e.g. by demonstrating that they are concerned about others, well-informed or high-performing in some domain, should thus increase its sharing value. Indeed, next to its association with sharing behavior, sharing self-relevant information has been shown to activate the brain's reward and valuation system (Tamir & Mitchell, 2012).

In consequence, value-based virality suggests that self-related processing is an important input to the calculation of information sharing value, so that expectations of more positive outcomes of sharing for one's self-image will increase valuation.

Social Cognition

Sharing, by definition, is a social process. Value-based virality thus argues that next to considering self-related outcomes of sharing, sharers also engage in social cognition when determining information sharing value. This argument receives support, for instance, by research on audience tuning, which describes adjustments to both the content and wording used by sharers to communicate information depending on characteristics of their audience such as knowledge or opinions (Barasch & Berger, 2014; Clark & Schaefer, 1989; Marwick & Boyd, 2011). In other words, sharers utilize audience characteristics, possibly to predict the audience's reactions and thoughts if they were to share information with them. This type of social processing is a form of mentalizing. The brain's mentalizing system includes the bilateral temporo-parietal junction (TPJ), right superior temporal lobe (STS), dorsal MPFC (along with other subregions of MPFC) and PCC, and tends to be activated when people consider what others might know, believe or desire (Dufour et al., 2013). Results from the study of "interns" and "producers" described above show that successful ideas not only engaged the brain's valuation system, but also typical mentalizing regions as "interns" were first exposed to each TV show idea (Falk et al., 2013). In addition, prior work further supports a direct link between expectations of social rewards (e.g. in the form of approval) and activity in the brain's valuation system (Fehr & Camerer, 2007; Rademacher et al., 2010). Consequently, value-based virality proposes that determining the impact of information on social connections can be described as an instance of mentalizing, where the sharer considers whether sharing might lead to favorable or valued social outcomes based on knowledge, needs, desires and potential reactions of their audience. If desirable social outcomes are expected, information sharing value will be higher.

Empirical Support for Value-Based Virality

We recently tested the value-based virality model empirically in a study on the real-world, population-level retransmission of New York Times articles. In this study, participants were shown abstracts and headlines of New York Times articles in three experimental conditions where they thought about whether they wanted to share the article with others (either on their Facebook wall or privately with one Facebook friend), whether they wanted to read the full text themselves, or to identify the main topic of the article (Figure 3).

[INSERT FIGURE 3 HERE]

We found support for the involvement of self-related, social, and value-related neural systems in sharing decisions (relative to other types of decisions) in our study participants (Baek, Scholz, O'Donnell, & Falk, 2016; Figure 4A). Activity in the valuation-system, the self-related processing system, as well as regions commonly associated with mentalizing as participants were exposed to the article headlines and abstracts were also significantly positively related to participants' self-reported intention to share each article with others. Further, whole brain analyses showed that the effects were most robust in hypothesized brain systems, reiterating the central role of these three processes in sharing.

Next, when looking at the reading condition, which is closest to a natural situation in which a reader browses the homepage of the New York Times, we found support for the mediation model outlined in Figure 2 when predicting population-level virality (Scholz, Baek, O'Donnell, Kim, et al., 2016). Specifically, neural data from the small group of imaged participants extracted while each article headline and abstract was presented was linked to indicators of population-level virality (# of shares through Facebook, Twitter, and e-mail) derived using the New York Times API (automated programming interface) and totaling over 100,000 shares. Results from path analyses support the predictions of value-based virality. That is, activity in both the self-related and social cognition systems during initial article exposure was significantly associated with value-related processing. Activity in the valuation system in the imaged participants, in turn, was related an article's number of shares in the larger population of New York Times readers (Figure 4B), and acted as a mediator for the effects of social cognition and self-related processing on virality. Encouragingly, these results were replicated in a second set of participants who performed a similar task using the same articles, strengthening the evidence for value-based virality.

[INSERT FIGURE 4 HERE]

In sum, empirical evidence for value-based virality supports a parsimonious model of decisions to share information with others, in which a domain general information sharing value signal integrates inputs from both self-related and socially relevant cognitions about the act of sharing the information. This domain general value signal then directly relates to virality, as has been shown for the population of readers of the online New York Times. Further, the fact that neural activity in a small group of people can predict population-level outcomes suggests that large groups of individuals can arrive at similar sharing values for the same information, possibly due to similar social motives and values within a culture.

Outcomes of Information Sharing: Reach and Impact

Value-based virality is a neurocognitive model of sharing decisions, which is one component contributing to how widely information is shared, termed virality or reach. Measures of reach include the total number of shares or the depth of penetration into a network (i.e. the length of a propagation chain). A full discussion of the factors that differentially influence each of these dimensions of reach is beyond the scope of this chapter. Here we assume that similar basic neurocognitive processes drive individual decisions in both broad and deep chains, across communication channels.[1] That is, while the specific type and scope of considerations that go into a sharing decision might differ at different locations in a propagation chain, we assume that the basic neurocognitive processes of self-related, social, and value-related considerations are central drivers across these contexts. Once information is shared, downstream outcomes encompass information impact. Measures of impact include behavior, attitude, or intention

[1] We briefly discuss communication channels as moderators of these effects in the moderators section of this chapter.

change in response to information exposure. As with reach, a full discussion of the multiple factors that influence impact is beyond the scope of this chapter. Instead, we focus on specific relations to the neurocognitive antecedents of sharing. Both reach and impact are determined in part by the sharers themselves, their audiences, and the communication between the two.

Sharers. Sharers can play at least two distinct roles in a propagation chain: First, sharers can influence audience members. Second, sharers might engage more intensively with information as a result of sharing it, thereby increasing the information's impact on the sharers themselves.

Existing neuroimaging work has mainly focused on the former, by examining what is shared (as described above; Baek et al., 2016; Scholz, Baek, O'Donnell, Kim, et al., 2016) and who is persuasive. Specifically, mentalizing activity in sharers is associated with greater persuasiveness, or the ability of a sharer to convince their audience of their own opinion about information. For instance, two studies showed increased activation in the mentalizing system in salespeople with superior skills in sales (Dietvorst et al., 2009) and in participants ("interns") who were more successful in convincing other participants ("producers") of their opinion about TV show ideas (Falk et al., 2013). In conjunction with the work supporting the role of mentalizing in value-based virality, these findings may suggest overlap in the neural antecedents that support sharing decisions, and persuasiveness during sharing. If sharers tend to share information that they expect will lead to positive outcomes (i.e., information with high sharing value), this may also make what they share more persuasive.

Comparatively less is known about the impact of interpersonal sharing on the brains of the sharers themselves. Consistent with self-perception theory (Bem, 1972) discussing information can affect its impact on those involved in the conversation (David, Cappella, &

Fishbein, 2006; Southwell & Yzer, 2007), including those who shared the information initially (Jeong, 2016). For instance, according to this view, recommending certain behaviors to others might increase a sharer's likelihood to engage in the same behaviors later. Consequently, additional research seeking to differentiate when and why sharers are more or less personally influenced by discussion of information can improve predictions of its overall impact on a population.

Audiences. Audiences can play at least two distinct roles in propagation chains. First, audiences may be conceptualized as passive receivers who are influenced by sharers. Second, audiences can be studied as active discussion participants who might influence the initial information sharer.

A growing body of literature has described how information takes hold in the brains of receivers (for reviews see, Cascio, Scholz, & Falk, 2015; Izuma, 2013), highlighting two key processes that increase susceptibility: 1) Elevated activity in dorsal anterior cingulate cortex (ACC) and anterior insula (AI) are implicated in conflict detection, and serve to signal when individuals are misaligned with others. This neural activity might underlie our sensitivity to social costs of rejection, and can lead to conformity and realignment with the group (Berns, Capra, Moore, & Noussair, 2010; Tomlin, Nedic, Prentice, Holmes, & Cohen, 2013); and 2) Elevated activity in the brain's positive value and reward system, including VS and VMPFC highlight and reward expected positive outcomes of conforming (Campbell-Meiklejohn, Bach, Roepstorff, Dolan, & Frith, 2010; Zaki, Schirmer, & Mitchell, 2011). Note that a similar valuation circuit has also been implicated in the computation of sharing decisions as described above.

Translating the findings above to the domain of sharing decisions, researchers who have studied susceptibility to social influence on interpersonal sharing decisions have found associations with both neural activity implicated in general susceptibility to influence and activity associated with successful/persuasive sharing. For example, a series of studies examined brain activity as participants learned about and recommended mobile game applications to others in the presence of peer feedback (as might be available through a recommender system on a mobile gaming website). Increased activity in the brain's valuation system (VS and VMPFC) when receiving group feedback (i.e. social influence) about their initial recommendations was associated with increased conformity to peer recommendations (Cascio, O'Donnell, Bayer, Tinney, & Falk, 2015). That is, expected positive social outcomes might have motivated the observed peer-conform recommendation behavior. In addition, participants who conformed more frequently, on average, showed increased activity in the mentalizing system. This activity might have originated in participants' considerations of why others have provided recommendations that differed from their own. Note that activity in the mentalizing system also distinguished successful and unsuccessful sharers as reviewed earlier (Dietvorst et al., 2009; Falk et al., 2013). The extent to which the same underlying psychological processes are driving the partial overlap in neural activations observed in successful sharers and those susceptible to influence remains an open question.[2] Nevertheless, the boundaries between what motivates receivers to share, and what motivates susceptibility to the peer influence on sharing may not be clear cut.

Sharer-Audience Interactions. One potential explanation for overlap in neural activity is the shared experience created when sharers and audiences engage in interpersonal communication. Another plausible reason is a causal dynamic in which persuasion requires

[2] Also see the discussion on reverse inference in the limitations section below.

sharers to impact neural processing in receivers' brains; extant research has not yet distinguished between these accounts.[3] What has been shown is that beyond isolated activation in the brains of either party, successful communication is associated with increased correlation in the time series of neural activity in key brain regions observed in a sharer and their audience. This includes both sensory and higher order processing systems in the brain (e.g., implicated in speech production and comprehension; Silbert, Honey, Simony, Poeppel, & Hasson, 2014, and mentalizing and self-related processing; Stephens, Silbert, & Hasson, 2010). Further, greater anticipatory coupling, that is the extent to which neural activity in an audience is correlated with future neural activity of a speaker (potentially due to predictions made about what will be said next), is associated with more successful communication (Stephens et al., 2010).

Sharing Processes in Individuals and Across Populations

Above, we have considered psychological mechanisms that underlie information sharing both by looking at individual-level outcomes such as correspondence between a sharer and their audience (Falk et al., 2013), and population-level outcomes such as the number of shares an article received from New York Times readers (Scholz, Baek, O'Donnell, Kim, et al., 2016) or the number of Tweets about a popular TV show episode (Dmochowski et al., 2014). These two levels of analysis roughly correspond to the propagation chain consisting of few individuals, on the one hand, and the underlying population or sharing context on the other hand (Figure 1).

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[3] Research on social networks suggests that effective influencers and those susceptible to influence are rather distinct entities (Aral & Walker, 2012). Unfortunately, no extant studies consider both neural processes of sharing information and taking the role of an audience member. If it is broadly true that those who are susceptible to influence are not usually good influencers themselves, potential differences in neural processing of sharing situations could give more specific insight as to why massively shared content usually achieves popularity (i.e. many separate sharing instances of broadcasted content) rather than structural virality (i.e. long propagation chains) (Goel, Anderson, Hofman, & Watts, 2016), though a full exploration of this idea is beyond the scope of this chapter.

Multiple studies now show significant relationships between these two dimensions. For instance, the extent to which neural activity during exposure to a TV show episode was correlated between individual study participants predicted scene by scene Tweet volume about this episode by the population of Twitter users (Dmochowski et al., 2014). Likewise, even though sharing outcomes in individuals and populations are assessed using different tools, there is some evidence that the psychological process underlying interpersonal sharing at the individual level and population-level virality overlap. Specifically, as described above, similar neural responses to New York Times article headlines and abstracts are associated with individual sharing decisions (Baek et al., 2016, Figure 4A) and population-level sharing rates of the same articles in two separate samples (Scholz, Baek, O'Donnell, Kim, et al., 2016; Figure 4B).

As such, although the specific inputs to the computation of self-relevance, social-relevance and value, which in turn inform sharing decisions almost certainly differ depending on context factors (e.g., personal characteristics of elite and lay sharers (Katz & Lazarsfeld, 1955) time; (Rogers, 2010); broader structural features such as social norms and cultural contexts), these divergent inputs stemming from sources at multiple levels of analysis likely feed into very similar basic processes which drive individual decisions in the brain. Thus, although neuroimaging studies typically rely on relatively small (though increasing) sample sizes, components of population-level virality and its underlying psychological processes can be studied by examining individual-level propagation chains. In doing so, differences in personal traits and social environments can be studied as moderators of self, social and valuation processes most relevant to sharing.

Sharing Contexts as Moderators of Sharing Processes

Sharing contexts (Figure 1) are shaped by characteristics of the original content, of the sharer, the communication channel or medium used for sharing, characteristics of audiences, and the larger cultural context in which sharing takes place. Each of these contextual factors may modulate the relationship between brain activity and sharing decisions or outcomes, for instance by affecting the weight on expected social outcomes or self-related consequences, and hence the overall value of sharing.

Audience Characteristics. Audience characteristics as basic as size (i.e. number of audience members) can affect neural mechanisms of interpersonal sharing and virality. For example, one study examined the neural correlates associated with sharing with a large audience (one's entire Facebook Wall; called broadcasting) or a small audience (one specific Facebook friend; called narrowcasting) (Scholz, Baek, O'Donnell, & Falk, 2016). Although narrow- and broadcasting were both associated with activity in the self-related and social brain regions depicted in Figure 2, the narrowcasting condition showed significantly stronger involvement in both systems compared to broadcasting. More intensive processing while narrowcasting might be caused by a more vivid and concrete representation of the audience in these situations. If so, potential downstream effects might include more effective tailoring of shared information to specific, small audiences, and, possibly, more favorable sharing outcomes during narrowcasting.

On the receiving end, several neuroimaging studies now indicate that individuals systematically differ in their susceptibility to social influence. This may affect information sharing by altering neural processes during the reception of information that can be consequential when an audience member decides to further retransmit that information (Cascio, O'Donnell, et al., 2015). Likewise, other audience characteristics may affect information sharing value by altering the expected social (e.g. likelihood of approval given group opinions) and self-related outcomes (e.g. aspect of identity that a sharer wants to present to a given group) of sharing.

Sharer Characteristics. Characteristics such as personality traits and a sharer's position in their social networks can influence both the reach and impact of information. As mentioned earlier, two studies suggest that sharers differ in their ability to convince others of their own opinions about information, and that this ability positively correlates with the extent of social processing during sharing (Dietvorst et al., 2009; Falk et al., 2013). Interestingly, two recent studies have identified relationships between neural indicators of persuasiveness and a sharer's position in their ego-network. First, a study of male teens suggests that those with higher ego-betweenness positions in their ego-networks, that is those who connect many of their friends who would otherwise not be directly connected, engaged in more social processing (right TPJ, PCC, and dorsal MPFC) while making recommendations about mobile game applications to peers. This activity might signify a higher tendency to consider mental states of others during sharing (O'Donnell, Bayer, Cascio, & Falk, under review). Further, a second study found that individuals who were more popular in their social network showed higher sensitivity to status differences of others as indicated by stronger effects of other's popularity on activity in their valuation system (VS, ventral VMPFC, amygdala). In addition, these individuals made more accurate predictions about how others in their network perceived them (Zerubavel, Bearman, Weber, & Ochsner, 2015). In sum, personality and social network position may affect key sharing processes, though more research is required to fully understand these relationships and, determine causal directions.

Content Characteristics. Many of the individual effects that make up the current corpus of neuroscientific knowledge about information sharing have been studied within rather narrow topic areas such as health-related New York Times articles (Scholz, Baek, O'Donnell, Kim, et al., 2016), or TV show descriptions (Falk et al., 2013). Replication studies using stimuli from different content areas are needed to properly describe content sensitivity (if any) of the effects described in this chapter.

One of the mechanisms by which content characteristics might affect sharing is through altering the information sharing value profile. For instance, positively valenced information may be more likely to be shared in order to avoid communicating a negative image of oneself to others (Berger, 2014). That is, the same piece of information framed in terms of its potential positive outcomes might be more likely to engage increased activity in the self-relevance system of the brain and, subsequently, increase information sharing value signals which affect sharing likelihood. Another interesting domain are dynamic changes in content and content characteristics that are due to editing and social annotations in form of comments, recommendations, or ridicule which might be applied to information as it moves from step to step through a propagation chain (Figure 1). Recent work shows that this kind of content mutation occurs frequently in online sharing (Adamic, Lento, Adar, & Ng, 2016), suggesting that the same piece of information might show variation in its sharing value throughout its progression through a social network or population.

Communication Channel Characteristics. Most of the studies presented here were restricted to a specific mode of communication between sharers and their audiences, such as Twitter (Dmochowski et al., 2014), Facebook (Scholz, Baek, O'Donnell, Kim, et al., 2016), or video messages (Falk et al., 2013). However, possibilities for sharing, reactions to shared information and dialogue are restricted and affected by the specific communication channel chosen by sharers (Meshi et al., 2015). For instance, complex topics might have higher sharing value in face-to-face rather than text messaging contexts due to the greater potential for followup discussion and explanation. Studying the variability of the neural processes of sharing across different channels is thus likely to uncover interesting dependencies and possibly new, unexpected mechanisms that will help us to triangulate more comprehensive theories of sharing.

More broadly, as briefly mentioned before, an important information characteristic is whether it originates from mass media or interpersonal sources (corresponding to different steps in the propagation chain shown in Figure 1). Communication scientists have demonstrated that information sources can differ in trustworthiness and persuasiveness (Hesse et al., 2005; Katz & Lazarsfeld, 1955), among others, and work on the diffusion of innovations suggests that the relative importance of mass media and interpersonal sources may vary over time (Rogers, 2010). Indeed, there is a complicated interplay between mass media broadcasts and interpersonal communication, involving both mediating and moderating relationships (Southwell & Yzer, 2007; van den Putte, Yzer, Southwell, de Bruijn, & Willemsen, 2011). How these dynamics affect neural processes during sharing remains an open question. Nevertheless, as mentioned above, here we make the assumption that the basic psychological building blocks (self-related, social, and value-related considerations, see Figure 2) are useful in evaluating information from any source. The specific input to each of these computations and their relative importance, on the other hand, might differ substantially.

Culture. Finally, cultural characteristics are known to affect social interactions as well as the flow of information in numerous ways (e.g. Rogers, 2010; Triandis, 2001), yet the neural mechanisms of sharing have almost exclusively been studied in American college students. To provide an example of a possible hypothesis, in cultures with more independent self-construals which emphasize the individual over the group (Hofstede, Hofstede, & Minkov, 1991), sharers might rely less on perceived social outcomes when estimating information sharing value than sharers in collectivistic cultures, which emphasize groups over individuals.

Strengths and Limitations of Neuroscience for the Study of Viral Information

As illustrated in this chapter, neuroimaging affords a few key strengths that complement the existing toolbox of sharing and virality researchers, as has been argued effectively for the fields of marketing, economics, communication and decision making elsewhere (Falk, Cascio, & Coronel, 2015; Kable, 2011; Plassmann, Venkatraman, Huettel, & Yoon, 2015). With regards to the study of virality, two critical advantages to incorporating neuroimaging methods into conventional study designs include improvements to measurement and prediction, and enhanced theory development.

Measurement and prediction. Neuroimaging affords the ability to capture multiple psychological processes as they occur. As such, the addition of neuroimaging to the methods repertoire of sharing and virality researchers can help to increase the predictive power of our explanatory models (Berkman & Falk, 2013). For example, variation in neural responses to stimuli such as advertisements (e.g., anti-smoking messages) predicts individual-level behavior (e.g., quitting smoking) as well as population-level behavior (e.g., calls to a tobacco quitline) over and above conventionally used self-report measures (Falk, Berkman, & Lieberman, 2012). Similar results have been documented in diverse contexts such as sunscreen use, smoking cessation, physical activity and music purchases (Berns & Moore, 2010; Cascio, Dal Cin, & Falk, 2013; Falk, O'Donnell, et al., 2015; Falk et al., 2012; Falk, Berkman, Mann, Harrison, & Lieberman, 2010; Falk, Berkman, Whalen, & Lieberman, 2011). In this chapter, we reviewed preliminary evidence that similar techniques can be applied to the sharing of news articles (Baek et al., 2016; Scholz, Baek, O'Donnell, Kim, et al., 2016), however, this only begins to scratch the surface of what is possible.

Theory development. Neuroimaging techniques can also generate novel theoretical insights that are hard to access otherwise. For example, although it can be hard for both lay persons and researchers to identify overlap between two phenomenologically different experiences, seemingly distinct processes are sometimes supported by the same neural structures and networks (Lieberman, 2010). In the realm of sharing and virality, one analysis conducted on the New York Times study mentioned above (Figure 3) uncovered, somewhat unexpectedly, substantial overlap between the neural processes that support sharing and the selection of content for private consumption (Baek et al., 2016). Specifically, similar to decisions to share an article (see Figure 4A), decisions to read the article oneself were also associated (though to a lesser extent) with neural activity in brain systems that support assessing the self-related and social outcomes and overall value of sharing.

Similarly, neuroimaging can be used to dissociate core processes from one another by demonstrating activation of distinct regions or neural networks in reaction to two types of stimuli or between two groups. Researchers found that mentalizing, which involves consideration of the thoughts and beliefs of others, distinguished skilled sharers from those who are less successful in convincing others of their own opinion about shared information (Dietvorst et al., 2009; Falk et al., 2013). Dietvorst and colleagues showed that those professional salespeople in their sample who scored higher on a skill called adaptive selling in which the salesperson adapts their interaction strategy to situational constraints such as the customer's needs and preferences also showed more activity in the mentalizing system during an fMRI task. In the study by Falk and others, which was mentioned before, "interns" who were more successful in convincing "producers" of their opinion about TV shows mentalized more overall during their first exposure to the show ideas.

Neuroimaging can further be useful for hypothesis generation given that it captures activity in the whole brain over time, corresponding to multiple different processes. That is, next to observing neural activity in a priori identified regions of interest to test existing theory, activations in unexpected areas can spur further exploration, hypothesis generation and subsequent theory testing.

In sum, the addition of neuroimaging techniques to the behavioral and computational measures often used in virality research can have important impacts on our understanding of why and how people share. In parallel, adding computational social science and network perspectives to the neuroscience toolbox advances our understanding of brain function by providing clues as to how specific regions or networks of regions create certain experiences or compute decisions (O'Donnell & Falk, 2015).

Limitations. A comprehensive discussion of the limitations of fMRI is available elsewhere (Poldrack, 2008). However, we highlight the issues of the correlational nature of most fMRI studies and reverse inference, because of their special relevance to the theoretical inferences that can be drawn from the work synthesized above. First, because fMRI is an observational technique that does not allow the controlled manipulation of brain activity, any relationship between neural activation discovered using fMRI and subsequent outcomes such as information sharing behavior are correlational, not causal. Tools such as transcranial direct current stimulation (TDCS) and transcranial magnetic stimulation (TMS), however, do allow the systematic alteration of neural activity in specific regions and can be used to establish causality with more confidence (Kable, 2011). Thus, promising candidate regions identified through fMRI that show strong relationships with an outcome of interest and that are theoretically meaningful can be examined using TDCS or TMS to establish causal order. In addition, researchers who use fMRI are in a better position to make causal claims regarding the origins of neural activation if it is observed in response to carefully controlled stimuli that are varied across experimental conditions. For instance, one study mentioned earlier compared situations in which participants considered narrowcasting to a broadcasting condition and observed activation differences in MPFC, VS, and PCC, among others, which are most likely due to the experimental manipulation (Scholz, Baek, O'Donnell, & Falk, 2016).

Second, reverse inference is a threat to the correct identification of psychological processes based on observed neural activations (Poldrack, 2011). The same brain region can be involved in a variety of psychological processes at any given time, and fMRI does not necessarily allow researchers to determine which one is activated by their experiment, or which one is related to their outcome of interest. Confidence in such reverse inferences can be systematically increased by carefully defining a priori hypotheses and identifying regions of interest that have been robustly or even selectively associated with a given cognitive process previously. Further, new resources allow neuroimagers to estimate the level of confidence in a given reverse inference. Based on data from large imaging databases such as www.neurosynth.org researchers can estimate the proportion of studies in which the manipulation of a given psychological process activated the region of interest (i.e. studies using forward inferences). For example, research on interpersonal sharing and virality can rely on extensive research on self-related, social, and value-related processing which have been studied extensively in social, affective, and cognitive neuroscience (Figure 2).

Conclusion

The neuroscience of information sharing and virality has made exciting initial strides. One line of inquiry suggests a parsimonious theoretical framework of the psychological mechanisms that lead to the decision to share (Baek et al., 2016; Scholz, Baek, O'Donnell, Kim, et al., 2016). Others have begun to elucidate the mechanisms of social influence in sharing situations (Cascio, O'Donnell, et al., 2015) and sharer-audience coupling and its relationship to successful communication (Stephens et al., 2010).

Much more remains to be understood regarding the mechanisms that drive certain types of sharing behavior, and especially regarding the interplay between several of the processes that have been identified so far. For instance: What is the relationship between the processes that drive initial decisions to share information and downstream effects such as the quality of conversations between sharers and their audience? Is it possible to systematically increase the sharing value and virality potential of information by designing it in such a way that is likely to engage neural activity in brain areas involved in sharing decisions? Recent trends in functional neuroimaging towards the integration of various methods such as computational social science and behavioral measures (O'Donnell & Falk, 2015) open the way for more complex and realistic studies that allow us to assess multiple processes simultaneously within a single experiment, and from multiple perspectives at the same time. In this chapter, we have reviewed existing experimental paradigms and approaches to the neuroscientific study of sharing, though this young and dynamically developing field provides substantial room for new, innovative paradigms that go well beyond what we have described here. Together, this research will advance knowledge of why and how people share information with others and of the likely downstream impact of these processes on individuals, groups, and society at large.

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