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A THREE ESSAY DISSERTATION ON SOCIAL MOVEMENTS AND SOCIAL MEDIA

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INTRODUCTION

The advent of the internet has enabled people to connect in new ways. Web developers have leveraged technology to build social media sites. People can now communicate with anyone who has access to the internet. This new form of media allows anyone to broadcast their message to a wide audience – virtually anyone with access to the internet. For example, Twitter users can broadcast short messages which can be read by anyone with internet access.

Users of social media are now empowered to self-organize in new ways. In particular, participants of social movements have used social media to spread their message, organize their activities, and recruit others. For example, people against the Stop Online Piracy Act used Twitter as one mode of communication to generate momentum for their cause. The stakes of the SOPA movement were quite high as a large number of people were concerned about their privacy rights. However, the same social dynamics can occur in low stakes situations such as brand communities. For example, within the Starbucks brand community, people attempted to motivate Starbucks management to bring back old customer service rewards programs.

I used text analysis in each of the three essays to dissect the messages and reveal the underlying social dynamics. The first essay investigates the use of influence tactics within text messages. The second essay is a grounded theory piece to understand how affective and cognitive processes evolve in a social movement based on the Twitter messages of the Stop Online Piracy Act. The theory developed in the second essay is re-visited in the third essay in a movement that can trace its roots back to the movement against the Stop Online Piracy Act. In doing so, this dissertation provides insights into understanding how the use of affective and cognitive words influences the trajectory of a social movement.

The first essay investigates the role of cognitive and affective influence tactics as used in brand community websites. Brand community websites are online environments where customers can communicate with other fans of the brand. One specific use of brand communities is to suggest new product or service ideas to a company. The customers' use of language based influence tactics along with the detailed content of the message was found to help garner support for their new idea or service and elicit more comments from the community.

The second essay investigated the role of the affective and cognitive dimensions in text based communication of an online social movement. Specifically, the goal of the essay was to describe how affective and cognitive dimensions were all treated as endogenous variables in vector autoregression. Using the results of the vector autoregression and the related Granger causality test, I developed a path model describing the relationships between the affective and cognitive dimensions.

The last essay looks at the role of affective and cognitive dimensions in text based communication of an online spin-off movement. A spin-off movement shares the same borrowed ideas, organizational structure, and tactics from another movement. Often, participants of an initiator movement will switch to a spin-off movement, bringing along the knowledge and experience. This knowledge and experience is expected to change the level of affective and cognitive processes and make the participants feel more confident and make quicker decisions.

SEEDS OF CHANGE: SUBSTANCE AND INFLUENCE IN BRAND COMMUNITIES

ABSTRACT

Corporations use social media to build online communities in order to create and maintain product loyalty and to source new product ideas. Community members discuss the corporation's products, services, or practices. Users communicate their grievances to each other and the company, hoping to garner support and instigate change. In addition to their coherence attributes, posted messages also incorporate cognitive and affective influence tactics. How do these embedded influence tactics moderate the efficacy of coherence in persuading others to support a burgeoning movement? I develop and test a model wherein influence tactics moderate the relationship between the coherence of a message and traction. The analytic results provide partial support for the model developed, indicating that (1) the efficacy of coherence on attracting community comments was negatively moderated by negative affect and assertiveness; (2) the efficacy of coherence on attracting votes by community members was positively moderated by rational persuasion; (3) the efficacy of coherence on attracting comments by corporate employees was positively moderated by rational persuasion. Traction, indicated by positive votes and comments from the community, indicates that the message has begun to capture the attention of other community members and corporate employees. Affective and cognitive influence tactics moderated some forms of traction.

Keywords: brand communities, influence, social movements, computer-mediated communication

INTRODUCTION

A brand community is "a specialized, non-geographically bound community based on a structured set of social relations among admirers of a brand" (Muniz & O'Guinn 2001, p. 412). Online brand communities are becoming an integral part of corporate communication and innovation strategies. Harley-Davidson uses a brand community to strengthen commitment and loyalty to their brand and its associated motorcycle lifestyle (Fournier & Lee, 2009). Dell (the computer company) uses its brand community, Dell IdeaStorm, as a source for new ideas and innovations (Di Gangi & Wasko 2009). Starbucks' MyStarbucksIdea is another brand community where customers can gather and discuss ways that Starbucks can improve their product and the atmosphere of the stores, as well as how Starbucks can become more involved in the community or with social issues.

These communities allow individuals to propose ideas and to comment on ideas proposed by others. Sponsoring firms monitor users' participation in discussion forums with an eye to early identification of ideas that are gaining traction within the community. Early identification of problems is beneficial because it allows the sponsoring firm to intervene when there is customer dissatisfaction with its products and services, and it allows the sponsoring firm to forestall negative publicity. Early identification of opportunities posed by the community may offer ideas for new products and services to the sponsoring firm. Given the high level of active participation in many of these communities, how can firms glean information from this participation to identify problems and opportunities early? While the computer-mediated communication (CMC) literature has yielded insights into how individuals in assigned online groups attract attention to the information they provide and to their opinions about solving assigned problems (Dennis 1996; Tan et al. 1998; Zigurs et al. 1988), there is little research that suggests how problem identification processes unfold in brand communities, where both the group and the task are emergent. Yet it is critical for firms to understand how a particular issue attracts community attention and support, how an issue becomes a problem that the firm must address, and when an issue might point to a successful new product or service opportunity for the firm.

The objective of this paper is to understand the characteristics of initial posts that elicit responses from other community members. Following earlier work (Kim & Miranda 2011), careful analysis of the messages in brand communities reveal the posts that initiate a social movement. The focus is on the first message in order to understand whether and how the characteristics of an initial post can predict that a social movement, defined as an informal collection of individuals that converge around issues related to social justice and change (Tilly 2004), will develop. According to Mills, movements emerge as individuals translate their "private troubles" into "public issues" (1959, p. 8).

Following the social movements literature, Kim and Miranda (2011) focused on the substance of the messages. Influence tactics embedded in a message can enhance or attenuate the attention the message receives (e.g., Tan et al. 1998). Because of the ephemeral nature of the face-to-face interactions that have characterized social movements until fairly recently, the micro-level exchanges that constitute social movements have not been available for analysis. Consequently, the social movement literature has little to say about how the manner in which a message is couched facilitates or impedes target-audience receptivity to its substance.

The current research, therefore, contributes to the social movement literature by examining the manner in which micro-level exchanges influence the development of a movement. The findings in this paper contribute to the literature on community-based innovation by shedding light on how community grievances and desires are identified and agreed upon. The current research also contributes to the CMC literature by indicating how the substantive and tactical elements of computer-mediated messages are implicated in the authors' ability to frame an issue. Finally, the findings contribute insights to the fledgling research on brand communities, suggesting ways to conceptualize interactions in these communities.

The rest of this paper is organized as follows. The next section discusses brand communities as social media. Following that, the substance and influence tactics found in messages in brand communities are examined. Specifically, substance will be described in terms of the coherence, a formative construct introduced by the author to measure the dimensions of a message, and two types of influence tactics will be discussed: cognitive and affective. The next section after that describes the proposed theoretical model, and this is following by a presentation of the method used to test the model and our results. The final sections discuss the findings and suggest directions for future research.

BRAND COMMUNITIES AS SOCIAL MEDIA

Brand communities are instrumental social media created by corporate sponsors to develop a community of loyal patrons and to enable the community to share ideas about the company, the brand, and the product or service. Brand communities are a form of social media, defined as "web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system" (Boyd & Ellison, 2008, p. 2). Individuals join brand communities to develop new relationships with others who share the same brand loyalty (Fournier & Lee, 2009). Corporations use these communities as a part of their relationship marketing. Relationship marketing is the establishment, development, and maintenance of successful relationship exchanges (Morgan & Hunt, 1994). Communication with the customer is a central component of relationship marketing. Corporations must develop and maintain a dialog with buyers to enhance brand loyalty (Andersen 2005). By harnessing the knowledge of such communities, corporations can reduce customer-service costs (Moon & Sproull 2008). Community-based "open" innovation enables corporations to both decrease innovation costs and ramp up product-to-market cycles (Chesbrough 2007).

Brand communities provide a platform for user-generated content (UGC), which is content that is publically available and created by end users (Kaplan & Haenlein 2010). The content may be in a variety of forms, such as animation, images, video, or text. The Organisation for Economic Co-operation and Development (OECD) has defined three broad characteristics of UGC. First, the content is published on a publically accessible website or social medium. Second, there must be evidence of the user's role in creating the content; a simple reposting of material does not suffice. Third, the content must be created outside one's professional or organizational practices. Users may generate content to connect with others or to fulfill the need to express themselves (OECD 2007).

TRACTION, SUBSTANCE, AND INFLUENCE IN COMPUTER-MEDIATED COMMUNICATIONS

The focal question of this research is: given the high level of active participation in their brand communities, how can firms identify discussion threads that elicit responses from other community members? Firms may use this information to foreshadow problems and opportunities early. Specifically, what are the characteristics of the initial message that predict the traction it will garner within the community? "Traction" refers to the quality and quantity of the responses that a message provokes from members of the community and the focal corporation.

Kim and Miranda (2011) found that messages can be described in terms of types of claims that are made. Coherence reflects the number of types of claims that are asserted in a message. The model in this paper extends Kim and Miranda (2011) by examining the moderator effects of influence tactics on the relationship between the message content and traction, the ability to garner reaction to a message.

Traction

Traction is the tendency of a message to garner response from others, regardless of whether they agree with or accept the message's claims. Traction differs from several seemingly related constructs of *consensus* or *idea acceptance*. Consensus is defined as the collective acceptance of an idea (Zelditch 2006). Dunning and Sincoff (1980) proposed the theoretical construct of *idea acceptance*, which is the interaction of a good idea and the management structure. Consensus and idea acceptance are similar to traction in that all three are measures of a group's interest of an idea. However, the members of a group who share consensus or idea acceptance have made a decision about their own belief or behavior. The consensus reflects the majority of choices made by the group members. Moreover, idea acceptance is preconditioned on a good idea. In a study of the acceptance of ideas generated through brainstorming, Graham (1977) viewed idea acceptance as a process occurring after evaluation.

The traction of a message is the ability of the message to make people react by inducing some behavior, e.g. writing a response. Traction is a less restrictive construct. Traction is less restrictive than idea acceptance because traction does not necessitate any value judgment about the idea; bad ideas can gain as much traction as good ideas. Traction is different from consensus because a message may have traction but not consensus. The group may be actively discussing a message, which reflects high traction; however, the group may be evenly split about accepting the idea, which reflects low consensus.

Substance Coherence

The substance of a message is coherent if it is logical, well founded, and sound. In a social movement, three types of claims are deemed essential to a coherent message in this context: program, identity, and standing claims (Tilly 2004). Program claims describe the actions that are to be taken. For example, the civil rights movement in the

United States, working to promote civic equality along racial lines, organized boycotts, marches, and sit-ins. Identity claims are proclamations of membership in a category or group of people. Usually, a common name is used to characterize the group: women, African-Americans, or coal miners. Standing claims invoke relationships that can confer legitimacy. For example, unions often spotlight their relationships with political actors who support their cause. The more claims contained in a message, the more coherent is the substance of the message. Movements or other calls for collective action that articulate all three claims are viewed as most coherent; therefore these movements are more likely to garner traction than movements with fewer claims.

Kim and Miranda (2011) modeled these three claims as components of a message's substance that are relevant for identifying "issues" within online communities. The coherence embedded in a post makes it more likely to garner traction because (1) a stated program claim increases the likelihood that the grievance is understood, (2) a stated identity claim increases the likelihood that people will perceive that the grievance is relevant to them, and (3) a stated standing claim increases the likelihood that people will perceive that the issue is legitimate. The following passage from the Starbucks brand community contains all three claims:

> I am a Starbucks gold card member and I love it! But what I don't love is waiting for my free drink and other exclusive coupons that I get for being a member through snail mail. I think that these special offers should be loaded right onto the card so that the next time I go to order a drink it will automatically take effect. Not only will this eliminate the waiting period but it takes the greener cause into effect. Get rid of the paper postcards that you mail out daily....send it to us immediately through our cards!

The identity claim occurs in the first sentence: "I am a Starbucks gold card member…." The program claim is a call for Starbucks to load special coupons directly onto members' gold cards rather than send paper coupons through the mail. The standing claim involves the reference to the green movement ("greener cause"), which is a movement that encourages minimizing negative impact on the environment. Messages that effectively articulate these three claims are more likely to initiate movements (Kim & Miranda 2011). Kim and Miranda (2011) developed their ideas based on the social media messages of the Coffee Party Movement, the Green Revolution in Iran, the Starbucks brand community, as well as the 2008 presidential election.

Social Influence

Social influence on the internet, referred to as influence in this paper, means causing a change in an individual's beliefs or behavior through real or imagined social pressure (Guadagno & Cialdini 2005). Authors influence others in the community not only through the substance of their messages, but also by influence tactics embedded in their messages. The basis for online influence differs from face-to-face interaction, where attributes such as physical appearance are often salient (Guadagno & Cialdini 2005). Understanding influence in brand communities can be more difficult because of the greater level of anonymity. However, while members of conventional CMC teams may sometimes be unaware of the source of a comment, they are typically aware of the identity of conversation participants or at least characteristics of the group to which those participants may belong (e.g., Kahai et al. 1998). While CMC moderates the salience of status and expertise by reducing participant access to associated cues (Dubrovsky et al. 1991), social media often resurrect the salience of these factors via cues such as electronic badges, group identification, and other signals of prominence.

To understand influence in online communities, we model influence based on Petty and Cacioppo's (1984) elaboration likelihood model (ELM). Researchers have argued that the central and peripheral routes are two ways individuals respond to persuasive information (Petty & Cacioppo 1984; Bhattacherjee & Sanford, 2006). The first is the central information processing route, which entails careful deliberation about the presented information (Petty & Cacioppo, 1984). The second is the peripheral route, through which information is processed when an individual forms an opinion based not on the factual merits of a message but rather on superficial and peripheral cues such as affect. Individuals can be influenced through both the central and peripheral routes (Angst & Agarwal 2009). This model thus highlights two types of cues implicated in persuasion: cognitive cues and affective cues.

ELM also highlights the role of the medium in determining how individuals process persuasive information. Matheson and Zanna (1989) found that individuals use the central processing route more frequently when evaluating CMC messages. This is most likely because of the paucity of affective cues available via online communication at the time. However, not only have online media evolved in their capacity to transmit social cues, but more importantly, our ability to both transmit and perceive affective cues increases with our continued use of online communication media (Carlson & Zmud 1999). Consequently, both processing routes should be available to participants in online communities.

Social Influence – Affect Infusion (Affective Influence)

Forgas (1995) defined affect infusion as "the process whereby affectively loaded information exerts an influence on and becomes incorporated into the judgmental process, entering into the judge's deliberations and eventually coloring the judgmental outcome." Affect has been shown to impact behaviors through cognitive processes, i.e., in the way readers judge a message (Foo et al. 2009; Forgas 1995). Affect colors our judgment by influencing which cues are perceived and how the cues are weighed and combined. Affect alters cognitive behavior through affect-as-information and affect-priming (Forgas, 1994). The affect-as-information processes occur when individuals ask themselves how they feel about something and use their affective state as piece of information in their decision making (Forgas, 1994). Affect priming works through memory and suggests that affect will trigger memories of related cognitive categories (Forgas, 1994).

The sample post quoted earlier uses affective words to describe the author's attitude. Affective influence entails primitive or deliberate communication of positive or negative affect (Barsade 2002; Hatfield et al. 1994). Researchers have observed that expressions of affect evoke mirror responses from others (Hatfield et al. 1994). These mirrored responses can also be caused by affect modulation. Affect modulation are communicative behaviors that "evoke[s] or alter[s] sentiment in such a way as to cause the redefinition of a situation" (Donnellon et al. 1986).

Communicated affect influences information processing in two ways. First, as noted above, affect is contagious. Infused affect subsequently influences people's judgments about target information. For example, Wehmer and Izard (1962) found that happy subjects assess a target more positively than unhappy subjects. Second, affect influences judgments through affect-based priming, whereby positive affect "primes" the peripheral route and negative affect primes the central processing route (Forgas 1995).

Positive affect has been found to increase social activity (Watson 1988). It is generally found to enhance creativity (Isen 2002). Entrepreneurs with positive affect are more creative, more able to recognize opportunity, and better able to navigate uncertain business conditions (Baron 2008). In the context of strategic decision making, positive affect has been shown to increase individuals' perception of information as an opportunity rather than a risk (Mittal & Ross 1998). In negotiation, positive affect diminishes the use of contentious tactics (Carnevale & Isen 1986). A positive affective state (mood) has been found to be positively related to cooperative behavior (Barsade 2002; George 1991). Positive affect enhances creativity, cognitive flexibility, and problem-solving skills (Estrada et al. 1994; Isen & Means 1983).

Negative affective states, in contrast, are correlated with systematic message processing (Schwarz et al. 1991). Negative affect has been found to be correlated with experienced stress (Watson 1988), and it tends to correlate with pessimistic judgments (e.g., Wehmer & Izard 1962). Subjects experiencing negative affect were found to perceive outcomes to be more negative (Mittal & Ross 1998). Angry subjects were found to make more judgments based on stereotype and status cues, compared to sad or neutral subjects (Bodenhausen et al. 1994).

Social Influence – Cognitive Influence Tactics

The efficacy of a message's substance is also moderated by the cognitive influence tactics embedded in the message. By cognitive influence tactics, we mean verbiage that explicitly attempts to persuade. In an analysis of cognitive influence, Higgins et al. (2003) meta-analyzed the six influence tactics used by workers— i.e., ingratiation, self-promotion, rationality, assertiveness, exchange, and upward appeal— and found that rational persuasion and assertiveness most frequently correlate with both subjective performance assessments and objective success criteria. We therefore limited our investigation of cognitive influence tactics to these two.

Rational persuasion refers to "using data and information to make a logical argument supporting one's request" (Higgins et al. 2003). Rational persuasion was found to be a successful tactic for obtaining raises, high performance reviews, and promotions (Higgins et al. 2003). Also, rational persuasion elucidates the causal structures underlying the claims. In the earlier sample message, the author states that "not only will this eliminate the waiting period but it takes the greener cause into effect." The justification is that the action will have the benefits of improving efficiency and reducing waste.

Assertiveness is the use of forceful means to obtain desired results (Higgins et al. 2003). Assertiveness is similar to pressure tactics, which are characterized by the use of demands, threats, or intimidation (Yukl & Fable 1990). Higgins et al. (2003) found that while assertiveness correlated positively with success in terms of raises and promotions, it correlated negatively with subjective performance assessments of the person exercising assertiveness. In the sample message, the author asserts "Get rid of the paper postcards that you mail out daily." The author of the message phrases the sentence in the form of a command to pressure Starbucks to change.

RESEARCH MODEL AND HYPOTHESES

The current research effort contributes incrementally to the literature by raising the question of how cognitive and affective influences embedded in the posting strengthen or weaken the relationship between claims and traction. Individuals who belong to the same social group as the claimant (as indicated by the identity claim) are more likely to feel an affinity for the claimant and lend their support. The program claim describes the proposed action. Members of the community will assess the program claim and decide whether it is feasible and worthy of pursuit. Finally, the standing claim, which gives legitimacy to the program claim, may sway others to believe in the worthiness of the cause. The research model is presented in Figure 1.

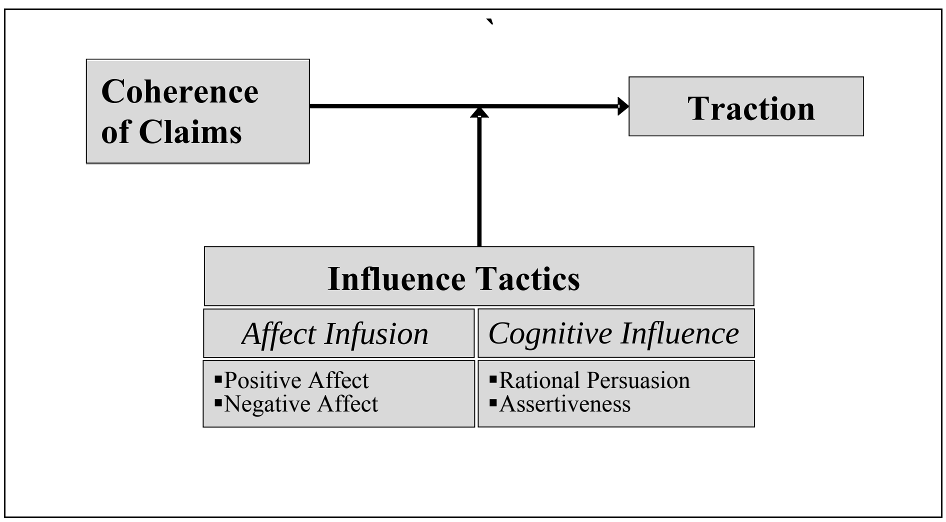

Figure 1: Research model

The current research effort contributes incrementally to the literature by raising the question of how cognitive and affective influences embedded in the posting strengthen or weaken the relationship between claims and traction. We posit that the effects of coherence are mitigated by the affective and cognitive influence tactics embedded in the post. We now consider the manner in which the two affective influences—positive and negative affect—and the two cognitive influences—rational persuasion and assertiveness—intervene in the traction that coherence garners.

As noted earlier, readers of a message will respond to the affect infused into the message as well as to the content of the message and the manner in which the message is presented. In particular, positive affect induces positive judgments. Consequently, messages that communicate positive affect are liable to garner greater traction, receiving more positive votes (which culminate in points earned) and comments. Because positive affect induces a creative mindset, readers of messages infused with positive affect will be more receptive to new and novel ideas and, when they disagree, will be more likely to find ways of creatively reconciling their perspectives with those articulated in the initial message (Isen 2002). Thus, readers of positive-affect-infused messages will evaluate the idea with a more open mind. We hypothesize that an idea will gain more traction if the message contains coherent substance *and* positive affect.

Hypothesis 1: Positive affect will positively influence the relationship between coherence and traction – positive affect will make the relationship stronger.

On the other hand, negative affect has been found to culminate in negative judgments. Further, through the "priming" of the information-processing pathways, readers experiencing negative affect will tend to process the communicated information more systematically. Then, because negative affect shuts down creative problem-solving, they will be less able to creatively reconcile substantive differences. Consequently, when messages communicate negative affect, they are likely to attract negative reactions from the community in terms of votes and comments.

Hypothesis 2: Negative affect will negatively influence the relationship between coherence and traction – negative affect will make the relationship weaker.

It is not enough to simply assert a claim. Sussman and Siegal (2003) have argued that the quality of the argument is an important antecedent to the perceived usefulness of the information. Further, ELM suggests that the central processing route is invoked more frequently when individuals process information that is personally relevant to them (Petty & Cacioppo 1984). Identity claims, in particular, aim to personalize the message to prospective readers and thereby attract their attention. However, this personalization means that they will process the information contained in the message systematically. Consequently, rational persuasion, whereby the author logically sets out the case (s)he wishes to make, is essential to ensuring reader buy-in to the coherence of the message. Haphazardly structured messages containing an identity claim are liable to be particularly unsuccessful. Although to a lesser extent, by attempting to translate the author's personal troubles into a public issue, program and standing claims also attempt to garner reader identification with the cause. This perspective is supported by research that has demonstrated that subjects who were personally concerned with the outcome of a decision were influenced by messages with strong arguments to a greater extent than when they were not personally affected by the outcomes (Petty et al. 1983). We therefore hypothesize that rationally argued messages with strong coherence will be the most successful.

Hypothesis 3: Rational persuasion will positively influence the relationship between coherence and traction – rational persuasion will make the relationship stronger.

In general, assertiveness garners attention (Derber 1979). This attention may be negative, though, as evidenced in research findings of a negative correlation between assertiveness and subjective performance appraisals (Higgins et al. 2003). In fact, assertiveness is what Derber (1979, p. 21) terms "being civilly egocentric" and engenders competitive, rather than collaborative, conversations. The purpose of communication is not simply to share information, but to collaborate with others in constructing shared meaning from multiple persons (Miranda & Saunders 2003). Coherence claims that are both assertive and complete will not invite such participatory construction of meaning. The completeness of the claims will leave little room for elaboration and the assertiveness will dissuade community efforts to participate in the social construction of meaning. Assertive framing of coherence claims will therefore result in fewer responses. Moreover, the competitive dynamic introduced by assertiveness (Derber 1979) will prompt community members to highlight deficiencies in assertive articulations of incomplete coherence claims. In particular, research on information processing has found that individuals in a competitive frame process information more systematically, identify more logical inconsistencies, and make more negative attributions about those inconsistencies than do individuals in a collaborative frame (Ruscher & Fiske 1990). We therefore anticipate that assertiveness will diminish the efficacy of coherence.

> *Hypothesis 4:* Assertiveness will negatively influence the relationship between coherence and traction – assertiveness will make the relationship weaker.

DATA

Data were collected from MyStarbucksIdea, an online brand community that Starbucks launched in March 2008. This virtual space enables customers to dialog among themselves and with the company, extending the coffeehouse experience beyond the brick-and-mortar locales.

After registering with the site, customers are encouraged to post ideas pertinent to three categories of Starbucks' engagement: Products (e.g., food, beverages, loyalty cards), Experience (e.g., payment and atmosphere), and Involvement (e.g., community building and social responsibility). Once a customer posts an idea, others can comment or vote on the idea. In addition to inviting these posts, the site serves as a rudimentary social networking site. Individuals are able to post information about themselves, such as location, favorite drink, or even a photograph. The site also posts statistics about the contributions made by customers, including number of ideas submitted, number of positive votes received, and number of comments and votes submitted.

Figure 2 is a snapshot of a post from mystarbucksidea.com and depicts a single unit of analysis. The text is the first message in the discussion thread and contains the idea proposed by the customer. User s can vote on an idea by clicking on the thumbs up or down icon. Points are displayed below the thumbs icon. The net number of votes multiplied by 10 calculates points. At the bottom of the post is the number of comments in brackets. Occasionally, Starbucks employees will comment on the idea. The comments by Starbucks employees can be found by clicking on comments hyperlink to list all the associated comments.

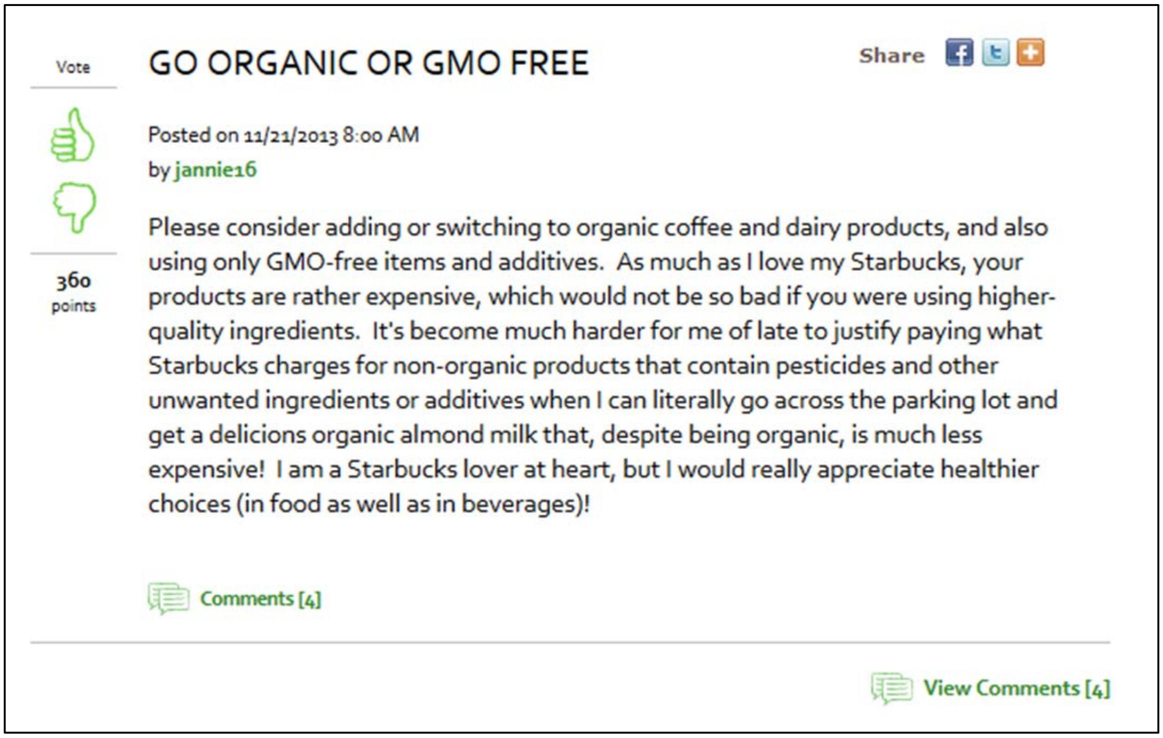

Figure 2: Example of a mystarbucksidea.com post

Sampling Approach

The dataset comprised a matched sample of 160 posts from mystarbucksidea.com. Half this sample consisted of ideas that were under consideration by Starbucks and labeled *Ideas in Action.* The other half of the sample was constructed by matching threads that were not tagged as *Ideas in Action* to reduce selection bias (Shadish, Cook, & Campbell, 2002). The latter threads were selected to match the posting date and category of each thread appearing in the *Ideas in Action* sample. *Ideas in Action* represent ideas that we know have gained traction since Starbucks is already evaluating the idea. The *Ideas in Action* posts were matched with posts that as of yet have not been considered by Starbucks. The matching criteria were date and category of each thread. These two variables may influence the independent variable. For example, the number of comments can be influenced by the age and the category of the comment. Older posts may have more comments as more people may have seen the original post. Also, the category type may influence the number of comments because some categories may be more popular than others for reasons that are unobservable.

Linguistic Inquiry and Word Count (LIWC)

I used the Linguistic Inquiry and Word Count (LIWC) software (Pennebaker et al. 2006) to measure the influence constructs. LIWC distinguishes between style words and content words. Style, or function, words help structure the sentence grammatically. Style words include pronouns, prepositions, articles, conjunctions, and auxiliary words. Content words reflect the attentional focus, social relationships, affect, status, social coordination, honesty, and thinking styles of the speaker.

LIWC compares each of the words in a text to a dictionary of words. Each word in the dictionary is assigned to a predefined category; these categories were developed, validated, and refined through extensive psychometric evaluation[1]. The algorithm of the LIWC software is to compare the word in a sample piece of text to the internal dictionary of words. The dictionary is the most critical component of the software because it is the basis of the LIWC scores.

The dictionary was developed in four steps. The first step consisted of collecting words. Words were collected from positive and negative affective rating scales such as PANAS (Watson, Clark, & Tellegen, 1988), standard dictionaries, and thesauruses. Three to six judges were used to augment the list through brainstorming

[1] Interested readers are encouraged to read Pennebaker et al. (2007) for the development and the psychometric properties of LIWC and Tauscizk and Pennebaker (2010) for a literature review of peer-reviewed studies using LIWC.

sessions. The goal of the second step was to rate the words and determine if the words should be included or excluded from one of the LIWC categories. The goal of the third step was psychometric evaluation. Text files from previous studies were analyzed. Categories that were used at low rates or had poor reliability or validity were dropped. The final step involved updating and expanding the categories by drawing on over several hundred thousand text files (Pennebaker, et al., 2007). LIWC has been used in more than 120 peer-reviewed articles, many of which have been published in premier journals such as the *Journal of Applied Psychology* and the *Journal of Personality and Social Psychology* (Tausczik & Pennebaker 2010).

Independent Variables

Coherence: At least one of the researchers coded the original message to determine which of the three coherence claims were present. Before coding the messages, the researchers developed and agreed upon the definition for each of the three claims. All of the messages contained a program claim; however, not all of the messages contained an identity claim or a standing claim. A second rater, a professor in the social sciences, was trained in the method and re-coded the messages. The Cohen's kappa coefficient was 0.63 for identity claims and 0.69 for standing claims. The Cohen's kappa for program claims was 1.00, as all the messages had a program claim.

The coherence score is determined as follows. One point was given for each type of claim, resulting in a range of zero to three points per message. The score is additive and gives equal weight to the three types of claims. Tilly has observed that the three types of claims are combined in social movements (Tilly, 2009). Further, he states, "The relative salience of program, identity, and standing claims varies significantly among social movements, among claimants within movements, and among phases of movements." (Tilly, 2009).

While Tilly has posited the existence of claims, he has not specified the weights. He does not argue that all three claims are required so I measure coherence using an additive model that allows coherence to range from zero to three. A multiplicative model, that requires all three claims to exist before a message is coherent, is not supported by Tilly's view as he considers claims to have various amounts in social movements. Without further empirical evidence, I use equal weights among the three claims.

Influence Strategies: The texts of the initial postings, stripped of message headers, timestamps, and author information, were placed into individual text files. The LIWC software was then run on the files to automatically code for constructs based on the presence of words matching the program's dictionary entries associated with the constructs.

The rational persuasion metric summed two LIWC cognitive process constructs that correlate with authors' efforts to persuade using rational arguments: cause and inhibition. Examples of causation words include *cause, know,* and *ought.* Inhibition words include *block, constrain,* and *stop*. Assertiveness was measured as the difference between the LIWC dictionary categories of certainty and tentativeness. Certainty words include terms such as *always* and *never*. Words in the tentativeness category include *maybe, perhaps,* and *guess.*

Positive affect was assessed as the number of positive affect words used, such as *love, nice,* and *sweet*. Negative affect was likewise assessed as the count of negative affect words, such as *hurt, ugly, and nasty*.

Dependent Variables

In order to ascertain the traction an initial posting garnered, we measured community support in terms of points allotted to the postings and comments in response to the posting. We measured corporate support in terms of comments from Starbucks employees.

Number of points (points): Registered users are able to vote on contributed ideas with a thumbs-up or thumbs-down. The site provides only aggregated votes, i.e., total votes for the idea minus total votes against it, multiplied by 10. The actual number of votes for and against an idea is not given. Because votes against an idea may outnumber votes in favor of the idea, Points may be negative.

Number of comments by community members (comments): The number of comments reflects the community's level of interest in the original post. Comments may be either supportive or unsupportive. The number of comments is displayed under each post. The contents of the comments were not included in the analysis.

Number of comments by Starbucks' IdeaPartners (IdeaPartner comments): Starbucks' employees, known within the community as IdeaPartners, occasionally interject their own comments into the discussion. These comments usually involve IdeaPartners sharing Starbucks' plans and directions pertinent to the thread. Minimally, IdeaPartner participation signals Starbucks' attentiveness to an emergent movement; optimally, it signals concessions garnered by the movement.

Control Variables

The size of the message is expected to attract attention and was controlled using word count. Message complexity, which may signal literacy, was controlled based on the number of words with more than six letters used following Pennebaker's convention (1999). As noted above, contributions appear in one of three major categories: products, experience, or involvement. Preliminary analyses noted that the product and experience dummies had similar effects on the dependent variables of interest, but differed from the effects of the involvement dummy. Consequently, in the interest of conserving power, only the involvement dummy was retained in the analyses reported. As the number of comments and points associated with a post correlates with the amount of time the post has been available for commenting and voting, the submission date of the original post is entered into the model as a control. Finally, because Starbucks' movement of posts to *Ideas in Action* conveys a legitimacy stamp to the posts, a dummy was included to account for legitimated posts.

A contributor's visibility and credibility on the site may potentially sway the opinion of others. In order to control for the contributor's presence on the site, an index of contributor clout was developed using the following metrics: number of badges, number of submissions, number of votes received, and number of points. The four metrics are found under the profile of each individual on the website. Badges are awarded to top commenters and authors of launched ideas. A launched idea is a suggestion made by a customer and implemented by Starbucks. Submissions is the count of all new ideas submitted to the website. A new idea is the initiation of a new discussion thread. The variable <u>votes received</u> contains the number of positive votes received from other individuals. <u>Points</u> reflect the author's activity on the site, such as number of comments or number of votes submitted for someone else's idea. The four metrics loaded satisfactorily on a single factor and the following weights were subsequently used to compute the index: Badges: 0.5219, Submissions: 0.8153, and Votes Received: 0.9260.

ANALYSES

Traction was measured using points, number of comments by community members and number of comments by Starbuck's IdeaPartners. Each is a different form of traction. The number of points reflects the net support of the community. The number of comments reflects the level of discussion. The number of comments by Starbuck's IdeaPartners reflects the amount of attention received from the company. I estimate a regression for each of the three measures of traction using the full sample. Within each regression, I test all four hypotheses.

One of three different types of regressions was run for each dependent variable. Each of these three dependent variables measures a different dimension of traction. The data for each of the three traction variables had characteristics that made them better suited to regression models other than ordinary least squares. For <u>points</u> I used a quantile regression model; for number of comments from the community, I used a negative binomial regression; for the number of <u>Starbucks Ideapartners' comments</u>, I used zero-inflated negative binomial regression. I will discuss in detail the characteristics of the dependent variables that motivated the regression modeling choices in the results section below.

RESULTS

Table 1 presents the descriptive statistics and Table 2 presents the correlation matrix for the key variables. The intercorrelations between the independent variables are quite low. The intercorrelations between the dependent variables are noteworthy. For example, the correlation between points and comments is 0.63 and the correlation between Comments and Comments by Starbucks (abbreviated by SbuxCom in Table 2) is 0.425. This is because Starbucks responds to popular ideas based on an internal decision rule using the number of points and the number of customer comments (Brennan, 2010).

Note that because the scale properties underlying each of the three dependent variables differed, it was not possible to test the hypotheses using a multivariate analysis. For each of the dependent variables, hierarchical regression was used to ascertain the incremental contribution of hypothesized effects to variance explained by the dependent variable of interest. Because of the modest sample size relative to the number of model parameters, a significance level of 0.10 was adopted.

Table 1: Descriptive statistics, n=160

Variable	Mean	Std. Dev.
Posts Legitimated by Starbucks	0.5	0.50157
Number of Points	3622.75	7209.043
Number of Comments	17.3125	27.60599
Number of Comments by Starbucks	1.06875	1.454215
Number of Ideas Submitted	1416.488	354.2607
Product Category	0.85625	0.351938
Experience Category	0.09375	0.292396
Word Count	77.1375	55.12918
Complexity	16.31963	6.489895
Clout	2932.903	7495.483
Coherence	1.8375	0.717153
Positive Affect	5.366875	4.057492
Negative Affect	0.990625	1.668033
Rational Influence	2.308937	2.787098
Assertiveness	-1.488	2.922296

Table 2: Correlation matrix

	Type	Points	Comments	SbuxCom	Submitted	Product	Experience	WC	SixLetter	Clout	Coherence	PosAffect	NegAffect	Rational	Assert
Type	1.000														
Points	0.349	1.000													
Comments	0.283	0.630	1.000												
SbuxCom	0.513	0.260	0.425	1.000											
Submitted	0.039	0.016	0.060	-0.007	1.000										
Product	0.053	0.078	0.066	0.019	-0.184	1.000									
Experience	-0.064	-0.017	-0.010	0.044	0.165	-0.022	1.000								
WC	0.029	0.098	0.053	0.073	-0.039	0.034	-0.022	1.000							
SixLetter	-0.007	-0.131	0.053	0.122	0.051	-0.104	0.034	0.008	1.000						
Clout	0.082	0.253	0.162	0.145	0.073	0.091	-0.048	-0.061	-0.020	1.000					
Coherence	0.018	0.112	0.074	0.017	-0.051	-0.068	-0.017	0.185	0.073	-0.090	1.000				
PosAffect	0.133	0.017	0.017	0.048	0.026	0.055	-0.081	-0.223	-0.111	0.012	-0.046	1.000			
NegAffect	0.024	0.093	-0.137	-0.078	-0.051	-0.060	0.015	0.019	-0.016	-0.131	-0.053	-0.015	1.000		
Rational	0.095	0.053	0.079	0.086	-0.117	0.016	-0.083	0.021	0.077	-0.046	-0.026	-0.022	0.015	1.000	
Assert	0.015	-0.065	-0.108	-0.041	-0.020	-0.089	0.103	-0.021	0.082	-0.133	-0.064	-0.074	0.111	0.165	1.000

We centered each variable that participated in the hypothesized interaction effects so that the estimated coefficients can be interpreted as effect of the variable at the sample means of the other variables Cohen et al. (2003, p. 261). Multicollinearity statistics are reported in Table 3 and indicate an average variance inflation factor of 1.17 across all independent variables and interaction terms. To account for the possibility that error terms for the same author across multiple posts were correlated, our analyses used standard errors clustered within authors.

Table 3: Multicollinearity statistics

Terms	Variance Inflation Factor	Tolerance
Word count	1.12	0.8959
Complexity	1.13	0.8829
Time	1.05	0.9486
Idea type	1.1	0.9080
Legitimated	1.07	0.9347
Clout	1.07	0.9340
Coherence	1.16	0.8619
Positive affect (PA)	1.15	0.8713
Negative affect (NA)	1.17	0.8566
Rational persuasion (RP)	1.48	0.6761
Assertiveness (Assert)	1.11	0.9036
Coherence × PA	1.08	0.9229
Coherence × NA	1.26	0.7907
Coherence × RP	1.47	0.6811
Coherence × Assert	1.07	0.9313

The distribution of points (μ = 3607.33; σ = 7214.16) was not normal (skewness = 2.98, kurtosis = 12.24); particularly the over-dispersion indicated by the high level of kurtosis suggests a regression model based on medians rather than means will reduce the influence of the over-dispersed data on the standard errors of our regression coeficients (Koenker 2005). Consequently, instead of an ordinary least squares regression (OLS), a quantile regression, which estimates median rather than mean points was used. The results are presented in Table 4.

Table 4: Quantile regression on points

Independent Variable	Controls	Moderated Effects
Word count	4.25 (0.024)	0.36 (0.93)
Complexity	1.99 (0.90)	-31.61 (0.82)
Time	0.01 (0.64)	-0.22 (0.75)
Idea type	-355.75 (0.431)	-836.52 (0.43)
Legitimated	1552.60 (0.00)	1580.73 (0.00)
Clout	0.079 (0.00)	.079 (0.01)
Coherence		663.25 (0.07)
Positive affect (PA)		-4.47 (0.94)
Negative affect (NA)		-109.04 (0.49)
Rational persuasion (RP)		165.85 (0.10)
Assertiveness (Assert)		-13.62 (0.87)
Coherence × PA		-55.84 (0.51)
Coherence × NA		-148.21 (0.57)
Coherence × RP		322.92 (0.01)
Coherence × Assert		-22.81 (0.83)
Pseudo R^2 (p)	.060	.065

*p-values are reported in parentheses; p-values ≤ 0.05 are shaded

The quantile regression produces a pseudo R^2. Since the quantile regression model provides estimates of how effect size varies by quantile, a single measure of goodness of fit, such as R^2 in a linear model, is not possible. Koenker and Machado (1999) have provided a measure analogous to the least squares R^2 that can be used in quantile regression. At any quantile of interest, errors from the restricted and unrestricted models are used to generate a pseudo R^2 that is calculated in exactly the same way as the R^2 in an OLS model. Specifically, pseudo R^2 is defined as one minus the ratio of the error sum of squares under the restricted model over the error sum of squares under the unrestricted model of the quantile regression (Koenker & Machado, 1999). Pseudo R^2 from the median quantile is reported in Table 4. From Table 4, observe that the pseudo-R^2 increases from the controls-only model to the moderated effects model. Unlike OLS, quantile regression does not permit calculation of incremental R^2 statistics. The data are not multicollinear, so the three interaction terms for all independent variables were included in the full model and run simultaneously.

The parameter coefficient for the interaction between <u>coherence</u> and <u>rational persuasion</u> was found to be significant, providing partial initial support for Hypothesis 3. Full support means that the interaction term between coherence and rational persuasion was found to be significant for not only <u>points</u>, but also for the number of <u>comments</u> and number of <u>IdeaPartner comments</u>. The interaction plot in Figure 3 is based on median splits for <u>coherence</u> and <u>rationality</u>. This plot substantiates Hypothesis 3, demonstrating an elevated response to coherent claims when rational persuasion is also employed.

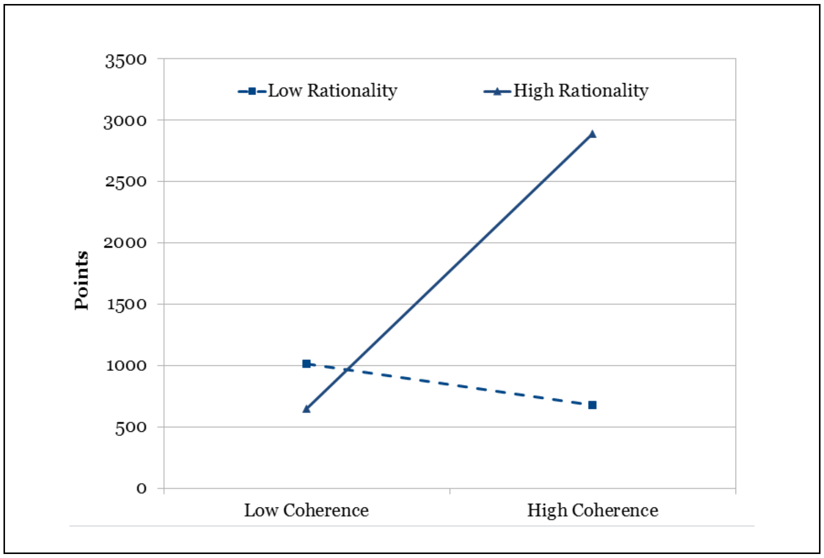

Figure 3: Interaction of coherence and rationality on points

Because comments were are over-dispersed and count data, a negative binomial regression was conducted. The negative binomial regression model is one of a class of mixed Poisson models, comprised of a mixture of a Poisson and gamma distribution. As a consequence, variance of the negative binomial regression model is comprised of an expected level of variance common across observations in the sample, and a second level that is allowed to vary across observations. This produces a regression model that is suitable for over-dispersed count data (Cohen et al. 2003, p. 531). Since the data are not multicollinear, the three interaction terms for all three dependent variables were included in the full model and run simultaneously. The results for Comments are presented in Table 5.

Table 5: Negative binomial regression on comments

Independent Variable	Controls	Moderated Effects
Word count	.00 (.45)	.00 (.02)
Complexity	.00 (.96)	.01 (.67)
Time	.00 (.97)	.00 (.82)
Idea type	-0.78 (.25)	-.60 (.10)
Legitimated	.88 (.00)	.83 (.00)
Clout	.00 (.06)	.00 (.05)
Coherence		-.08 (.52)
Positive affect (PA)		.03 (.12)
Negative affect (NA)		-.20 (.00)
Rational persuasion (RP)		.05 (.21)
Assertiveness (Assert)		-.04 (.09)
Coherence × PA		-.04 (.05)
Coherence × NA		-.21(.01)
Coherence × RP		.03(.58)
Coherence × Assert		-.07(.01)
McFadden's Adj R^2	0.014	0.019
χ^2 (p)	34.91 (.00)	125.65(.00)

*p-values are reported in parentheses; p-values ≤ 0.05 are shaded

Since the algorithm for fitting the negative binomial regression model iterates over maximizing the regression's likelihood function with respect to the mean parameter and then the shape parameter, the usual R^2 measure (from an OLS model, e.g.,) cannot be calculated. Instead we report the McFadden's R^2, which treats the log likelihood of an intercept-only model as 'total sum of squares' and the log likelihood of the full model as 'sum of squared errors' in an equation analogous to the one used to calculate R^2 in an OLS model. Also, similar to the Adjusted R^2 from OLS, McFadden's Adjusted R^2 penalizes the model when regressors are added. McFadden's R^2 increased with the inclusion of the moderating effects, and the moderated effects model χ^2 exceeds the χ^2 for the controls only model. Three interaction terms were found to be significant; the significant interactions between coherence and positive affect, negative affect, and assertiveness will be discussed in turn.

The interaction between coherence and positive affect was found to be significant (p = 0.05). However, the sign of the coefficient is in the opposite direction to our hypothesized relationship. A high degree of positive affect and a high level of coherence dampened the number of points.

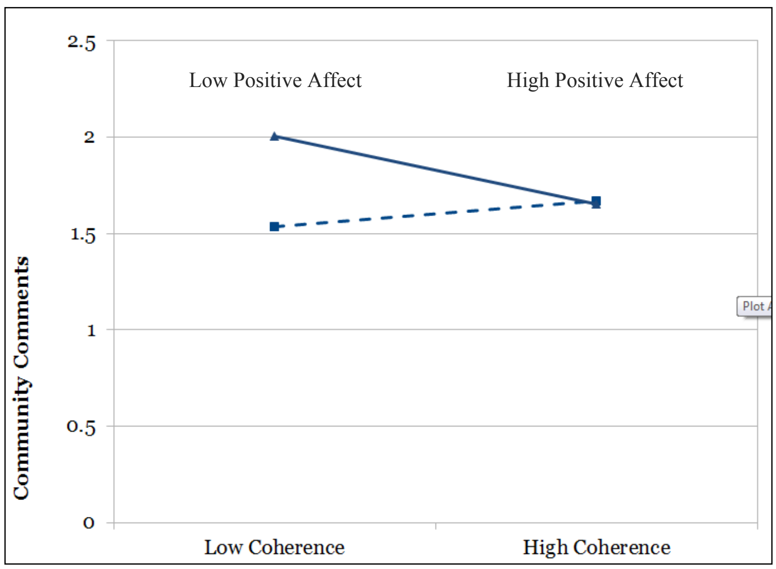

Figure 4: Interaction of coherence and positive affect on community comments

As is evident from Table 5, the coefficient for the interaction of coherence and negative affect was found to be significant (p = .01) and negative. Likewise, the interaction of coherence and assertiveness was significant and negative (p = .01). In each case, we therefore observe that responses to messages with complete coherence claims are dampened by negative affect or assertiveness. Thus, Hypotheses 2 and 4 received preliminary support with regard to community member comments.

To further investigate these effects, interaction plots for coherence × negative affect and coherence × assertiveness effects were constructed, also based on median splits of the independent variables. These plots, presented in Figure 5 and Figure 6, substantiate the hypothesized dampening effect of negative affect and assertiveness on complete coherence claims.

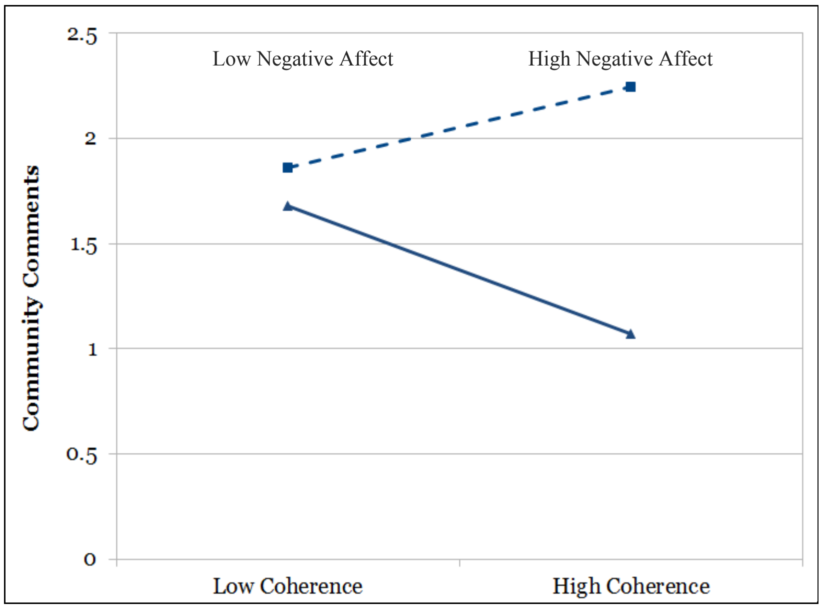

Figure 5: Interaction of coherence and negative affect on community comments

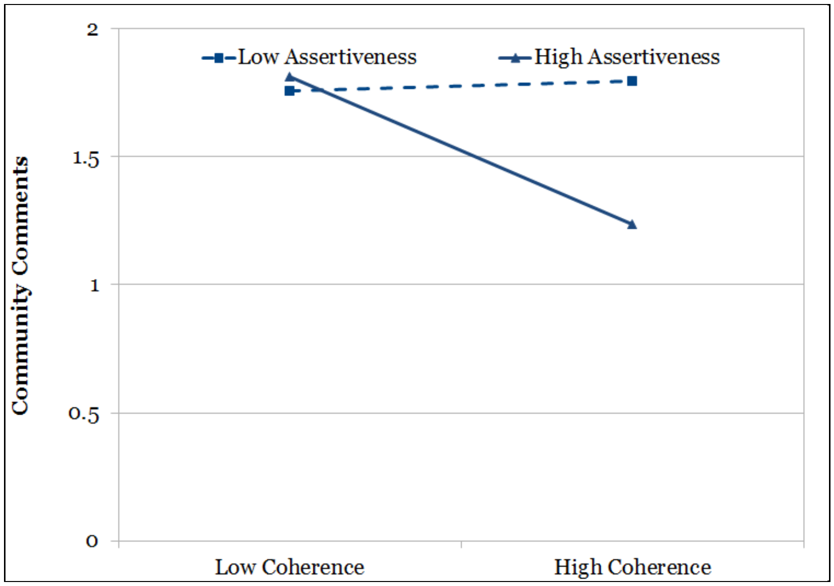

Figure 6: Interaction of coherence and assertiveness on community comments

In addition to Starbucks' IdeaPartner Comments count data being subject to overdispersion ($\sigma = 1.45 > \mu = 1.07$), inspection of its frequency distribution revealed the frequency of zero counts to be inflated (45% of the data). Consequently, a zero-inflated negative binomial regression was conducted, because it assumes the zero and non-zero count values are generated by two separate stochastic processes and may be modeled independently (Freese & Long, 1997). Modeling the zero and non-zero count values independently produces a better fitting model than the negative binomial model, which does not allow for this flexibility when a high number of zeroes present in the data. Inspection of residuals based on preliminary analyses further revealed the presence of five severe outliers, which, as recommended in Andersen (2008), were dropped from analyses. The results for Starbucks' IdeaPartner comments are presented in Table 6. None of the interaction terms were found to be significant. Further, McFadden's Adjusted R^2 decreases when the dependent variables and interaction terms were added, indicating that these variables did not have a high degree of explanatory power in the case of Starbucks IdeaPartner comments.

Table 6: Zero-inflated negative binomial regression on Ideapartner comments

Independent Variable	Controls	Moderated Effects
Word count	.00 (.70)	.00 (.60)
Complexity	.02 (.87)	.02 (.32)
Time	-.00 (.85)	-.00 (.23)
Idea type	-.49 (.21)	-.50 (.19)
Legitimated	.80 (.01)	.81 (.00)
Clout	.00 (.72)	.00(.05)
Comments	.01 (.69)	.01 (.00)
Points	-.00 (.56)	-.00 (.00)
Coherence		.37 (.70)
Positive affect (PE)		-.01 (.61)
Negative affect (NE)		.03 (.66)
Rational persuasion (RP)		-.01 (.71)
Assertiveness (ASSERT)		-.00 (.91)
Coherence × PE		.02 (.73)
Coherence × NE		.13(.62)
Coherence × RP		.00(.95)
Coherence × Assert		-.03(.50)
McFadden's Adj R^2	0.193	0.16
χ^2 (p)	33.83 (.00)	62.17 (.00)

*p-values are reported in parentheses; p-values ≤ 0.05 are shaded

DISCUSSION

The purpose of this study was to determine whether influence tactics embedded in a message would mitigate the effects of a claim's coherence in garnering community and corporate traction. To investigate this question, we examined the content of the message, coding for both coherence and influence tactics. The results of our study are summarized in Table 7.

Table 7: Summary of results

Hypothesized Interaction with Coherence	Points	# of Comments	# of Starbucks Comments
H1: Positive Affect (+)		Significant, but in opposite direction	
H2: Negative Affect (-)		Supported	
H3: Rational Persuasion (+)	Supported		
H4: Assertiveness (-)		Supported	

As evident from Table 7, Hypotheses 2, 3, and 4 garnered some support from points and the number of comments. There were no significant interactions when the number of Starbucks IdeaPartner comments were used as the dependent variable. In contrast, our findings failed to support Hypothesis 1. In fact, the direction of the relationship was found to be negative.

Positive affect was not found to sway either community or corporate participants in the brand community in the case of coherent messages. Rather, a message with low coherence and high positive affect was found to induce a high level of community response. I argued in the hypotheses section that the interaction of a coherent message with positive affect would generate more comments or votes since people would react to the comments, the positive affect, or both. However, the results indicate that individuals only look at positive affect when deciding to comment on a post.

It does not, however, support or disprove a priming perspective, as positive affect expressed in highly coherent messages could have primed respondents to be more attuned to the message, but their subsequent agreement or disagreement with the claims of the highly coherent message may have influenced their response or failure to do so.

While negative affect was found to dampen the effects of claim coherence on community comments, it had no significant impact on the points allotted by the community or on comments from IdeaPartners. This finding is not inconsistent with our arguments based on ELM. Specifically, we posited that negative affect would "prime" the central processing route; coupled with this priming, the communicated negative affect would evoke critical initial responses, which would staunch the fledgling movement. However, given the tendency for negative affective states to be associated with more systematic information processing (Schwarz et al. 1991), community members' responses under such circumstances are more likely to take the form of detailed verbal responses than the exercise of a simple vote, which carries only 10 points. This explains why our findings with regard to the points variable were insignificant. Corporate representatives, likely wishing to appear neutral, are liable to react more dispassionately to affective displays, both positive and negative.

Rational persuasion explicating the facts and causal structure underlying coherence claims, when the coherence claims were complete, garnered positive responses in terms of points allotted by the community. In contrast, when coherence claims were incompletely articulated, the interaction plots indicate that the use of rational persuasion conveyed no advantage or disadvantage. We observed no significant interaction effect in the case of comments from the community. Retrospectively, this is not entirely surprising: while complete and persuasive coherence attract a positive nod from both types of constituencies—community and corporate—they leave little room for elaboration by the community. Consequently, aside from preemptory statements of support, such posts do not encourage conversation oriented toward shared understanding.

The hypothesized negative effect of assertiveness was found only in the case of comments from the community. The premise underlying this fourth hypothesis was that assertiveness would be received by the community and corporation as competitive, rather than collaborative, dissuading response when the underlying coherence claims were completely articulated and inviting contention when they were incomplete. Such contention is most likely to be conveyed verbally, though, rather than through a negative vote, which constrains the voter's influence to a mere ten points. Again, because of the company's need to maintain a neutral stance, company representatives are unlikely to react competitively to assertiveness.

Finally, there are some limitations to this study. First, the format of the website itself has unique qualities that must be recognized. For example, the home page presents a list of the ten most recently submitted ideas and another list of the "Ideas in Action" that Starbucks has recognized as valuable. Potential respondents may focus their attention on these messages and ignore others. In particular, if an idea does not garner sufficient traction while it is on the list of the ten most recently submitted ideas, it may never do so. Time spent on this list is not a function of the attributes of the message itself or the traction it gains, but of the rate at which subsequent ideas arrive.

The analysis assumes that the participants are not involved in deception. There are a number of possible motives for deception: e.g., privacy concerns, identity play, and elevating an individual's status (Caspi & Gorsky 2006) However, we see very little advantage for engaging in deception in this environment since the stakes are so low and participants typically accept the content of the messages at face value. Nonetheless, in controlling for word count and language complexity in the initial message posted to a thread, we do in fact control for these two of the key linguistic correlates of deception identified in prior online deception research (Zhou et al. 2004; Zhou & Zhang 2008).

IMPLICATIONS FOR PRACTICE

These findings suggest several ways in which corporations can be prescient in responding to posts on brand communities. Specifically, our findings suggest that posts that more completely articulate coherence, when combined with rational persuasion, are liable to gain traction within the community and ultimately require the company to cede to the community's demands. In contrast, completely articulated coherence, when coupled with either negative affect or high assertiveness, is liable to fizzle and can more safely be ignored.

On the other hand, individuals too can benefit from this knowledge. Communicators' ability to rehearse their messages prior to transmitting them via electronic media enables them to scan for combinations of substance and influence that are likely to garner support for their cause.

THEORETICAL IMPLICATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This research makes an important contribution to the social movements literature. Specifically, it suggests that substantive coherence and influence tactics may combine in previously unanticipated ways in determining the momentum of a fledgling movement.

Borrowing from the social movement literature, this research contributes insights to research on brand communities and computer-mediated communication about the effects of coherence claim completeness and influence tactics. In particular, our research identifies “coherence” as a construct that is new to these bodies of literature and speaks to the likely manner in which coherence evokes responses from others within a community.

While our research has focused on brand communities, our findings may generalize to open-innovation and open-source communities, as well as to corporations’ social-media-based internal communities. Future research should explore the generalizability of a social movement’s perspective to these other types of instrumental online communities.

This study treated all negative affective transmissions equally. As noted earlier, though, individuals have been found to react differently in the presence of different negative affect, e.g., anger versus sadness (Bodenhausen et al. 1994). Consequently, future research will need to adopt a more granular view of negative affect.

Finally, the temporal aspects of the conversation threads also need to be investigated. Temporal trajectories are key to understanding the evolution and success of social movements in general. The speed at which the conversation moves forward may impact the growth of a movement. If comments are posted at a slow pace, the issue may not attract the attention of the corporation. If the issue does attract the support of many individuals over a long period of time, the external environment may have changed to make the issue moot. If the issue gathers support at a breakneck speed only to suddenly falter, the corporation may view the issue as a flash in the pan or a fad that is no longer of concern to the community. A diminishing number of comments may also signal that the conversation has come to a natural end and that members have reached a consensus.

Online communities, in particular, impose certain technical constraints on the naturalness of temporal trajectories that need to be understood. Features of technology such as asynchronicity and archival capabilities create possibilities for social movements within the virtual world of social media to become separated from the environment that the movement seeks to change.

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COMMUNICATION OF COLLECTIVE ACTION OVER TIME: THE AROUSAL, INTERPRETATION, AND REALIZATION MODEL

ABSTRACT

Social media have recently been used by participants in social movements. Twitter was a key tool in the 2011–2012 protest against the Stop the Online Piracy Act (SOPA). This research develops a theory of the role of affective and cognitive mechanisms in online social movements. Twitter data from the protest against SOPA was analyzed using vector autoregression and Granger causality analysis. The results of the Granger causality were used as empirical data points in building a theory of communication of collective action over time. Affect was found not only to spread through the community, but also to influence cognitive mechanisms. Cognitive mechanisms were used to identify problems and their solutions.

Keywords: Emotional Contagion, LIWC, Social Movements, Social Cognition, Vector Autoregression

INTRODUCTION

Social media such as Facebook and Twitter enable large numbers of individuals to communicate with each other and coordinate activities. For example, the 2009 Iranian election protesters used Twitter to communicate with each other after the government began to censor traditional media. The international community relied on Twitter to gather news on the ground to such an extent that the protest became known in the popular press as the “Twitter Revolution” (Keller, 2010). Other examples include a 2010 a Reddit.com campaign that helped Stephen Colbert host a rally in Washington, DC called “Restoring Truthiness” (Friedman, 2010), and in 2011 protesters in the Occupy Wall Street movement used Twitter to coordinate rallies and marches (Pearce, 2013).

Social-media-based protests often target political and commercial entities. Consumers have used social media to protest Monsanto’s role in the proliferation of genetically modified foods and aggressive business tactics against small family farmers (“Millions march against GM crops”, 2013). Apple, the maker of computers, mobile phones, and other electronic devices, has faced social-media-based consumer backlash about the working conditions at the factories of one of its Chinese manufacturers (Barboza & Bradsher, 2012). Walmart’s working conditions, opposition to the Affordable Care Act (Public Law 111-148), and antiunion tactics have been critiqued on social media. Protests that garner widespread support can have negative repercussions for the targets of those protests. For example, Chik-Fil-A, a fast-food chain, found itself embroiled by a social media firestorm over the company president’s donations to antigay charities in 2012. Northeastern University canceled plans to allow a franchise on its campus in protest of the company's position on gay rights ("Chick-Fil-A Scrapped", 2012). Thus, prospective protest targets will want to understand the social media discourse characteristics that can be early warning signals of effective protests. Such understanding may be important for firms' effective management of their external environments in the social media era. Given the largely textual nature of these protests, the salient cues available to us come from the language that is used.

In the previous paper, I investigated how affective and cognitive processes mitigate the effects of message claims. The context for that investigation was a brand community, in which collective action by consumers was necessary to garner resources from the brand community sponsor. The challenge for collective action in that context was that the consumers were not affiliated with (and possibly were not even known to) each other. Larger-scale protest actions have an even less structured context. While there is a priori consensus on the target of brand community collective action—the sponsoring firm and its products—the participants of larger-scale protests must socially negotiate the target of their actions through collective discourse. The objective of this study is to understand the role that affective and cognitive processes, as reflected in language use, play in the mobilization efforts of individuals in unstructured collectives. Affective and cognitive processes are integral to motivating and sustaining collective action (e.g., McAdam, Tarrow, & Tilly, 2003). For example, Gould (2009) has posited that grief helped to sustain the AIDS movement in the gay community. Benford and Snow (2000) have argued that cognitive framing processes are discursive processes used to negotiate a shared understanding of their condition.

I use a grounded theory approach to understand how these processes unfold in efforts to mobilize collective action. Existing literature is used as source material and observations from a statistical analysis are used to generate the model. The social movement literature provides insight into the role of affect and cognition in social movements and the social psychology literature provides insight about the relationships between affect and cognition. These two streams help inform the interpretation of relationships that are uncovered in the quantitative analysis. The data for this investigation come from the mobilization of protests in response to U.S. congressional bill H.R. 3261, commonly referred to as the Stop Online Piracy Act (SOPA). Two months of Twitter messages related to SOPA were analyzed. In lieu of qualitative analyses, I apply a novel analytic technique, vector autoregression (VAR), to identify relationships among affective and cognitive processes over time. My analysis results in a three-stage model identifying the affective and cognitive processes that are essential to the mobilization of collective action as well as the sequencing of these mobilization processes.

My work makes two key contributions to the literature that can inform future research. First, it adds to the emergent work on cognition and emotion in social movements by modeling affective and cognitive processes. Second, it provides a model of how these processes unfold in efforts to mobilize collective action. Practically, my work can guide activists who wish to successfully initiate and sustain collective action. It can also help firms manage their external environments by identifying cues that signal the likelihood that individual protests and organized collective action will threaten a firm's legitimacy.

The rest of this essay is organized as follows. I first consider the role of social media in mobilizing social movements. I then consider the role of affective and cognitive processes in online social movements. Next, I present my grounded theoretic approach to this investigation including a description and use of text analysis software. Then I describe my methods for data collection and analysis using vector autoregression (VAR). Finally, after presenting the study's findings based on the VAR, I develop and present a three-stage model of the relationships between affective and cognitive processes in the mobilization of collective action.

SOCIAL MEDIA: THE "IT ARTIFACT"

Social media are internet applications such as social networking sites that allow for the creation and publication of user-generated content (Kaplan & Haenlein, 2010). Boyd and Ellison (2007) looked at twenty social media sites to develop a working definition. The three characteristics of a social media site are that users are able to (1) create a profile page containing identity information, (2) create relations through hyperlinks to the profile pages of other users, and (3) allow others to view the user's list of relations (Boyd & Ellison, 2007).

Krumm, Davies, and Narayanaswami (2008) have described user-generated content as data, media, or information that comes from "regular people" and is available to others on the internet. Research of user-generated content is still nascent and there is yet to emerge a consensus definition (Schivinski & Dabrowski, 2014; OECD, 2007). Daugherty, Eastin and Bright (2008) emphasize that the content is created by the public and not paid professionals. Researchers at the Organisation for Economic Co-operation and Development (OECD) put forth a working definition by describing three central characteristics of user-generated content: publication, creative effort, and nonprofessional origin (OECD, 2007).

The publication requirement is simply that the work must be published online, for example, on a public website. This research focuses on user-generated content on a social networking site. Addressed communications such as emails or instant messages do not meet this requirement, as their content is directed to a specific individual or group of individuals. Listservs, software for managing email distribution lists, are not social networking sites as they lack profile information and transmit content to specified users. The second requirement is that creative effort was exerted in the creation of the work. Inserting a hyperlink or simply copying content does not fulfill this requirement; the user must add value in the process. Finally, user-generated content is not created for commercial gain or to advance the objectives of a formal organization such as a government. Individuals have myriad motives for generating content, but the salient point is that they do it for themselves. This is what Krumm et al. (2008) mean by the phrase “regular people.”

Recent textual analysis of the communications of social movements occurring through social media has been fruitful. Kim and Miranda (2011a) demonstrated that participants negotiate to forge claims about their program, their identity, and their standing. Program claims describe collective goals; identity claims declare who the claimants are; and standing claims describe any individuals, groups, or organizations that support the claimants (Tilly, 2004). Further, Kim and Miranda (2011b) showed that affective and cognitive influence tactics embedded in messages impact the traction of these claims in brand communities.

SOCIAL MOVEMENTS AND AFFECTIVE AND COGNITIVE PROCESSES

Social movements are a group of individuals dedicated to fighting or undoing social change related to social injustice (Tilly, 2004). Three major components of Tilly's definition warrant attention in this study. First, the social movement is a collection of people, and Della Porta and Diani (1999) describe the collection as a network. The network helps to spread information about available resources and the broader ideals of the movement (Della Porta & Diani, 1999). The second component refers to what the group does. The group attempts to change the social injustice with protests (Della Porta and Diani, 1999) and the network to share the protest acts. These protest acts are learned from struggle; people learn to march, petition the government, or break windows (Tilly, 1995).

Cognitive Processes

The third, and cognitive, element of Tilly's definition is social injustice, which is conveyed in social injustice frames (Gamson, 1992). Individuals in a social movement, like people in any situation, attempt to make sense of their environment, other people, and themselves. Participants in a social movement use frames to help understand the objectives of, identify with, and participate in a movement (Snow, Rochford, Worden, & Benford, 1986). The production of frames entails the construction of meaning (Snow & Benford, 1988). The frames are produced to give meaning not only to the participants, but also to the antagonist and casual observers (Benford & Snow, 2000). Individuals engaged in the framing process use existing ideas and social forces to produce frames that help give significance to movement. Individuals in a social movement must continually define and redefine the meaning of the movement in a process that may alter or replace existing frames with new interpretations of meaning.

The idea of a frame is similar to the psychological concept of a schema. However, "collective action frames are not merely aggregations of individual attitudes and perceptions but also the outcome of negotiating shared meaning" (Gamson, 1992: 111). The negotiated shared meaning occurs in dialog with the collective (Gamson, 1992). The dialog in an online social movement is text based and the negotiation occur on social media.

Affective Processes

Along with the cognitive process of framing, social movements are shaped by the emotions of the participants. Common and ordinary events in our lives can evoke emotions. However, unusual events may evoke stronger responses and shape the responses and the goals of the participants (Jasper, 1998). The 'injustice frame' is a recurring theme in the discourse of a social movement (Gamson, 1992). Incidences of perceived injustice can generate an emotional response (Jasper, 1998). For example, racist behavior can incite anger in members of a targeted group.

Past research of emotion in collective behavior has focused on the sudden surge of emotion in a crowd (Aminzade & McAdam, 2002). Gould (2009) posited that grief helped to sustain the AIDS movement within the gay community. Vanderford (1989) found that leaders on both side of the abortion debate used emotional language to define their opponents. The leaders used vilification to tap into the fears of their supporters. Vilification helped to define the opponent as an adversary with evil motives as opposed to good people with misguided intent (Vanderford, 1989). Emotions in a social movement not only help define a common foe but also create a common bond among the participants by positive reciprocal emotions (Jaspers, 1998).

Affect and Cognition in Social Psychology

Social movement researchers have not elaborated on the underlying mechanism of affective and cognitive processes. I look to the social psychology literature for the possible relationships between affective and cognitive processes. Within a social movement, it is unclear as to the direction of the relationships, but previous research has described how affect and cognitive processes are spread through a group. There are four possible permutations of causal realtionships. Affective processes in one person can cause affective processes in others. Affective processes in one person can cause cognitive processes in others. Cognitive processes in one person can cause affective processes in others. Cognitive processes in one person can cause cognitive processes in others. I briefly outline the major theories in Table 1. The rows represent causes and the columns represent effects. For example, row 1 column 2 of the table contains theories that describe how affect impacts cognition. Next, I will describe each in turn.

Table 1: Social Psychology Theories of the Relationships between Affective and Cognitive processes.

	Affect	**Cognition**
Affect	• Emotional Contagion Theory	• Affect Infusion Model • Elaboration Likelihood Model
Cognition	• Interruption Theory • Appraisal Theory	• Cognitive diffusion

Emotion Contagion (Affect to Affect) – Emotional contagion is the process of transferring emotions among members in a group (Barsade, 2002). Emotion contagion theory suggests that emotions can be spread through a group of individuals. The adage that laughter is contagious exemplifies this belief, and producers of situation comedies provide laugh tracks to help cue the audience to jokes and make the show easier to follow, and thus more enjoyable for an audience.

Hatfield, Cacioppo, and Rapson (1994) posit that mimicry and synchrony provide a mechanism for emotion contagion: individuals engaged in a conversation consciously or unconsciously mimic and synchronize their movements, gestures, and other instruments of communication. Individuals' emotional states are affected by these mimicked instruments of communication and so individuals "catch" emotions from moment to moment (Hatfield et al., 1994). Mimicry can take the form of facial imitation. People tend to spontaneously and unconsciously match their facial expressions to those of nearby individuals (Dimberg, Thunberg, & Elmehed, 2000). People also mimic others' actions. A wide range of gestures such as smiling, laughter, and slapping the forehead are mimicked to convey empathy or understanding. People mimic in order to establish a rapport or build a social relationship (Bargh & Chartrand, 1999).

Individuals coordinate their words with their actions; approximately 60% of individuals' gestures convey the same information as the content of their words (Bavelas & Chovil, 2000). The information contained in words and the information conveyed by gestures therefore have a level of redundancy. In an online environment where nonverbal cues are lacking, we therefore lose only some of the information contained in nonverbal communication. Further, adept users of computer-mediated communication (CMC) technology are able to convey more information than novices, and they are able to glean more information from such communications as their familiarity with their communication partners increases. Adept users rely on past experiences with the CMC channel, the topic, the organizational setting, and communication coparticipants to increase information (Carlson & Zmud, 1999). Thus, sophisticated CMC users and users familiar with their communication partners will communicate and receive more information about their emotional states. In other words, as individuals become more experienced with the media, topic, organizational setting, and other participants, the emotional contagion process becomes more efficient.

Affect to Cognition – Affect has been shown to alter social cognition in different ways. People use social cognition to understand themselves and other people (Fiske & Taylor, 1991). Forgas (2007) found that affect impacts how people use persuasion, a cognitive task. In an experiment, participants were asked to produce persuasive arguments on two social issues. Before the persuasion task, the participants watched either a happy film clip or a sad film clip. Forgas found that people who watched the sad film clip were more persuasive (Forgas, 2007). Furthermore, negative emotion has been shown in an experimental setting to induce a negative impact on group outcomes with respect to cooperativeness, conflict, and task performance (Barsade, 2002).

The Affect Infusion Model posits that when faced with information infused with emotion, a person's judgment is influenced or biased (Foo, Uy, & Baron, 2009; Forgas, 1995). Positive affect has been shown to be inversely related to the use of contentious tactics in negotiations (Carnevale & Isen, 1986), to promote cooperative behavior (George, 1991), and to enhance creativity and problem-solving skills (Estrada, Isen, &

Young, 1994; Isen & Means, 1983). In general, positive people tend to be more expansive, inclusive, and pleasant to each other.

Research has shown that positive affect may incline individuals to become more susceptible to persuasion (Fiske & Taylor, 1991). However, when faced with tasks that require great engagement or a high degree of cognitive activity, individuals may not be susceptible to affect infusion. The Elaboration Likelihood Model (ELM) suggests that there are two distinct routes for processing information: the central route and the peripheral route (Petty & Cacioppo, 1986). The central route requires deep analytical thinking; the individual considers the information and the merits of an argument. The peripheral route is a mental shortcut that does not consider the information in great detail. Judgments made through the peripheral route are based on assessing environmental characteristics such as the identity of the speaker, the quality of the presentation of the information, and aesthetics (Petty & Cacioppo, 1984).

Additionally, ELM highlights the role of the medium in determining how individuals process persuasive information. The dearth of affective cues available in online communication constrain individuals to use the central processing route more frequently when judging online messages (Matheson & Zanna, 1989). Alternatively, online media have evolved in their capacity to transmit social cues, and just as importantly, our ability to transmit and perceive affective cues increases with continued use of online media (Carlson & Zmud 1999). Consequently, individuals using online communication should have both processing routes available to them.

Cognition to Affect – Cognition has been posited to influence affect in different ways in interruption theories, matching theories, and appraisal theories (Fiske & Taylor, 1991). Interruption theories are based on external disruptions that cause mental arousal. The cognitive or perceptual discrepancy of some external event impedes or blocks our actions and creates cognitive dissonance (Plous, 1993). This dissonance becomes the focus of our cognition; we attempt to explain, understand, and interpret the new stimulus. The interruption is interpreted as either helping or hindering our progress towards some goal, or the interruption disrupts our understanding of the social world, both of which shapes our affect (Gaver & Mandler, 1987). Further, the degree of interruption moderates the relationship between cognitive processes and affective states (Gaver & Mandler, 1987). A minor and novel interruption may be perceived as interesting, new, and enjoyable, while wholesale change may cause negative feelings and rejected outright (Gaver & Mandler, 1987).

Appraisal theories suggest that individuals may also evaluate situations in terms of their personal significance (Lazarus & Smith, 1988). Individuals first determine the personal relevance of a situation, and secondary appraisal includes problem-focused and emotion-focused cognition. The former concerns what the individual can do about the situation, while the latter concerns what the individual can do about his or her emotion (Fiske & Taylor, 1991).

Cognitive Diffution (Cognition to Cognition) – Social cognitive theory helps to explain how individuals self-organize through symbolic communication (Bandura, 2001). According to this perspective, individuals are “self-organizing, proactive, self-reflecting, and self-regulating” agents (Bandura, 2001; p. 266). Individuals can learn from their environment, which includes other people. They can develop causal relationships and generate solutions to problems, which they share through their social network. Individuals can adopt new behavior based on observations within social media and social networks (Bandura, 2001).

Further, members of a group engaged in lengthy discussion have been found to rely on shared information more than unshared information (Stasser, Taylor, & Hanna, 1989). Shared information is information possessed by most or all of a group while unshared information is information possessed by an individual. Stasser et al. performed an experiment using college students. The students were randomly assigned to groups and were asked to rate a hypothetical candidate for president of the student government. The amount of information about the candidate was varied. For some groups 66% of the information was shared and for other groups 33% of the information was shared. Stasser et al. found that the groups gave greater weight to shared information arriving at group decisions (Stasser et al., 1989).

Groupthink can hamper decision making in a group of individuals who are otherwise rational in their decision-making. *Groupthink* refers to a restrictive mode of thinking where the desire for consensus overwhelms analytical thinking (Miranda, 1994). The desire to belong to a group may also distort cognitive processes by suppressing minority opinions. The symptoms of groupthink include "overestimating the group's capabilities, biased perceptions, pressures to conform, and defective decision strategies (Baumeister & Finkel, 2010, p. 520). Researchers have used groupthink as a theoretical lens to understand historical events such as the Bay of Pigs, Watergate, and the Challenger disaster (Esser, 1998; Ettlie & Pavlou, 2006; Miranda, 1994). Group cohesiveness has been found to be a contributing factor to groupthink;

members of noncohesive groups have been found to engage in self-censoring (Leana, 1985).

In contrast to groupthink, researchers have noted that group consensus decision making is better than the decision of a single individual. Michaelson, Watson, & Black (1989) found that groups with experience working together outperformed the best member of the group. In their study, Michaelson et al. used groups in their experiment with at least thirty-two hours of working together, which the researchers believe contributed a sense of mutual trust and understanding that allowed them to perform so well. The study consisted of students drawn from organizational behavior classes over a five-year period.

OVERVIEW OF THE GROUNDED THEORY APPROACH

The objective of grounded theory is to methodically collect and analyze observations of a phenomenon for the purpose of developing a new theory. While this approach has evolved to be largely qualitative (Corbin & Strauss, 1990, 1998), it originally derived from empirical work by sociologists at Columbia University and embraced quantitative analyses of archival datasets of established constructs to discover novel insights (Glaser & Strauss, 1967). Corbin & Strauss (1998) advocate for open, axial, and selective coding. Open coding is the process of searching for and identifying concepts in the data. Axial coding is the process of organizing the concepts into categories and subcategories. Selective coding is the process of organizing all the categories around a core category in order to refine a theory. Although the recent emphasis in grounded theory is on construct discovery through open, axial, and selective coding, I return to grounded theory's early emphasis on discovery of novel relationships among established constructs.

For this purpose, I perform the linguistic analyses with the Linguistic Inquiry and Word Count (LIWC) software (Pennebaker, Booth, & Francis,2006).. I describe the LIWC software, its validation, and the categories operationalized for this study in the next subsection.

The LIWC software delivers measures of the linguistic categories used by the authors of the text to be analyzed. I used VAR and Granger causality tests, to analyze the relationships among the cognitive and affective categories present in the text. VAR is a technique for determining the underlying relationships between variables of time series data. This approach is compatible with a grounded theoretic investigation because, while previous theories from social psychology informed the choice of the LIWC categories, all the variables in the VAR are treated as endogenous and do not rely on a particular theory (Sims, 1980). Details of VAR for time-series analysis is described in the section titled Review of Time-Series and Vector Autoregression.

Linguistic Inquiry Word Count

LIWC provides counts for each category of words that are in its dictionary. The categories were developed, validated, and refined through extensive psychometric evaluation. Pennebaker et al. (2007) developed the most recent dictionary in 2007. The dictionary was developed in four steps. The first step consisted of collecting words from emotional rating scales such as PANAS (Watson, Clark, & Tellegen, 1988), standard dictionaries, and thesauruses. Three to six judges participated in brainstorming sessions to add to the list. In the second step, the judges rated the words and determined if the words should be included or excluded from one of the LIWC categories. The third step evaluated the categories. Text files from previous psychological studies were analyzed, and categories that were used at low rates or had poor reliability or validity were dropped. The final step involved updating and expanding the categories by drawing on over several hundred thousand text files (Pennebaker, et al., 2007). See Tausczik and Pennebaker (2010) for full details of LIWC's development.

There are pros cons of using any text analysis tool, especially within the context of social media. The software was designed to analyze a piece of work as small as a short essay by a single author. However, the 140 character limit of Twitter messages alters how Twitter users write. Twitter users may abbreviate words to communicate. These abbreviations are not contained in the dictionary and would not contribute to any of the LIWC scores, even if the abbreviation represents a word that is present in the dictionary. Another limitation is that the software was designed to analyze the text written by a single individual. However, I am analyzing the Twitter messages of many people as a single unit. All of the psychometric validation occurred at the individual level and not the group level. Finally, the LIWC dictionary is designed to analyze the text of native speakers of American English. The software may not capture the affective and cognitive dimensions of other variations of English or the text of non-native speakers of American English.

These limiting factors could potentially bias the LIWC scores. However, there is no other automated method to analyze text based on pre-determined categories. Since my study employs time series techniques, it requires a tool such as LIWC that produces a measure for a set of predetermined categories in each period. This is in contrast to another popular method of text analysis, latent semantic analysis. For more on alternative approaches to text analysis please see appendix I.

Other dictionaries have been developed to generate word count based analysis, but the LIWC dictionary is the only one to have undergone testing for external validity. Pennebaker and Francis (1996) performed an experiment using college students who were asked to write about their college experience for three consecutive days. One group was asked to write about their deepest thoughts and feelings about coming to campus while a control group was asked to write about anything. There were 72 participants in total with 37 students in the control group. Four judges coded the essays for emotional, cognitive and other linguistic dimensions. The study concluded that the LIWC scores and the judges' ratings of the text were highly correlated with the LIWC scores of the text.

Kahn, Tobin, Massey, and Anderson (2007) conducted an extensive validation study of the emotional dimensions of LIWC. The researchers conducted three studies using undergraduate students. In the first study the students were asked to split into three groups. One group was asked to write about a sad experience, one group was asked to write about an amusing experience and one group was instructed to write about a typical day. The LIWC scores for affect terms correlated with each of the conditions. In a second group, the experiment was repeated except that the students conveyed their stories verbally. Finally, in a third experiment, the students were primed by watching a comedy movie or a funeral movie. The students were then asked to perform the same tasks as in the second experiment. Students who watched the comedy movie used more positive affect words than students who watched the funeral movie and students who watched the funeral movie used more negative affect words than students who watched the comedy movie when asked to write (Kahn, Tobin, Massey, & Anderson, 2007).

The macro-level constructs affect and cognition processes are known to be used in social movements. As noted earlier, emotions in a crowd may surge (Aminzade & McAdam, 2002), and affect can help sustain a movement (Gould, 2009), and define the opposition (Vanderford, 1989). The development of frames in a social movement is a cognitive task requiring constant negotiation (Benford & Snow, 2000). However, there is a paucity of literature that pinpoints how specific affective and cognitive processes are used and interact. As such, I use VAR as intended by Sims (1980) and do not discriminate among the LIWC measurements of affect and cognition. Sims advocates starting with the most general model subject to degrees of freedom determined by data availability. As variables are added, the degrees of freedom drop by the square of the number of variables (Sims, 1980). With this methodology I use all the measures of affective and cognitive linguistic processes available in LIWC. These are described in more detail in the next section.

Emotional LIWC Categories

Four emotional dimensions were used in the analysis and summarized in Table 2. LIWC measures three emotions that reflect negative affect: sadness, anxiety, and anger, which differ in the level of arousal. A*nger* reflects a high level of activation, *sadness* reflects a low level of activation, and *anxiety* falls between the two.

LIWC groups all *positive affect* terms together as a single measurement. Positive emotions were measured by separate categories (e.g., optimism and positive feeling) in the 2001 version of the software, but Pennebaker et al. found that subcategories of positive emotion terms were not useful for conducting text analysis; the sub-categories had low usage rates and were seldom used (Pennebaker, Booth, & Francis, 1996). The subcategories of positive affect terms were removed in the latest (2007) version. Although researchers have found it fruitful to partition negative affect into discrete factors (Bodenhausen, Sheppard, & Kramer, 1994), researchers have not been as successful partitioning positive emotion in text analysis. Also, the activation dimension of positive emotion may not manifest itself in writing. For these reasons, positive emotion terms such as "contentment" and "jubilation" were all grouped together.

Cognitive LIWC Categories

Six cognitive dimensions were used in the analysis and are summarized in Table 2. In their empirical work on cognition, Pennebaker, Booth, and Francis (2006) identified these six key cognitive processes and their associated vocabulary in text communications. *Insight* is a process of self-reflection with the purpose of understanding one's self or one's experience (Pennebaker & Francis, 1996). Examples of insight terms include *realize*, *see*, and *understand*. Insight terms have been shown to reflect complex cognitive processes in autobiographical essays (Burke & Dollinger, 2005). *Discrepancy* seeking also helps give a person insight, but of external objects rather than one's self (Beevers & Scott, 2001). Examples of discrepancy terms include *besides*, *hope*, and *regret*. Negative mood suppression may improve mood but at the cost of also suppressing discrepancy seeking, insight, and causation (Beevers & Scott, 2001). *Causation* is a process of reasoning. Causal terms include *because*, *why*, and *thus*. The individual is engaged in thought about cause and effect (Pennebaker &

Francis, 1996). Individuals who were asked to write down their thoughts about a negative job experience used more causal words (Barclay, Skarlicki, & Pugh, 2005). *Tentativeness* reflects a state of hesitation. Tentativeness is indicated by such terms as *maybe* and *possible*. The individual has yet to make a decision (Pennebaker & Francis, 1996), or has not processed an event into a coherent narrative (Tausczik & Pennebaker, 2010). Tentativeness may be expressed more frequently by individuals of lower rank (Sexton & Helmreich, 2000) and is characterized by an open mental state (Laursen & Salter, 2010) *Certainty* terms, which include *always* and *never*, are often used by leaders in online settings (Huffaker, 2010). Analyses of cockpit communications show that captains use certainty words often (Sexton & Helmreich, 2000). *Inhibition* terms reflect a process of actively censoring or restraining one's thoughts. Terms that reflect inhibition include *hesitate*, *guard*, and *protect*. Mental inhibition requires cognitive and physical effort and has been associated with poor information processing and poor health (Bodenhausen et al., 1994; Pennebaker, 1989; Pennebaker, Francis, & Booth, 1999).

Table 2: LIWC Categories Employed in the Analysis

Linguistic Process	**Example**
Positive Affect	love, nice, sweet
Anxiety	worried, fearful, nervous
Anger	hate, kill, annoyed
Sadness	crying, grief, sad
Insight	think, know, consider
Causation	because, effect, hence
Discrepancy	nut, if, must
Tentativeness	maybe, perhaps, guess
Certainty	always, never
Inhibition	block, constrain, stop

THE CONTEXT

The empirical context for this study is the 2011–2012 opposition to the Stop Online Piracy Act (SOPA) enacted on Twitter. This section describes SOPA and also describes Twitter as a medium for the enactment of social movements.

The Stop Online Piracy Act (2011–2012)

Senator Patrick Leahy introduced S. 968, or the Protect Intellectual Property Act (PIPA), in the U.S. Senate on May 12, 2011. Texas Republican Lamar Smith and 12 cosponsors introduced the bicameral counterpart, H.R. 3261, or SOPA, on October 26, 2011. The objective of these bills was to protect the intellectual property rights of the owners of digital content. Corporate proponents of the legislation included movie studios and record companies that wanted to staunch the flow of pirated movies and music that was impacting their revenue streams and profits. Corporate opponents included Internet companies that feared that the lack of a judicial process would grant intellectual property owners too much power and that the Internet companies could be shut down at the whim of the intellectual property owners.

The bills would have allowed the Department of Justice to seek court orders to force U.S. internet service providers to block access to sites accused of enabling piracy. The bills would also have allowed owners of intellectual property to sue such search engine companies and blog hosting companies and anyone who linked to these sites. The bills also gave the owners of intellectual property the right to cut off the funds of infringing websites by forcing advertisers and payment services (e.g., PayPal) to cancel their accounts. Opponents therefore feared that the bills, if enacted, would promote censorship and restrain creativity.

Internet companies began an online campaign against SOPA and PIPA. The opposition included the juggernauts Reddit, Wikipedia, Google, and Mozilla. This protest movement culminated with a series of coordinated protests in both the virtual and the real world. The hashtag '#SOPA' was used in millions of tweets denouncing the proposed legislations (Downes, 2012). The timeline of events provided in Table 3 is taken from wwww.sopastrike.com.

Table 3: Timeline for SOPA Protest

Date	Event Type	Description
5/12/11	Legislative	Protect Intellectual Property Act (PIPA) introduced in U.S. Senate
5/26/11	Legislative	PIPA passes Senate Judiciary Committee by unanimous vote
6/16/11	Legislative	Commercial Felony Streaming Act passes Senate Judiciary Committee (S. 978)
6/30/11	Community	Fans of computer games begin to recognize broad implications of S. 978 by posting videos on YouTube
10/19/11	Community	FreeBieber.org launched by the nonprofit group Fight for the Future in opposition to Commercial Felony Streaming Act (S. 978), which later became a part of the Stop Online Piracy Act
10/25/11	Community	Anti-PIPA/SOPA video released online by Fight for the Future (http://vimeo.com/31100268)
10/26/11	Legislative	SOPA introduced in the U.S. House of Representatives
10/28/11	Community	Justin Beiber speaks out against S. 978 (http://www.startribune.com/politics/statelocal/132782298.html)
11/16/11	Legislative	House Judiciary Committee holds hearings on SOPA. GoDaddy provided the House with a written statement in support of the bill.
11/16/11	Community	American Censorship Day: Over 1 million people contact Congress; 2 million sign a petition; Tumblr blacks out page
11/17/11	Community	Nancy Pelosi tweets opposition to SOPA (https://twitter.com/#!/NancyPelosi/statuses/137234283667537920)
11/29–12/15/11	Community	Hundreds of thousands of calls to Congress against SOPA
12/1/11	Media	Colbert covers SOPA/PIPA
12/15/11	Legislative	House Judiciary Committee holds hearings on SOPA
12/16/11	Legislative	Hearings end without completing markups ,process of debating and amending the language of a bill or resolution in a House committee)
12/22/11	Community	Reddit, a social news website, suggested boycott of Internet service provider GoDaddy for its support of SOPA.
12/29/11	Community	GoDaddy issues statement against SOPA
1/2/12	Community	Reddit generates $15,000 for a congressional candidate to run against Paul Ryan, a congressman who was for SOPA
1/5/12	Community	People begin organizing in person to meet with their senators over the January recess
1/13/12	Community	Fight For The Future, a nonprofit group supporting digital rights, announces the creation of the website sopastrike.com to organize protests
1/13–1/18/12	Legislative	Members of Congress begin to come out against the bill after meeting with constituents
1/14/12	White House	U.S. President opposes PIPA/SOPA
1/18/12	Community	Web Blackout: Major Internet companies participate in online protest

Communication on Twitter

Twitter is a microblogging site that allows users to send messages with a maximum length of 140 characters, known as "tweets." Twitter is open to the public; anyone who has a device with Internet access can create an account to participate in Twitter. The default setting for Twitter accounts is that all tweets are public. All public tweets are entered into the public timeline, a stream of tweets that are ordered chronologically and visible to any (both those with and without a Twitter account can view the public timeline). A user with an account is provided with a profile page, which provides space to display personal information and it lists recent tweets that the user has posted. The tweet will show up in the public timeline and in the home timeline of anyone who is following the user. A home timeline shows a user a stream of tweets written by people they have chosen to follow displayed in reverse chronological order. The tweets of all one's followers generate a timeline curated specifically to the interests of the user.

The Twitter site also allows individuals to make private tweets directed to specific individuals that are not public. However, I do not discuss private tweets in this essay because I examine public tweets exclusively. It is reasonable to assume that the majority of tweets in the public movement studied here will be public tweets, because the individuals are commenting on a public policy issue and are trying to sway the trajectory of the proposed legislation. Individuals who wish to break off to form a subgroup would not use Twitter to hold private group discussions because there are no private twitter streams. While individuals may have communicated and developed tactics using private channels, these ideas would also need to be made public in order to gain public support.

There are three major conventions used in tweets. The first is the use of a hashtag, where the character # is inserted before a word. The hashtag allows the word to be searchable both on the Twitter website and through secondary websites that search tweets, such as www.Tweetgrid.com. If a hashtag is used frequently by the Twitter community, the hashtag may become a *trending topic*, which identifies the most discussed hashtags at any given time.. Trending topics are listed on users' Twitter home pages.

The second convention involves the use of the @ character in front of a Twitter ID. This convention specifies a message directed to a specific user. The targeted person is able to see that a message has been posted to him or her on his/her timeline and profile page. For example, a tweet may be "I agree with @john" or "I disagree with @john who has it all wrong." If the @ sign is in the first position of the tweet, then only followers of both parties can see the message, and the message is referred to as an @Reply. If the @ sign appears anywhere else in the message, then the message is public and is referred to as a 'mention.'

The third convention is the *retweet.* Retweets are when users tweet other users' messages under their own user profile. The retweeted message begins with the letters *RT* to indicate that the message was originally posted by someone else. The original author of the tweet often follows *RT* with *@username*. The original message is copied and pasted and allows the retweeter to add additional comments. This is akin to forwarding an email after adding personalized comments. Alternatively, users can use a button appearing under tweets that allows them to retweet messages of their choice. In this case, only the original message is retweeted. A user who retweets not only repeats the message on the public timeline, but also pushes the message to his followers. Thus, the tweet is amplified as more people see the tweet. While private tweets cannot be re-tweeted using a shortcut button, users can cut and paste the message in a new tweet.

The different types of tweets affect the ways users can interact with the Twitter website and the tweets. Public tweets, tweets without any restrictions, automatically appear on the public timeline. The inclusion of a hashtag allows a tweet to be searchable within the public timeline. The public timeline can be viewed from the Twitter website or through third-party websites such as Tweetgrid.

The Mention and Interaction tabs provide filters that allow a user to track his or her own tweets that have been retweeted or made "favorite" as well as other users' tweets in which they are mentioned. A "mention" is when a message contains an @ sign followed by another Twitter user's name. The tweet will appear on the public profile of the sender and on the recipient's home timeline and Mention and Interaction tabs. The Mentions tab lists only messages that are directed to them with an '@' sign. The Interaction tab allows users to see which of their tweets have been retweeted, made favorite, or directed to them. A user can "favorite" another person's tweet, which means that the user likes the tweet. Tweets that have been made favorite are signified with a star.

Only the messages that are related to the user are displayed in the Mention and Interaction tabs. The time between the first and last tweet displayed by these tabs is dependent on the activity of that user. If the user is popular and active, there may also be a lot of tweets displayed by the Interaction or Mention tabs. Since a fixed number of tweets is displayed on a screen, the time of the first and last displayed tweet may be short. If there is less activity, the time between the first and last displayed tweets may be very long.

REVIEW OF TIME SERIES AND VECTOR AUTOREGRESSION

Time series analysis derives statistics based on repeated observations over time, the last 1,000 end-of-day prices of the Dow Jones Industrial average, for example. Generally, a fixed interval of time is used to space out the repeated measurements, which may be taken every minute, hour, day, quarter, or year. However, a fixed interval is not necessary; keeping the measurements in chronological order is more important than what the length of the interval is (Enders, 2004).

In this essay, I use VAR to look at how past events influence later events. To provide some background for VAR, I first present the assumptions of general linear models such as regression and ANOVA, extensions to autoregressive techniques, the properties of covariance stationary processes, and finally I introduce the VAR model.

Linear Models

The first assumption of general linear models is that they take the following functional form:

$$y_i = \alpha + \beta x_i + \varepsilon_i, \qquad i = 1, \dots, n.$$

The polynomial is linear since all of the independent variables are raised to the first power. In the equation, y_i is the value of the dependent variable of the ith trial, and x_i is a known value or predictor of the ith trial.

The second assumption is that the expected value of the error term is zero: $E[\varepsilon_i] = 0$. The variance of ε_i is assumed to be a constant σ^2, and the covariance of ε_i and ε_j is zero ($\varepsilon_i \sim i.i.d. N(0, \sigma^2)$) for i = 1, …, n.

Statistical modeling of time series data involves describing a variable as a function of prior observations, which can introduce autocorrelation in the error term. For example, the price of gasoline today is correlated with the price of gasoline yesterday, the price of gasoline two days ago, and perhaps with even the price of gasoline even further back in time. The autocorrelation between the dependent variable and the lagged independent variable in time lagged equations violates the assumption of linear models that the variables are independent and identically distributed (Shumway & Stoffer, 2000), and requires special consideration when using time series data.

Autoregressive Techniques

Autoregressive techniques include lags of the dependent variable as explanatory variables in the regression model. Including a sufficient number of lagged dependent variables removes the autocorrelation present in the error term (Greene, 2008; Kutner, Nachtsheim, Neter, & Li, 2005).

Once autocorrelation is removed the error term becomes white noise, as required. Rewriting the linear regression above with time subscripts and one lag of the dependent variable, the model is as follows:

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 x_{t-1} \varepsilon_t, \qquad i = 1, \ldots, n.$$

White noise is characterized by the following properties:

1) The means of the error terms have an expected value of zero for all time periods *t*.

$$E(\varepsilon_t) = E(\varepsilon_{t-1}) = \cdots = 0$$

2) The variance is a constant for all time periods.

$$var(\varepsilon_t) = var(\varepsilon_{t-1}) = \ldots = \sigma^2$$

3) The covariance between the error terms of any two periods is zero.

$$cov(\varepsilon_t, \varepsilon_{t-s}) = cov(\varepsilon_{t-j}, \varepsilon_{t-j-s}) = \ldots = 0 \; for \; all \; j, s \in \{1 \ldots t\}$$

Note that the subscript in the notation for the linear regression identifies a specific trial, whereas the notation for the autoregression represents a measurement at a specific point in time. The order of events is maintained in the analysis (Enders, 2010).

Covariance-Stationary

Time series data differ from generalized linear models where the temporal dimension is not important. For example, a researcher does not enter *when* a trial is executed into a statistical model when performing an ANOVA analysis. Time series data are characterized by the fact that the dependent variable is influenced by past values of the independent variable or past values of the dependent variable (Shumway & Stoffer, 2000). When the series of observations is assumed to be unaffected by a change of the time origin, the process is considered to be stationary. More formally, a stochastic process is covariance-stationary if it satisfies the following conditions for all *t* and *t* – *s*:

1) The expected value of a variable is constant through time:

$$E(y_t) = E(y_{t-s}) = \mu$$

2) The variance is constant through time:

$$var(y_t) = var(y_{t-s}) = \sigma_y^2$$

3) The covariance is also constant through time:

$$cov(y_t, y_{t-s}) = cov(y_{t-j}, y_{t-j-s}) = \gamma_s$$

where μ, σ_y^2, and γ_s are all constants (Enders, 2010). It is important that all variables used in estimating the time series model are covariance stationary because if they are non-stationary they will produce super-consistent estimates of the regression coefficients, which means the null hypothesis that the regression coefficient is equal to zero is rejected with far greater frequency than implied by the standard p-values of the typical asymptotic distribution of the test statistic (Enders 2010). Covariance stationarity is typically tested for with an Augmented Dickey-Fuller test (Enders 2010).

Vector Autoregression (VAR)

One model for this type of data is the VAR model, which uses the lagged values of the dependent variables as independent variables (Kauffman & Techatassanasoontorn, 2005), as does the autoregressive techniques described above. Additionally, in VAR, no assumptions are made about which variable is the dependent variable and which is the independent variable. The model is completely endogenous, since a lag of each variable is a dependent variable of every other variable included in the model. The customary notation represents all variables with an *x* instead of *x* and *y* to reflect this property.

A simple model includes only time lag of the variables and is denoted a VAR(1). That is, the first-order VAR model includes observations only from the previous time period. Below a VAR(2) model is represented where $\boldsymbol{x}$ is a vector of *n* observations. At time t, $\boldsymbol{x}_t$ is the dependent variable and the lagged values of $\boldsymbol{x}$ are the regressors.

$$\boldsymbol{x_t} = \boldsymbol{\alpha} + \boldsymbol{\Phi_1 x_{t-1}} + \boldsymbol{\Phi_2 x_{t-2}} + \boldsymbol{w_t} \qquad (1)$$

The system of equations represented in the vector notation above would look like the following:

$$x_{1,t} = \alpha_1 + \varphi_{1,1} x_{1,t-1} + \varphi_{1,2} x_{2,t-1} + w_{1,t}$$

$$x_{2,t} = \alpha_2 + \varphi_{2,1} x_{1,t-1} + \varphi_{2,2} x_{2,t-1} + w_{2,t},$$

where the first subscript identifies which x variable it represents and the second subscript identifies the time period.

The $\boldsymbol{\alpha}$ is an $n \times 1$ column of constants akin to the intercept term in a linear regression. The vector $\boldsymbol{w}$ is a white noise process with covariance matrix, $E(\boldsymbol{ww}^T)$. The matrices $\boldsymbol{\Phi}_\mathbf{i}$ are of size $k \times k$, where k is the number of variables (two in this case). The matrices $\boldsymbol{\Phi}_\mathbf{i}$ are transition matrices that expresses the relationship between $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-1}$ (Enders, 2004; Kauffman & Techatassanasoontorn, 2005; Shumway & Stoffer, 2000).

In the case where VAR has more than one lag, recent information generally has a stronger effect than information in the distant past. An example from economics illustrates this point. The best estimate of a stock price today is yesterday's price. More information may be contained in the price by looking further back—thus more lags are entered into the equation. However, the stock price of a year ago has very little influence on today's price. Seasonal and annual considerations can also be included in the model. For example, the Halloween season is characterized by large purchases of candy, and sales forecasts for candy companies should be adjusted accordingly. The number of lags to be included should be determined to ensure that the time-lagged variables are significant and add to the explanatory power of the model. The statistical package R, which I used for the VAR, uses the Akaike Information Criterion (AIC) to determine the optimal lag length (Enders, 2004).

Granger causality can be used to interpret the results of a VAR (Enders, 2004; Stock & Watson, 2001); Granger causality is named after Clive Granger, who developed the test. If the lags of one variable, say x_1, enters into the equation for another variable, say x_2, and improves the forecasting performance of the model, then we say x_1 Granger causes x_2. For example, as in the previous hypothetical model:

$$x_{1,t} = \alpha_1 + \varphi_{1,1}x_{1,t-1} + \varphi_{1,2}x_{2,t-1} + w_{1,t}$$

$$x_{2,t} = \alpha_2 + \varphi_{2,1}x_{1,t-1} + \varphi_{2,2}x_{2,t-1} + w_{2,t},$$

if $\varphi_{2,1}$ is significant, then x_1 is said to Granger cause x_2. An F-test is conducted by testing the parameters of all the lags, and the standard assumption is that the parameter is equal to zero.

DATA

The data in this study contains all the tweets containing the word SOPA from 12/9/11 to 1/18/12. We end the study on January 18 because this was the day the SOPA protest culminated with an internet blackout. The secretive activist group Anonymous claimed responsibility for denial of service attacks on the website of the Department of Justice (DOJ) on January 19, 2012. The DOJ had shut down the website Megaupload.com which as a popular site for illegal downloads. The goal of the SOPA act was to thwart websites like Megaupload.com. However, it is not clear if the actions of Anonymous were taken in reaction to SOPA or the shutdown of the site (Segall, 2012). Thus, 1/19/12 was not included in the analysis. The movement ended on January 20 when the House postponed plans to draft the bill (Weisman, 2012).

To obtain all the tweets from the period of interest I had to combine data from two sources because Twitter does not return search results of more than 3,200 tweets. Thus, older tweets are not available unless obtained from someone who archived them in real time. The first source from which I obtained data contains Twitter messages dated between 12/09/11 and 1/14/12 with the hashtag "#SOPA." These data were obtained in a text file from Public Knowledge, a Washington, DC nonprofit public interest group that is involved in the protection of intellectual property rights and the digital marketplace. Public Knowledge's mission statement states that their work "preserves the openness of the Internet and the public's access to knowledge; promotes creativity through balanced copyright [*sic*]; and upholds and protects the rights of consumers to use innovative technology lawfully" (Public Knowledge, 2014). Public Knowledge collected and archived the data in real time. The second source from which I obtained data contains Twitter messages dated between 1/15/12 and 1/18/12 with the hashtag "#SOPA." These data were obtained in a text file from the website www.r-shief.org. According to their website, R-Shief has been aggregating and analyzing internet content in English and Arabic since 2008. R-Shief collects social media data and offers software tools to promote crowdsourced research. Like Public Knowledge, R-Shief is also a nonprofit organization. Each organization collected data for their own interests and neither had all the tweets for the date range I was interested in. The data set from Public Knowledge was the most complete and I used all of it. I added the last few days from the R-Shief data set.

The Public Knowledge dataset was obtained first. The data were analyzed before obtaining the dataset for the remaining three days from R-Sheif. The combined dataset contains more than 1.5 million tweets. I deleted approximately 5,000 messages because of embedded commas that were not formatted correctly in the comma-delimited files. These incorrectly coded tweets were identified after importing the data into Microsoft Excel. I also deleted all non-English tweets because I was using text analysis tools that were designed for English. There were 281,952 non-English tweets. In total, 1,354,516 messages were retained for analysis. Since the search is not case sensitive, many Spanish tweets were captured as well because the word 'sopa' means soup. These Spanish tweets were clearly referring to food and unrelated to the social movement of interest. If we had included the Spanish tweets they would have diluted the frequency scores because it would have increased the total number of words which is used in the denominator of the LIWC frequency scores.

Table 4 lists the number of tweets per day, which ranged from 4 to 288,159. The average was 33,037 tweets per day. Figure 1 graphs the number of tweets for each day. The graph reflects three spikes in the number of tweets, which occurred on 12/15/2011, 12/23/2011, and 1/18/2012. These spikes correspond to the congressional hearings, the GoDaddy protest, and the online blackout protest noted in the timeline of events. The congressional hearings in the House Judiciary Committee regarding SOPA were held on December 15, 2011. GoDaddy, an Internet service provider, became the target of a boycott due to the company's initial support of the proposed legislation. On December 22, 2011, Reddit suggested a boycott of GoDaddy. The boycott was successful, and GoDaddy reversed its support on December 29,2011. The English-language version of

Wikipedia decided to protest by temporarily closing its website on January 18, 2011, the same day as the first scheduled congressional hearings on the bill.

Table 4: Twitter Messages per Day

Date	**Day**	**# of Messages**	**Date**	**Day**	**# of Messages**
12/9/2011	Fri	47	12/30/2011	Fri	24,312
12/10/2011	Sat	6	12/31/2011	Sat	12,675
12/11/2011	Sun	4	1/1/2012	Sun	6,755
12/12/2011	Mon	73	1/2/2012	Mon	9,228
12/13/2011	Tue	105	1/3/2012	Tue	13,408
12/14/2011	Wed	121	1/4/2012	Wed	17,975
12/15/2011	Thu	78,151	1/5/2012	Thu	23,277
12/16/2011	Fri	56,922	1/6/2012	Fri	20,566
12/17/2011	Sat	27,989	1/7/2012	Sat	15,691
12/18/2011	Sun	18,730	1/8/2012	Sun	12,582
12/19/2011	Mon	14,263	1/9/2012	Mon	23,141
12/20/2011	Tue	23,217	1/10/2012	Tue	27,215
12/21/2011	Wed	23,569	1/11/2012	Wed	29,699
12/22/2011	Thu	55,079	1/12/2012	Thu	56,453
12/23/2011	Fri	91,491	1/13/2012	Fri	52,278
12/24/2011	Sat	33,270	1/14/2012	Sat	57,836
12/25/2011	Sun	14,624	1/15/2012	Sun	19,909
12/26/2011	Mon	15,837	1/16/2012	Mon	36,180
12/27/2011	Tue	20,458	1/17/2012	Tue	87,943
12/28/2011	Wed	19,196	1/18/2012	Wed	288,159
12/29/2011	Thu	26,082	Total		1,354,516

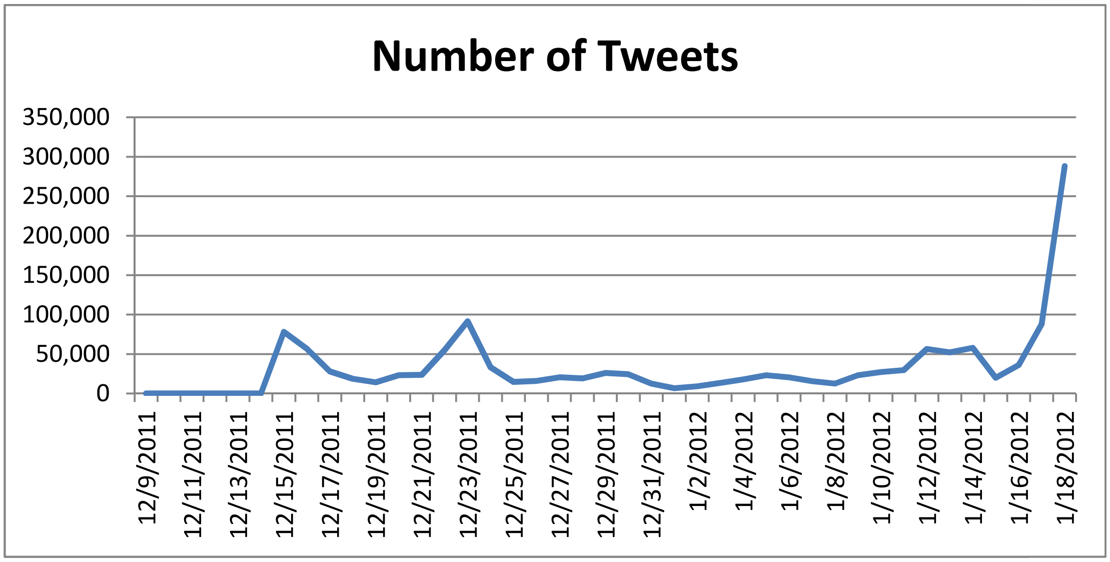


Figure 1: Twitter Messages per Day

Processing the Tweets with LIWC into Time Series Variables

In my analysis I want to examine the use of emotional and cognitive words in the twitter messages associated with the social movement protesting the SOPA. To this end I need to process the tweets using LIWC to generate a time series of LIWC scores for the linguistic categories I identified earlier in the subsection describing LIWC. There are a number of technical decisions that must be made at this point regarding the level at which the LIWC scores will be generated. For example, I could group the tweets by day, and generate a LIWC score for each linguistic category on each day. Alternatively the tweets could be grouped at any temporal level that will result in sufficient data points for the VAR analysis. For example, if the tweets were grouped by day I would have forty-one observations for the VAR analysis and if the groups contained two days' worth of tweets I would only have twenty observations for the VAR analysis.

Grouping tweets by time may not even be the best approach because the time between each individual tweet is not constant. Therefore, grouping by time results in a non-constant number of tweets in each period. This could influence the LIWC scores in ways that are not reflective of the underlying linguistic properties of the messages themselves, because the number of tweets is correlated to the number of words in the denominator of the LIWC scores.

There is no guidance in previous literature on an optimal procedure for processing tweets into time series of scores of linguistic categories, so I performed an extensive sensitivity analysis in Appendix II. I varied the number of tweets per file and examined the properties of the fitted VAR using a bootstrap analysis; I explored the fit of the VAR when the tweets were grouped by day; I explored the fit of the VAR using a horizontal split of the data; and I explored the fit of the VAR when using a subsample of the first 1,000 tweets every 100,000 was used. After performing all these sensitivity analyses, I choose grouping the tweets into files of size 4,000 based on the decision rule that produced the minimum number of tweets per file and a one lag VAR model because this decision rule seemed to produce time series variables that were most amenable to the VAR analysis. This decision rule seemed reasonable because decreasing the number of tweets per file increases the number of files (or observations) which in turn increases the power of hypothesis tests performed on the VAR. However, I found that increasing the number of files also tended to introduce autocorrelation into the statistical model, which required the addition of higher orders of lags of the variables (and thus decreasing the power of the hypothesis tests performed on the VAR). So I chose the file size as a tradeoff between these two opposing effects on power in the VAR model. However, the optimal approach in this type of endeavor remains an open question and warrants a full treatment in future research.

Figure 2 provides a summary of the text analysis process that takes a raw stream of tweets as input and produces a time series of LIWC scores suitable for examination using time series methods.

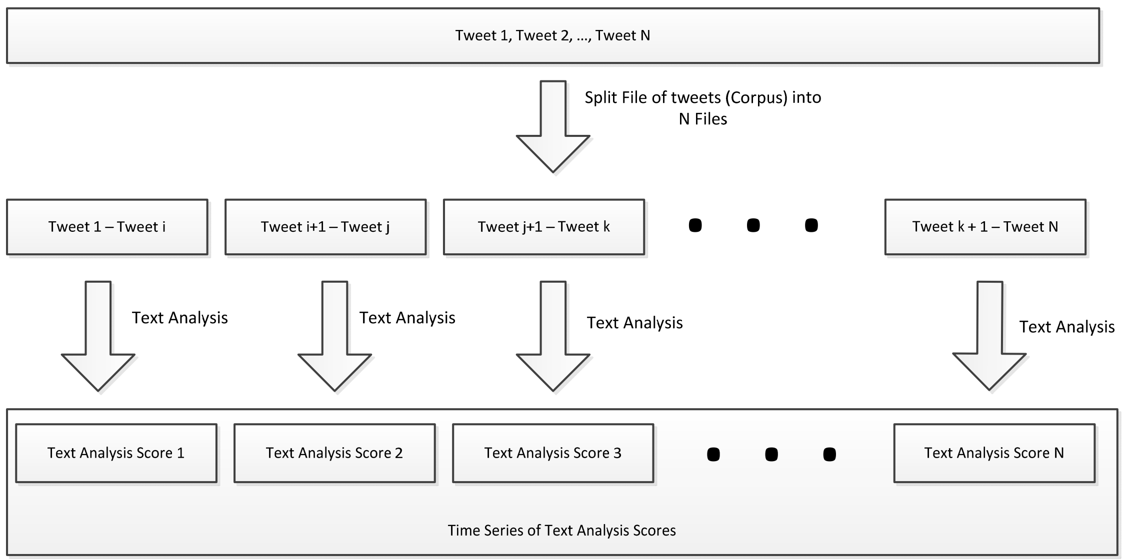


Figure 2. How Tweets are Processed by LIWC into Time Series Variables

RESULTS OF VECTOR AUTOREGRESSION

Based on the AIC, one lag was chosen for VAR the model. Each time series of linguistic LIWC category scores were subjected to an Augmented Dickey Fuller test, and I concluded that all variables are stationary. A time series is stationary if the mean, variance, and autocorrelations are not functions of time (Enders, 2004).

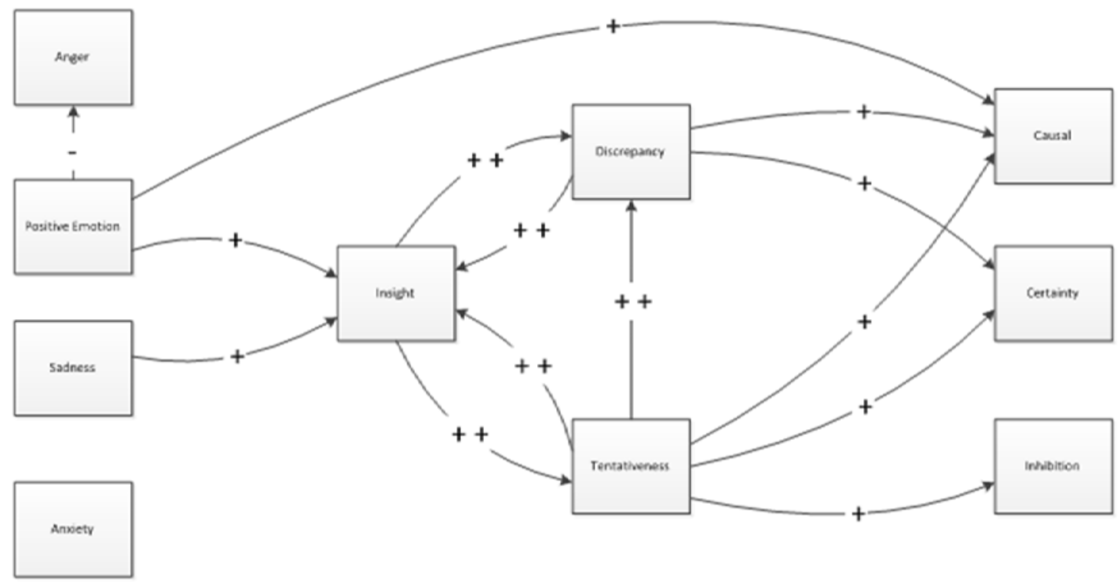
The significance and direction of causality among the variables is of primary interest in this study and these are summarized in Table 5. Of secondary interest is the estimated effect sizes, so I present the full results from the estimated VAR(1) model in Appendix III. Table 5 was constructed by placing a '+' or '++' in a cell if variable in the row heading has a positive estimated coefficient and Granger causes the variable in the column heading, one ‘+’ indicates statistical significance at the 0.05 level and two ‘++’s indicate statistical significance at the 0.01 level of the associated t-tests. Similarly for cells with a “-“ or “--”; they indicate a negative relationship and statistical significance at the analogous level.

A notable result is that most of the statistically significant relationships are positive in their direction. Either the relationship was positive or no relationship was found except for positive emotion to anger, which was statically significant at the 0.05 level and negative. In the next section we consider these results further and develop a model of the cycles of these processes.

Table 5: Granger Causality Test

	To:	Positive emotion	Anxiety	Anger	Sadness	Insight	Discrepancy	Tentativeness	Causality	Certainty	Inhibition
From	Positive emotion	**		-		+			+		
	Anxiety		**								
	Anger			**							
	Sadness				**	+					
	Insight					**	++	++			
	Discrepancy					++	**		+	+	
	Tentativeness					++	++	**	+	+	+
	Causality								**		
	Certainty									**	
	Inhibition										**

* significant at p < .05; ** significant at p < .01
+ positive and significant at p < .05; ++ positive and significant at p < .01
- negative and significant at p < .05; -- negative and significant at p < .01



- 4K tweets per file
- +/- indicates the direction of the correlation
- ++ or -- = .001
- + or - = .01

Figure 3: 4,000 Tweets per File Path diagram
The boxes represent the LIWC scores for Anger, Positive Emotion, Sadness, Anxiety, Insight, Discrepancy, Tentativeness, Causality, Certainty, and Inhibition terms.

DEVELOPMENT OF THE AROUSAL, INTERPRETATION, AND REALIZATION MODEL: COGNITIVE AND AFFECTIVE STAGES

While conducting grounded theory, a researcher will often seek data that integrate all the observations and theoretical concepts that may be relevant (Langley, 1999). The objective of a grounded theory approach is to integrate the observations into an abstract explanation of a process (Creswell, 2006) that can be summarized by testable propositions (Strauss & Corbin, 1994). A figure of the theory is often used to illustrate the propositions relating the constructs (Creswell, 2006; Morrow & Smith, 1995). As we showed in Table 5 in the previous section, a number of relationships were found to exist among the linguistic constructs. The objective was to find a relationship structure that persists independently of time and that dominates other structures. The relationships between discrepancy, insight, and tentativeness consistently emerged, and these three items became the focus of the theory development, which I describe next.

The Granger-causal relationships between the variables identified in Table 5 were traced in the path diagram shown in Figure 3, which helps to illustrate the relationships and delineate distinct stages. The variables that were only causes, i.e., that were found to Granger cause another variable but were not found to be Granger caused by any variables, were placed on the left side of the diagram with arrows pointing away from them. The variables that were only effects, i.e., that were found to be Granger caused by another variable but were not found to Granger cause any variables, were placed on the right side of the diagram with arrows pointing towards them. Finally, the mediating variables with arrows pointing both towards them and away from them were placed in the center of the diagram. These variables both Granger caused another variable and were Granger caused by another variable. Figure 4 shows the grouping of the variables into three stages, forming the Arousal, Interpretation, and Realization (AIR) model.

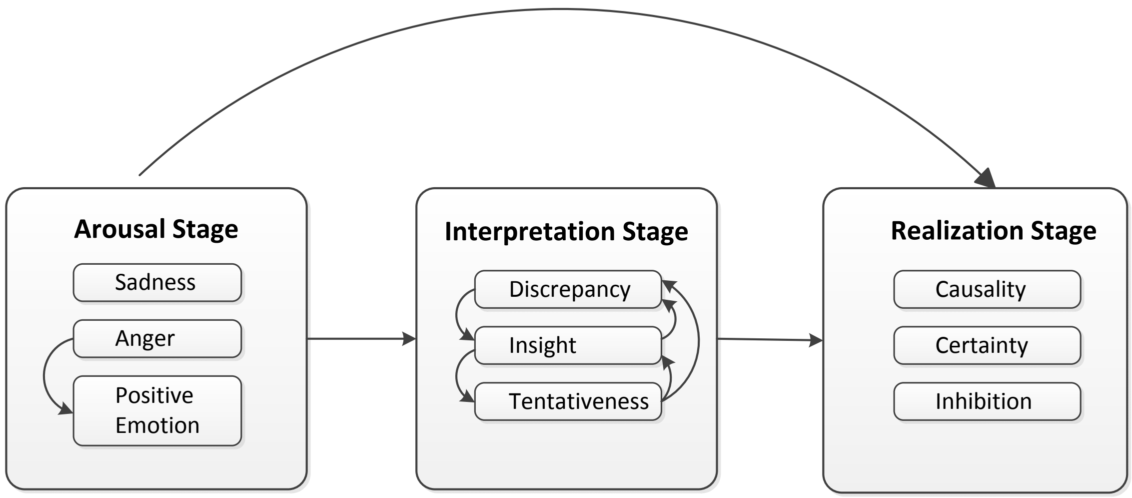


Figure 4: Stages of Affect and Cognition in Online Social Movements

I: The Arousal Stage

The first stage in the model, labeled *arousal*, is characterized by the salience of affective processes, i.e., emotional reactions to external events. Only emotions were found to play a role at this stage, and individuals' responses to Twitter messages are imbued with affect terms. Of the four types of emotion analyzed—anger, positive emotion, sadness, and anxiety—only three were found to have significant relationships with other variables. These are *anger*, *positive emotion,* and *sadness*. Anxiety was not found to be a significant cause or effect in any of the possible relationships.

The use of affect terms reflects the collective psychological state of the Twitter users. This grouping of affective variables at the inception of an episodic cycle suggests that participants in the Twitter conversation begin by exploring their personal feelings or reflecting on the feelings of others. Emotional priming occurs when emotionally significant stimuli reach the amygdala, the almond-shaped portion of the brain that controls emotional processes (Phelps, 2006) and helps to process emotionally-infused text. Anderson and Phelps (2001) demonstrated that emotionally charged words are easier for readers to detect than neutral words. In this case, the arousal stage represents the emotional reactions of the SOPA protesters who, as Twitter users and protesters, are reacting to what they read on Twitter as well as to external events connected with SOPA. The first wave of discussion is centered on their emotional states.

The emotional reactions become contagious within the online collective. Individuals begin to engage in the collective discussion and mimic others' actions. The most obvious form of mimicry is the act of retweeting a message. A retweet is a message that an individual has rebroadcasted under his or her own user name.

The antecedents to the cognitive engagement in the interpretation stage are positive emotions and sadness. An increase in positive emotion words or sadness words causes an increase in insight words. The masses of individuals use both positive emotions and sadness to assess the situation at hand. Positive emotions have been shown to increase creativity in problem solving (Estrada, Isen, & Young, 1994; Isen & Means, 1983) and sensemaking (Mittal & Ross, 1998). Individuals experiencing sadness become more introspective in order to explain their emotional state. Sadness may reflect expressions of doubt or disappointment at offered solutions and explanations. Sad individuals are reflective about social information (Bodenhausen et al., 1994). Community members experiencing positive affect demonstrate interpersonal understanding (Isen, 2001). Either way, members of the community are evaluating and analyzing their social environment.

II: The Interpretation Stage

The interpretation stage follows the arousal stage that is replete with emotion. Information processed through the central route is logically analyzed (Petty & Cacioppo, 1984), resulting in new insights. Other judgments are made using the peripheral route, to process the sheer volume of tweets. The crowd has moved from emotion to cognition.

The interpretation stage can be described as the part of an episodic cycle where the participants begin to develop an understanding of the unfolding events. During the interpretation stage, the collective begins to develop a narrative of the environment and events. As humans, we endeavor to create structure and meaning for our world through the construction of narratives (Pennebaker & Seagal, 1999). For example, after the attacks on the World Trade Center on September 11, 2001, bloggers were found to use more cognitive analytic terms (Cohn, Mehl, & Pennebaker, 2004). Individuals use narratives to interpret their feelings and observations and foster a feeling of self-determination. Children learn the art of storytelling by developing their ability to construct narratives and attributing causal relationships (Mancuso & Sarbin, 1998). In the SOPA movement, the participants are trying to make sense of the proposed legislation and its impact for the online community, the legislative process, and the principal members of Congress.

Over time a consensus arises, as the collective develops an understanding of the situation. The collective uses words expressing insight, discrepancy, and tentativeness to search for an answer. This is sensemaking. Sensemaking helps an organization understand its environment and begins with a change in the environment or some uncertainty (Weick, Sutcliffe, & Obstfeld, 2005). The emotional arousal prompts the cognitive processes that will try to make sense of the situation. The three cognitive processes that surface at this stage are *discrepancy*, *insight*, and *tentativeness*. Discrepancy reflects an unclear understanding of the situation. Examples of discrepancy terms include *hope*, *inadequate*, and *assume*. Insight is reflected in words demonstrating a deeper level of thinking. Insight terms include words like *aware*, *meaning*, and *insight*. Tentativeness terms reflect a lack of confidence on the part of the speaker, who is shying away from any definite conclusions. Tentativeness is reflected in the use of words like *almost*, *apparently*, and *barely*.

The discourse reflecting insight, tentativeness, and discrepancy indicates that participants in the conversation are trying to understand not only the SOPA legislation but also countervailing tactics. Sensemaking begins with noticing and bracketing by comparing existing mental models to a new phenomenon (Weick et al., 2005). The tentativeness reflects individuals' attempts to propose labels for the events. "Sensemaking is about labeling and categorizing to stabilize the streaming of experience" (Weick et al., 2005, p. 411). The collective uses words like *depend*, *maybe*, and *seem* to define what they see, the possible courses of action, and the desired outcomes.

III: The Realization Stage

The realization stage is the final stage of an episodic cycle in a movement. The transition from the interpretation stage to the realization stage can be partially explained through cognitive diffusion. The individuals reflect on their own experience and learn from their environment to create explanations and solutions (Bandura, 2001). There are three variables reflected in this process. These are *causality, certainty,* and *inhibition* terms. Causality terms include words such as *because*, *depends*, and *thus*. The use of these terms implies that the group has an understanding of cause and effect. They understand the implications of various courses of action and the use of different protest tactics. Causal terms are subsumed under coherence (Pennebaker & Francis, 1996), are also used after traumatic events (Tausczik & Pennebaker, 2010), and help to form narratives (Mancuso & Sarbin, 1998). While the proposed legislation may not be as traumatic as a personal breakup, it was the cause of many emotionally loaded messages. Moreover, the use of these terms implies that the collective has reached an understanding of the situation and courses of action.

The certainty words also indicate that a course of action has been decided upon. Sensemaking includes the development of a course of action. Certainty words include terms such as *total*, *unambiguous*, and *sure*. Certainty words are used by leaders in online communities (Huffaker, 2010). But in the case of the SOPA movement, there is no leader. The participants are not members of a larger organization. However, the use of causal terms in conjunction with certainty terms may reflect a call to arms. No single person is dictating what to do, but rather the collective, after understanding the consequences, begins a rallying cry. The significance of the certainty words can also be explained by noting that the terms appear as a result of insight, discrepancy, and tentativeness terms. I interpret this to mean that the collective has debated and reached a decision about the issue and the course of action.

Inhibition words include terms such as *stop*, *restrain*, and *guard*. Inhibition requires psychological effort (Pennebaker, 1989). The effort impedes cognitive functions such as information processing. However, in this case the inhibition terms seem to reinforce a call to action. The buzzwords in this movement are *Stop Online Piracy Act*, as the objective is to prevent the SOPA legislation from being passed by the U.S. Congress. I modified the dictionary for the inhibition terms to omit the term *stop*. Nevertheless, inhibition terms continued to play a significant role at this stage. The category name is a bit of a misnomer. The category was originally intended to describe individual level mental process that constrains behavior or thought. However, in the context of the SOPA movement phenomenon, a call to arms or plan of action seems to be a more appropriate description of this category.

In summary, the AIR model has three stages: arousal, interpretation, and realization. Within each stage, three emotional or psychological dimensions were identified. The arousal stage comprises *sadness*, *anger*, and *positive emotion* terms; the interpretation stage comprises *discrepancy*, *insight*, and *tentativeness* terms; and the realization stage comprises *causality*, *certainty*, and *inhibition* terms. The stages help delineate the type of discourse occurring over time. Delving deeper, the result of the VAR also revealed relationships between the different types of terms. These causal relationships between the types of terms used occur both during and between stages. I will now discuss each of the relationships.

UNDERSTANDING THE CAUSAL RELATIONSHIPS REVEALED IN THE AIR MODEL

In this section, I will explore each causal relationship revealed by the VAR and Granger causality test. I interpret the relationships in the light of extant research in order to develop a set of propositions regarding how social movements gain momentum and mobilize action.

Within the arousal stage, the Granger causal analysis revealed that an increase in anger expressions was followed by a decrease in positive emotion expressions. Expressions of anger negatively influence expressions of positive emotion in three ways. First, since anger is a strong emotion, individuals are liable to experience mood carryovers from one period to the next (Russell, 2003) and because individuals cannot *experience* both negative and positive states concurrently (Diener & Emmons, 1984), they are unlikely to *express* both negative and positive emotions concurrently. Therefore, an individual's expressions of anger in one period will inhibit that individual's expressions of positive affect in the next period. Second, through the mechanisms of empathy and emotional contagion (Davis, 1983; Hatfield et al., 1994), individuals' expressions of anger will result in increasing states of anger in others; again, given an individual's inability to sustain both positive and negative affect concurrently and hence to express both affects concurrently, one individual's expression of anger at time *t* will result in a decrease in others' expressions of positive affect at time *t*+1. Finally, social norms typically require participants in a social exchange to mirror their partners' emotions rather than express contradictory emotions (Derber 2000), thereby socially constraining expressions of positive emotion following an expression of anger. All of this leads us to the first proposition:

> ***Proposition 1:*** *During the arousal stage, expressions of anger will cause a decrease in expressions of positive emotion.*

The Granger causal analysis revealed that an increase in positive emotion expressions was followed by an increase in indicators of causal processes. Such causal processes entail analytical thinking as reasons are developed and cognitive relationships are established (Pennebaker, 2011). Causal cognitive processes are linked to positive emotion in two ways. First, positive emotion has been shown to enhance problem-solving skills (Estrada et al., 1994; Isen & Means, 1983). Second, positive emotion helps people to be more open to the world and therefore to change their perspectives (Pennebaker, 2011). This observation leads to the next proposition:

> ***Proposition 2****: Between the arousal and realization stages, expressions of positive emotion will cause an increase in indicators of causal cognitive processes.*

The Granger causal analysis revealed that an increase in positive emotion expressions was followed by an increase in indicators of insightful cognitive processes. Insight is associated with creative cognitive processes (Förster et al. 2004). Positive emotions increase creativity and insight in two ways. First, positive affect helps people to broaden their cognitive repertoires (Fredrickson, 2001) and accept new information (Estrada et al., 1994). Second, positive affect enhances individuals' experience of the psychological security that is necessary for engaging in divergent thinking (George & Zhou, 2007). Consequently, research has shown that positive emotion enables divergent thinking, novelty, and imagination (Clore, Gasper, & Garvin, 2001; Schwarz, Bless, & Bohner, 1991), and individuals in a positive mood tend to engage in more creative and insightful cognitive processes than do individuals in a negative or neutral mood (Isen, 2000).

> ***Proposition 3:*** *Between the arousal and interpretation stages, an increase in expressions of positive emotion will cause an increase in insightful cognitive processes.*

The Granger causal analysis revealed that an increase in sadness terms was followed by an increase in indicators of insight. Sadness terms can increase expressions of insight in three ways. First, individuals experiencing negative affect are motivated to change their affective state (Mittal & Ross, 1998). This motivation can stimulate problem-solving activities oriented toward changing the circumstances causing the negative affective state. Second, sadness was found to increase the creativity of employees in supportive work environments (George & Zhou, 2007). The solidarity of online movements offers individuals such a supportive context (Polletta & Jasper, 2001). Third, individuals experiencing sadness focus inward and try to understand their feelings through introspection, specifically looking to the past and the future to make sense of their emotions (Pennebaker, 2011). Such introspection has been found to be positively related to creative insights (Verhaeghen, Joorman, & Khan, 2005).

Proposition 4: *Between the arousal and interpretation stages, an increase in expressions of sadness will cause an increase in insightful cognitive processes.*

The Granger causal analysis revealed that an increase in indicators of discrepancy was followed by an increase in indicators of insight. While discrepancy and insight have reciprocal relationships, the underlying causal logic is different when discrepancy is the antecedent. We know that discrepancies will cause insight for two reasons. First, discrepancies are pieces of information that are incongruent with an individual's conception of the world or schema (Sujan & Bettman, 1989). Schemas provide frameworks for understanding people, places, and events (Baumeister & Finkel, 2010). In other words, schemas are expectations of a domain (Sujan & Bettman, 1989). Schemas help us to interpret new information or discrepancies. When faced with a discrepancy, individuals may assimilate or accommodate the new information. Assimilation occurs when individuals attempt to incorporate the new piece of information into an existing mental schema. In the case of a large discrepancy, individuals accommodate the information by changing their mental schema (Sujan & Bettman, 1989). In a study of brand positioning, Sujan and Bettman (1989) found that individuals recalled brands with strongly discrepant features better than brands with less discrepant features. Scientific achievement is often the result of attempting to resolve discrepancies (Kuhn, 1970). In microbiology labs, focusing on discrepant information inconsistent with expectations has been found to lead to discovery (Dunbar, 1995). Hence, in order to develop new insights, the facts must be recalled and reconciled.

As discrepancies surfaced in the Twitter conversation, individuals begin to collectively make sense of the new information. The individuals are negotiating a shared schema, and the discrepancies need to be either assimilated or accommodated. Either way, the group then proceeds to process the discrepancies and gains *new* insights. The schema is either enriched with new information or enhanced with modifications. Hence, there is an evolution in the collective thinking. This supports Weick's (1995) conceptualization of observations of discrepancy as the inception of sensemaking. New understanding begets more questions. Specifically, the findings suggest that the co-occurrence of two cognitive processes—insight and discrepancy—represents the inception of sensemaking.

Second, in public forums, individuals participate in the discussion after reflection (McLeod et al., 1999). This period of reflection allows individuals to ponder what they observe. Reflection is an antecedent to participation. After reflection, individuals contribute ideas that are clearer and offer more insight. Proposition 5 posits the relationship between increases in discrepancy and increases in insight:

> ***Proposition 5:*** *During the interpretation stage, an increase in discrepancy will cause an increase in insight.*

The Granger causal analysis revealed that an increase in indicators of insight was followed by an increase in indicators of discrepancy. Discrepancies are concepts that do not fit with an existing schema (Sujan & Bettman, 1989). Insightful cognitive processes can increase expressions of discrepancy in two ways. First, insightful processes are used to help compare and contrast ideas. The insight terms help to connect abstract ideas to concrete ones. Bracketing activities helps to delineate ideas by including relevant ideas and excluding irrelevant ones (Weick et al., 2005). In qualitative research, bracketing is a technique of suspending belief about a phenomenon until it can be clearly understood (LeVasseur, 2003). The use of insight terms reflects the individuals' experience of a higher degree of understanding than simple intuition and hazy feelings; they are forming an understanding of the unfolding events.

The new insights generate discrepancies. The discrepancy terms reflect the group's attempt to define and evaluate possible courses of action. Researchers have found that after a discussion of the issues in public forums like town hall meetings, individuals begin a process of dynamic reflection in which they attempt to assemble new information into a knowledge structure that provides utility (McLeod et al., 1999). In the same way, members in the online collective are making abstract ideas concrete and defining possible courses of action to realize the collective desire to protest the legislative bill. However, in this period of reflection, expressions of insight lead to an accumulation of discrepancies (Cowan, 1986).

> ***Proposition 6:*** *During the interpretation stage, an increase in insight will cause an increase in discrepancy cognitive processes.*

The Granger causal analysis also revealed that an increase in indicators of insight was followed by an increase in indicators of tentativeness. Tentativeness is characterized by a lack of confidence and openness to alternative perspectives. The use of insight terms reflects deep analytical thinking and the formation of strong opinions (Pennebaker, 2011). Within the collective, the use of insight terms reflects a level of understanding beyond mere observation and intuition. Insight allows for cognitive clarity to emerge from deep analysis. An increase in the use of insight terms reflects an increase in the formation of strong opinions that begin to circulate through the collective.

Insight will increase tentativeness for the following two reasons. First, too much information may overwhelm the community. Information overload occurs when an individual is faced with a plethora of raw data that have not been synthesized or summarized (Chervany & Dickson, 1974). Information overload has been shown not only to adversely influence the amount of time necessary to make a decision and the quality of the decision, but also to decrease decision makers' confidence, i.e., increase their tentativeness (Chervany & Dickson, 1974). Second, if the insight reflects a potential goal or course of action, the individual may experience tentativeness in the face of needing to commit to the goal (Tiedeman, 1967).

> ***Proposition 7:*** *During the interpretation stage, an increase in insight will cause an increase in tentativeness.*

The Granger causal analysis revealed that an increase in indicators of tentativeness was followed by an increase in indicators of insight. Tentativeness will increase insight for two reasons. First, for decision makers, tentativeness is a mental state characterized by openness to new ideas and perspectives (Etzioni, 2001). Expressions of tentativeness therefore reflect cognitive openness, which is a key antecedent to creative insight (Feist, 1998). Second, tentative ideas undergo a process of *bolstering*, which is the creation of rationales to increase the acceptability of an idea compared to competing ideas (Schwenk, 1984), and this increases the insights experienced by the collective. The next proposition reflects this dynamic:

Proposition 8: *During the interpretation stage, an increase in tentativeness will cause an increase in insight.*

The Granger causal analysis revealed that an increase in indicators of tentativeness was followed by an increase in discrepancy processes. Tentativeness reflects openness in the mental state of the collective. As tentative ideas undergo further cognitive processing and become bolstered (Schwenk, 1984), the collective will notice and identify discrepancies. Thus, Cowan (1986) noted that the refinement of ideas leads to an accumulation of discrepancies to be resolved.

Proposition 9: *During the interpretation stage, an increase in tentativeness will cause an increase in discrepancy cognitive processes.*

The Granger causal analysis revealed that an increase in expressions of discrepancy processes was followed by an increase in causal cognitive processes. Causal processes involve explaining the relationship between two ideas (Whetten, 1989). Discrepancy processes reflect logical thinking, i.e., placement of concepts in relation to each other. Discrepancy processes increase causal cognitive processes because individuals tend to recall discrepancies better than congruent information (Stangor & McMillan, 1992) and identification of discrepant information triggers systematic processing (Maheswaran & Chaiken, 1991). Thus, identification of discrepancies at time *t* will be strongly recalled at time *t*+1, prompting systematic processing of information that results in incorporation of the discrepant information into a cognitive map or causal schema. Proposition 10 formalizes this relationship.

> ***Proposition 10:*** *Between the interpretation and realization stages, an increase in discrepancy cognitive processes will cause an increase in causal cognitive processes.*

The Granger causal analysis revealed that an increase in discrepancy processes was followed by an increase in certainty. Discrepancy increases certainty for two reasons. First, discrepancies are data points that are incongruent with an individual's current schema (Sujan & Bettman, 1989). As those discrepancies are incorporated into schemas and bolstered through group discussions, individuals' confidence in their schemas will increase (Schwenk, 1984). Second, Yates et al. (1978) found that ideas are evaluated for completeness of information and that ideas with incomplete information are devalued, as the lack of complete information increases uncertainty (Yates et al., 1978). Discrepancies therefore motivate individuals to seek explanations, thereby leading group members to incorporate more complete information (Kanazawa, 1992). As members of a group collaborate on incorporating information into cognitive maps, their certainty about their maps will increase.

> ***Proposition 11:*** *Between the interpretation and realization stages, an increase in discrepancy cognitive processes will cause an increase in certainty.*

The Granger causal analysis revealed that an increase in tentativeness was followed by an increase in indicators of causality. If the collective is open to new possible ideas, then there is a rise in the increased usage of tentativeness terms. As previously noted, tentativeness reflects an openness to new ideas and perspectives (Etzioni, 2001). Tentativeness indicates new and uncommitted ideas. While tentative ideas are accommodated and assimilated through discrepancy to certainty, an increase in tentative terms also increases causality terms. Causal processes entail specification of a theoretical rationale for the relationship between concepts (Whetten, 1989). The more tentative terms there are, the more ideas are being put forth to the group for evaluation. The more ideas that are put forth, the more likely will be a change in which good ideas are absorbed by the group. Whether the ideas are assimilated into a schema or accommodated by a schema (Sujan & Bettman, 1989), the justification will be explained through causal language. Thus, the increase of tentativeness terms will be followed by an increase of causality terms.

Proposition 12*: Between interpretation and realization stages, an increase in tentativeness will cause an increase in causal cognitive processes.*

The Granger causal analysis revealed that an increase in tentativeness was followed by an increase in certainty. Lüscher and Lewis (2008) found that managers in a company undergoing organizational change were encouraged to describe the messy situation, explore each other's perspectives to reveal potential dilemmas, and reflect on the implications for themselves in order to reveal the underlying paradox before a concrete solution was found through strategic questioning (Lüscher & Lewis, 2008). Similarly, the SOPA protesters faced a contentious fight against a common foe. The situation was evolving and unknown and the collective group was unstructured. There was no formal hierarchy or leadership.

The individuals in the collective began to put forth tentative ideas to reveal discrepancies. Proposition 9 posited that tentativeness leads to discrepancy processes. However, some tentative ideas that are put forth will be self-evident and result in a deeper understanding, reflected by developing causal relationships. Ideas are generated before choices are made (Simon, 1947). Good ideas are selected as they are bolstered with supporting arguments (Sujan & Bettman, 1989). While the collective determined the causal relationships between ideas, bad ideas were discarded (Simon, 1947). The good ideas were agreed upon. Hence, the collective became more certain about their ideas.

> ***Proposition 13****: Between the interpretation and realization stages, an increase in tentativeness will cause an increase in certainty.*

The Granger causal analysis revealed that an increase in tentativeness was followed by an increase in inhibition. Attentional inhibition is a priming process that renders some constructs or categories less relevant or salient (Bodenhausen & Macrae, 2013). While the exchange of tentative positions and information may lead to elaboration and bolstering, resulting in cognitive certainty, the exchange may also lead to the realization that the tentatively espoused positions are unfounded. When the latter occurred, the collective then distanced themselves from those positions, culminating in attentional inhibition. This leads to the following proposition:

Proposition 14: *Between the interpretation and realization stages, an increase in tentativeness will cause an increase in inhibition.*

This observed relationship may also be an artifact of the movement, i.e., it may reflect the collective's agreed-upon plan of action to thwart or "stop" or "block" the Online Piracy Act. Because these terms are operationalizations of inhibition, Proposition 14 is offered with the caveat that it may simply reference the collective's plan of action rather than a cognitive process (Pennebaker, 1989).

CONTRIBUTIONS OF THIS RESEARCH

This research contributes to three broad areas of knowledge. It provides a better understanding of (1) social movements, (2) contagion in CMC, and (3) individual sensemaking and group cognitive processes.

Contributions to the Social Movements Literature

The outcome of this study is the AIR model. This model first highlights the presence of multiple episodic cycles revealed in communications surrounding a movement. Within each cycle, the three stages of discourse are the arousal stage, the interpretation stage, and the realization stage. In other words, the crowd reacts to some external event, attempts to understand the event, and comes to a consensus regarding a plan of action. The AIR model gives us a clearer understanding of the underlying dynamics of social movements. The tweets of individuals were analyzed using text analysis and VAR, which helped provide an understanding of how emotional and cognitive processes sweep through a large crowd of individuals in an online setting. I found that emotion is the driver of online social movements. After reacting emotionally to external events or other messages, individuals begin to interpret what they observe in order to develop an understanding of their environment. This interpretation evolves into realization.

Further, this research contributes to understanding public opinion as a social process that leads to change. Davison's (1958) model of public opinion reflects the notion that issues are transmitted from the individual to the group and back to the individual (as cited in Glynn, 2005). Noelle-Neumann's (1984) model incorporates moral and psychological components (fear of isolation) to explain the formation of public opinion. Crespi (1997) models the formation of public opinion using individual and social aspects. The lack of convergence of these three theories is due to a lack of detail, partly because communication has been oversimplified (Glynn, 2005). Further, among the most overlooked concepts in studies of public opinion are the rise and fall of individual and group emotions (Glynn, 2005). This AIR model offers a way to unify these three models of public opinions because it describes the stages of communication within a large group.

The sociologists and political scientists who study social movements do not address specific emotions or delve deep into the idea of emotion as the psychologist do. A third contribution of this research is that it analyzes sentiment and communication at a granular level in order to understand micro-level communication along the cognitive and affective dimensions, specifically within social movements. This research provides new analytical techniques combining text analysis and vector autoregression to reveal new cognitive and emotional relationships.

Understanding Contagion in Large Groups on Computer Mediated Communication

The application of text analysis to tweets gives us a better understanding of the spread of emotion in large groups. Emotional contagion helps to explain some of the transmission of emotion through a large crowd of online individuals: positive emotion engenders more positive emotion; anger engenders more anger, and so on. In addition, by analyzing all the emotional variables simultaneously, It was possible to determine whether the expressions of emotion caused changes in the expression of other emotions within the crowd. Positive emotion was found to have a negative effect on anger emotion. Moreover, it was possible to understand the impact of negative affect at a more granular level. George and Zhou (2007) noted the salience of negative affect in general; the present research suggests that sadness, but not anger, prompts a group to begin the process of sensemaking.

Research on social contagion theory has demonstrated that people tend to act in groups (Marsden, 1998). The use of time series analysis in combination with text analysis is a new technique that can be extended to understand larger groups over time. The ebb and flow of emotion and cognition in a group can now be observed at a more granular level. This may provide a deeper understanding of affect and cognitive constructs and their role in groups. Specifically, four types of theories from social psychology that describe the impact of affective and cognitive mechanisms in social contagion have been investigated simultaneously. The model provides insights of how the two types of mechanisms impact social contagion simultaneously.

Contributions to the Sensemaking Literature

In addition, the model helps to explain the attribution process at a group level. This cognitive process was a shared negotiation among the participants in the movement against SOPA, who used words that reflect insight, discrepancy, and tentativeness. The participants refined their thoughts using Twitter to clarify what they saw and the proposed courses of action.

This research complements the work of Cohn, Mehl, and Pennebaker (2004), who used text analysis to study online diaries after the September 11, 2001 attacks in the United States. They found that in the short run, the participants were cognitively and socially engaged and expressed negative emotion, while in the long run, there was an increase in psychological distancing (Cohn et al., 2004).

While these authors studied the writing of individuals who shared the same trauma and expressed themselves as individuals, I study the text messages of individuals who share the same experience but attempt to collectively understand their shared view to determine a course of collective action.

Further, I contribute to the sensemaking literature by putting forth a theoretical model of the stages of communication in a social movement. The model is based on the electronic messages of thousands of individuals. Past studies of sensemaking focused on smaller groups. For example, Weick studied the sensemaking of a small group of firemen in the Mann Gulch disaster (Weick 1993).

LIMITATIONS

The limitations of the model are a consequence of the nature of the phenomenon, the design of the social medium, and the choice of analytical techniques. Each of these components needs to be examined to determine the boundaries of the theory.

The Twitter messages concerning SOPA were used as observation points to develop the theory. It is not clear whether the theory is generalizable to other social movements. Do all movements cycle through the three stages proposed by the AIR model? Moreover, the SOPA protest movement can be deemed a success, but it is unclear whether unsuccessful movements will evolve in a similar manner. Lamar Smith, chairman of the House Judiciary Committee, postponed the drafting of the legislation. Senator Harry Reid, the Senate majority leader, announced that the vote would be deferred, and the announcement was appropriately made on the medium of the SOPA protest, Twitter.

Broadly speaking, the Twitter messages reflect the participants' thoughts about the proposed legislation. The dynamics of the social movement point to some limitations. First, the movement existed outside of a structured institution. The participants did not work for a single organization with hierarchies, social norms, and shared schemas. The AIR model needs to be tested in different environments to determine whether the theory applies to both structured and unstructured environments. Second, analytical techniques use characteristics of the English language. The use of language varies from culture to culture. Thus, the theory can only be confidently applied to online social movements conducted in English.

Finally, the choice of LIWC dictionary to categorize the words limits the research. LIWC has undergone a large number of validation studies (Pennebaker, 2007). However, there are other software packages with different word categories that categorize words by meaning and function differently from LIWC, which may be useful for similar analyses.

FUTURE RESEARCH DIRECTIONS

The AIR theory was developed using a single online social movement. The theory needs to be validated against other movements to assess its generalizability. In paper 3, another movement will be analyzed using these techniques in order to empirically test the model.

The corpus, or entire body of text, includes over 1 million tweets. The texts of the tweets were analyzed using automated methods. Software was used to calculate text analysis scores. The scores were then used as input to a VAR. The procedure to parse and analyze the tweets would benefit from complete academic treatment of the method. Further, context analysis of the tweets might help to triangulate the theory. A sample of tweets needs to be coded to cross-validate the theory.

An unstated context of this study is that the phenomenon of the movement is an American one. The proposed legislation was introduced in the U.S. Congress. It is reasonable to assume that most of the interested parties were American, or at the very least, fluent in American culture. Further, the language used was English. It is not clear whether the AIR model would hold in other cultures where the show of emotion may differ online.

Finally, the theory also needs to be tested against unsuccessful social movements. The underlying dynamics may evolve differently when a movement fails. For example, does the conversation ever reach the realization stage in an unsuccessful movement, or is does the conversation remain in the first stage, discussing the emotional reaction? Perhaps the movement is stuck in the second stage, interpretation, and the collective cannot comprehend the events around them. Clearly, unsuccessful movements need to be tested as well.

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APPENDIX I: APPROACHES TO TEXT ANALYSIS

There are three broad approaches to studying text: judge-based thematic content analysis, word pattern analysis, and word count strategies (Pennebaker, Mehl, & Niederhoffer, 2003). Judge-based thematic content analysis involves raters or judges who read the text to code for thematic content based on a previously developed coding scheme. Multiple raters are used to permit empirical assessment of inter-rater reliability. Word pattern analysis is a new technique that uses computer software to look for patterns and relationships between words. While judge-based thematic content analysis uses previously defined psychological dimensions, word pattern analysis looks at the text to determine sets of words that covary (Pennebaker et al., 2003). Latent semantic analysis (LSA) is a good example of word pattern analysis. LSA identifies larger clusters of words, akin to factor analysis, by looking for clusters of individual words that are close together, where the distance is measured as the number of words between the two words of interest. LSA was originally developed as an algorithm for search engines (Mehl, 2006), but the approach has been extended to determine the similarity between two texts (Mehl, 2006; Pennebaker et al., 2003).

LSA is a bottom-up approach, since a body of text is scanned for semantic similarities (Mehl, 2006). The result of LSA is a cluster of words that are deemed similar to each other—the meanings of the words are not important. If a researcher is interested in determining the similarity of two bodies of text or doing a search, then LSA will suffice. To extract meaning, however, the researcher must interpret the cluster of words. The interpretation is the same process one might use in factor analysis or cluster analysis.

This study's parsing of the files to create time series data requires an interpretation of data clusters for each file. There is no guarantee that the same variable will emerge as is required by vector autorgression. So, the use of LSA is not appropriate. In other words, the entire body of tweets was split into smaller files and each of these files was subject to text analysis. The results of multiple LSA results from multiple files would need to be interpreted. Since the underlying text varies from text file to text file, there is no reason to believe that the interpretations would result in consistent categories that would persist through time. Repeated measures of the same variable are needed to conduct time series analysis. The variables need to be measured using the same approach at each time stage.

The third technique for text analysis is a word count strategy. Words reflecting grammatical structure and words reflecting psychological dimensions are counted (Pennebaker et al., 2003). Grammatical structure is measured by counting words such as pronouns, articles or auxiliary verbs. The underlying assumption is that word choice reflects psychological cues above and beyond the literal meaning. The advantages of a word count strategy over a judge-based thematic content analysis include the ability to analyze large bodies of text. Also, while human judges can rate content, they may not be able to recognize the significance of word choices (Pennebaker et al., 2003). The benefit of a word count strategy over LSA is that word count strategies have categories that are static and persistent through time which is required of any time series analysis. Thus, I employed a word count strategy in this research.

APPENDIX II: SENSITIVITY ANALYSIS

This appendix provides a variety of sensitivity analyses regarding the procedure for parsing the tweets for generating the time series of LIWC categories. In the first subsection a horizontal split of the data was performed; next, the file size was varied to determine the optimal file size to generate time series of the LIWC categories for the VAR analysis; then bootstrapped partitions with a random starting point were generated to determine if the location of the partitions of the tweets impacted the VAR results; the tweets were analyzed individually (i.e., with a file size of one); and finally by date. Each of these sensitivity analyses are described in detail below.

Horizontal Split

This generates two subsamples that should produce statistically identical VAR results if there is no systematic bias in the data that would affect the overall results. The entire corpus of tweets was split into two by placing every other tweet into one of two separate files. The two files were then split into files of 1,000 tweets each, as described above. File A was analyzed using a VAR. Using the parameter estimates produced by the VAR on File A, I constructed a confidence interval with its corresponding standard error. I then ran a VAR on File B to estimate the same parameters.

All the estimates for File B were within the confidence intervals of the parameter estimates for File A when the confidence intervals were based on two standard errors. I then compared the parameter estimates for File B against a more restrictive confidence interval of one standard error. Of the 444 parameter estimates, 50 parameter estimates, or 11%, for File B were outside the parameter confidence intervals for File A.

Not all of the 444 parameters in File A were significant, however. Of the 89 variables that were significant at < 0.10, 8 variables, or 0.09%, were impacted. Similarly, of the 64 variables that were significant at < .05, 6 variables, or 0.09%, were impacted. The percentages are much lower than the 32% chance of lying outside one standard error, assuming a normal distribution. Overall, the parameter estimates were found to be stable and reliable.

Varying the File Size

The next analysis was to determine how sensitive VAR was to the size of the file. LIWC creates percentage scores. The corpus of tweets was split into sizes ranging from 100 to 10,000 tweets per file. The files were processed using LIWC and VAR. The file sizes were found to make a difference. The major observation was that the optimal number of lags varied by file size. The VAR procedure in the R software calculates the optimal number of lags. I used a maximum of 7. The following table shows the numbers of lags chosen by the software.

Table 6: Number of Lags Chosen for Number of Tweets

Number of Tweets per File	Number of Files	Number of Lags Chosen
100	13,412	R crashed, as the number of LIWC scores (or files), 13,411, was too large
500	2,704	6 lags
1,000	1,342	4 lags
2,000	677	3 lags
3,000	452	2 lags
4,000	339	1 lag
5,000	272	1 lag
6,000	226	1 lag
7,000	194	1 lag
8,000	170	1 lag
9,000	151	7 lags
10,000	136	7 lags

As the number of tweets per file increases, the number of lags decreases until we reach 8,000 tweets per file, and then it suddenly jumps to 7 lags. The decreasing numbers of lags seem to follow a reasonable pattern. There seems to be stability in the choice of lags between 4,000 tweets per file and 8,000 tweets per file. The single lag implies that most of the variance in the current time period can be explained by the information in the immediately preceding time period if the file size is large enough. Also, notice that for the smaller file sizes with multiple lags, the product of the number of lags multiplied by the number of tweets per file get close to one of the file sizes with one lag. For example, the VAR with 1000 tweets per file used 4 lags. The product of these numbers is 4000. If we look at 4000 tweets per file, we see that the VAR procedure used one lag. In other words, most of the variance is explained by the preceding 4,000–8,000 tweets. The choice of one lag makes the model easier to understand and minimizes the number of parameters estimated. Further, the number of tweets per file should be chosen so that VAR has the maximum statistical power. The tradeoff between the file size and VAR suggests that the smallest file size should be used to ensure enough data points for the VAR. Thus, a file size of 4,000 was found to be optimal.

Bootstrap Analysis

Next, I ran a bootstrap analysis to determine how sensitive the LIWC scores were to file breaks. All file sizes in table 7 where one lag chosen were considered in the bootstrap analysis, with the smallest file size being 3,500 tweets and the largest being 8,000 tweets. The bootstrap was conducted as follows. First, a random starting point was selected by generating a random number *r*. Then the remainder of the tweets were partitioned every *n* tweets where *n* is the file size under consideration. Within each partition, *n* tweets were randomly selected with replacement to generate bootstrapped files of size *n*. LIWC scores were generated for each file of bootstrapped data. Afterwards I calculated the descriptive statistics of the LIWC categories. The following file sizes were tested: 3,500, 4,000, 5,000, 6,000, 7,000, and 8,000 tweets per file. Table 7 provides the LIWC scores for each category by file size.

Table 7: Bootstrap of Mean of LIWC Scores by Number Tweets by File Size

	Tweets Per File					
LIWC Category	3500	4000	5000	6000	7000	8000
Positive Emotion	2.6390	2.6469	2.7563	3.2058	3.2973	3.2743
Negative Emotion	1.4839	1.5440	1.6895	1.5985	1.6259	1.6701
Anxiety	0.1653	0.1704	0.1640	0.1493	0.1463	0.1419
Anger	0.7797	0.7923	0.9043	0.8345	0.8791	0.9147
Sadness	0.2796	0.3050	0.3204	0.3172	0.3176	0.3181
Cognitive Mechanism	10.7474	10.6718	10.4079	10.0744	10.1691	10.2677
Insight	1.2898	1.2711	1.2119	1.1337	1.1193	1.1529
Causal	1.1101	1.1294	1.1410	1.2185	1.3245	1.3950
Discprepancy	0.9551	0.9786	1.0397	1.0611	1.1505	1.1688
Tentativeness	1.3276	1.3246	1.3642	1.3094	1.3397	1.2916
Certainty	0.5620	0.6165	0.5959	0.6235	0.6260	0.6513
Inhibition	1.7469	1.7177	1.6341	1.4915	1.4758	1.5533
Inclusive	2.4697	2.4002	2.2647	2.1685	2.0786	2.0362
Exclusive	1.4648	1.4640	1.4878	1.4414	1.4503	1.4170

Then I regressed each LIWC category average by file size on file size. To control for file size, I divided the LIWC scores by the number of words. If file size is found to be statistically significant in explaining the average LIWC score, then there would be reason the worry that choice of file size will affect the results presented in the main text of this paper. The results are displayed in Table 8. In each category the estimated coefficient on file size is not statistically different from zero, and I therefore concluded that the file size does not matter.

Table 8: Regression of LIWC Scores by Number of Tweets in File

LIWC Score	Estimate	Std. Error	t value	Pr(>|t|)
Positive Emotion				
(Intercept)	1.42E-05	1.98E-05	0.716	0.514
File Size	1.84E-09	3.40E-09	0.539	0.618
Anxiety				
(Intercept)	1.55E-06	1.18E-06	1.312	0.26
File Size	-4.12E-11	2.04E-10	-0.202	0.849
Anger				
(Intercept)	5.45E-06	5.98E-06	0.912	0.414
File Size	2.93E-10	1.03E-09	0.284	0.79
Sadness				
(Intercept)	2.32E-06	2.19E-06	1.062	0.348
File Size	5.40E-11	3.76E-10	0.144	0.893
Cogntive Mechanisms				
(Intercept)	7.52E-05	8.05E-05	0.934	0.403
File Size	1.71E-09	1.39E-08	0.124	0.908
Insight				
(Intercept)	9.88E-06	9.32E-06	1.06	0.349
File Size	-1.25E-11	1.61E-09	-0.008	0.994
Causal				
(Intercept)	6.23E-06	8.13E-06	0.767	0.486
File Size	6.81E-10	1.40E-09	0.486	0.652
Descrepancy				
(Intercept)	5.91E-06	7.15E-06	0.827	0.455
File Size	5.12E-10	1.23E-09	0.416	0.699
Tentativeness				
(Intercept)	9.89E-06	9.90E-06	0.999	0.374
File Size	1.95E-10	1.70E-09	0.114	0.914
Certainty				
(Intercept)	4.32E-06	4.38E-06	0.986	0.38
File Size	1.47E-10	7.54E-10	0.195	0.855
Inhibition				
(Intercept)	1.33E-05	1.26E-05	1.057	0.35
File Size	-4.00E-11	2.17E-09	-0.018	0.986

LIWC Score	Estimate	Std. Error	t value	Pr(>|t|)
Inclusion				
(Intercept)	1.91E-05	1.79E-05	1.067	0.346
File Size	-1.48E-10	3.08E-09	-0.048	0.964
Exclusion				
(Intercept)	1.08E-05	1.10E-05	0.986	0.38
File Size	2.14E-10	1.89E-09	0.113	0.915

Individual Tweet Analysis

The corpus of tweets surrounding SOPA was analyzed one tweet at a time, as this reflects one possible way users use Twitter. The first assumption of this analysis is that a user responds to only the most recent postings. The second assumption is that a user will respond immediately with a tweet of his or her own: the response is assumed to appear immediately proximate to the initial post. The propinquity of related tweets is important in understanding the underlying relationships between the variables over time. If the original tweet and the response tweet are separated by a number of unrelated tweets, then the VAR may not find significant models.

A sample of tweets was selected from the body of tweets for the individual tweet analysis, due to the processing limitations of LIWC and R. A set of the first 1,000 tweets was selected from every 100,000 tweets. Table 9 lists the start and end times for each group of analyzed tweets. Note that the average time span for all the groups is 687 min, or 11 hr 27 min. Group 0 is the only group of tweets that spans multiple days. There were very few tweets at the beginning of the movement. The average elapsed time within a group, excluding Group 0, was 41 min.

Table 9: Groups of 1,000 Tweets Sampled Every 100,000 Tweets

Group Number	First Tweet #	Start Date	Start Time	End Date	End Time
Group 0	0	9-Dec-11	5:15 PM	15-Dec-11	1:47 PM
Group 1	100,000	16-Dec-11	11:59 AM	16-Dec-11	12:16 PM
Group 2	200,000	20-Dec-11	8:37 AM	20-Dec-11	9:34 AM
Group 3	300,000	23-Dec-11	12:36 AM	23-Dec-11	12:56 AM
Group 4	400,000	24-Dec-11	8:03 AM	24-Dec-11	8:59 AM
Group 5	500,000	29-Dec-11	11:13 AM	29-Dec-11	11:52 AM
Group 6	600,000	4-Jan-12	7:30 PM	4-Jan-12	8:43 AM
Group 7	700,000	10-Jan-12	1:57 AM	10-Jan-12	4:39 AM
Group 8	800,000	12-Jan-12	7:28 PM	12-Jan-12	7:48 PM
Group 9	900,000	14-Jan-12	3:46 PM	14-Jan-12	4:02 PM
Group 10	1,000,000	17-Jan-12	5:43 PM	17-Jan-12	6:01 PM
Group 11	1,100,000	18-Jan-12	9:33 AM	18-Jan-12	9:41 AM
Group 12	1,200,000	18-Jan-12	8:52 PM	18-Jan-12	9:02 PM

On the assumption that a person would respond to a specific tweet soon after reading it, 41 min is a reasonable upper bound.

Each sample of 1000 tweets was analyzed in the following manner. Within each group, each tweet was processed using LIWC in order to obtain text proportion scores. The LIWC scores across the sample were then analyzed using VAR and the Granger causality test. For each relationship (e.g., sadness causes insight), the number of times the relationship was significant was counted.

Table 10: Granger Causality Relationship Counts

	Positive emotion	Anxiety	Anger	Sadness	Insight	Discrepancy	Tentativeness	Causality	Certainty	Inhibition
Positive emotion	13	2	1	1	2	0	0	0	1	1
Anxiety	1	13	1	0	2	0	2	0	0	0
Anger	1	2	13	1	0	2	1	3	1	1
Sadness	0	0	2	13	5	2	2	2	1	0
Insight	2	0	1	2	13	1	0	3	1	1
Discrepancy	2	0	0	0	0	13	1	2	2	1
Tentativeness	3	1	2	1	1	2	13	1	1	4
Causality	1	2	1	3	3	2	2	13	2	1
Certainty	2	1	1	0	4	2	3	0	13	4
Inhibition	2	1	1	4	2	2	3	2	0	13

Table 10 counts the number of times in the 13 files that the row variable causes the column variable. Along the diagonal we can see that a lagged variable will cause itself in later periods. There are only five relationships that occur at least four times, and only one of the five occurrences occurs five times:

Sadness → Insight 5 times

Tentativeness → Inhibition 4 times

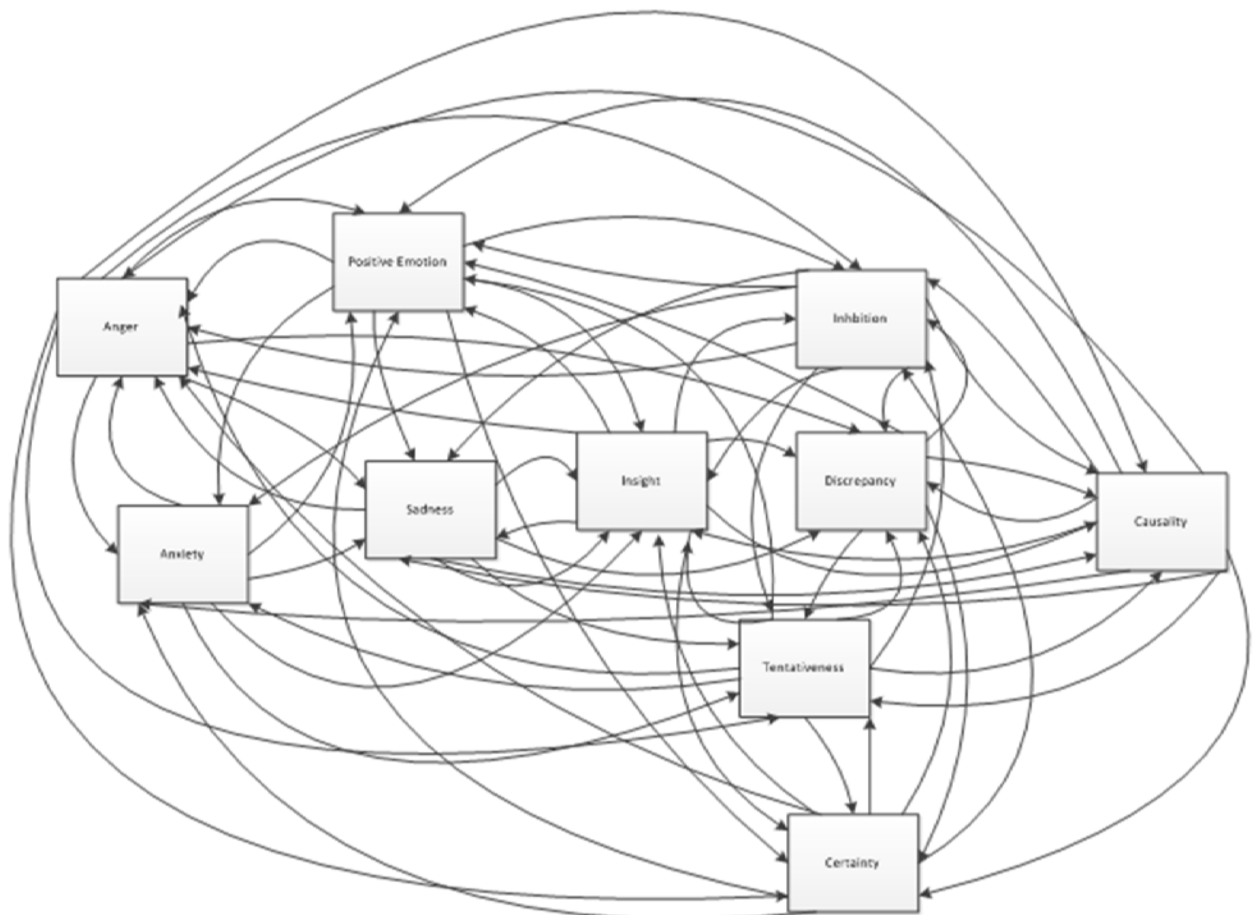
Certainty → Insight 4 times

Certainty → Inhibition 4 times

Inhibition → Sadness 4 times

The rest of the matrix cells filled in with 0, 1, or 2. Twenty percent of the cells are filled with zeros. Looking at this matrix, there does not seem to be a pattern emerging from analyzing individual tweets. This makes sense. A massively large number of individuals were participating in the discussion. Individuals were continuously moving in and out of the discussion through time. Time is also a factor in that responses to tweets may happen at different points in the public timeline; other competing tweets may explain and dilute the individual level effects. Thus, it is not clear who is responding to whom and to what. However, the above relationships were noted since they could also appear in the other models. This model reflects the untenable assumption that related tweets are close together in the public timeline. In fact, however, numerous conversations were going on simultaneously. Following tweets on the Twitter timeline is akin to eavesdropping on all the conversations in a football stadium. We may be able to hear pieces of conversation here and there, but may not be able to ascertain their meaning or temporal ordering.

Figure 5 shows the path model implied by the results of the Granger causality tests. Only the direction of causality is shown in the graph. The counts for the relationships were used to create the diagram. Note that there were only 21/100 causal relationships that did not show up.



- Analysis by individual Tweet

Figure 5: Individual Tweets Path Diagram
The boxes represent the LIWC scores for Anger, Positive Emotion, Sadness, Anxiety, Insight, Discrepancy, Tentativeness, Causality, Certainty, and Inhibition terms.

The diagram of the implied paths, included for completeness, does not shed any light on the relationships within a collective group.

Analysis by Date

The entire corpus of tweets was also analyzed by date. The tweets were separated into 37 files, one for each date. Each file was analyzed using LIWC in order to provide the proportions of words used for each category. There are two reasons to analyze tweets by date. First, users may be watching the tweets throughout the day using the built-in Twitter search of trending topics or a second party site such as www.tweetgrid.com. After watching for a while, the Twitter user may decide to post a tweet to enter into the discussion. Second, recent studies on text analysis through time have separated tweets by date (Bollen, Mao, & Zeng, 2011).

The analysis of tweets by date also makes some behavioral assumptions about Twitter users. The first assumption is that Twitter users read a day's worth of tweets before responding to the tweets and entering a posting into the public timeline. That is, users read Twitter tweets all day long before forming an opinion and making it publicly available. Some users may in fact exhibit this behavior. For example, they may have a Twitter application on their desktop at work and casually observe tweets as they scroll by. However, given the immediate nature of the medium, is more likely that people react when they have something to say. Twitter messages are short and do not take a lot of time to post once a user is logged into an application.

Table 11 represents all of the significant relationships for the Granger causality test. If a table cell is blank, then no relationship exists. The number of signs represents the significance level. The VAR procedure, using AIC, chose a model with two significant lags. In some cases, the sign of the estimated parameter is different at lag 1 from the estimated parameter at lag 2. In this case they are represented with two signs. The slash separates a lag of one and a lag of two. The first sign is the direction of the relationship in lag 1 and the second sign is the direction of the relationship in lag 2. For example, in the insight equation, discrepancy terms had a negative effect in lag 1 and a positive effect in lag 2.

Table 11: Granger Causality Test for Analysis by Date

	Positive emotion	Anxiety	Anger	Sadness	Insight	Discrepancy	Tentativeness	Causality	Certainty	Inhibition
Positive emotion	+++									
Anxiety		+++				+++	++	+/-	+	--
Anger			+++		+	++	+++			---
Sadness				+++						
Insight		++	+		+++	+/-	-			+++
Discrepancy					--/+++	+++	--			-
Tentativeness							+++			
Causality					---	--		+++		
Certainty					+				+++	-/+
Inhibition					+	+/-				+++

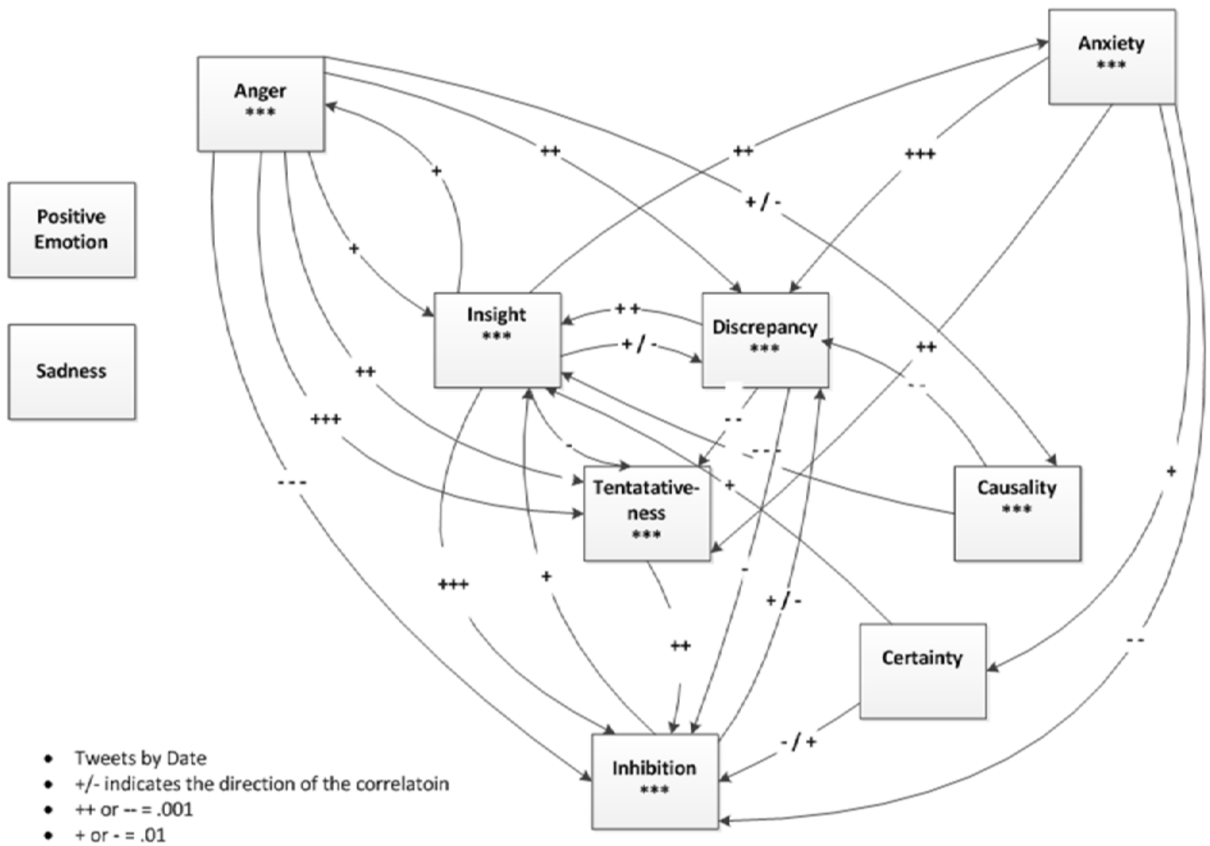


Figure 6: Daily Tweets Path Diagram
The boxes represent the LIWC scores for Anger, Positive Emotion, Sadness, Anxiety, Insight, Discrepancy, Tentativeness, Causality, Certainty, and Inhibition terms.

Figure 6 stitches together the Granger causality in Table 11.

There are a number of things to be learned from this model. First, positive emotion terms and sadness terms do not matter on a day-by-day basis. In contrast, anxiety and anger terms drive the model the most. Anger causes five other variables to change. Anxiety causes four other variables to change. I interpret this to mean that the tone of the discussion has a longer-term impact. The lag chosen by the VAR procedure was two lags, or two days of tweets. This matches with a reading of the tweets that express frustration with SOPA.

Four types of terms had the most causes: inhibition, insight, discrepancy, and tentativeness terms. Three variables are also interlinked to each other. This is the cognitive core process within crowds of people which is similar to the model proposed in the body of this paper.

Relationships with Opposite Signs in the Two Lags

The optimal number of lags found by the VAR when splitting the body of tweets by date was two. Executing the VAR using LIWC scores of the tweets by day, the following variables were found to be not stationary: positive emotion, anxiety, anger, sadness, causality, certainty and inhibition. So any of these results may be spurious. After running the Granger causality test, the following relationships were found to have different signs for the two lags:

- Insight ~ Discrepancy_lag1 – Discrepancy_lag2
- Discrepancy ~ Insight_lag1 + insight_lag2

- Discrepancy ~ Inhibition_lag1 – Inhibition_lag2
- Causality ~ Anxiety_lag1 – Anxiety_lag2
- Inhibition ~ -Inhibition_lag1 + Inhibiton_lag2.

Sensitivity Analysis Conclusions

Based on the sensitivity analysis, I determined that 4,000 tweets per file was the optimal size. The file size of 4,000 was selected because it was generated time series that maximized power of the VAR and minimized the number of lags for interpretability. The location of the file split did not matter, based on the bootstrap analysis. The individual tweet analysis and the by date analysis did not provide insight into the relationships.

APPENDIX III – ESTIMATION OF VECTOR AUTOREGRESSION PARAMETERS

The following are the vector autoregression results using the CISPA tweets with control variables for the exogenous shock of the blackout and the experience with SOPA. Tables 12-21 provide the estimates from the VAR.

Table 12: Estimation Results for Equation Positive Affect

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.02574	0.02574	34.5	< 2e-16	***
Anxiety	0.23026	0.23026	0.302	0.76281	
Anger	0.05012	0.05012	-1.233	0.21833	
Sadness	0.10771	0.10771	0.094	0.92496	
Insight	0.08538	0.08538	2.194	0.02897	*
Discrepancy	0.09247	0.09247	3.025	0.00269	**
Tentativeness	0.09483	0.09483	-2.416	0.01625	*
Causal	0.07687	0.07687	-0.516	0.60637	
Certainty	0.06508	0.06508	-1.171	0.24241	
Inhibition	0.05394	0.05394	-0.643	0.52095	
Constant	0.16076	0.16076	1.638	0.10243	

Significance codes: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’

Residual standard error: 0.422 on 327 degrees of freedom

Multiple R-Squared: 0.8732

Adjusted R-squared: 0.8694

F-statistic: 225.3 on 10 and 327 DF, p-value: < 2.2e-16

Table 13: Estimation Results for Equation Anxiety

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.000959	0.005242	0.183	0.8549	
Anxiety	0.591573	0.046896	12.615	<2e-16	***
Anger	-0.01808	0.010207	-1.771	0.0774	.
Sadness	-0.00436	0.021937	-0.199	0.8427	
Insight	-0.01101	0.017389	-0.633	0.5271	
Discrepancy	-0.00047	0.018833	-0.025	0.9801	
Tentativeness	0.014445	0.019312	0.748	0.455	
Causal	0.024467	0.015656	1.563	0.1191	
Certainty	0.006995	0.013255	0.528	0.598	
Inhibition	0.014462	0.010985	1.317	0.1889	
Constant	0.036678	0.032739	1.12	0.2634	

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.08595 on 327 degrees of freedom

Multiple R-Squared: 0.4468

Adjusted R-squared: 0.4299

F-statistic: 26.41 on 10 and 327 DF, p-value: < 2.2e-16

Table 14: Estimation Results for Equation Anger

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	-0.05906	0.01971	-2.996	0.002941	**
Anxiety	-0.08448	0.17635	-0.479	0.632212	
Anger	0.74527	0.03838	19.418	< 2e-16	***
Sadness	-0.06784	0.08249	-0.822	0.411442	
Insight	0.06508	0.06539	0.995	0.320345	
Discrepancy	-0.09284	0.07082	-1.311	0.190794	
Tentativeness	-0.02555	0.07262	-0.352	0.725166	
Causal	0.11799	0.05887	2.004	0.045872	*
Certainty	-0.01378	0.04984	-0.277	0.782302	
Inhibition	0.0512	0.04131	1.239	0.216067	
Before Blackout (Y/N)	0.41036	0.12311	3.333	0.000957	***
SOPA (Y/N)	-0.05906	0.01971	-2.996	0.002941	**

Significance codes: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’

Residual standard error: 0.3232 on 327 degrees of freedom

Multiple R-Squared: 0.6629

Adjusted R-squared: 0.6526

F-statistic: 64.31 on 10 and 327 DF, p-value: < 2.2e-16

Table 15: Estimation Results for Equation Sadness

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.013484	0.008759	1.54	0.12463	
Anxiety	0.151107	0.078359	1.928	0.05467	.
Anger	-0.01201	0.017054	-0.704	0.48172	
Sadness	0.74533	0.036654	20.334	< 2e-16	***
Insight	0.036066	0.029055	1.241	0.21538	
Discrepancy	0.000561	0.031469	0.018	0.98578	
Tentativeness	-0.00346	0.032269	-0.107	0.91457	
Causal	-0.07058	0.02616	-2.698	0.00734	**
Certainty	0.021393	0.022148	0.966	0.33479	
Inhibition	0.009073	0.018355	0.494	0.62143	
Before Blackout (Y/N)	0.033131	0.054705	0.606	0.54518	
SOPA (Y/N)	0.013484	0.008759	1.54	0.12463	

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.1436 on 327 degrees of freedom

Multiple R-Squared: 0.6283

Adjusted R-squared: 0.617

F-statistic: 55.28 on 10 and 327 DF, p-value: < 2.2e-16

Table 16: Estimation Results for Equation Insight

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.036827	0.014852	2.48	0.01365	*
Anxiety	-0.03844	0.13287	-0.289	0.77254	
Anger	-0.01015	0.028918	-0.351	0.72575	
Sadness	0.093853	0.062153	1.51	0.13201	
Insight	0.580381	0.049267	11.78	< 2e-16	***
Discrepancy	0.140464	0.05336	2.632	0.00888	**
Tentativeness	0.086432	0.054718	1.58	0.11517	
Causal	-0.02802	0.044359	-0.632	0.52808	
Certainty	0.006504	0.037555	0.173	0.8626	
Inhibition	-0.00482	0.031124	-0.155	0.87694	
Before Blackout (Y/N)	0.160702	0.092761	1.732	0.08414	.
SOPA (Y/N)	0.036827	0.014852	2.48	0.01365	*

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.2435 on 327 degrees of freedom

Multiple R-Squared: 0.6257

Adjusted R-squared: 0.6143

F-statistic: 54.67 on 10 and 327 DF, p-value: < 2.2e-16

Table 17: Estimation Results for Equation Discrepancy

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.000127	0.015425	0.008	0.99344	
Anxiety	0.216979	0.138001	1.572	0.11685	
Anger	-0.00401	0.030035	-0.134	0.89378	
Sadness	0.050023	0.064553	0.775	0.43895	
Insight	0.137028	0.051169	2.678	0.00778	**
Discrepancy	0.507767	0.05542	9.162	< 2e-16	***
Tentativeness	0.123343	0.056831	2.17	0.0307	*
Causal	0.031247	0.046072	0.678	0.49811	
Certainty	0.014494	0.039005	0.372	0.71044	
Inhibition	0.021006	0.032326	0.65	0.51626	
Before Blackout (Y/N)	0.147671	0.096343	1.533	0.1263	
SOPA (Y/N)	0.000127	0.015425	0.008	0.99344	

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.2529 on 327 degrees of freedom

Multiple R-Squared: 0.5762

Adjusted R-squared: 0.5633

F-statistic: 44.46 on 10 and 327 DF, p-value: < 2.2e-16

Table 18: Estimation Results for Equation Tentativeness

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	-0.00422	0.014343	-0.294	0.7689	
Anxiety	0.065218	0.128318	0.508	0.6116	
Anger	0.006261	0.027927	0.224	0.8227	
Sadness	0.11401	0.060024	1.899	0.0584	.
Insight	0.197114	0.047579	4.143	4.37E-05	***
Discrepancy	0.021151	0.051532	0.41	0.6817	
Tentativeness	0.648647	0.052843	12.275	< 2e-16	***
Causal	-0.00903	0.042839	-0.211	0.8331	
Certainty	0.047529	0.036268	1.31	0.1909	
Inhibition	0.056669	0.030058	1.885	0.0603	.
Before Blackout (Y/N)	0.021114	0.089583	0.236	0.8138	
SOPA (Y/N)	-0.00422	0.014343	-0.294	0.7689	

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.2352 on 327 degrees of freedom

Multiple R-Squared: 0.7004

Adjusted R-squared: 0.6912

F-statistic: 76.44 on 10 and 327 DF, p-value: < 2.2e-16

Table 19: Estimation Results for Equation Causal

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.04732	0.01624	2.914	0.00382	**
Anxiety	0.30743	0.14529	2.116	0.0351	*
Anger	0.05147	0.03162	1.628	0.10452	
Sadness	-0.01166	0.06796	-0.172	0.86388	
Insight	-0.04976	0.05387	-0.924	0.35628	
Discrepancy	0.03784	0.05835	0.648	0.51713	
Tentativeness	0.12323	0.05983	2.06	0.04022	*
Causal	0.55587	0.0485	11.46	< 2e-16	***
Certainty	-0.03476	0.04106	-0.847	0.39786	
Inhibition	-0.04602	0.03403	-1.352	0.17718	
Before Blackout (Y/N)	0.23707	0.10143	2.337	0.02003	*
SOPA (Y/N)	0.04732	0.01624	2.914	0.00382	**

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.2663 on 327 degrees of freedom

Multiple R-Squared: 0.5083

Adjusted R-squared: 0.4933

F-statistic: 33.81 on 10 and 327 DF, p-value: < 2.2e-16

Table 20: Estimation Results for Equation Certainty

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	-0.00245	0.01549	-0.158	0.875	
Anxiety	0.124597	0.138585	0.899	0.369	
Anger	0.026414	0.030162	0.876	0.382	
Sadness	0.046924	0.064827	0.724	0.47	
Insight	0.003456	0.051386	0.067	0.946	
Discrepancy	0.048863	0.055655	0.878	0.381	
Tentativeness	0.092172	0.057071	1.615	0.107	
Causal	-0.01337	0.046267	-0.289	0.773	
Certainty	0.689343	0.03917	17.599	<2e-16	***
Inhibition	-0.00564	0.032463	-0.174	0.862	
Before Blackout (Y/N)	0.029542	0.096751	0.305	0.76	
SOPA (Y/N)	-0.00245	0.01549	-0.158	0.875	

Significance codes: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’

Residual standard error: 0.254 on 327 degrees of freedom

Multiple R-Squared: 0.5847

Adjusted R-squared: 0.683

F-statistic: 46.05 on 10 and 327 DF, p-value: < 2.2e-16

Table 21: Estimation Results for Equation Inhibition

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	-0.03796	0.019838	-1.913	0.05658	.
Anxiety	0.099614	0.177483	0.561	0.575	
Anger	0.017407	0.038628	0.451	0.65256	
Sadness	0.041713	0.083022	0.502	0.6157	
Insight	0.028778	0.065809	0.437	0.66219	
Discrepancy	0.023054	0.071276	0.323	0.74656	
Tentativeness	0.041844	0.07309	0.572	0.56738	
Causal	0.003393	0.059253	0.057	0.95437	
Certainty	-0.01116	0.050164	-0.223	0.82403	
Inhibition	0.679778	0.041574	16.351	< 2e-16	***
Before Blackout (Y/N)	0.369445	0.123906	2.982	0.00308	**
SOPA (Y/N)	-0.03796	0.019838	-1.913	0.05658	.

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.3253 on 327 degrees of freedom

Multiple R-Squared: 0.5186

Adjusted R-squared: 0.5038

F-statistic: 35.22 on 10 and 327 DF, p-value: < 2.2e-16

COMMUNICATION OF A SPIN-OFF SOCIAL MOVEMENT OVER TIME: THE SPIN-OFF AROUSAL, INTERPRETATION, AND REALIZATION MODEL

ABSTRACT

The Arousal, Interpretation, and Realization (AIR) model posited that communication in online social movements follows a three stage sequence. The first stage, arousal, is characterized by the use of affective words. The second stage, interpretation, is characterized by the use of words that reflect sensemaking. Finally, the third stage, realization, is marked by the use of words that reflect comprehension. This paper considers how the AIR model unfolds differently in a initiator movement versus a spin-off social movement that addresses similar issues. Two types of disparaties are considered: differences in the levels of different affective and cognitive processes in the two movements, and differences in the causal relationships among these processes. Findings indicate levels of affective and cognitive processes are dampened and spin-off movements transition through the three stages like an initiator movement.

Keywords: Emotional Contagion, LIWC, Social Movements, Social Cognition, Vector Autoregression

INTRODUCTION

The internet, electronic communication, and social media have altered individual and organizational behavior by augmenting the mode of communication between individuals, collectives, and organizations (Mosca & Della Porta, 2009). The terms 'e-movements', 'e-protest', and 'e-activism' reflect the significance of the use of the internet as a vehicle for social change (Hara & Huang, 2011). I focus my attention on online social movements, i.e., collective action that involves public actions designed to extract change from the target authorities (Tilly, 2008). In particular, I look at spin-off movements, which borrow the ideas and tactics from another movement.

Movements are not singular events in history. Initiator movements begin a new cycle of protests (Tarrow, 1983; Tarrow 1989, MacAdam, 1995). An often-used example of an initiator movement from U.S. history is the U.S. civil rights movement (Minkoff, 1997). More common than initiator movements are spin-off movements that draw inspiration, ideologies, and tactics from initiator movements (McAdam, 1995). For example, the Women's Movement followed the Civil Rights Movement. While addressing different interest groups, both movements were concerned with ensuring citizens had equal protection under the law. Such related movements share not only ideology but also repertoires of contention, i.e., sets of actions that are learned, chosen and shared among the protesters (Tilly, 1995). The Women's Movement not only modeled their organizational structure on the National Association for the Advancement of Colored People (NAACP) but also pursued similar tactics (Minkoff, 1997). Some participants of the Civil Rights Movement also joined the Women's Movement and brought along their experiences, ideologies, and knowledge. The participants, ideologies, and repertoires of action help thread together individual movements (Tarrow, 1983, Tarrow, 1989).

Statement of Problem

The objective of this paper is to understand how participants' communicative actions expressing affective and cognitive processes culminate in shared understanding within a spin-off movement. To this end, two research questions are considered. The first question is: do communicative actions expressing affect and cognitive states differ in an initiator movement and a spin-off movement? The second question is: how does the Arousal, Interpretation, and Realization (AIR) model, which describes the stages of communication, need to be modified for spin-off movements? Since an initiator movement informs the participants of a spin-off movement, participants learn how to frame the movement (Tarrow, 1994) and what courses of action might be effective (Della Porta & Diani, 1999). Therefore, knowledge of past movements changes the frequency with which they use terms expressing affective and cognitive states. The changes in language require a modification of the AIR model presented in paper 2.

State of Knowledge about Problem

Tarrow argued that social scientists should focus on related initiator and spin-off movements as opposed to isolated movements (Tarrow, 1983). One concern is that by focusing on a single social movement, researchers tend to focus on emergence of movements (McAdam, 1995). By shifting the focus to initiator and spin-off movements, new relationships between ideologically and temporally proximate movements may emerge (McAdam, 1995). Thus, Tarrow hopes to broaden the scope of research from one of simple emergence to include ongoing social processes.

Tilly noted there are five important dimensions of a collective action: interest, organization, mobilization, opportunity, and the collective action (Tilly, 1978). There are three major theories that help to explain social movements along these dimensions. *Collective Behavior Theory* suggests fear or anxiety motivates a collective response (McAdam, 1995). *Resource Mobilization Theory* de-emphasizes the social psychological perspective of grievances, focusing instead on resource availability. The participants may provide financial, material, or labor resources (McCarthy & Zald, 1977). The participant in the resource mobilization view may not feel fear or anxiety. The *Political Opportunity* theory posits three pre-requisites factors for movement emergence. The three factors are political opportunity, protest organizations, and shared perspective (McAdams, 1995, p 220). The current theories explain how social movements begin. However, researchers deferred questions about the use of language and displays of emotion within social movements (Calhoun, 2005). Furthermore, notably absent from Tilly's five dimensions of collective action are the cognitive and affective processes that permeate social movements.

In order to understand the role of cognitive and affective processes and the use of language in social movements, I developed the Arousal, Interpretation, and Realization (AIR) model using micro-level data of communication within a single online social movement in paper two. The theory described three communication stages in a social movement: arousal, interpretation, and realization. Communication among movement participants begins with use of affect terms, signifying reactions to a change in the environment. Next, the participants begin to interpret the focal environmental change. Finally, participants arrive at an understanding or realization of the meaning of that change. The AIR model surfaces dynamics of affective and cognitive expression within an online social movement. The AIR model was grounded in a study of an online initiator movement. Specifically, I studied the Twitter messages of the Stop Online Piracy Act (SOPA).

What We Do Not Know

Past research of emotion focused on a narrow range of affective events, e.g. the sudden outpouring of emotion of a crowd (Aminzade & Mcadam, 2002). Collective behavior has looked at some dimensions of negative affect as causes of social movements. Historically, affect has been equated with irrational behavior (Aminzade & Mcadam, 2002). However, researchers are beginning to unravel the role of affect in sustaining a movement. For example, grief helped sustain the AIDS movement within the gay community (Gould, 2009). The AIR model added to this literature by describing the interplay between affective and cognitive processes of initiator movements. There has been no previous study of the role of both affective and cognitive processes in a spin-off movement. This paper furthers this line of research by investigating the affective and cognitive processes in spin-off movements and proposes a spin-off AIR model.

Contributions to Theory

This paper contributes to existing theory in two ways. First, this paper will empirically test the differences of affective and cognitive processes in an initiator and spin-off movement as reflected in language usage. Second, this paper will shed light on the relationships between affective and cognitive processes that undergird a spin-off movement. To this end, the AIR model will be modified to incorporate the differences in affective and cognitive processes.

The paper is organized as follows. In the following section, I describe the initiator and spin-off movements studied. Next, I briefly review the AIR model and prior literature on initiator and spin-off movements. I then develop two sets of hypotheses– the first concerning language differences between an originating movement and a spin-off movement and the second considering the relevance of the relationships proposed in the AIR model to spin-off movements. Following a description of the methods, results of simple hypothesis testing and a vector autoregression model are presented. Finally, conceptual and practical implications of these results are considered.

INITIATOR AND SPIN-OFF SOCIAL MOVEMENTS

McAdam (1995) offered four observations regarding the evolution of social movements. First, movements are not distinct entities with clear boundaries like an organization. Rather, the membership in a movement is fluid as participants come and go. Second, movements are tied to a broader 'family of movements.' Third, researchers should attempt to explain these 'families of movements' or 'cycles of protest' as a whole, rather than zeroing in on a single social movement. Finally, McAdam states, "most social movements are caused by other social movements and the tactical, organizational, and ideological tools they afford later struggles" (McAdam, 1995, p 218).

An *initiator* social movement begins a new and identifiable cycle of protest (McAdam, 1995). In Tarrow's terms, 'early risers' are protesters who initiate actions to take advantage of political opportunities (Tarrow 1991). The majority of social movements, however, are *spin-off* movements. Initiator social movements help motivate spin-off movements. Spin-off movements borrow their ideologies, tactics (McAdam, 1995), and knowledge from earlier movements (Minkoff, 1997). Collective action frames bound the ideologies. Collective action frames help define the identity of the participants, identity of the opponents, and the grievances of the group (Tarrow, 1994). Movement participants rely on shared trust to coordinate their actions. The shared trust is dependent on a shared understanding of the collective action frames that help to justify their actions (Tarrow, 1998). Frames provide meaning and ideologies to justify further action (Tarrow, 1998). Frames help to give meaning and shared ideologies since the frames help to give social movements a 'common pattern of perception, interpretation and a sense of direction in action" (Cheta, 2004, p 207). For example, in the 1960's, the 'equal rights' of the Civil Rights Movement became the master frame that helped propel the women's rights movement (Snow & Benford, 1992; Minkoff, 1997).

Spin-off movements employ past knowledge to adapt the tactical repertoire of an initiator movement. Tactical repertoires are a ‘limited set of routines that are learned, shared, and acted out through a relatively deliberate process of choice’ (Tilly, 1995, p.26). The repertoires include how the collective chooses its means of reporting information, choosing master frames, and ways of protest (Tilly, 1995). For example, the women’s rights movement created organizations that could lobby on behalf of women in the same way as the NAACP. Coalitions like National Organization for Women and the National Women’s Political Caucus borrowed the organizational structures and tactics of the Civil Rights Movement (Minkoff, 1997).

SOPA AND CISPA: INITIATOR AND SPIN-OFF MOVEMENT

The focal movement phenomena for this paper are the Twitter discussions of two online movements, the movements against the Stop Online Piracy Act (SOPA) and the Cyber Intelligence Sharing and Protection Act (CISPA). SOPA, Congressional bill H.R. 3261, was introduced with the objective of expanding the authority of U.S. law enforcement to protect the intellectual property rights of owners of digital work such as music, movies, and books. CISPA was congressional bill H.R. 3523, which the House of Representatives passed on April 18, 2013. The objective of the bill was to permit the U.S. government to monitor and investigate cyber threats against the government and private entities.

With SOPA, the executives of entertainment companies sought to staunch the flow of lost profits due to illegal downloads. The anti-SOPA protesters leveraged their knowledge of internet technology. They used Twitter as one means of communication to share information and help coordinate their activities. Protesters coordinated an online protest in the form of an internet blackout. The internet blackout included tactics such as altering their website to dark colors, redirecting their page to other webpages inviting others to participate, or restricting normal services. The blackout occurred on 18 January 2012.

The CISPA bill was introduced on 30 November 2011; about 1 month after the SOPA bill was introduced in the House. The bill would have allowed the U.S. government and private corporations to share internet traffic with the purpose of protecting the country's information network from cyber-attacks. The House passed the legislation on 26 April 2012, a few months after the SOPA internet blackout. The bill was re-introduced on 12 February 2013 and again passed the house on 18 April 2013. Due to the legislative timeline, the SOPA protest occurred first. Thus, though the introduction of the bills was separated by barely a month, CISPA protests did not culminate in an online internet blackout until 22 April 2013 – over 1 year after the SOPA blackout.

Table 1: Chronology of CISPA

Date	Event
30 Nov 2011	Legislation introduced in the House of Representatives: H.R. 3523
26 Apr 2012	Legislation passed in the House of Representatives
12 Feb 2013	Legislation re-introduced in the House of Representatives: H.R. 624
18 Apr 2013	Legislation passed in the House of Representatives
22 Apr 2013	Internet Blackout Day initiated by Anonymous, the activist group
22 Apr 2013	Senate refuses to vote

The SOPA and CISPA movements can be considered initiator and spin-off movements respectively. Note that the Anti-Counterfeiting Trade Agreement (ACTA) in Europe also drew its inspiration from the SOPA blackout. Polish websites borrowed the online protest tactics from the SOPA movement. Polish websites altered their websites to display a statement against ACTA. I focus on the CISPA movement for two major reasons. First, the SOPA and CISPA movements used Twitter in the same language. Using data in the same language controls for any variability due to translation issues. Second, the ACTA was a multinational treaty and protesters reacted differently by nation. Polish protesters used the alteration of websites like the SOPA blackout. Polish politicians donned Guy Fawkes masks in parliament to express disapproval. In Sweden, people signed up for a Facebook event and protested in cities across the country. In other words, the target of the ire of the protesters was towards treaty signatories' authorities within their respective countries and not necessarily against the legislators or authors of the agreement. On the other hand, SOPA and CISPA were being considered within one nation and by one legislative body.

One component of the SOPA movement was the unprecedented online opposition to the legislative bill. Amy Goodman from *The Guardian* described the blackout as "the largest online protest in the history of the internet" (Goodman, 2012). The New York Times described the protest as a "political coming of age" (Wortham, 2012). Some CISPA movement participants also participated in the SOPA movement and borrowed ideas and tactics. For example, the Electronic Frontier Foundation, Center for Democracy and Technology, Demand Progress, Entertainment Consumers Association, Freepress.org, and the Mozilla foundation were all against both SOPA and CISPA. However, the CISPA movement was not as popular as the SOPA movement as some large companies supported CISPA who were against SOPA. Notably, Facebook and Microsoft supported CISPA.

The Stop Online Piracy Act (SOPA) act shared four characteristics with the CISPA movement. First, both legislative bills were perceived as threatening digital privacy rights. Second, both bills were vigorously debated in the media and online forums and were met with resistance from members of the online community. Third, both social movements used an internet blackout as a means of protest. Finally, movement participants overlapped as some individuals and organizations participated in both protests. I consider the CISPA movement as a spin-off movement because of these shared elements.

The CISPA and SOPA movement participants shared communication modes, i.e., social media, and shared protest tactics such as the online blackout. I focus specifically on communication via Twitter[2]. While the protesters may have used other types of social media or used their own webpages to communicate with others, the study of twitter messages gives us unparalleled access to real time discussions. Twitter allows people to engage in public conversation that is organized by hashtags, which represents a single topic. In other words, the conversation is public and anyone can read the discussion and participate. Other forms of internet communication are not as open. For example, individuals organize discussions on Facebook that are displayed on their personal page. There may be multiple conversations about the same topic on different users' Facebook pages. The discussion threads on Facebook are not connected by topic. In contrast, Twitter allows massive numbers of participants to discuss a topic at the same time.

During the SOPA movement, owners of websites altered their homepage so that visitors were aware of the protest. Wikipedia disabled their website. The Mozilla Foundation blacked out their page and included links to instructions of how to contact congressional representatives. Creative Commons used a black banner across the top of their page and encouraged people to sign a petition. The participants of the CISPA movement reused these tactics; on 22 April 2013, opponents of CISPA blacked out their sites.

[2] Twitter is an online social media platform that allows participants to broadcast messages of 140 characters. The platform is accessible by personal computer, mobile tablets and smartphones. Participants include hashtags within the message to enable the messages to be searched. A hashtag is identified by a leading pound (#) sign. The hashtag for the CISPA movement was '#CISPA'.

THE AIR MODEL

Affective and Cognitive Processes

The AIR model uses four affective and six cognitive processes organized into stages of discourse in analyzing online movements. The four affective processes occur in the arousal stage and are positive affect, anger, anxiety, and sadness. Positive affect broadens an individual's thought-action repertoire (Fredrickson, 1998). Anger is a reaction to a violation of an individual's autonomy (Fischer & Roseman, 2007). Anxiety is a feeling of unease or tension (Mcnair & Lorr, 1964; Bollen et al., 2011). Sadness is an appraisal of low control or low power (McNair & Lorr, 1964).

The six cognitive processes occuring in the interpretation and realization stages include insight, discrepancy, causality, inhibition, and tentativeness. Insight is the production of useful ideas and is related to creativity (Amabile et al., 1996). Discrepancy is the processing of pieces of information that are incongruent with one's schema (Kuhn, 1970). Causality is the theoretical rational for the relationship between two concepts (Mumby & Putnam, 1992). Inhibition is a priming process that makes other cognitive processes or affect less salient (Bodenhausen & Macrae, 2013). Tentativeness is a mental state that reflects openness to new ideas (Laursen & Salter, 2006). Certainty is a lack of vigilance to potential problems or confidence (Kuvaas & Kaufmann, 2004).

Initiator Movement and the AIR Model

The AIR model identified three stages of episodic cycles of individuals' expression during protest communication: arousal, interpretation, and realization. At some time period, *T*, expressions of arousal occur. In the following period, $T + 1$, expressions of interpretation occur. In the period $T + 2$, expression of realization occur. Note that within a time period, all stages of expressions occur; however, the stages are from a different cycle. Table 2 illustrates the overlapping pattern of the AIR model.

Table 2: Overlapping Structure of AIR Model

Cycle	Time 1	Time 2	Time 3	Time 4	Time 5
A	Arousal Cycle A	Interpretation Cycle A	Realization Cycle A		
B		Arousal Cycle B	Interpretation Cycle B	Realization Cycle B	
C			Arousal Cycle C	Interpretation Cycle C	Realization Cycle C

RESEARCH MODEL

There are three aspects needed to determine if a spin-off movement conforms to the stages of the AIR Model. First, any differences in the frequency of text reflecting affective and cognitive processes are investigated. Next, the spin-off movement is tested against the propositions of the AIR Model; i.e., the relationship between psychological constructs that occur within or between stages are verified or rejected.

Hypotheses

The academic literature on spin-off movements suggests the following hypotheses. Participants in a spin-off movement will have a higher expectation of desired outcomes than participants in the initial movement, i.e., their sense of self-efficacy in the movement will be higher. The participants in a spin-off movement will benefit from the establishment of master frames (McAdam, 1995). This master frame provides a rationale for their beliefs, which engenders feelings of self-efficacy. Master frames span across multiple movements and contribute to the tactical repertoire of a social movement (Snow & Benford, 1992). Master frames appeal to a higher principle and are not tied to a specific movement. Master frames include injustice frames, rights frames, and environmental justice frames (Benford & Snow, 2000). Participants in a spin-off movement use frames to not only view their current situation but also as a reference point to evaluate the initiator movement. Understanding what worked and what did not work in the past gives the participants a greater feeling of self-efficacy.

Further, spin-off movements often use the same established lines of communication and organization (McAdam, 1995). Finally, the participants of a spin-off movement experience less repression (Meyer, 2004) or as McAdam describes as "cognitive liberation" (McAdam, 1995; p. 224). The process of cognitive liberation is the development of a shared understanding that helps to support collective action (McAdam, 2013). The lines of communication and organization provide a shared understanding of the collective efficacy (McAdam, 2013)

The experience of more self-efficacy and less repression leads to positive affect, as the protesters are less anxious about their situation. Prior research demonstrated the positive association between self-efficacy and positive affect (e.g., George & Brief 1996). Thus, participants are expected to manifest greater positive affect – specifically optimism – when participating in a spin-off than the participants in the initiator movement will.

Hypothesis 1: The participants in the spin-off movement will express more positive affect than participants in the initiator movement.

Self-efficacy is a person's perception of their own efficacy to control dangerous aspects of one's environment (Bandura, 1977; Bandura, 1988). The perceived threat is not affixed to characteristics of the environment and unfolding events. Rather, self-efficacy is the perceived ability to control a potential threat (Bandura, 1988). It is a self-assessment and may or may not be a valid assessment. Potential threats will not bother individuals who believe that they can control the situation. The perceived ability to manage a potential threat increases self-efficacy and reduces anxiety.

Participants in a spin-off movement have the experience of the initiator movement and have a better understanding of how to respond to new situations tactically and strategically. Consequently, participants will experience – and therefore express – less anxiety in the spin-off movement than will participants in the initiator movement.

Hypothesis 2: The participants in the spin-off movement will express less anxiety than the participants in the initiator movement.

Anger is a reciprocal feeling that is reinforced by others (Jasper, 1998). Repeated attacks of a particular kind lose their element of surprise and acquire a veneer of normalcy. When attacks on personal rights come to be viewed as normal, visceral responses to the attacks diminish, leaving only deliberate expressions of anger. This expectation is supported by research that has found individuals to react with greater anger to unexpected experiences of injustice (Mikula et al. 1998). Thus, overall expressions of anger will be lower in a spin-off movement than in the initiator movement.

Hypothesis 3: The participants in a spin-off movement will express less anger than the participants in the initiator movement.

Sadness is an appraisal of low control or low power (McNair and Lorr 1964). Enhanced self-efficacy therefore can alleviate feelings of sadness, as the individuals perceive more control over their environment. Thus, the overall expressions of sadness in a spin-off movement will be lower than expressions of sadness in the initiator movement.

Hypothesis 4: The participants in a spin-off movement will express less sadness than the participants in the initiator movement.

In a spin-off movement, participants will be able to draw upon the initiator movement in completing the first task – i.e., understanding the problem and its origins.

In designing and activating solutions, movement participants develop and draw upon repertoires of actions, i.e., sets of tactics (Tilly & Wood, 2009). Individuals in the initiator movement may certainly draw upon tactics used by unrelated movements. However, such re-use represents a "far transfer" of knowledge and is typically viewed as a more difficult task than the transfer of knowledge across more proximate tasks (Barnett & Ceci 2002). Such transfer will therefore require more deliberation than will knowledge transfer across more proximate movements as participants make sense of how earlier tactics may be repurposed. Therefore, cognitive processes in a spin-off movement will be abbreviated and accelerated compared to cognitive processes in an initiator movement.

As cognitive processes are abridged, opportunities for "aha" moments or insight diminish. In spin-off movements, insight will therefore be less evident than in the initial movements they reference.

> *Hypothesis 5:* The participants in a spin-off movement will express less insight terms than the participants in the initiator movement.

Having previously fleshed out their understanding of the problem and its origins and having enacted responses to the problem, individuals in a spin-off movement will experience greater confidence in their understanding of the problem and self-efficacy in their planned response. Consequently, tentative processes will be less visible in spin-off movements than in the initial movements they reference.

Hypothesis 6: The participants in a spin-off movement will express less tentativeness terms than the participants in the initiator movement.

Referencing a previous movement is inherently a comparative activity, wherein individuals note similarities and contrasting features between the initial and the spin-off movement in order to best appropriate prior action repertoires. Use of discrepancy terms will therefore be higher in a spin-off movement relative to the initial movement.

Hypothesis 7: The participants in a spin-off movement will express more discrepancy terms than the participants in the initiator movement.

Causal and inhibition processes are concerned with the ordering of concepts. Because these will have been undertaken in the initiator movement, the spin-off movement will be able to draw upon these cognitions. The spin-off movement will not only describe the past events of the initiator movement, but also describe the sequence of events. The spin-off movement will elaborate on the description of past events by explaining the causal sequence of events. Consequently, we should see higher levels of causal terms in the spin-off movement relative to the initiator movement.

Hypothesis 8: The participants in a spin-off movement will express more causal terms than the participants in the initiator movement.

Individuals in an initiator movement will experience a level of tentativeness as they undertake sensemaking of their situation and determine the appropriate tactics. In drawing upon the experience from the initiator movement, individuals in the spin-off movement will be able to bypass the tentativeness that accompanies such sensemaking.

With the benefit of experience, individuals in a spin-off movement will attain – and therefore express – a sense of certainty sooner than will individuals in the initiator movement.

Hypothesis 9: The participants in a spin-off movement will express more certainty terms than the participants in the initiator movement.

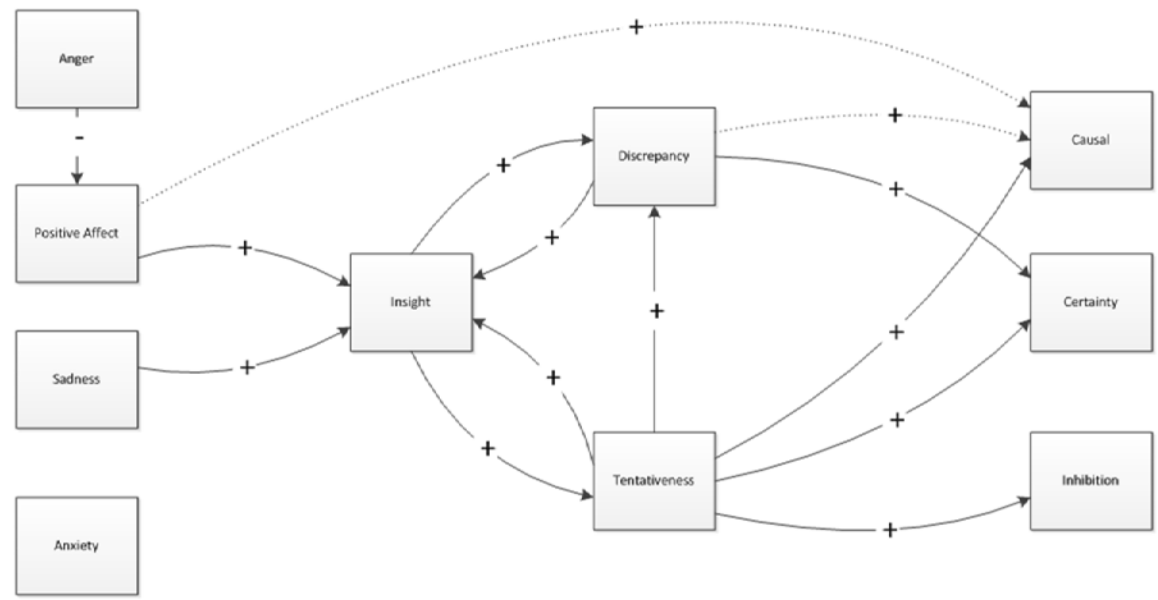
Inhibition is a priming process that renders some constructs less relevant (Macrae & Bodenhausen, 2000). Participants in an initiator movement are open to any and all ideas; they have no preconceived notions. On the other hand, participants in a spin-off movement who experienced prior successful movements will perceive some constructs as beneficial and some constructs detrimental. The participants may be inhibited from using a construct in a spin-off movement because of negative perceptions or negative past experiences.

Hypothesis 10: The participants in a spin-off movement will express less inhibition terms than the participants in the initiator movement.

AIR Model Hypotheses and Spin-off AIR Model Hypotheses

The AIR model described the relationships among affective and cognitive processes. In the previous section, we hypothesized ways in which a spin-off movement manifests different levels of affective and cognitive processes than in the initiator movement. Generally speaking, I expect to see higher levels of positive affect in spin-off movements. Positive affect is the driver of the AIR model in spin-off movements.

Figure 1 presents the AIR model developed for initial movements. The dotted arrows indicate relationships expected to carry forward to spin-off movements.



- Dotted arrow indicates relationships carried forward to the Spin-off AIR model
- +/- indicates the direction of the correlation
- ++ or -- = .001
- + or - = .01

Figure 1: AIR Model

Anticipating lower levels of anxiety, anger, sadness, insight, tentativeness, and inhibition in spin-off movements relative to initiator movements, we expect many of the relationships noted in initiator movements not to exist in spin-off movements. Lower levels of negative emotion deprive spin-off movements of the arousal-based stimulus experienced by initiator movements. Spin-off movement participants' ability to draw upon the cognitions of earlier movements will also bypass insight- and tentativeness-based cognitive processes. Discursive processes that remain salient to spin-off movements include positive emotion and discrepancy, certainty, and causal cognitions. Psychometrically, the mechanism through which relationships germane to initiator movements become irrelevant to spin-off movements is that of range-restriction. Low levels of one or more variables participating in a relationship constrain the variance when the measurement scale has a fixed lower bound (as does LIWC data). A consequence of the variance-restriction accompanying such range-restriction is that observable relationships between two variables are weakened (Bobko, 2001). I now discuss the three relationships not involving variables for which lower mean levels and restricted ranges are anticipated. Two of these relationships are carried over from the Initiator AIR model and one more is developed specifically for the spin-off AIR model.

Positive affect helps people be more open to new ideas and their surroundings. Causal process reflects analytical thinking, which is characterized by developing an understanding of the relationship between objects or ideas (Pennebaker 2011). Positive affect also leads to an expansion of focus (Fredrickson, 1998) and helps improved problem-solving skills (Estrada et al., 1994; Isen & Means, 1983). The increase in analytical thinking, expanded focus and improved problem solving skills will lead to a deeper understanding of the relationship between things. In other words, positive affect will cause an increase in causal cognitive processes.

> *Hypothesis 11:* Between arousal and realization stages, expressions of positive affect will cause an increase in indicators of causal cognitive processes.

Participants activate discrepancy processes when an observation or new learning cannot be incorporated easily into their cognitive schema (Sujan & Bettman, 1989). As the participants discuss the new observation, they begin to collaborate on how to incorporate the observation into their schema. Individuals who have thoughtfully placed new observations into their schema will have increased confidence in their schema (Schwenk, 1984). Further, individuals evaluate ideas based on the completeness of information (Yates et al., 1978). Any discrepancy increases uncertainty, which motivates individuals to seek out new information (Kanazawa, 1992). As the participants incorporate more information into a coherent schema, the participants will understand the cause and effect and use more causal terms.

> *Hypothesis 12:* Between interpretation and realization stages, an increase in discrepancy cognitive processes will cause an increase in causal cognitive processes.

Positive affect will increase expressions of discrepancy cognitive processes. Discrepancy processes are a form of logical thinking to put concepts in relation to each other (Stangor & McMillan 1992). Positive affect helps to ‘enlarge the cognitive context' (Fredrickson, 1998, p. 10). Individuals who experience positive affect will generate more categories when focusing on differences than individuals in other affect states (Murray, Sujan, Hirt, & Sujan, 1990). Participants aware of the initiator movement and the spin-off movement may increase expressions of discrepancy.

Hypothesis 13: Between arousal and interpretation stages, expressions of positive affect will cause an increase in expressions of discrepancy cognitive processes.

METHODS

The Twitter messages of the SOPA and CISPA movement were analyzed using text analysis software. The time series of text analysis scores were analyzed using t-tests and vector autoregression (VAR). A description of the data collection effort and analysis is described next.

Data

Twitter is a micro-blog website where registered users broadcast messages, commonly referred to as tweets, on the internet that are a maximum of 140 characters in length. Both the SOPA and CISPA movements used Twitter to broadcast information to the community. Twitter is a good source of conversational data because all interested parties are speaking in the same public space, there are many people, and the conversation is recorded verbatim electronically. Anyone can broadcast a tweet to the entire community. Interested parties who are listening to the conversation need only to search for the appropriate hashtag and do not need to navigate to the webpages of individuals to get information. Instead, the tweets reflect the ebb and flow of the conversation of the movement.

CISPA Tweets – Tweets from 19 April 2013 to 29 April 2013 containing the hashtag '#CISPA' were obtained, resulting in a dataset of 101,132 tweets. In order to capture the Tweets, I used a commercial vendor, Tweet Archivist. I provided the hashtags and they collected all tweets with that hashtag. Table 3 lists the number of tweets per day. The number of tweets increases to 17,897 on the day of the blackout (22 April 2013) and then decreases.

Table 3: Number of Tweets per Day

Date	Number of Tweets
4/19/2013	4,927
4/20/2013	9,998
4/21/2013	16,410
4/22/2013	17,897
4/23/2013	17,194
4/24/2013	10,665
4/25/2013	10,375
4/26/2013	7,905
4/27/2013	2,796
4/28/2013	1,913
4/29/2013	1,052
Total	101,132

SOPA Tweets – I used two sources for the SOPA Twitter data. The first set of data contains Twitter messages dated 12/09/11 to 1/14/12 with the hashtag "#SOPA". I obtained the data from Public Knowledge, a Washington, D.C. non-profit public interest group. This organization is involved in protection of intellectual property rights and the digital marketplace. In its mission statement, they state their work "preserves the openness of the Internet and the public's access to knowledge; promotes creativity through balanced copyright; and upholds and protects the rights of consumers to use innovative technology lawfully." The tweets from 1/15/12 to 1/18/12 came from the website www.r-shief.org. R-Shief collects social media data and offers software tools to promote crowd-sourced research. R-Shief, like Public Knowledge, is also a non-profit organization.

Each organization collected the tweets for their own reasons and in order to get the range of tweets from 12/09/11 to 1/18/12, I needed to piece together the data set. The Public Knowledge data set contained the oldest tweets as well as tweets over a longer period so I used all of the Public Knowledge tweets and augmented the remaining days of tweets from R-Shief. I used the time stamp in the tweets to splice the files together to ensure that there were no inconsistencies and no overlap. The combined data set contained all the tweets from 12/9/11 to 1/18/12. January 18 was the day of the internet blackout, the culmination of the SOPA protest. There were over 1.3 million tweets.

CONTROL VARIABLES

I include two indicator variables in the statistical analysis as a control for possible exogenous effects. The first variable controls for the CISPA internet blackout. The second variable controls for experience with the SOPA movement, the initiator movement.

The dates of the collected tweets from the CISPA movement spanned the internet blackout and end after the U.S. Senate signaled that they would not vote on the bill. The blackout, as a high visibility protest event, was a major topic of conversation of the protesters. However, the nature of the discussion may have been different before and after the blackout. The discussions about the blackout before the blackout focused on future expectations while discussions after the blackout focused on past events. Before the blackout, the nature of the future events may have been uncertain and the discussion may have been speculative; after the blackout, the events were known and the discussions may have been interpretive.

An indicator variable was added to the VAR model that coded dates on or after the blackout date with a '1'. If the corresponding LIWC scores were calculated using tweets before the blackout, then the variable was coded with a '0'. A time series of the indicator variable was constructed and included in the VAR. The indicator variable is used to determine if there has been a sudden shift, up or down, in the time series. A sudden shift captures a change in the structure of the model. In other words, the conversation topic may have changed.

Controlling for Past Experience with SOPA

I controlled for the reference to the prior SOPA movement because many of the participants of the CISPA protest were aware of, or experienced success during the SOPA protest. Specifically, I control for the re-use of the internet blackout, a public movement and show of numbers against the proposed legislation. Webmasters placed movement pages on the homepages of their websites announcing to their web audience their position against bill. The participants hoped to demonstrate a show of force by blacking out a large number of internet sites so that internet users would repeatedly reach sites that were participating in the movement. This shared experience of the SOPA internet blackout within the memories of the CISPA protesters may have influenced how they thought and communicated with each other. Some of the protesters of the CISPA movement were clearly aware of the SOPA movement as evidenced by direct reference to the SOPA internet blackout contained within the tweets.

These individuals had experience with a past successful movement and had expectations of how the events would unfold. Tilly refers to these recycled forms of tactics as 'repertoires of action' (Tilly, 1995). The shared knowledge of past experiences includes an inventory of tactics to oppose or push for claims (McAdam, 1995). The CISPA participants used the past experiences of the blackout to frame the issue, garner support and employ tactics to protest against the CISPA legislative bill. This shared understanding of a movement's repertoires of action may have had an effect on the discourse during the CISPA movement.

The tweets were coded with a '1' in an indicator variable if the term 'SOPA' was contained in a tweet. The analytical objective was to untangle the communication of the CISPA movement and communications about past repertoires of actions.

Analytical Methods

The tweets of the CISPA data were parsed into files with a fixed number of tweets. The number of tweets per file was chosen to maximize the power of VAR and to minimize the number of lags. The lag length was one in both cases. The parsing method is the same as used in paper 2. The file size for the CISPA data was 200 tweets per file. The file size for the SOPA data was 4000 tweets per file. The file sizes are different due to the number of tweets collected. There were 10 times as many SOPA tweets collected compared to CISPA tweets. Since the number of tweets per file was sufficiently large to yield acceptable statistical power, the rule to choose the file size was identical in the two cases and there should be no consequences to the statistical tests[3]. Next, I analyzed each file using Linguistic Inquiry Word Count (LIWC), which compares the words in the tweets to words in its dictionary. I concatenated the LIWC scores in chronological order to create a time series for each affective and cognitive mechanism, resulting in 10 time-series variables.

The first ten hypotheses were tested using t-tests for equality of means of the LIWC scores for each affective and cognitive mechanism in the SOPA and CISPA movement. Due to the different number of tweets per file between CISPA and SOPA, I

[3] Appendix IV contains the power analysis of the Granger Causality tests conducted using the CISPA DATA

used Welch's t-test for equality of means, which adjusts for the inequality of variances. In general, Welch's t-test is the preferred alternative to the Student's t-test and the Mann-Whitney U test when faced with inequality of variances (Ruxton, 2006).

The 10 time series of LIWC scores for the affective and cognitive mechanisms involved in hypotheses 11-14 were fitted to a vector autoregression (VAR) that includes one lag of each variable. Next, I performed Granger causality test to determine the statistically significant causal relationships, which facilitates statistical tests of hypotheses 11-14.

ANALYSIS AND FINDINGS

Spin-off Movement Hypotheses Results – Hypotheses 1-10

Table 4 presents the mean, standard deviations, and standard errors of LIWC scores for the SOPA and CISPA movements. The LIWC score are percentages, where a score of 2.891 means 2.891 percent of the total words in a corpus were"positive affect" words from the dictionary.

Hypotheses 1 through 4 pertain to the affective mechanisms in the arousal stage. Hypothesis 1 posited there would be more expression of positive affect in the spin-off movement than in the initiator movement. This hypothesis is not supported; the difference in means indicated that there was less expression of positive affect in the spin-off movement. Hypothesis 2 is not supported. The CISPA movement exhibited statistically significantly more anxiety than did the SOPA movement. Hypothesis 3 is not supported; the t-statistic is not significant. Hypothesis 4 posited that there would be less expression of sadness in the spin-off movement than the initiator movement. This hypothesis is also supported by the t-test.

Table 4 – Descriptive Statistics

	Arousal Stage				Interpretation Stage			Realization Stage		
	Positive affect	**Anxiety**	**Anger**	**Sadness**	**Insight**	**Tentativeness**	**Discrepancy**	**Causal**	**Certainty**	**Inhibition**
SOPA n = 339										
Mean	2.891	0.175	1.354	0.256	1.207	1.200	1.189	1.218	0.778	1.309
SD	1.116	0.114	0.548	0.232	0.392	0.424	0.385	0.374	0.388	0.461
Standard Error	0.063	0.006	0.030	0.013	0.021	0.023	0.021	0.020	0.021	0.025
CISPA n = 506										
Mean	2.146	0.240	1.403	0.148	1.136	0.953	1.083	1.249	1.019	1.242
SD	0.828	0.213	0.683	0.151	0.556	0.493	0.527	0.719	0.610	0.652
Standard Error	0.038	0.009	0.030	0.007	0.025	0.022	0.023	0.032	0.027	0.029

Hypotheses 5 through 7 pertain to the interpretation stage. Hypothesis 5 and hypothesis 6 are supported since the CISPA movement exhibited decreased insight and tentativeness terms. Hypothesis 7 is not supported because there was a significant decrease in discrepancy terms.

Hypotheses 8 through 10 pertain to the realization stage. Hypothesis 8 is not supported because the t-statistic is not statistically significant. Hypothesis 9 is supported as CISPA exhibited statistically significantly more certainty terms than the SOPA movement. Hypothesis 10 is not supported because the CISPA movement used more inhibition terms than the SOPA movement.

Although I do not accept all the hypotheses, I do see a general pattern of dampened emotion terms that are the drivers of the AIR Model. In the next section, I discuss the results from the vector autoregression as it relates to hypotheses from the AIR and spin-off AIR models.

Vector Autoregression Results: AIR and Spin-off AIR, Hypothesis 11 - 13

The VAR model was estimated and Granger causality tests were performed (Enders, 2008) for each pair of psychological constructs in the VAR model. The Granger causality test determines whether a causal link are possible between a pair of variables. Then, the causal relationships detected by the Granger causality tests were used to construct the path model depicted in Figure 2. In Figure 2, causality is represented by an arrow from one psychological construct to another. Further, each arrow contains a '+' sign indicating that all the estimated causal relationships were positive. For example, the topmost arrow in the figure indicates an increase in the use of anger terms causes an increase in the use of causal terms.

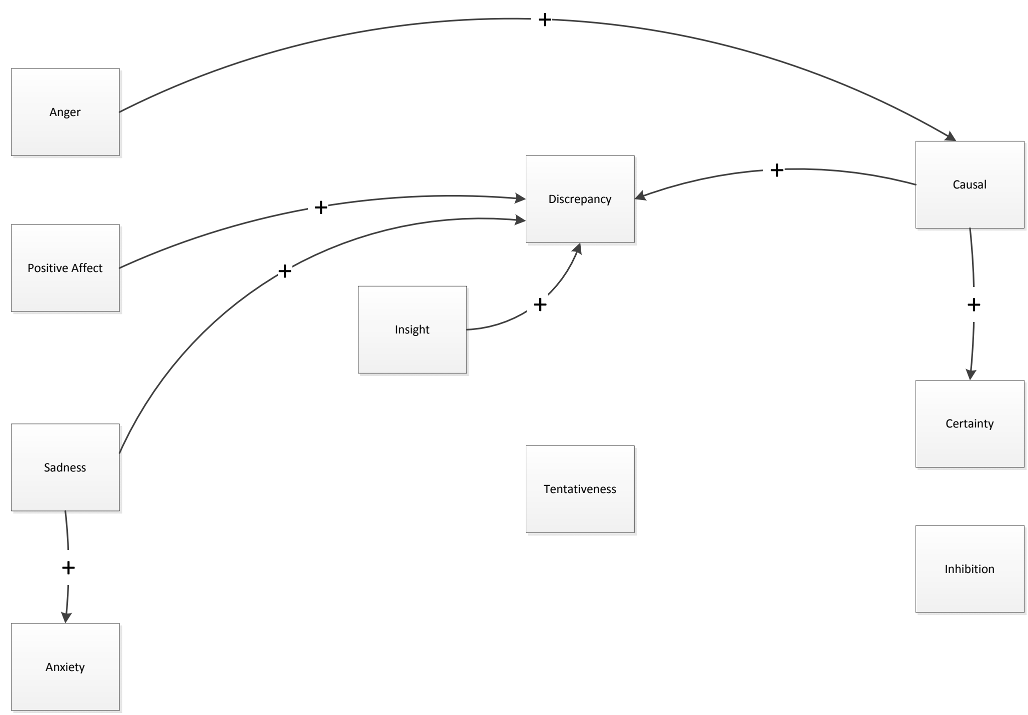


Figure 2: Path Diagram using CISPA tweets[4]

[4] The diagram was created from the Granger causality tests in the VAR using the CISPA data. The file size for the text analysis is 200 tweets per file. The plus sign indicates the direction of the relationship; there were no inverse relationships.

Table 5: Summary of Results

Number	Initiator vs Spin-off Hypotheses	Supported?
1	The participants in the spin-off movement will express more positive affect than the participants in the initiator movement.	No
2	The participants in the spin-off movement will express less anxiety than will the participants in the initiator movement.	No
3	The participants in a spin-off movement will express less anger than will the participants in the initiator movement.	No
4	The participants in a spin-off movement will express less sadness than will the participants in the initiator movement.	Yes
5	The participants in a spin-off movement will express less insight terms than will the participants in the initiator movement.	Yes
6	The participants in a spin-off movement will express less tentativeness terms than will the participants in the initiator movement.	Yes
7	The participants in a spin-off movement will express more discrepancy terms than will the participants in the initiator movement.	No

Number	Initiator vs Spin-off Hypotheses	Supported?
8	The participants in a spin-off movement will express more causal terms than will the participants in the initiator movement.	No
9	The participants in a spin-off movement will express more certainty terms than will the participants in the initiator movement.	Yes
10	The participants in a spin-off movement will express less inhibition terms than will the participants in the initiator movement.	No
	Shared AIR Hypothesis	
11	Between arousal and realization stages, expressions of positive affect will cause an increase in in indicators of causal cognitive processes.	No
12	Between interpretation and realization stages, an increase in discrepancy cognitive processes will cause an increase in causal cognitive processes.	Direction Reversed
	Spin-off AIR Hypothesis	
13	Between arousal and interpretation stages, expressions of positive affect will cause an increase in expressions of discrepancy.	Yes

Post-Hoc Analysis

The results of the Spin-off AIR hypothesis were mixed. Expressions of positive affect did not correlate with an increase in causal cognitive processes as argued in hypothesis 11. Instead of discussions of discrepancy spurring causal thinking as anticipated in hypothesis 12, higher levels of causal thinking preceded discussions of discrepancies. This finding is consistent with my earlier discussion of spin-off movements benefiting from knowledge accumulated by initiator movements. Specifically, discussions of cause-and-effect within the context of the spin-off movement likely engendered comparisons between the initiator and spin-off movement and consequently higher levels of discrepancy discursive processes. Hypothesis 13, anticipating an increase in discrepancy processes commensurate with increases in positive emotion, was supported.

The Granger causality tests also indicated five causal relationships that were not hypothesized. First, unlike initiator movements, expressions of sadness were followed by increased expressions of anxiety. Thus, while expressions of sadness in an initiator movement lead to constructive insightful thinking, sadness in a spin-off movement leads to anxiety. This suggests expressions of sadness in spin-off movements heighten defeatist sentiments. Second, expressions of sadness were followed also by increased discussions of discrepancy. Third, increases in discussions reflecting insight were followed by increased discussions of discrepancy. Together with findings regarding hypothesis 13, these two findings highlight the central role of discrepancy cognitive processes in spin-off movements. In other words, three distinct cognitive and emotional discursive processes prompted discussions of discrepancy. Fourth, discussions of causality culminated in expressions of certainty. Finally, expressions of anger were followed by an increase in casual process.

The AIR Model posits that there are three stages of communication in a social movement. I explore whether spin-off movements conform to the stages of the AIR model. In order to validate the stages, there must be evidence that the psychological constructs align themselves as predicted within each stage. The psychological constructs in the arousal stage are sadness, anger and positive affect. If the stages of the AIR model are to be confirmed, these three constructs should emerge from the vector autoregression model with no antecedents. In the final stage, realization, the psychological constructs are causality, certainty, and inhibition. These constructs should emerge from the vector autoregression model only as outcomes. Finally, the interpretation stage variables, discrepancy, insight, and tentativeness should appear as outcomes variables to arousal variables and antecedents to realization variables.

Further, the stages of the AIR model imply a communication flow beginning with arousal, passing through interpretation, and settling on realization (movement from left to right in figure 2). While I hypothesized that constructs in the arousal and interpretation would be dampened due to past-related experiences, another way to view this phenomena is that the participants are accelerating through the stages, perhaps taking different micro-level routes. Nonetheless, there should be evidence that the three stages exist and that they are traversed in sequential order.

First, the AIR model states that arousal terms lead to increased interpretation terms. Since positive affect and sadness are both antecedents to discrepancy, I find support that this progression holds in the spin-off AIR model as well.

Next, the AIR model states that the interpretation stage leads to the realization stage. While I found a relationship between the two stages in the spin-off movement, the causal direction is in the wrong order. In this case, causal terms were found to increase discrepancy. Discrepancies are concepts that diverge from an existing schema (Sujan & Bettman, 1989). The causal terms in a spin-off movement are higher. While more may be initially known by the participants, new members need an opportunity to absorb the experience of others. The new members may attempt to adopt ideas but have trouble integrating it with their current knowledge. Hence, there is an increase in discrepancy terms, which then leads the group back to the interpretation stage. This progression from realization to interpretation is in contrast with the AIR model.

I expect that in the spin-off movement arousal terms will lead to an increase in realization terms. As people observe their environment or new events, they become aroused with emotion. While some observations require interpretation to understand, others do not. Individuals rely on their own knowledge or past experience to come to quick conclusions. I also find support for this progression because I found that anger terms caused causal terms. A summary of these stage progression findings are presented in Table 6 and reflect the results of the Granger Causality tests.

Table 6: Comparison AIR Stage Progression

Stage Progression from the Initiator Movement Air Model	**Occurrence in Spin-Off Movements?**
An increase in arousal terms will lead to an increase in interpretation terms.	Yes
An increase in interpretation terms will lead to an increase in realization terms	No
An increase in arousal terms will lead to an increase in realization terms	Yes

There were three intra-stage relationships, which were discovered during the Granger causality analysis. There is one intra-stage relationship for each stage of the AIR model. These relationship reinforce the notion that the intra-stage affective and cognitive processes occur at the same time. First, an increase in sadness terms led to an increase in anxiety terms. Sadness is an appraisal of low control (McNair & Lorr, 1964) and anxiety is a state of affective unease (Fischer & Roseman, 2007). The participants of the CISPA movement may have experience a feeling of low control because many large corporations that were opposed to SOPA supported CISPA. The lack control creates a sense of unease, as the participants are unsure of their future.

Second, an increase in insight terms led to an increase in discrepancy terms. I hypothesized that there would be a dampening of insight terms in a spin-off movement and did not expect to see any relationship with insight. However, the relationship between insight terms and discrepancy terms is consistent with the findings of the initiator AIR model. Insight cognitive processes help to compare and contrast ideas by using bracketing activities that help to delineate ideas (Weick et al, 2005). Ideas that do not fit into an existing schema reflect discrepancy cognitive processes (Sujan & Bettman, 1989).

Third, an increase in causal terms led to an increase in certainty terms. Causality is the theoretical rational for how two ideas are related (Kuhn, 1970). Certainty is a lack of vigilance to potential problems (Kuvaas & Kaufmann, 2004). In other words, certainty appraisals promote heuristic cognitive processes rather than systematic ones. The participants using causal terms have formed concrete relationships between ideas. Having a causal understanding of the world deepens a feeling of understanding and is reflected by the use of more certainty words. In a spin-off movement, the collective applies quick rules of thumb to events that are similar to an imitator movement and use a more logical approach to dissimilar events.

DISCUSSION

Past research has investigated affective and cognitive processes at a macro-level. Affect was not entirely ignored in past research but was narrowly defined and did not contribute to the literature in a meaningful way (Aminzade & McAdam, 2002). Benford and Snow's (2000) theory of the framing processes in a social movement help us to understand the cognitive processes of the participants at a macro level. The framing process helps to carry beliefs and ideologies (Benford & Snow, 2000). Now, the advent of social media has opened the door into the conversations that spontaneously occur among a large number of participants. The detailed online communications can be empirically analyzed to determine the affective and cognitive processes at a more granular level. Using text analysis software, I compare the use of affective and cognitive terms across an initiator movement and a spin-off movement and found a dampening of affective and cognitive processes due to the past experiences of the group. Furthermore, the spin-off AIR model was found to echo the structure of the initiator AIR model. Past research has hinted at these ideas. This is the first study, however, to look at affective and cognitive processes in detail.

Theoretical Contributions

The AIR model was modified and tested using data from the CISPA movement, which was a spin-off movement to the SOPA movement. Hypotheses were developed to shed light on the difference in communication between participants in an initiator movement and a spin-off movement. This study makes three major contributions. First, expressions of arousal terms in the spin-off movement were found to be less than the expressions of arousal terms in the initiator movement because of experiences and expectations formed during the initiator movement.

The findings provide further evidence that spin-off movements benefit from the experience and knowledge of an initiator movement. The focal point of discussion is discrepancy processes, which indicate constant analysis of the differences between the initiator movement and the spin-off movement. As shown in figure 2, three affective processes and one cognitive process drive discrepancy cognitive processes.

Second, I found the underlying structure changed in the spin-off AIR model relative to the AIR model. In the spin-off movement only the relationships between positive affect, discrepancy, and certainty are found to be salient.

Implications for Practice

This research benefits two groups of individuals: organizers of social movements and the targets of social movements. The leaders of a spin-off movement will be able to anticipate the dampening levels of affective and cognitive levels of the participants due to knowledge of an initiator movement. The leaders may be able to alter their communication strategy to increase the level of affect or to engage the participants at a cognitive level. Targets of social movements, such as corporations or government entities, can leverage the results of this study to monitor social movements. The targets of social movements will be able to understand the strength of the movement and redress issues before the issues escalate into a public relations nightmare.

Limitations

The objective of this paper was to verify the AIR model in a spin-off movement. The AIR model was developed using an initiator movement as a foundation to describe how affective and cognitive mechanisms imbued in the discourse of a social movement unfold over time. A limitation of this study is that the size of the spin-off movement was smaller than the initiator movement, thus it remains to be seen if the same behavior would be observed in a stronger (i.e., larger) spin-off movement. Ideally, the model would be tested in a large number of social movements to determine their generalizability.

Suggestions for Future Research

This research can be extended in a number of areas. The use of vector autoregression has proven to be useful when used in conjunction with text analysis. The combination of these two techniques has given a micro-level foundation to macro-level phenomena. In other words, the analysis of text messages originating from individuals aggregated over time sheds light on how social movement may evolve. Further use of related techniques may prove to be useful.

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APPENDIX I – ESTIMATION OF VECTOR AUTOREGRESSION PARAMETERS

The following are the vector autoregression results using the CISPA tweets with control variables for the exogenous shock of the blackout and the experience with SOPA.

Table 7: Estimation Results for Equation Positive Affect

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.606	0.036	17.071	< 2e-16	***
Anxiety	-0.077	0.153	-0.500	0.617	
Anger	0.150	0.051	2.954	0.003	**
Sadness	0.299	0.221	1.354	0.176	
Insight	0.034	0.065	0.525	0.600	
Discrepancy	0.015	0.072	0.204	0.838	
Tentativeness	0.150	0.068	2.198	0.028	*
Causal	0.129	0.051	2.524	0.012	*
Certainty	0.087	0.051	1.686	0.093	.
Inhibition	0.121	0.050	2.436	0.015	*
Before Blackout (Y/N)	0.066	0.071	0.923	0.356	
SOPA (Y/N)	-0.238	0.086	-2.752	0.006	**

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.7068 on 493 degrees of freedom

Multiple R-Squared: 0.9086

Adjusted R-squared: 0.9064

F-statistic: 408.6 on 12 and 493 DF, p-value: < 2.2e-16

Table 8: Estimation Results for Equation Anxiety

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.010	0.009	1.077	0.282	
Anxiety	0.488	0.040	12.144	<2e-16	***
Anger	0.030	0.013	2.271	0.024	*
Sadness	0.142	0.058	2.451	0.015	*
Insight	-0.012	0.017	-0.681	0.496	
Discrepancy	0.008	0.019	0.418	0.676	
Tentativeness	0.030	0.018	1.667	0.096	.
Causal	0.007	0.013	0.513	0.608	
Certainty	0.003	0.013	0.188	0.851	
Inhibition	0.019	0.013	1.425	0.155	
Before Blackout (Y/N)	-0.033	0.019	-1.745	0.082	.
SOPA (Y/N)	-0.011	0.023	-0.486	0.627	

Significance codes: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’

Residual standard error: 0.1856 on 493 degrees of freedom

Multiple R-Squared: 0.6726

Adjusted R-squared: 0.6647

F-statistic: 84.42 on 12 and 493 DF, p-value: < 2.2e-16

Table 9: Estimation Results for Equation Anger

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.077	0.025	3.063	0.002	**
Anxiety	0.036	0.109	0.333	0.739	
Anger	0.568	0.036	15.695	< 2e-16	***
Sadness	-0.206	0.157	-1.312	0.190	
Insight	0.124	0.047	2.662	0.008	**
Discprepancy	0.024	0.051	0.460	0.646	
Tentativeness	0.082	0.048	1.704	0.089	.
Causal	-0.065	0.036	-1.783	0.075	.
Certainty	0.090	0.037	2.454	0.014	*
Inhibition	0.039	0.035	1.099	0.272	
Before Blackout (Y/N)	0.010	0.051	0.198	0.843	
SOPA (Y/N)	0.521	0.061	8.491	0.000	***

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.5026 on 493 degrees of freedom

Multiple R-Squared: 0.8987

Adjusted R-squared: 0.8962

F-statistic: 364.4 on 12 and 493 DF, p-value: < 2.2e-16

Table 10: Estimation Results for Equation Sadness

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.012	0.007	1.840	0.066	.
Anxiety	0.027	0.028	0.942	0.347	
Anger	0.012	0.009	1.312	0.190	
Sadness	0.480	0.041	11.761	<2e-16	***
Insight	0.017	0.012	1.378	0.169	
Discrepancy	0.015	0.013	1.147	0.252	
Tentativeness	-0.014	0.013	-1.114	0.266	
Causal	-0.006	0.009	-0.602	0.548	
Certainty	0.016	0.009	1.677	0.094	.
Inhibition	-0.004	0.009	-0.433	0.665	
Before Blackout (Y/N)	0.000	0.013	-0.018	0.986	
SOPA (Y/N)	-0.002	0.016	-0.114	0.910	

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.1305 on 493 degrees of freedom

Multiple R-Squared: 0.6282

Adjusted R-squared: 0.6192

F-statistic: 69.43 on 12 and 493 DF, p-value: < 2.2e-16

Table 11: Estimation Results for Equation Insight

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.061	0.022	2.740	0.006	**
Anxiety	0.058	0.096	0.607	0.544	
Anger	0.049	0.032	1.548	0.122	
Sadness	-0.002	0.138	-0.014	0.989	
Insight	0.597	0.041	14.550	< 2e-16	***
Discrepancy	-0.030	0.045	-0.668	0.505	
Tentativeness	0.051	0.043	1.204	0.229	
Causal	0.042	0.032	1.296	0.196	
Certainty	0.037	0.032	1.155	0.249	
Inhibition	0.055	0.031	1.766	0.078	.
Before Blackout (Y/N)	0.097	0.045	2.167	0.031	*
SOPA (Y/N)	-0.034	0.054	-0.623	0.534	

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.4431 on 493 degrees of freedom

Multiple R-Squared: 0.8803

Adjusted R-squared: 0.8774

F-statistic: 302.1 on 12 and 493 DF, p-value: < 2.2e-16

Table 12: Estimation Results for Equation Discrepancy

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.067	0.022	3.011	0.003	**
Anxiety	0.002	0.096	0.020	0.984	
Anger	0.060	0.032	1.878	0.061	.
Sadness	0.286	0.138	2.070	0.039	*
Insight	0.047	0.041	1.137	0.256	
Discrepancy	0.481	0.045	10.657	< 2e-16	***
Tentativeness	0.049	0.043	1.150	0.251	
Causal	0.091	0.032	2.826	0.005	**
Certainty	0.006	0.032	0.173	0.863	
Inhibition	0.086	0.031	2.745	0.006	**
Before Blackout (Y/N)	-0.046	0.045	-1.018	0.309	
SOPA (Y/N)	-0.059	0.054	-1.082	0.280	

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.443 on 493 degrees of freedom

Multiple R-Squared: 0.8676

Adjusted R-squared: 0.8644

F-statistic: 269.2 on 12 and 493 DF, p-value: < 2.2e-16

Table 13: Estimation Results for Equation Tentativeness

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.033	0.022	1.547	0.123	
Anxiety	0.173	0.093	1.860	0.064	.
Anger	0.073	0.031	2.354	0.019	*
Sadness	0.101	0.134	0.756	0.450	
Insight	0.056	0.040	1.398	0.163	
Discrepancy	-0.026	0.044	-0.596	0.552	
Tentativeness	0.608	0.041	14.709	<2e-16	***
Causal	0.018	0.031	0.571	0.568	
Certainty	0.046	0.031	1.480	0.140	
Inhibition	0.010	0.030	0.314	0.754	
Before Blackout (Y/N)	0.038	0.043	0.879	0.380	
SOPA (Y/N)	-0.072	0.052	-1.381	0.168	

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.4295 on 493 degrees of freedom

Multiple R-Squared: 0.8434

Adjusted R-squared: 0.8396

F-statistic: 221.3 on 12 and 493 DF, p-value: < 2.2e-16

Table 14: Estimation Results for Equation Causal

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.042	0.025	1.682	0.093	.
Anxiety	0.072	0.108	0.671	0.503	
Anger	-0.022	0.036	-0.618	0.537	
Sadness	0.185	0.156	1.192	0.234	
Insight	0.086	0.046	1.875	0.061	.
Discrepancy	0.058	0.051	1.145	0.253	
Tentativeness	0.006	0.048	0.135	0.893	
Causal	0.546	0.036	15.095	<2e-16	***
Certainty	-0.006	0.036	-0.170	0.865	
Inhibition	0.079	0.035	2.261	0.024	*
Before Blackout (Y/N)	0.098	0.050	1.950	0.052	.
SOPA (Y/N)	0.518	0.061	8.510	<2e-16	***

Significance codes: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’

Residual standard error: 0.498 on 493 degrees of freedom

Multiple R-Squared: 0.8834

Adjusted R-squared: 0.8805

F-statistic: 311.1 on 12 and 493 DF, p-value: < 2.2e-16

Table 15: Estimation Results for Equation Certainty

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.030	0.025	1.207	0.228	
Anxiety	0.100	0.107	0.941	0.347	
Anger	0.097	0.035	2.726	0.007	**
Sadness	0.222	0.154	1.443	0.150	
Insight	-0.021	0.046	-0.464	0.643	
Discrepancy	-0.032	0.050	-0.633	0.527	
Tentativeness	0.084	0.047	1.768	0.078	.
Causal	0.016	0.036	0.436	0.663	
Certainty	0.667	0.036	18.631	< 2e-16	***
Inhibition	-0.001	0.035	-0.021	0.983	
Before Blackout (Y/N)	0.070	0.050	1.403	0.161	
SOPA (Y/N)	-0.095	0.060	-1.585	0.114	

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.493 on 493 degrees of freedom

Multiple R-Squared: 0.8316

Adjusted R-squared: 0.8275

F-statistic: 202.9 on 12 and 493 DF, p-value: < 2.2e-16

Table 16: Estimation Results for Equation Inhibition

	Estimate	Std. Error	t value	Pr(>|t|)	
Positive affect	0.018	0.025	0.732	0.464	
Anxiety	0.107	0.106	1.010	0.313	
Anger	0.119	0.035	3.378	0.001	***
Sadness	-0.003	0.153	-0.020	0.984	
Insight	-0.063	0.045	-1.385	0.167	
Discrepancy	0.084	0.050	1.686	0.092	.
Tentativeness	0.012	0.047	0.247	0.805	
Causal	0.033	0.036	0.914	0.361	
Certainty	0.020	0.036	0.554	0.580	
Inhibition	0.648	0.035	18.716	< 2e-16	***
Before Blackout (Y/N)	0.200	0.050	4.033	0.000	***
SOPA (Y/N)	-0.143	0.060	-2.381	0.018	*

Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'

Residual standard error: 0.4903 on 493 degrees of freedom

Multiple R-Squared: 0.8807

Adjusted R-squared: 0.8778

F-statistic: 303.4 on 12 and 493 DF, p-value: < 2.2e-16

APPENDIX II: STATISTICAL RESULTS

Table 17: Levene's test, t-test and Power Calculation

	Levene's Test for Equality of Variances			Welch's t-test for Equality of Means						95% CI of Differences	
	F	Sig.		t	df	Sig.		Mean Diff.	Std. Error Diff.	Lower	Upper
H1: Positive affect	24.005	.15E-06	***	10.069	576.928	2.20E-16	***	-0.745	0.074	-0.890	-0.599
H2: Anxiety	45.417	.95E-11	***	5.777	808.340	1.09E-08	***	0.065	0.011	0.043	0.087
H3: Anger	10.133	.51E-03	**	1.136	816.229	2.50E-01		0.048	0.043	-0.035	0.132
H4: Sadness	8.3826	.89E-03	**	-7.549	529.302	1.93E-13	***	-0.108	0.014	-0.136	-0.080
H5: Insight	16.489	.35E-05	***	-2.177	840.718	2.98E-02	*	-0.071	0.033	-0.135	-0.007
H6: Tentativeness	0.5695	.51E-01		-7.793	792.408	2.05E-14	***	-0.248	0.032	-0.310	-0.185
H7: Discrepancy	11.903	.88E-04	***	-3.357	836.726	8.24E-04	***	-0.105	0.031	-0.167	-0.044
H8: Causal	49.579	.95E-12	***	0.827	800.349	4.08E-01		0.031	0.038	-0.043	0.106
H9: Certainty	33.567	.72E-09	***	7.029	840.889	4.32E-12	***	0.241	0.034	0.174	0.309
H10: Inhibition	21.482	.14E-06	***	-1.768	840.482	7.74E-02		-0.068	0.038	-0.143	0.007

Table 18: Correlation Table of LIWC Scores

	Positive affect	Anxiety	Anger	Sadness	Insight	Discrepancy	Tentativeness	Causality	Certainty	Inhibition
Positive affect	1.000	-0.143	0.021	0.180	0.200	0.038	-0.048	-0.032	-0.034	0.152
Anxiety	-0.143	1.000	0.031	0.067	-0.042	0.166	0.146	0.160	-0.066	-0.102
Anger	0.021	0.031	1.000	-0.016	0.160	0.116	-0.032	0.255	-0.063	-0.016
Sadness	0.180	0.067	-0.016	1.000	0.102	0.183	0.041	0.046	0.198	-0.086
Insight	0.200	-0.042	0.160	0.102	1.000	0.172	0.177	0.238	0.081	0.001
Discrepancy	0.038	0.166	0.116	0.183	0.172	1.000	0.375	0.204	0.230	0.070
Tentativeness	-0.048	0.146	-0.032	0.041	0.177	0.375	1.000	-0.045	-0.059	-0.058
Causality	-0.032	0.160	0.255	0.046	0.238	0.204	-0.045	1.000	-0.050	0.031
Certainty	-0.034	-0.066	-0.063	0.198	0.081	0.230	-0.059	-0.050	1.000	-0.130
Inhibition	0.152	-0.102	-0.016	-0.086	0.001	0.070	-0.058	0.031	-0.130	1.000

APPENDIX III - SIGNIFICANCE IN THE GRANGER CAUSALITY TEST

Table 19: Significance in the Granger Causality Test

		To									
		Positive affect	Anxiety	Anger	Sadness	Insight	Discrepancy	Tentativeness	Causality	Certainty	Inhibition
From	Positive affect	**					+				
	Anxiety		**								
	Anger			**					+		
	Sadness		+		**		+				
	Insight					**	+				
	Discrepancy						**				
	Tentativeness							**			
	Causality						+		**		
	Certainty									**	
	Inhibition										**

* significant at p < .05, ** significant at p<.01. The plus sign indicates the direction of the relationship.

APPENDIX IV – POWER ANALYSIS OF GRANGER CAUSALITY TEST

In order to confirm the power of the Granger causality test, I conducted an ex-post power analysis of the Granger causality test, an F-test of the model generated from the vector autoregression. I calculate power as a function of the significance criterion, sample size, and effect size (Cohen, 1988). I use the standard libraries from the statistical programming language R.

The standard libraries are appropriate since the model from a vector autoregression converge asymptotically to the model from a linear regression (Hamilton, 1994).

The standard library provides standard power routines for *t*-tests. The models derived from CISPA had a lag length of 1. Since there was only one regressor and one intercept term, I took the square root of the f-statistic to convert it to a t-statistic. The t-statistic was used in the power analysis.

Cohen notes that a power of 0.8 is an acceptable benchmark (Cohen, 1988). Table 21 contains the results for the ninety power analyses. Eighty-one tests have a power greater than or equal to 0.90 and seventy tests have a power of 1.0. However, nine tests have a power of less than .8. They are listed in Table 20. Note that the power of the test of the relationship from Anxiety to Sadness is at 0.79, which is barely at an acceptable level of power according to Cohen's benchmark. Thus, there may not have been enough statistical power to observe these relationships. The only relationship in Table 21 that was found in the original AIR model with low power is the relationship between Tentativeness and Certainty.

Table 20: Granger Causality Tests with Power < 0.8

Cause	Effect	F-Statistic	P-Value	t-Statistic	Power
Certainty	Anger	0.00	1.00	0.00	0.05
Anxiety	Causal	0.00	0.99	0.01	0.06
Positive Emotion	Anxiety	0.00	0.97	0.04	0.09
Anger	Insight	0.00	0.97	0.04	0.09
Positive Emotion	Anger	0.00	0.95	0.07	0.19
Anger	Tentativeness	0.01	0.94	0.07	0.22
Insight	Anger	0.01	0.91	0.12	0.47
Tentativeness	Certainty	0.02	0.90	0.12	0.51
Anxiety	Sadness	0.03	0.86	0.17	0.79

Table 21: Power Analysis of Granger Causality Test.

Cause	Effect	F-Statistic	P-Value	t-Statistic	Power
Anxiety	Positive Emotion	1.84	0.18	1.36	1.00
Anger	Positive Emotion	0.69	0.41	0.83	1.00
Sadness	Positive Emotion	1.72	0.19	1.31	1.00
Insight	Positive Emotion	3.46	0.06	1.86	1.00
Discrepancy	Positive Emotion	1.89	0.17	1.38	1.00
Tentativeness	Positive Emotion	0.30	0.58	0.55	1.00
Causal	Positive Emotion	2.38	0.12	1.54	1.00
Certainty	Positive Emotion	0.06	0.80	0.25	0.98
Inhibition	Positive Emotion	2.52	0.11	1.59	1.00
Positive Emotion	Anxiety	0.00	0.97	0.04	0.09
Anger	Anxiety	1.63	0.20	1.28	1.00
Sadness	Anxiety	5.56	0.02	2.36	1.00
Insight	Anxiety	0.60	0.44	0.77	1.00
Discrepancy	Anxiety	1.06	0.30	1.03	1.00
Tentativeness	Anxiety	0.46	0.50	0.68	1.00
Causal	Anxiety	0.06	0.81	0.24	0.97
Certainty	Anxiety	0.40	0.53	0.63	1.00
Inhibition	Anxiety	0.04	0.84	0.20	0.90
Positive Emotion	Anger	0.00	0.95	0.07	0.19
Anxiety	Anger	0.58	0.45	0.76	1.00
Sadness	Anger	1.58	0.21	1.26	1.00
Insight	Anger	0.01	0.91	0.12	0.47
Discrepancy	Anger	0.05	0.82	0.22	0.94
Tentativeness	Anger	0.17	0.68	0.41	1.00

Cause	Effect	F-Statistic	P-Value	t-Statistic	Power
Causal	Anger	0.07	0.79	0.26	0.99
Certainty	Anger	0.00	1.00	0.00	0.05
Inhibition	Anger	3.22	0.07	1.79	1.00
Positive Emotion	Sadness	1.29	0.26	1.14	1.00
Anxiety	Sadness	0.03	0.86	0.17	0.79
Anger	Sadness	1.06	0.30	1.03	1.00
Insight	Sadness	2.14	0.14	1.46	1.00
Discrepancy	Sadness	1.15	0.28	1.07	1.00
Tentativeness	Sadness	1.08	0.30	1.04	1.00
Causal	Sadness	0.05	0.82	0.23	0.96
Certainty	Sadness	2.09	0.15	1.44	1.00
Inhibition	Sadness	0.76	0.38	0.87	1.00
Positive Emotion	Insight	1.99	0.16	1.41	1.00
Anxiety	Insight	0.77	0.38	0.88	1.00
Anger	Insight	0.00	0.97	0.04	0.09
Sadness	Insight	0.05	0.82	0.22	0.95
Discrepancy	Insight	0.47	0.49	0.68	1.00
Tentativeness	Insight	0.54	0.46	0.74	1.00
Causal	Insight	0.40	0.53	0.63	1.00
Certainty	Insight	0.49	0.48	0.70	1.00
Inhibition	Insight	2.32	0.13	1.52	1.00
Positive Emotion	Discrepancy	6.43	0.01	2.54	1.00
Anxiety	Discrepancy	0.29	0.59	0.54	1.00
Anger	Discrepancy	1.90	0.17	1.38	1.00
Sadness	Discrepancy	4.83	0.03	2.20	1.00
Insight	Discrepancy	4.64	0.03	2.15	1.00
Tentativeness	Discrepancy	0.21	0.65	0.45	1.00
Causal	Discrepancy	6.08	0.01	2.46	1.00
Certainty	Discrepancy	1.48	0.22	1.21	1.00
Inhibition	Discrepancy	3.39	0.07	1.84	1.00
Positive Emotion	Tentativeness	0.32	0.57	0.56	1.00
Anxiety	Tentativeness	0.23	0.63	0.48	1.00
Anger	Tentativeness	0.01	0.94	0.07	0.22
Sadness	Tentativeness	0.42	0.52	0.65	1.00
Insight	Tentativeness	1.64	0.20	1.28	1.00
Discrepancy	Tentativeness	0.26	0.61	0.51	1.00
Causal	Tentativeness	0.17	0.68	0.41	1.00
Certainty	Tentativeness	0.19	0.66	0.44	1.00

Cause	Effect	F-Statistic	P-Value	t-Statistic	Power
Inhibition	Tentativeness	2.20	0.14	1.48	1.00
Positive Emotion	Causal	1.23	0.27	1.11	1.00
Anxiety	Causal	0.00	0.99	0.01	0.06
Anger	Causal	5.55	0.02	2.35	1.00
Sadness	Causal	0.77	0.38	0.88	1.00
Insight	Causal	0.12	0.73	0.34	1.00
Discrepancy	Causal	0.71	0.40	0.84	1.00
Tentativeness	Causal	0.20	0.66	0.44	1.00
Certainty	Causal	0.71	0.40	0.84	1.00
Inhibition	Causal	1.01	0.32	1.01	1.00
Positive Emotion	Certainty	0.33	0.57	0.57	1.00
Anxiety	Certainty	0.05	0.82	0.23	0.95
Anger	Certainty	0.06	0.80	0.25	0.98
Sadness	Certainty	1.53	0.22	1.24	1.00
Insight	Certainty	0.13	0.72	0.36	1.00
Discrepancy	Certainty	0.34	0.56	0.58	1.00
Tentativeness	Certainty	0.02	0.90	0.12	0.51
Causal	Certainty	0.66	0.42	0.81	1.00
Inhibition	Certainty	1.79	0.18	1.34	1.00
Positive Emotion	Inhibition	0.45	0.50	0.67	1.00
Anxiety	Inhibition	0.05	0.82	0.22	0.95
Anger	Inhibition	0.94	0.33	0.97	1.00
Sadness	Inhibition	0.06	0.81	0.24	0.96
Insight	Inhibition	0.15	0.70	0.38	1.00
Discrepancy	Inhibition	1.60	0.21	1.27	1.00
Tentativeness	Inhibition	0.55	0.46	0.74	1.00
Causal	Inhibition	0.38	0.54	0.61	1.00
Certainty	Inhibition	0.14	0.71	0.38	1.00

CONCLUSION

The objective of the three essays in this dissertation was to shed light on the role of affective and cognitive processes in collective action on social media. Social media allows large numbers of individuals to communicate with each other simultaneously. Text based communication on social media was examined to glean insights into the ebb and flow of discussion to understand the social dynamics in collective action. Specifically, text messages were analyzed on the Starbucks online brand community, the Twitter messages of the Stop Online Piracy Act movement, and the Twitter messages of the spin-off movement to protest the Cyber Intelligence Sharing and Protection Act.

The first essay looked at the use of influence tactics within text messages of the Starbucks brand community. The influence tactics were used to draw attention to member wants from other community members as well as from the Starbucks's employees. A moderating effect between the customers' use of language based influence tactics and the content of the message was found to generate discussion and help garner support for their new product or service idea.

The second essay examined how affective and cognitive processes evolve in a social movement based on the Twitter messages of the Stop Online Piracy Act. The examination resulted in the AIR model, which described the transition of affective and cognitive processes in three stages: arousal, interpretation, and realization. The arousal stage reflects affective processing, and the two stages, interpretation and realization, reflect the use of cognitive terms.

The third essay revisited the AIR model developed in essay two and was tested in the context of a spin-off social movement. The participants in a spin-off movement have the advantage of hindsight to accelerate through the stages of the AIR model. The AIR model in a spin-off movement reflects participants' knowledge and experience of past movements. Findings include that this knowledge and experience translates into a dampening of emotion and fewer causal relationships in the AIR model of a spin-off movement than an initiator movement.