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Infectious Ideas: Investigating Information Contagion Effects Associated with Dispositional Traits of Social Media Users and Textual Features of Posts

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Infectious Ideas: Investigating Information Contagion Effects Associated with Dispositional Traits of Social Media Users and Textual Features of Posts

A Dissertation submitted in partial satisfaction of the requirements
for the degree Doctor of Philosophy

in

Cognitive Science

by

Michael Robert Haupt

Committee in charge:

Professor Seana Coulson, Co-Chair
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Professor Steven Dow

2024

The Dissertation of Michael Robert Haupt is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

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ABSTRACT OF THE DISSERTATION

Infectious Ideas: Investigating Information Contagion Effects Associated with Dispositional Traits of Social Media Users and Textual Features of Posts

by

Michael Robert Haupt

Doctor of Philosophy in Cognitive Science

University of California San Diego, 2024

Professor Seana Coulson, Co-Chair
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Information has always been contagious. Rumors, gossip, advice, knowledge, and wisdom have reliably spread between people via mediums such as radio waves, the written word, and in-person conversations among others. However, the scale of information contagion has expanded to a global scale with the proliferation of wireless communication technologies. While increased accessibility to information can produce mass societal benefits, these technologies can

also facilitate the spread of conspiracies and misinformation, which has been an ongoing issue on social media platforms over the past decade. Previous work has adapted epidemiological approaches for modeling information contagion, where information is conceptualized as a biological pathogen. Despite the utility of the disease metaphor, information contagion differs in that the successful transmission of a message relies on cognitive processes of the receiver. These processes can involve a person's capability and willingness to evaluate a post, emotional reaction to the topic content, and perceived credibility of the message sender. The current work will examine mechanisms for information contagion by assessing how factors related to cognitive effort, emotional affect, and social conformity influence social media engagement on the level of users (i.e., dispositional traits) and posts (i.e., textual features). Chapter 1 tests how dispositional traits of users such as tendency for reflective thinking, narcissism, and political orientation influence the likelihood to propagate health-related information in a newsfeed simulation exercise. Chapter 2 explores how properties of social media posts, specifically textual characteristics reflecting linguistic complexity, emotional affect, and use of social references influence contagion effects on the platforms Reddit and X (formerly 'Twitter'). Chapter 3 adapts graph theory to construct semantic networks of message content to characterize differences in associations between topics (e.g., "Trump," "health") across political, scientific, and conspiratorial discourses on Reddit. The use of influential words in posts, as measured using network centrality metrics, are also shown to be statistically significant predictors of upvoting and commenting. This work assesses how both dispositional traits of users and textual properties of posts influence information contagion, and showcases how semantic network analysis can be used to identify influential words that are more likely to evoke engagement.

INTRODUCTION

Breakthroughs in communication technologies have historically been tied to massive societal change on a global scale. Examples of such technologies include: the invention of writing systems and paper, the Guttenberg press that allowed for mass-scale print, and devices that transmit audio and visual signals such as radio and TV. By expanding the reach and accessibility of other people's thoughts, knowledge and experiences to wider audiences, these technologies can radically challenge cultural norms and facilitate wide-spread social reorganization that often impact existing political and economic systems (Postman, 2005). In recent years, the emergence and wide-spread adoption of the internet has led to a new era of technology-driven social reorganization. This new era is the age of social media. In this relatively young age, many existing institutions are pressured to adapt to ongoing shifts in communication dynamics, where the average citizen now has access to a world of information on their mobile phone and can instantly send a message to someone across the planet with a few strokes of a finger.

Social media is novel in that it encourages active engagement from its audience. In fact, the ability to interact with this form of media is what makes it "social." As opposed to traditional broadcast mediums where audiences are typically passive recipients (e.g., tv, radio), those who view a social media post are able to facilitate dialogues directly with the sender and converse with others who also viewed the post in comment sections. Users can also give instant feedback to the sender by rating the post ("upvotes", "likes") or share it with others, although possible actions for engagement vary by platform. The ability to receive immediate feedback from others regardless of geographic proximity allow individuals to communicate information with people outside their social circles and promote more effective exchange of ideas on a global scale. However, like any ground-breaking technology, these innovations can also be abused.

The same capabilities that facilitate rapid communication at relatively low costs are unfortunately used to disseminate false information, rumors, conspiracies, and confusion. Studies show that for many online discussions, misinformation and false news stories were often more prevalent on popular platforms such as X (formerly Twitter) than factual information (Haupt et al., 2021; Mackey et al., 2021; Shin et al., 2018; Vosoughi et al., 2018). The most recent example of wide-scale misinformation spread was during the COVID-19 pandemic where the World Health Organization declared an ‘infodemic’ in response to the prevalence of health-related conspiracies about the virus on social media (Zarocostas, 2020). Conspiracies claimed that 5G signals were used to transmit the virus (Bruns et al., 2020, 2021; Haupt et al., 2023), COVID vaccines contained microchips (Lee et al., 2022), and the anti-malaria drug hydroxychloroquine was an effective treatment for COVID-19 (Haupt et al., 2021; Mackey et al., 2021). Mass confusion also resulted from misinformation propagation surrounding the 2016 U.S. presidential election where social media platforms were consistently flooded with false narratives about the candidates (Bovet & Makse, 2019; Budak, 2019). Even in the early stages of the internet before the proliferation of contemporary social media platforms, the spread of conspiracies, rumors, and misinformation were ongoing concerns (Eysenbach, 2002, 2006).

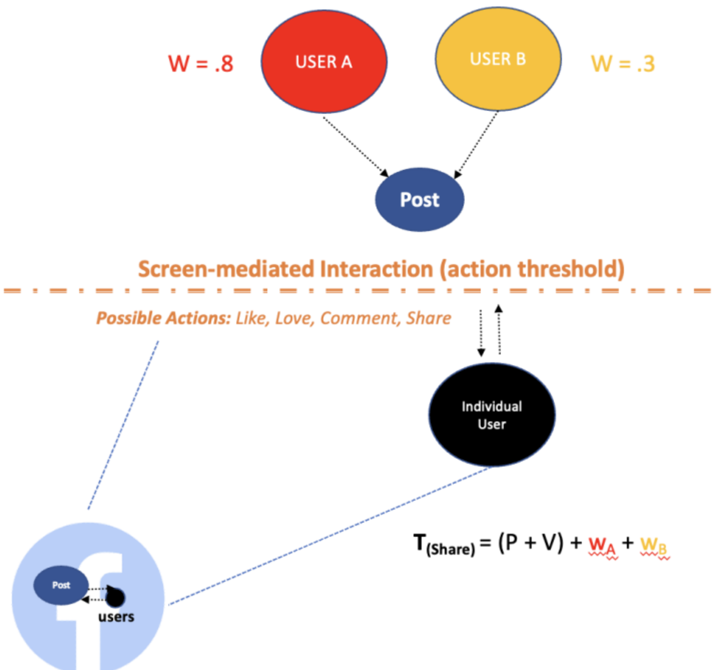
To mitigate misinformation propagation and promote healthier (and more informative) online discourse, effective interventions need to address multiple factors. These factors include: dispositional traits of users (DeVerna et al., 2022; Guess et al., 2019; Pennycook & Rand, 2019, 2021; Sternisko et al., 2021), textual features of posts (e.g., use of emotion words, linguistic complexity) (Brady et al., 2017; Crockett, 2017; Pfitzner et al., 2012; Stieglitz & Dang-Xuan, 2012), and social conformity factors (Osmundsen et al., 2021). Previous approaches attempting to account for the complexity of contagion effects often adopt epidemiological models that conceptualize information as a biological pathogen (Jia & Lv, 2018; Jie et al., 2016; Kauk et al., 2021; Xiong et al., 2012). These studies are often based on a popular approach for computationally modeling disease contagion called the SIR model (Chowell et al., 2016; Cooper et al., 2020) where agent nodes can be in 3 different states: Susceptible, Infected, Recovered/Removed. When a node is in the Susceptible state, it has not been infected with the modeled disease although it is vulnerable to contagion. Infected nodes are exposed to the disease and can subsequently spread the disease to other nodes while in this phase. Recovered nodes are no longer infected and typically will not become infected again. Typically, a susceptible node becomes infected after making a contact point with an infected node. The frequency in which agent nodes transition between states are based on the infection rate (Susceptible to Infected) and cure rate (Infected to Recovered), which are set as parameters based on the pathogen being modeled (Wu et al., 2022). By tracking the change in states across nodes, these simulation models provide predictions for when the spread of a given disease outbreak is at its peak.

While there is much flexibility in the SIR model as it can be adapted for multiple types of pathogens (e.g., the Recovered state can be removed for illnesses where there is no long term immunity such as the common cold), the utility of using disease transmission as a metaphor for modeling information contagion is limited. Previous work adapting the SIR model use the following agent states when simulating information contagion: susceptible agents are those that have never read the information, infectors are agents that retweet the information and spread it to their neighbors, contacted agents have read the topic and have not yet decided to retweet the information, and refractory agents have completely lost interests in the information (Xiong et al., 2012). For these simulation models, the transmission of information is based on parameters corresponding to the infection and cure rates used in biological contagion models, where the spread rate is the frequency of nodes transitioning from susceptible to infected (i.e., retweeting) and the refractory rate for when agents lose interest. While these disease-based models can generate useful insights into information contagion dynamics, an important drawback is that they do not consider cognitive mechanisms in which information is transmitted between humans.

Disease contagion primarily requires physical contact or shared proximity to transmit infectious pathogens between people. Unlike biological pathogens, the transmission of information requires the conscious attention of the receiver and their ability to interpret the message. For instance, most humans are limited in how much information they can process each day and hold cognitive biases in which they weigh the value of information differently. Differences in cultural knowledge are also relevant, as a message in Spanish is unable to be contagious among a group of non-Spanish speakers. Receivers who are too busy or uninterested to read will not become infected by a message as well. While attention restraints and cultural knowledge of people are not relevant when modeling contagion effects of biological pathogens, they are directly related to the mechanisms in which information is transmitted between people. Therefore, an overreliance on the disease metaphor can cause information contagion models to overlook these factors and assume that every agent is equally susceptible to be infected by a message and that all messages are equally contagious.

To improve these shortcomings, models for information contagion would benefit from having cognitively plausible agents, in that simulated agents process information in a similar manner as humans. Within the literature, varying factors have been proposed as distinct explanations for psychological susceptibility to misinformation which includes: personality traits, psychopathy, authoritarian preferences, attitudes and beliefs, reflective thinking tendencies, group identity, and various other cognitive and psychometric constructs (Chen et al., 2023; Delmastro & Paciello, 2022; Ecker et al., 2022; Kaufman et al., 2022; Tsamakis et al., 2022; van der Linden, 2022). Further, how the information is formatted and presented to users, such as linguistic complexity of a message (Davis et al., 2019; Deng et al., 2021; Gligorić et al., 2019; Jones et al., 2004; Temnikova et al., 2015) use of emotional affect words (Pfitzner et al., 2012; Stieglitz & Dang-Xuan, 2012), and the credibility and influence of a post's author (Calac et al., 2022; Fan et al., 2021) can also influence the likelihood that a post receives engagement. In general, each individual holds cognitive dispositions that makes them susceptible to some messages but completely immune to others, and units of information (such as social media posts) can be more or less contagious based on the cognitive effort required to comprehend the message and whether it evokes emotions or references group identities.

One recent approach to develop cognitively plausible agent-based models is the "Agent Zero" framework (Epstein, 2014), which posits that social contagion for all possible behaviors between people can be divided into 3 components: cognitive, affective, and social conformity. In this mode, agent nodes are exposed to social behaviors in their environment which subsequently influence their own behavior. For any given stimuli that agents are exposed to, there is an emotional response that corresponds to "System 1 reasoning" (automative, associative, intuitive) and a cognitive evaluation, which corresponds to "System 2 thinking" that is analytical, reflective, and deliberate. For each agent node, their personal evaluation is based on the sum weights of the emotion and cognitive components. If they observe other nodes engaging in a behavior, then that influence is represented as weights from the social component. Each of the 3 components contribute a dispositional weight, and an agent engages in the modeled behavior if the weights sum up past a specified threshold. See **Figure 1** for visualization of the agent zero framework adapted to information contagion on social media.



Note: P = dispositional weight from Cognitive component , V = dispositional weight from Emotional component

Figure 1. Agent Zero Framework Adapted for Information Contagion on Social Media

With the growing interest in using computational approaches to model social phenomenon such as information contagion, empirical work is needed to inform how relevant factors should be parameterized. While the agent zero framework improves on previous work by considering cognitively plausible agents instead of relying on assumptions based solely on disease metaphors, other factors such as individual variance among users and properties of posts are still not considered. For instance, differences in personality traits can influence propagation behaviors among nodes while posts that require greater cognitive effort for comprehension may receive less engagement. Distinctions between message content and social conformity can also be blurred when accounting for the ability of language to both signal group membership and create social cohesion within communities. The tendency for groups to produce their own language (e.g., slang, jargon) suggests that use of contextually influential words in a post may influence contagion effects with online communities as well, however, this potential factor remains unexplored.

To shed further light onto the complex dynamics of information contagion, this dissertation will build on the previously established agent zero framework (Epstein, 2014) to examine how factors related to cognition, emotion, and social conformity influence social media engagement on the level of users (i.e., dispositional traits) and posts (i.e., textual features). See **Figure 2** for visualization for how the previously described components of contagion (cognitive, emotion, social) map onto both posts and users. The first chapter tests how dispositional traits of users such as tendency for reflective thinking, narcissism, and political orientation influence the likelihood to propagate health-related information in a newsfeed simulation exercise. Chapter 2 examines how properties of social media posts, specifically textual characteristics reflecting linguistic complexity, emotional affect, and use of social references influence contagion effects on the platforms Reddit and X (formerly 'Twitter'). The final chapter adapts graph theory to construct semantic networks of message content to characterize differences in associations between topics (e.g., "Trump," "health") across political, scientific, and conspiratorial discourses on Reddit. This chapter also investigates whether the use of influential words in posts, as measured using network centrality metrics, are significant predictors of social media engagement.

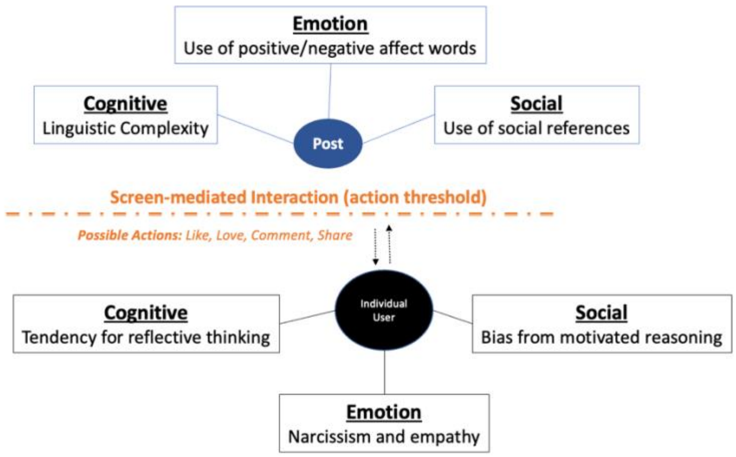


Figure 2. Cognitive, Emotion, and Social Components of Information Contagion - Post & User Levels

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Chapter 1 Examining User Dispositions on Engagement Behaviors

The present state of misinformation research is heavily colored by the COVID-19 pandemic: since the emergence of COVID-19, misinformation related to the novel coronavirus became prevalent across social media platforms with topics ranging from sensational rumors about its origin (e.g., signals emitted by 5G towers) (Bruns et al., 2020a, 2022; Haupt et al., 2023), claims about the efficacy of debunked treatments (Haupt, Li, et al., 2021a; T. K. Mackey et al., 2021a), and false claims about the COVID-19 vaccine (Lee et al., 2022; Zhao et al., 2023). However, misinformation propagation has long been an issue in public health discourse. For example, false claims that the MMR (measles, mumps, rubella) vaccine causes autism (Kata, 2010, 2012) were subsequently associated with measle outbreaks among unvaccinated children in the US (Nelson, 2019) and more widespread outbreaks in Greece and the United Kingdom (Robert et al., 2019). The topic of misinformation was also prominent during the 2016 US Presidential election, when misinformation concerning the election was prevalent on social media (Bovet & Makse, 2019a; Budak, 2019). In recent years, it has become increasingly difficult to distinguish between political and health-related misinformation, as public health debates have been used to exacerbate political discord across party lines as reflected in COVID-19 discourse surrounding masks, treatments, and vaccines (Bruine de Bruin et al., 2020; Kerr et al., 2021; Levin et al., 2023; Pennycook et al., 2022).

Despite the large body of research investigating misinformation susceptibility, the literature has not converged on a single explanation for the large-scale volume of misinformation that continues to propagate on social media (Chen et al., 2023; Ecker et al., 2022; Wang et al., 2019). Within the field of cognitive science, two competing theoretical accounts for misinformation spreading behaviors related to dispositions of individuals (as opposed to environmental factors such as features of platforms) include a failure to engage in classical reasoning (Pennycook et al., 2021; Pennycook & Rand, 2021) and a tendency for motivated reasoning (i.e., conformity to group opinions) (Kahan et al., 2017; Osmundsen et al., 2021). Within the field of psychology, effects from personality traits such as narcissism are more popular explanations (Sternisko et al., 2021; Vaal et al., 2022). However, an ongoing challenge is that this literature is balkanized with some researchers arguing misinformation propagation is attributable to a single primary cause (Osmundsen et al., 2021; Pennycook & Rand, 2019, 2021) and others failing to consider alternative explanations (Wang et al., 2019).

Lack of classical reasoning

One of the more popular explanations for misinformation propagation is the classical reasoning or "inattention" account that claims people unintentionally spread misinformation due to a lack of careful reasoning and relevant knowledge (Pennycook & Rand, 2019, 2021). Because they lack the time and energy to adequately assess the large volume of content on social media, people use heuristics or mental shortcuts that lead to the spread of misinformation (van der Linden, 2022).

The classical reasoning account draws on a dual-process theory of human cognition that posits two distinct reasoning processes: System 1 processing is predominantly automatic, associative, and intuitive, while System 2 is more analytical, reflective, and deliberate (Evans, 2003). According to this account, misinformation spread is due to an overreliance on System 1 processing and can be mitigated by interventions that activate System 2-type reasoning (Pennycook et al., 2021). The most common metric used to operationalize System 2-type reasoning is the Cognitive Reflection Test (CRT), a set of word problems in which the answer that comes “first to mind” is wrong, while the correct answer requires one to pause and carefully reflect (Frederick, 2005). CRT is widely used in the misinformation literature to measure individuals’ propensity to engage in analytic thinking. Accordingly, CRT scores have been shown to be positively correlated with truth discernment of headlines (Pennycook & Rand, 2019), and negatively associated with sharing low credibility news sources on Twitter (Mosleh et al., 2021).

Despite the large body of evidence supporting the classical reasoning account, this explanation is limited in that it does not consider the influence of social factors such as group identity (e.g., political affiliation) or how users relate to others socially (e.g., being narcissistic or highly empathetic). Since sharing information to one’s network is a social behavior, exclusively focusing on the recognition of misinformation may not fully account for all factors associated with online propagation behaviors. It is also worth noting that while CRT is often used in the literature to operationalize classical reasoning, it is a proxy measure that does not directly reflect one’s *capacity* but rather tendency to engage in System 2-type thinking. Within the context of misinformation propagation, whether someone engages in classical reasoning before deciding to share a post is more relevant than general reasoning ability since those adept at System 2-type thinking may nonetheless fail to exert the energy required to deliberate on the content of a post. Therefore, it is more productive to conceptualize CRT as a trait that corresponds to a tendency to engage in reflective thinking rather than a direct measure of classical reasoning ability such as IQ.

Motivated reasoning

An alternative explanation for misinformation propagation that is also based on dual-process theory is the motivated reasoning account, which states that individuals tend to assess information based on pre-determined goals, and to selectively endorse and share content that coincides with those goals (Kahan, 2015; van der Linden, 2022). These goals could involve: maintaining a positive self-conception (Dunning, 2003), avoiding anxiety from unwelcome news (Dawson et al., 2002), and rationalizing self-serving behavior (Hsee, 1996). In politically motivated reasoning, the goal is presumed to be *identity protection*, as people form beliefs that maintain their connection to a social group with shared values (Kahan, 2015). Consequently, social media users may be motivated to share factually incorrect posts that align with their beliefs and group identities, and to ignore posts that challenge those beliefs. Indeed, research suggests participants' political identities influence their recognition of misinformation on controversial issues (Kahne & Bowyer, 2017), as well as their willingness to share political fake news (Osmundsen et al., 2021).

Relative to classical reasoning, motivated reasoning adopts a somewhat different perspective on rationality and its role in social behavior. Like classical reasoning, motivated reasoning suggests misinformation susceptibility results from an overreliance on System 1 processing (i.e., intuitive response). However, the failure to engage System 2 (i.e., deliberation) results not from a lack of effort or ability, but from the desire to maintain a political identity. Although motivated reasoners may have different beliefs, they all utilize an optimal procedure for updating those beliefs when considering new information. The Bayesian inference framework involves a "prior", that is, an existing estimate of the probability of some factual hypothesis (e.g., getting vaccinated for COVID-19 will prevent the spread of the virus), novel information or evidence (e.g., a new study showing evidence of vaccine efficacy), a "likelihood ratio" that reflects how much more consistent the new information is with the relevant hypothesis than some rival one, and a revised estimate reflecting the weight given to the new information (Kahan, 2015). Individuals display politically motivated reasoning when they utilize a likelihood ratio that weighs priors aligned with their political identity higher than factual evidence.

Within the context of COVID-related misinformation, those higher in conservatism have been shown to be more likely to resist taking COVID-19 precautions (Conway et al., 2021; Havey, 2020), more susceptible to misinformation (Calvillo et al., 2020, 2021; Kaufman et al., 2022), and more likely to share low credibility news sources (DeVerna et al., 2022; Guess et al., 2019). While the literature mostly focuses on politically motivated reasoning, there are other relevant bias factors concerning COVID-related misinformation that are often overlooked. Previous studies showing that lower trust in science is associated with greater likelihood to believe in COVID-19 misinformation narratives (Agley & Xiao, 2021; Pickles et al., 2021; Roozenbeek et al., 2020) indicate that motivated reasoning may also be driven by distrust towards medical scientists. Despite there being no religious scriptures that directly address suspicion to scientific institutions, higher religious belief within the US (more specifically Christianity) has been associated with science skepticism (Azevedo & Jost, 2021) and susceptibility to conspiracy theories and false news (Bronstein et al., 2019; Frenken et al., 2023). Therefore, those higher in religiosity may be more likely to evaluate evidence as factual if it is in opposition to scientific institutions.

Personality traits

An explanation for misinformation spread that does not draw upon dual-process theory attributes misinformation propagation to personality traits. Using measures such as narcissism and other "dark triad" traits of psychopathy, researchers in this tradition argue that engagement with conspiracy theories results from interpersonal and affective deficits, unusual patterns of cognition, and manipulative social promotion strategies (Barron et al., 2018; Bruder et al., 2013; Cichocka et al., 2016; Douglas & Sutton, 2011; Hughes & Machan, 2021; March & Springer, 2019; Vaal et al., 2022). For example, susceptibility and dissemination of conspiracy theories related to COVID-19 has been associated with collective narcissism (Hughes & Machan, 2021; Sternisko et al., 2021). Also referred to as "national narcissism," collective narcissism is tied to the belief that one's ingroup is exceptional, deserves special treatment, and that others do not sufficiently recognize it (de Zavala et al., 2009; Golec de Zavala et al., 2019). Because they have a national image of invulnerability and self-sufficiency, collective narcissists may be attracted to COVID-related conspiracies that deny the disease's existence.

There are also more personal variants of narcissism that are underexamined in the misinformation propagation literature. Grandiose narcissism, associated both with greater activity on social media platforms (Gnambs & Appel, 2018; McCain et al., 2016; McCain & Campbell, 2018) and higher incidence of belief in conspiracy theories (Cichocka et al., 2016), is a dispositional trait characterized by an unrealistically positive self-view, a strong self-focus, and a lack of regard for others (Miller et al., 2011). Covert or "vulnerable" narcissism in contrast, reflects an insecure sense of grandiosity that obscures feelings of inadequacy, incompetence, and negative affect (Miller et al., 2011), and tends to involve social behavior that is characterized by a lack of empathy, higher social sensitivity, and increased frequency of social media use

(Dickinson & Pincus, 2003; Fegan & Bland, 2021). Individuals high in narcissistic traits were less likely to comply with COVID-related guidelines (e.g., wearing a mask) due to an unwillingness to make personal sacrifices for the benefit of others, a desire to stand out from consensus behavior, a tendency to engage in paranoid thinking, and a need to maintain a sense of control in response to government-imposed regulations (Hatemi & Fazekas, 2022; Sternisko et al., 2021; Vaal et al., 2022).

As opposed to narcissistic individuals, those higher in empathy may be more concerned about the well-being of others, and thus less likely to share health-related misinformation. This is suggested in previous work showing that empathetic messaging interventions can correct erroneous beliefs (Moore-Berg et al., 2022), improve misinformation discernment (Lo, 2021), and reduce the incidence of online hate speech (Hangartner et al., 2021). However, there is currently no work examining how trait empathy influences COVID-related misinformation propagation on social media. Other relevant personality traits to misinformation propagation, as highlighted in a recent review (Sindermann et al., 2020), are conscientiousness and openness from the Big Five Inventory (BFI). Conscientiousness, which measures the tendency to be organized, exhibit self-control, and to think before acting (Jackson et al., 2010), has been shown to be negatively correlated with disseminating misinformation (Lawson & Kakkar, 2022). Openness to experience, which assesses one’s intellectual curiosity and propensity to try new things, has been shown to be negatively associated with belief in myths (Swami et al., 2016) and positively associated with tendencies to scrutinize information (Fleischhauer et al., 2010). Both BFI traits are also positively associated with better news discernment (Calvillo et al., 2021). While previous research examines these traits separately, there is currently no work that tests these traits against other relevant factors for misinformation propagation.

Present study

If we hope to design effective interventions to minimize the propagation of misinformation on social media platforms, it is important to understand how and why it occurs. Unfortunately, there is almost no contact between misinformation researchers in the ‘cognitive’ traditions (classical versus motivated reasoning) and those in the more ‘social’ traditions that focus on personality traits (Chen et al., 2023). The existence of these parallel tracks of inquiry presents a need to compare the influence of the variety of factors that contribute to misinformation spreading behaviors. Although some researchers have advocated a unitary explanation of online misinformation spread (Pennycook & Rand, 2019; 2021), others have argued there are likely multiple factors at play (Batailler et al., 2022; Chen et al., 2023; Ecker et al., 2022),. Here we test all three major accounts and quantify their relative importance for online misinformation propagation.

One limitation of previous research is the use of tasks that do not resemble social media settings, such as the headline evaluation task in which participants rate the truthfulness of news headlines (Bago et al., 2020; Pennycook & Rand, 2019; Ross et al., 2021; Vegetti & Mancosu, 2020). Consequently, some have questioned the external validity of headline evaluation tasks, calling for more realistic experimental settings that resemble social media environments (Sindermann et al., 2020). Relatedly, it is important for researchers to distinguish between passive social media use (e.g., scrolling through the newsfeed without engaging with posts) and more active behaviors (e.g., sharing a post on your profile) (Burke et al., 2011; Verduyn et al., 2015, 2017; Yu, 2016). Clearly, deciding whether to retweet a post, which will broadcast it to other users on the site, is not the same as privately rating a news headline on its truthfulness.

To address these shortcomings, the present study employs a Twitter simulation task in which participants are shown real tweets from COVID-19 discourse and asked to engage with them (e.g., “retweet”) as they would on the platform. A similar task has been used in previous research examining misinformation susceptibility for platforms such as Facebook, Twitter, and Reddit (Bode & Vraga, 2018; Mourali & Drake, 2022; Porter & Wood, 2022; Tully et al., 2020), and for eliciting responses from participants on issues related to early COVID-19 quarantine guidelines (Coulson & Haupt, 2021). Rather than allowing participants to engage directly with misinformation stimuli, these prior studies have used simulated newsfeeds to expose participants to misinformation and then asked them in a separate section to rate their belief in the information or intention to share. The present study differs from past work in that our main outcome measure is direct engagement with posts within the simulated newsfeed. Analysis will focus on “liking” to observe more passive forms of social media engagement, and “retweeting” (i.e., sharing) COVID-related misinformation since it is most directly related to real world propagating behaviors. See **Table 1** and **Figure 3** for examples of tweet stimuli and simulation task.

While researchers have identified multiple types of misinformation which ranges from propaganda, misleading advertising, news parody and satire, manipulated news, and news that has been completely fabricated (Tandoc et al., 2018; Waszak et al., 2018), within the current study misinformation was defined based on whether it made a declarative statement about a false claim related to each health-related topic according to scientific consensus at the time of data collection. Despite there being multiple studies that investigate how individual traits influence misinformation spreading behaviors, effects related to whether one shares misinformation *corrections* are understudied, as reflected in a recent call for research (Vraga & Bode, 2020). Since the propagation of misinformation corrections is underexamined, here we conduct an exploratory analysis to inform future work. A misinformation correction was defined as a tweet that directly counters false rumors or provides factual information concerning a topic.

Our approach is to assess the adequacy of these theoretical accounts of misinformation propagation on social media by quantifying relevant factors using psychometrically validated scales. The relative importance of these variables on misinformation propagating behavior will then be modeled using multivariate regression. See **Table 2** for a full list of tested variables and hypotheses, and Methods for description of tested variables. If CRT is the only variable that is negatively associated with liking and retweeting misinformation tweets, then those results would indicate that the classical reasoning account is the primary explanation for propagation. Evidence that supports the motivated reasoning account would show positive associations between higher conservatism, higher religiosity, and lower trust in medical scientists with liking and retweeting Covid-related misinformation. If misinformation engagement is positively associated with narcissism traits and negatively associated with empathy and BFI traits, results would support the personality traits account. The multiple regression analysis adopted here allows us to recognize the impact of multiple different factors and to quantify their relative importance for the propagation of misinformation. In the case where variables from multiple accounts show significant effects, then the results would suggest there is no singular explanation for online misinformation spread, but rather multiple factors that influence different aspects of propagating behavior.

Table 1. Examples of Tweets in Simulation Task

Category	*Public Health Topics*		
	Vaccine	Hydroxychloroquine	Mask
Misinformation	COVID-19 syringes will have microchips on outside, not in vaccine. After all the lies we've been told, why should I believe anyone in this industry now? I smell something rotten.	Friendly reminder the only reason DC Swamp Rats are against Hydroxychloroquine is because Big Pharma can't make money off it It's too cheap and easily accessible	" Can public health officials get any more stupid? Putting masks on children is idiotic. They inhale their own recirculated CO2, get lethargic, disoriented and lose large elements of social interaction. Masks don't work anyway. Putting them on children is close to criminal.
Misinformation Correction	How is the #Pfizer / BioNTech vaccine developed? #SARSCoV2 is covered w/Spike proteins that it uses to grab human cells. The vaccine consists of a small genetic material "messenger RNA" that provides instructions for a human cell to make a version of that Spike protein	DEBUNKING HYDROXYCHLOROQUINE (again) w/ that viral HCQ video today it's time to bump up this thread on the mega RECOVERY randomized trial of HCQ with 4700 people showing NO benefit for mortality & even higher risk of ventilator+mortality. And no subgroups benefit.	I study the impact of CO2 on human health so I figured I would weigh in on this JAMA article purporting to show masks create high and unsafe CO2 exposures for kids. (spoiler alert: they don't)

Table 2. Tested theoretical accounts, variables, and hypotheses

Theoretical Account	***Tested Variables***	***Hypotheses***
Classical Reasoning	• Cognitive Reflective Thinking (CRT)	***H1***: CRT is negatively associated with liking/retweeting misinformation
Motivated Reasoning	• Political orientation • Religiosity • Trust in medical scientists	***H2***: Higher conservatism, higher religiosity, and lower trust in medical scientists is positively associated with liking/retweeting misinformation
Personality Traits	• Grandiose narcissism • Covert narcissism • Perspective-taking empathy • Emotional-concern empathy • BFI Conscientiousness • BFI Openness	***H3***: Grandiose Narcissism is positively associated with liking/retweeting misinformation ***H4***: Covert Narcissism is positively associated with liking/retweeting misinformation ***H5***: Empathy (PT and EC) is negatively associated with liking/retweeting misinformation ***H6***: BFI Conscientiousness and Openness is negatively associated with liking/retweeting misinformation

Methods

Data collection

1000 Twitter users were recruited from Amazon Mechanical Turk (MTurk) during September 2021. Participants were considered Twitter users if they reported having a Twitter account. After filtering for data quality, a final sample of 858 people was used for analysis. Data quality was based on failing an attention check question ("In order to make sure you're paying attention please select option five") and having a survey completion time in the top 10^{th} percentile (<12 minutes, median survey completion time = 26.85 minutes). Of the total sample, 60% identified as male with a mean age of 37.26 (SD=10.22). Further, 76% were White, 14% Black, 4% Asian, and 2% Hispanic. Median income was between \$50,000 to \$74,999 and participants reported spending an average of 3.18 hours per day on social media (SD=2.2). Informed consent was obtained from participants before taking the survey and the research was conducted in accordance with guidelines for posting a survey on the platform. Participants were compensated based on standard survey-taking rates on Amazon Mechanical Turk and no personal identifying information is reported in this study. See the Open Science Framework (OSF) account under the author's name for supplementary material, and the dataset and R syntax file used to generate the results from the present study.

Twitter simulation task

Participants engaged in a Twitter simulation task where they were asked to 'like', 'reply', 'retweet', 'quote', or select "no engagement" for tweets related to three public health topics (vaccines, hydroxychloroquine, masks). As for actual Twitter use, participants were able to select multiple reactions to a tweet (or to simply select "no engagement"). If "reply" or "quote" was selected, a text box would appear under the tweet for participants to generate a written response. Tweets were presented in random order. See **Figure 3** for examples of the Twitter simulation task. 36 tweets were tested in the simulation task with 12 tweets for each public health topic. For each topic, 4 of the tweets contained misinformation and 2 misinformation corrections, resulting in a total of 12 misinformation and 6 correction tweets tested in the simulated newsfeed. A higher number of misinformation posts were tested than corrections to better reflect newsfeed dynamics, where previous studies show that misinformation is more prevalent than factual information on Twitter (Haupt, Li, et al., 2021a; J. Shin et al., 2018; Vosoughi et al., 2018; Zarocostas, 2020a). Six additional tweets on each topic were also tested; these tweets neither contained misinformation nor were they corrections but expressed varying sentiment towards the topic (2 positive, 2 negative, 2 neutral). Tweets were further categorized as "problematic sentiment" if they did not contain misinformation but still expressed sentiment that was contrary to public health guidelines. Therefore, negative sentiment towards vaccines and masks, and positive sentiment towards hydroxychloroquine were defined as problematic sentiment. See **Table 1** for examples of tweets used in the current analysis. These tweet stimuli were also used in a separate study where 9.32 of the 12 misinformation tweets on average were correctly classified as containing misinformation by a sample of 132 undergraduate students as further described in Kaufman et al. (2022).

Figure 3. Example Tweets from Twitter Simulation Task, (Top) Vaccine Misinformation Tweet, (Bottom) Vaccine Misinformation Correction Tweet

Classical reasoning

Cognitive reflective thinking (CRT)

Three questions (α=.79) from the Cognitive Reflection Test were used to measure CRT. Questions from this test initially have an answer that appears "intuitive". However, producing the correct answer requires careful reflection. For example, Question 1 asks “A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?” The intuitive answer is 10 cents, while the correct answer is 5 cents (since $1.05 is $1 more than 5 cents and together they total $1.10). Number of correct answers corresponds to CRT score.

Motivated reasoning

To examine how motivated reasoning influences engagement with misinformation posts, this study measures political orientation and two other factors relevant to bias in politicized health-related misinformation: trust in medical scientists and religiosity.

Political orientation

A question asking participants to select where their political beliefs best fall, with 1 = Very Conservative to 6 = Very Liberal.

Trust in medical scientists

One 4-item scale adapted from the 2019 Pew Research Center’s American Trends Panel survey (Funk et al., 2019) asking respondents "How much confidence, if any, do you have in each of the following to act in the best interests of the public?" The institutions asked about were elected officials, news media, medical scientists, and religious leaders with response options ranging from 1 = No confidence at all to 4 = A great deal.

Religiosity

One 7-item scale (α=.87) from the Centrality of Religiosity Scale (Huber & Huber, 2012), which measures the intensity, salience, and importance or centrality of religious meanings for an individual. The interreligious version was used for the current study.

Personality traits

Narcissism

Grandiose narcissism was measured using the 16-item version (α=.81) of the Narcissism Personality Inventory (NPI)(Ames et al., 2006). Each item in the NPI-16 asks participants to select which of a pair of statements describes them most closely. Grandiose narcissism scores are calculated based on the number of statements selected that are consistent with narcissism. Covert narcissism was measured using the 10-item (α=.89) Hypersensitive Narcissism Scale (Hendin & Cheek, 1997) with each item rated on a 5-point Likert scale ranging from 1 (“very uncharacteristic or untrue, strongly disagree”) to 5 (“very characteristic or true, strongly agree”).

Empathy

The current study tests two types of empathy: perspective-taking and emotional-concern. Perspective-taking (PT) empathy refers to the capacity to make inferences about and represent others' intentions, goals, and motives (Frith & Frith, 2005; Stietz et al., 2019). Emotional-concern (EC) refers to other-oriented emotions elicited by the perceived welfare of someone in need (Batson, 2009). Empathy was assessed by having participants respond to Perspective Taking (PT) (α=.60) and Emotional Concern (EC) (α=.71) subscales taken directly from the Interpersonal Reactivity Index (M. H. Davis, 1983), with each item rated on a 5-point Likert scale ranging from 1 (“does not describe me well”) to 5 (“describes me well”).

BFI conscientiousness and openness

Two 8-item subscales from the Big Five Inventory (BFI)(John et al., 2008) were used to evaluate participants across the personality dimensions conscientiousness (α=.72) and openness (α=.65). Each item was rated on a 5-point Likert scale ranging from 1 (“Disagree strongly”) to 5 (“Agree strongly”).

Regression analysis

Multiple regression analysis was conducted to assess the relationship between tested traits and engagement with misinformation tweets. A Shapley value regression was also implemented that allows us to determine the proportion of variance attributed to each independent variable when controlled for multicollinearity (Budescu, 1993). This technique has been used in economics (Israeli, 2007; Lipovetsky & Conklin, 2001), in data science for interpreting machine learning models (Covert & Lee, 2021; Okhrati & Lipani, 2021; Smith & Alvarez, 2021), and for evaluating how dispositional traits of crowd workers influence accuracy of detecting misinformation in Twitter posts (Kaufman et al., 2022).

Results

Distribution of engagement behaviors

Overall, passive engagement behavior occurred more often than active behavior with participants being more likely to “Like” than to “Retweet,” “Quote,” or “Reply” to posts containing both misinformation and corrections. Participants on average liked half of the total misinformation tweets (median = 6). By contrast, on average only 1.5 of the 12 misinformation tweets were retweeted. Correction tweets received more engagement on average with two-thirds of correction tweets being liked and 1 out of 6 retweeted. See **Figure 4** and **Figure 5** for distribution of behaviors from simulation task.

Figure 4 shows the distribution for the different engagement behaviors when shown misinformation tweets. Passive behavior (i.e., Like) is depicted in a lighter color than the more active behaviors (e.g., Retweet). Liking misinformation tweets shows a bimodal distribution, where many participants either did not like any of the misinformation tweets (n=181) or liked all 12 of them (n=158). However, most of the sample fell between these two extremes (see upper left panel). For retweeting behavior, a large portion of participants did not retweet any misinformation posts (n=363), and the vast majority of participants retweeted 6 or fewer misinformation tweets (n=729). Participants were also less likely to Reply or Quote a post than Like and Retweet. Since replying and quoting also require users to generate a written response to the tweet, participants may be less likely to initiate these behaviors due to the extra costs in effort and time.

Figure 5 shows the distribution for the different engagement behaviors when shown tweets that correct misinformation. Passive behavior (i.e., Like) is depicted in a lighter color than the more active behaviors (e.g., Retweet). Liking correction posts resembles more of a normal distribution compared to liking misinformation (see Figure 2). However, there is also a sizable proportion of participants who liked all 6 correction tweets (n=211), which skews the distribution towards the right. The distribution for retweeting correction posts is similar to that for retweeting misinformation with a large portion of participants not retweeting any at all (n=340) and the majority of participants retweeting half or less of the available correction tweets. Also, similarly to misinformation tweets, participants were less likely to Reply or Quote a post than Like and Retweet.

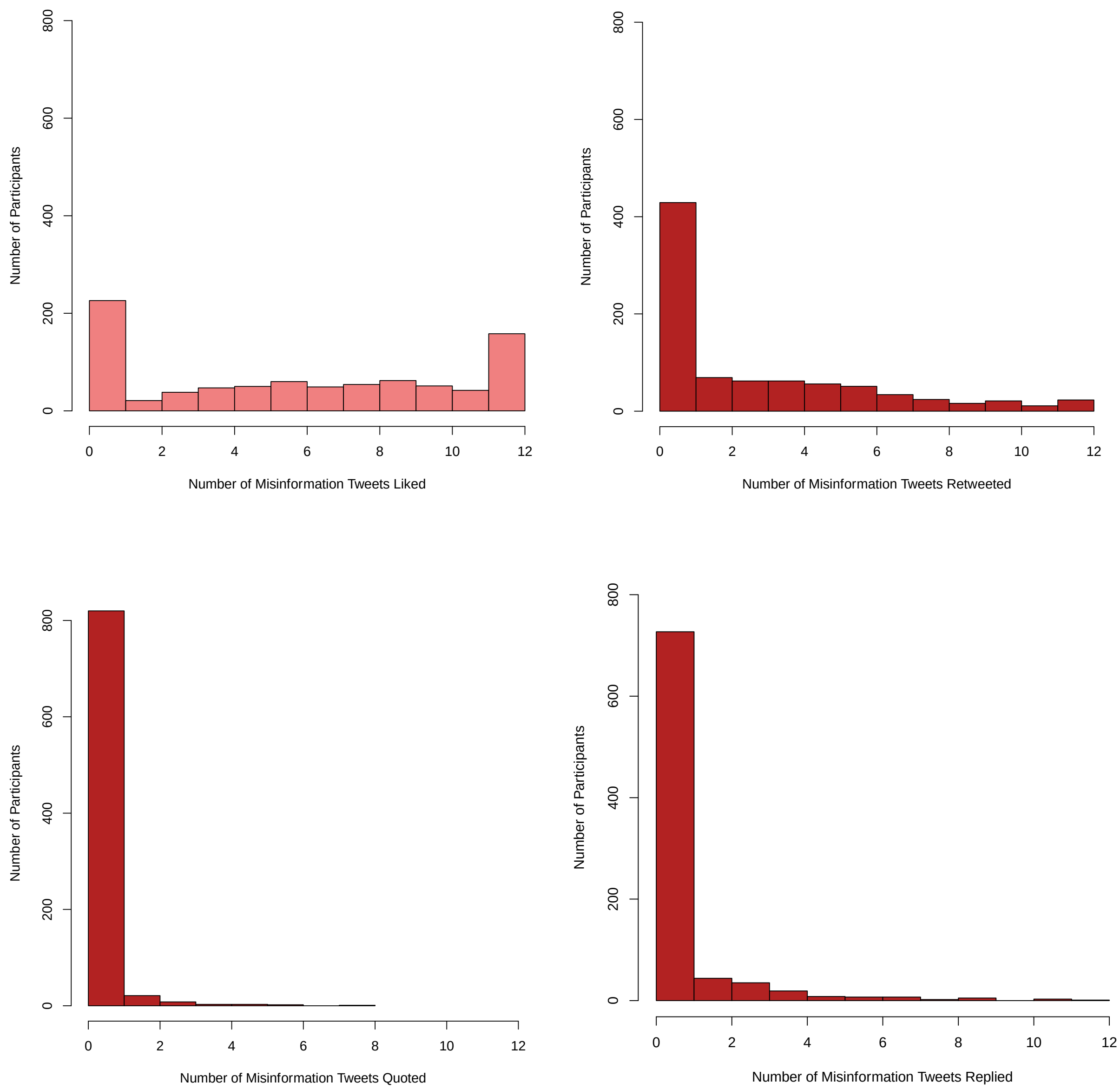

Figure 4. Distribution of engagement (Like, Retweet, Quote , Reply) with misinformation tweets

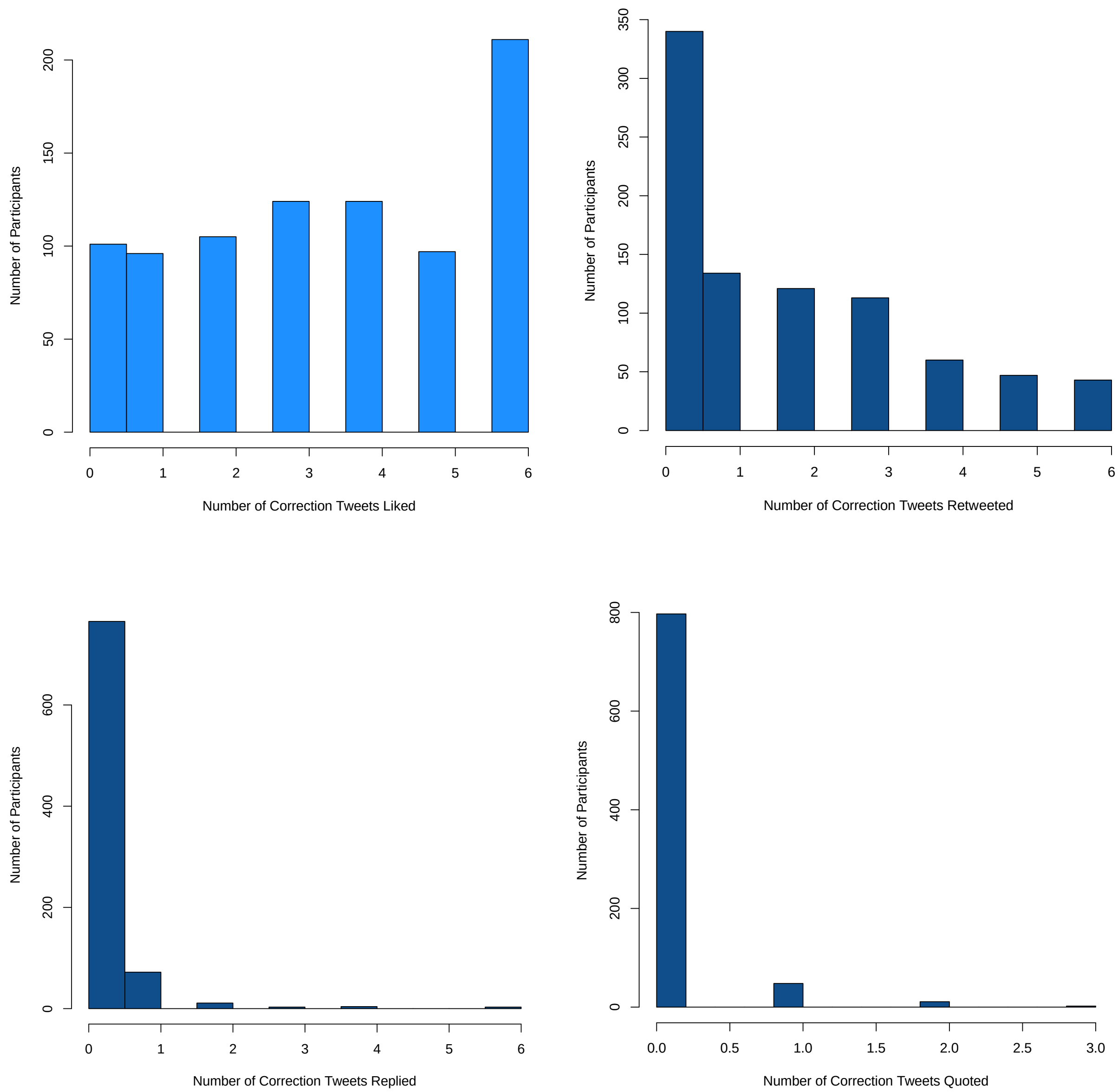

Figure 5. Distribution of engagement (Like, Retweet, Quote, Reply) with misinformation correction tweets

Logistic mixed effects regression model

To control for individual variation in participants and stimuli, mixed effects models were run to assess the likelihood of liking and retweeting posts, as shown in **Table 3**. The fixed effects were the information classification (e.g., misinformation) while the random effects were variation from individual respondents and tweet stimuli. For information classifications, the reference level is neutral sentiment tweets. The dependent variables are whether the participant liked or retweeted each tweet. Before modeling, the data was restructured from the participant level to the tweet level, resulting in 30,888 observations.

Models of both liking and retweeting posts showed that variance from individual participants was greater than the variance from tweet stimuli. Compared to neutral sentiment, participants were less likely to like tweets classified as misinformation (-.47 logits, $p < .05$) and problematic sentiment (-.52 logits, $p < .05$), and more likely to like nonproblematic sentiment (.45 logits, <.05). For the retweet model, participants were less likely to retweet misinformation (-.37 logits, <.001) and problematic sentiment tweets (-.32 logits, $p < .01$) compared to neutral sentiment. Within both models, correction tweets showed no statistically significant differences in engagement compared to neutral posts. Since engagement with corrections is indistinguishable from neutral sentiment engagement, the remainder of the analysis will focus on examining misinformation propagating behaviors. See **Supplementary Discussion S1** on the author's OSF account for further interpretation on engagement with correction tweets.

Table 3. Mixed effects models for likelihood of liking and retweeting

Mixed Effects	Like		Retweet	
	Variance	*Std. Dev*	*Variance*	*Std. Dev*
Individual Participant	5.35	2.31	5.03	2.24
Individual Tweet	0.14	0.37	0.03	.17

Fixed Effects		Like				Retweet			
		Est.	*Std. Error*	*z value*	*Pr (>|z)*	*Est.*	*Std. Error*	*z value*	*Pr (>|z)*
Information Classification	(Intercept)	0.72	0.17	4.14	<.001	-1.68	0.11	-15.04	<.001
	Correction	-0.04	0.22	-0.21	0.84	0.01	0.11	0.09	0.93
	Misinformation	-0.47	0.19	-2.48	<.05	-0.37	0.10	-3.85	<.001
	Non Problematic Sentiment	0.45	0.22	2.06	<.05	0.05	0.11	0.49	0.63
	Problematic Sentiment	-0.52	0.22	-2.36	<.05	-0.32	0.11	-2.86	<.01

Number of observations: 30,888; *Number of Participants*: 858; *Number of Individual Tweets*: 36; *AIC (Like)*: 30068; *AIC (Retweet)*: 26214

Regression analysis – engagement with misinformation

Multivariate regression was conducted with measures outlined above as independent variables, and the number of misinformation tweets that were liked and retweeted as dependent variables. To determine which variable contributes most to tweet engagement, we used a Shapley value regression, which assesses the relative importance of the independent variables by computing all possible combinations of variables within the model and recording how much the R^2 changes with the addition or subtraction of each variable (see Groemping, 2007) for further description using an example dataset with a higher degree of multicollinearity than the current analysis, and **Supplementary Table S2** and **Supplementary Discussion S2** for correlation matrix of tested variables). Shapley weights were standardized in **Table 5** to show the proportion of the model's total R^2 that is attributed to each tested variable.

As shown in **Tables 5** and **6**, personality traits and religiosity were among the most influential for predicting passive engagement with misinformation tweets. When controlled for the other variables in the model, CRT was negatively associated with liking misinformation tweets ($p<.001$). Based on the results from the Shapley value regression, CRT ranks 5th in explaining variance for liking misinformation. However, CRT shows no significant effect in the retweet model, indicating classical reasoning shows an inhibitory effect on passive but not active forms of misinformation propagation.

Among traits relevant for the motivated reasoning account, religiosity was positively associated with both liking ($\beta = 0.85$, $p<.001$) and retweeting misinformation ($\beta = 0.52$, $p<.001$), while trust in medical scientists was negatively associated with these behaviors (liking: $\beta = -0.31$, $p<.05$; retweeting: $\beta = -0.34$, $p<.01$). Based on the Shapley results, religiosity explained the second highest amount of variance for both liking and retweeting misinformation. Political orientation had no statistically significant effects and ranked lowest in variance for both liking and retweeting misinformation when controlled for all tested variables.

Among variables testing the personality trait account, grandiose narcissism was positively associated both with liking ($\beta = 2.49$) and retweeting ($\beta = 3.27$) misinformation

($p<.001$). Grandiose narcissism ranked as the top predictor in the retweet model and 4th for liking misinformation. Covert narcissism showed no statistically significant effects for liking or retweeting misinformation when controlled for all tested variables. EC empathy was the only empathy trait to have a statistically significant effect and was negatively associated with liking misinformation ($\beta = -0.63$, $p<.05$). When controlled for the other variables in the model, BFI Conscientiousness and Openness were both negatively associated with liking misinformation tweets ($p<.001$). Based on the results from the Shapley value regression, Openness ranks as the variable that explains the most variance in liking misinformation and Conscientiousness ranks 3rd among the tested variables. Neither BFI traits show significant associations with retweeting misinformation.

Additionally, the adjusted r-squared of the models suggest that the selected predictor variables performed better when predicting the more passive engagement behavior of liking ($r^2 = .52$) than for the more active engagement behavior of retweeting ($r^2=.15$).

Table 4. Standardized Shapley Weights for Misinformation Tweet Engagement (Like and Retweet)

Like: *Independent Variables*	Like: *Shapley R^2*	Retweet: *Independent Variables*	Retweet: *Shapley R^2*
Openness	**17.9%**	**Grand Narc**	**39.1%**
Religiosity	**16.4%**	**Religiosity**	**23.7%**
Conscientiousness	**15.0%**	EC Empathy	9.0%
Grand Narc	**12.7%**	Covert Narc	6.4%
CRT	**11.6%**	**Trust in Med Sci**	**5.3%**
Covert Narc	10.6%	Openness	5.2%
EC Empathy	**9.6%**	PT Empathy	4.6%
PT Empathy	3.0%	Conscientiousness	3.8%
Trust in Med Sci	**2.1%**	CRT	1.8%
Political	1.0%	Political	1.0%

Note: Independent variables for each model are ranked ordered based on Shapley weight. **Bold** row indicates statistically significant effects of at least p<.05. Shapley weights are standardized so that the sum of each variable adds up to 100%.

Table 5. Multiple Regression – Engagement (Like and Retweet) with Misinformation Tweets

Theoretical Account	*Independent Variables*	**Like** *Beta*	**Like** *p-value*	**Retweet** *Beta*	**Retweet** *p-value*
Classical Reasoning	CRT	**-0.54**	**<.001**	.18	.07
Motivated reasoning	Political	-0.03	.64	.03	.66
	Trust in Med Sci	**-0.31**	**<.05**	**-.34**	**<.01**
	Religiosity	**0.85**	**<.001**	**.52**	**<.001**
Personality traits	PT Empathy	0.17	.45	-.17	.47
	EC Empathy	**-0.63**	**<.05**	-.35	.12
	Grand Narc	**2.49**	**<.001**	**3.27**	**<.001**
	Covert Narc	0.3	.09	.15	.39
	Openness	**-1.49**	**<.001**	-.11	.66
	Conscientiousness	**-1.03**	**<.001**	.31	.20
	Adj R-squared	.52		.15	

Note: **Bold** row indicates statistically significant effects of at least p<.05.

Discussion

The results from the current study suggest there is no singular explanation for online misinformation spread, but rather there are multiple factors that influence different aspects of propagating behavior. CRT, which corresponded to the classical reasoning account, was negatively associated with liking misinformation and explained a moderate amount of variance in this behavior, suggesting deliberative processes have an inhibitory effect on passive engagement. However, CRT was unrelated to retweeting. In accordance with predictions of motivated reasoning, religiosity was positively associated with sharing COVID-19 misinformation, while trust in medical science was negatively associated. Contrary to what is indicated in the literature, the motivated reasoning account was driven primarily by religious-based motivations rather than political ones. After controlling for all other variables, political orientation had no significant association with any form of engagement. Grandiose narcissism was associated with both liking and retweeting misinformation, in keeping with accounts that suggest personality traits lead to misinformation propagation. Among the tested factors, narcissistic tendencies and religiosity showed the closest association with active misinformation spreading behaviors.

As revealed in the present study, the variance attributed to grandiose narcissism dwarfs effect sizes associated with CRT and political orientation for retweeting misinformation. These findings provide strong support for the personality trait account over classical reasoning and politically motivated reasoning accounts of online misinformation propagation. This effect is also consistent with previous work showing that individuals high in grandiose narcissism were less likely to comply with COVID-related guidelines (Hatemi & Fazekas, 2022; Vaal et al., 2022), and more likely to engage in conspiratorial thinking (Cichocka et al., 2016). Overall, the prominence of the effect of grandiose narcissism on retweeting when controlled for factors related to classical and motivated reasoning indicate that personality traits are highly relevant for active propagating behaviors and should be considered when designing interventions to attenuate misinformation spread.

The increased propagation of misinformation by individuals high in grandiose narcissism may be driven in part by the greater tendency of these individuals to be active on social media (Gnambs & Appel, 2018; McCain et al., 2016; McCain & Campbell, 2018) (see also **Supplementary Discussion S3** and **Supplementary Tables S3** and **S4** for relevant analysis on engagement with all types of tweet stimuli). Additionally, grandiose narcissism was the only tested variable significantly associated with retweeting correction posts (**Supplementary Table S5)**. It is possible that those higher in grandiose narcissism are more likely to retweet corrections due to receiving positive attention from other users, as grandiose narcissists can act as "strategic helpers" by engaging in prosocial behaviors in order to increase their esteem through attention or praise (Konrath et al., 2016), which includes helping behaviors during the COVID-19 pandemic (Freis & Brunell, 2022).

Religiosity was the second most influential factor for retweeting misinformation, which also provides support for the motivated reasoning account. Since the majority of the sample identified as Christian (78.2%), higher religiosity refers primarily to those with stronger Christian beliefs. Despite political conservatism showing a significant correlation with misinformation engagement when tested alone using bivariate correlations (**Supplementary Table S6**), its influence disappears when controlled for religiosity and the other tested factors. Although religiosity and political orientation are generally correlated with each other (Jost et al., 2014), the findings from this study indicate religiosity is a more influential factor for the propagation of misinformation about COVID-19. This suggests researchers investigating politically motivated reasoning should also measure and control for effects from religiosity.

The present results are only partly consistent with previous studies (Azevedo & Jost, 2021; Frenken et al., 2023) that show religiosity and conservatism are both associated with scientific trust and conspiracy theory endorsement, even when controlled for each other. This inconsistency may be due to differences in outcome measures and tested covariates from previous work (Agley & Xiao, 2021). Like grandiose narcissism, religiosity was positively associated with engagement with all types of tweet stimuli (**Supplementary Table S4**). Additional research is needed to disentangle effects that are belief-driven from those that reflect a greater tendency to be active online. Lastly, trust in medical scientists was negatively associated with both liking and retweeting misinformation, in keeping with results reported in other studies investigating misinformation susceptibility (Agley & Xiao, 2021; Pickles et al., 2021; Roozenbeek et al., 2020). However, the effect size from medical scientist trust is relatively small compared to those for grandiose narcissism and religiosity, suggesting it should be a lower priority for targeting when designing interventions.

Findings from the present study reveal a noteworthy limitation for the classical reasoning account. CRT only showed a negative effect on liking misinformation tweets, which indicates that those who have a higher tendency to engage in deliberative processes are less likely to interact with posts containing false information. This is consistent with previous work showing that CRT is associated with better news discernment (Mosleh et al., 2021; Pennycook & Rand, 2019). However, when observing the most direct form of propagation on social media (i.e., retweeting), CRT showed no statistically significant effects. Other personality traits when controlled for CRT show a similar inhibitory effect on passive misinformation engagement but no association with retweeting (see **Supplementary Discussion S4**). In general, the lack of any significant effects for CRT, conscientiousness, openness, and empathy with active engagement behavior suggest they are less important variables in misinformation propagation. Although passive engagement is relevant to propagation dynamics (since liking a post can be shown to one's followers and influence the content that gets promoted by newsfeed algorithms), identifying factors that influence more direct forms of propagation are more integral to understanding large-scale misinformation spread.

The distinction between passive and active engagement behaviors could further explain discrepancies in the literature since the more private nature of liking a social media post may be more aligned with results from studies using truthfulness ratings of headlines (Pennycook & Rand, 2019), but not extend to studies using measures of active, socially-oriented behaviors such as sharing links (Osmundsen et al., 2021). Comparing results here to those in a prior study using the same tweet stimuli on a task more reminiscent of headline evaluation, CRT was a much stronger predictor for misinformation classification accuracy than it was for retweeting misinformation (Kaufman et al., 2022). This suggests truth evaluation tasks reflect cognitive processes more associated with passive engagement behaviors than with active propagation. As demonstrated in the present study, the social media simulation task was able to detect more nuanced effects than a headline evaluation task and reflects behaviors more consistent with real-world Twitter activity (Benevenuto et al., 2009; Lerman & Ghosh, 2010; Papakyriakopoulos et al., 2020; Van Mieghem et al., 2011). Future work investigating propagation behaviors should adapt newsfeed simulation tasks to better reflect possible behaviors that occur within online environments, such as the following open-source platform created to address the lack of ecologically valid social media testing paradigms (Butler et al., 2023).

While we detected distinct effects from both personality traits and motivated reasoning, these accounts could be integrated. For example, the insecure nature of those higher in narcissistic tendencies may make them more likely to engage in motivated reasoning to maintain their identity and self-esteem. Narcissistic dispositions may also provide insight into a related theory for misinformation propagation described as the motivated numeracy account, which claims those who are more capable of engaging in deliberative processes are in fact more likely to show biased thinking due to being better equipped at selecting information that aligns with pre-existing beliefs (Kahan et al., 2012, 2017; van der Linden, 2022). Further, the conceptual distinctions between narcissistic tendencies and motivated reasoning are blurred in the case of collective narcissism, that is, the belief that one's ingroup is exceptional and deserves special treatment (Nowak et al., 2020). In collective narcissism, over adherence to an identity leads to preferential and biased behaviors that prioritize gains to the in-group over the wellbeing of society (Sternisko et al., 2021). This is exactly the proposed mechanism for why people engage in politically (or other group-based) motivated reasoning (see e.g., (Kahan, 2015)). While grandiose narcissism shows distinct variance from motivated reasoning factors in the current study, effective interventions that address misinformation spread stemming from nationalistic variants of narcissism will have to account for motivated reasoning processes that aim to protect group-related identities held by users.

The position of users within a network can also be a relevant factor in misinformation propagation as indicated in previous work showing that online misinformation discourse is typically driven by a handful of influential accounts (Grinberg et al., 2019a; Haupt, Jinich-Diamant, et al., 2021a; Haupt, Li, et al., 2021a). The distinction between influential and non-influential users can be important for disentangling effects related to each theoretical explanation. For example, users who are hosts of political cable tv news shows may post a low credible news article due to narcissistic tendencies while their less influential followers may reshare the post due to motivated reasoning.

Concluding Remarks

While there is a tendency for scientific researchers to frame questions implying there is only one “correct” answer, online misinformation spread is likely too complex for a single explanation. The present study provides partial support for all the tested accounts in that reasoning ability was negatively associated with passive misinformation engagement, grandiose narcissism was positively associated with active engagement, and factors related to group identity exhibited effects in the predicted directions for the COVID-related misinformation content. Since narcissistic tendencies and religious-based motivated reasoning showed the strongest association with the most direct form of misinformation propagation (i.e., retweeting), interventions should focus particularly on users high in these traits.

Ultimately, the decision to share a post is a social behavior, whether the intent is to genuinely inform others, signal a social identity, or evoke emotional reactions. While much prior research has treated online misinformation spread as mainly related to how people assess what is true, the fact that these interactions occur on social media platforms embed these actions within contexts where users typically consider how their actions are perceived by others. To fully investigate online propagation behaviors, the influential role of socially oriented traits, group identity, and the social contexts of online environments need to be taken into account.

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Chapter 2 Investigating Textual Properties of Posts on Information Contagion

Since the early years of the internet, there has been a growing interest to understand the dynamics of information transmission, as evidenced by the emergence of multiple fields focusing on the scientific study of information as a phenomenon. One such field is infodemiology. Also known as “information epidemiology,” infodemiology is the study of the determinants and distribution of health information and misinformation, and identifies areas where there is a knowledge translation gap between best available evidence and what most people do or believe, as well as markers for “high-quality” information (Eysenbach, 2002, 2009). Other information-focused fields have existed much longer than the internet. This includes information science, which has been around since the 1950s, that investigates the “properties and behavior of information,” and the “forces governing the flow of information” (Borko, 1968), and information theory, developed in applied mathematics, that studies the quantification, storage, and communication of information (Gamal & Kim, 2011). Social scientists have also examined phenomenon related to information diffusion, as seen by cognitive scientists who posit the theory of “distributed cognition.” According to distributed cognition framework, human intelligence extends beyond the boundaries of individual actors to encompass interactions between people and resources within the environment (Cash, 2013; Hollan et al., 2000; Rogers, 1997), social organization determines the way information flows through groups (Hollan et al., 2000), and cognition is distributed over a vast array of social and technological systems that are shaped by, and shape, the individuals who develop and operate within them (Cash, 2013; Gallagher, 2013).

The emergence of these fields and theories highlights the importance of examining how properties of information (e.g., message content, emotional affect evoked) influence patterns of engagement and transmission across social networks. Research investigating diffusion dynamics of social media posts has traditionally examined linguistic properties of messages to assesses the likelihood that a post is propagated. One previously identified property is the use of emotional affect words. Studies show that posts shared more often on social media tend to have higher numbers of both positive and negative sentiment words (Pfitzner et al., 2012; Stieglitz & Dang-Xuan, 2012) as well as moral-emotional language (Brady et al., 2017; Crockett, 2017). The cognitive effort required for comprehension of a text is another property that can influence post engagement. This is illustrated by previous work showing that properties related to linguistic complexity such as higher word count and use of big words (6 letters or more) decreases likelihood of post engagement (S. W. Davis et al., 2019; Deng et al., 2021; Gligorić et al., 2019; Jones et al., 2004; Temnikova et al., 2015). These inhibitory effects on post propagation are typically attributed to higher efforts required for processing fluency, where content that is easier to comprehend is more likely to be perceived as favorable to the reader (Reber et al., 2004; Song & Schwarz, 2008). Information contagion effects can also be influenced by social factors embedded within user networks: posts that reference or are sent from influential users often receive higher engagement and propagation on platforms such as Twitter (Calac et al., 2022; Fan et al., 2021; Ye & Wu, 2010; Zareie et al., 2019).

While social media platforms are an incredible tool for communicating with others, the nature of information contagion can simultaneously make them a source of uncertainty and fear, which are often accompanied by increased dissemination of unverified rumors, misinformation, and fringe or conspiracy theories (Freckelton QC, 2020; van Prooijen & Douglas, 2017). In fact, discourses surrounding conspiracies and misinformation tend to have an emotional signature, as they are often associated with higher a frequency of anger and anxiety words (Freckelton QC, 2020; Rains et al., 2021; van Prooijen & Douglas, 2017) and focus on topics such as death, religion, and power (Fong et al., 2021; Gerts et al., 2021; Rains et al., 2021). During the 2016 US presidential election, online misinformation spread had become a ubiquitous topic in public discourse with rising concerns related to the proliferation of “fake news” on social media platforms such as Facebook and Twitter (Allcott & Gentzkow, 2017; Bovet & Makse, 2019b; Grinberg et al., 2019b). Public concern about misinformation spread has only grown since then, as shown by the proliferation of misinformation related to the COVID-19 pandemic (Zarocostas, 2020b). Previous work examining propagation patterns between factual and non-factual information also found that false information is often shared more often and for longer durations than scientifically-aligned information (Haupt, Li, et al., 2021b; J. Shin et al., 2018).

To gain a more thorough understanding of the dynamics of information propagation, this study conducted sentiment analysis on texts from social media posts to assess how language requiring greater cognitive effort for comprehension (i.e., word count, use of big words, analytic language), and reflecting emotional affect (i.e.,, positive and negative emotion) and social processes (e.g., social behaviors, social references) are associated with user engagement across political, scientific, conspiratorial discourses on Twitter and Reddit. This study builds on the work previously conducted in Chapter 1 on users, which showed that dispositional traits associated with differences in tendencies for reflective thinking, affect regulation towards social relations (e.g., grandiose narcissism, emotional concern empathy) and adherence to social conformity (i.e., religious-based motivated reasoning) influenced post engagement, regardless if the post contained factual or nonfactual information. However, the focus of this section will be on the properties of *posts* that correspond to cognitive, emotion, and social components of contagion instead of characteristics of users.

Overview of Sentiment Analysis

Sentiment analysis is often used to rapidly identify semantic content of text documents of varying lengths (e.g., tweets, transcripts, novels). Measuring sentiment from posts only requires basic arithmetic, where sentiment scores are calculated by first counting the number of words associated with a sentiment category and then dividing that count by the total number of words within the post (Tausczik & Pennebaker, 2010). Each sentiment category includes a dictionary, which is the list of words selected to represent the category. Sentiment dictionaries can measure a wide array of topics and content, such as cognitive processes (e.g., certainty, causation), emotional affect states (e.g., anger, anxiety, joy) and linguistic properties (e.g., word count) (Boyd et al., 2022).

Assigning words to sentiment dictionaries can be accomplished using data-driven approaches, as shown by Stanford's Empath project that derived over 200 classification categories from analyzing more than 1.8 billion words of modern fiction (Fast et al., 2016). However, for online misinformation research, psychometrically validated sentiment dictionaries provided by the software Linguistic Inquiry and Word Count (LIWC) have been widely used for characterizing misinformation discourse (Fong et al., 2021; Rains et al., 2021) and calculating sentiment features across multiple studies that evaluate performance of misinformation classifiers (Castelo et al., 2019; Che et al., 2018; Giachanou et al., 2022).

Interpreting sentiment scores can be further complicated when accounting for the fact that the discussion topic can influence the emotional tone of a discourse. For example, a post containing 5% of death-related words may be in the 95th percentile for discourse about gardening, making it a "high" amount, but be within the 50th percentile for pandemic-related discourse, making it a typical percentage within the context of that corpus. The type of language that is more likely to evoke further discourse also varies by online communities. For instance, a sentiment that has a positive association with engagement for one type of discourse but has a negative association in another (or no effect at all) indicates differences in the type of textual stimuli that evoke participation between groups. Sentiments that have strong effects across multiple discourses may indicate sentiments that are more universal drivers of conversation while sentiments that only show effects for a particular discourse may be contextually-dependent. In the present study, sentiments corresponding to cognitive effort, emotional affect, and social processes will be measured to compare how types of language influence user engagement across discourses and platforms.

To examine the dimension of cognitive effort in posts, the current study uses the following sentiments from LIWC: *word count*, *big words*, and *analytic*. Word count corresponds to the number of words contained in a post. Posts with greater number of words to read require more cognitive effort to understand. The number of big words contained in a post, defined by LIWC as words with greater than 6 letters, may also require more mental effort, especially if bigger words tend to refer to more complex subject matters compared to shorter words (albeit this is not always the case). This study also measures LIWC's sentiment category for *analytic thinking* language, which captures the degree to which people use words that suggest formal, logical, and hierarchical thinking patterns as opposed to using language that is more intuitive and personal. Language scoring high in analytic thinking has been linked to better academic performance (Pennebaker et al., 2014) and may also require greater cognitive effort for comprehension.

Language reflecting emotional affect has also been shown to be consistent predictors for post propagation across social media platforms. According to previous findings, posts containing words that signal both positive and negative emotions are more likely to evoke engagement from users (Pfitzner et al., 2012; Stieglitz & Dang-Xuan, 2012). Therefore, the current study uses LIWC sentiment dictionaries measuring positive and negative emotion to examine effects from emotional language on post engagement.

Other work argues that social conformity factors driven by motivated reasoning processes (i.e., selecting information that aligns with pre-existing beliefs) are also predictors of information contagion effects (Osmundsen et al., 2021). The current analysis examines the effects of conformity factors by using LIWC's sentiment dictionaries *social references*, which are words that refer to other people within a sentence (i.e., he, her), and *social behaviors*, which are words corresponding to interpersonal dynamics such as conflict and morality. For Twitter, conformity effects were further examined by calculating the percentage of tweet volume that is attributed to the most retweeted tweets across topic clusters derived from an unsupervised machine learning model.

Background on discourses examined for analysis

This study examines information diffusion effects across discourses on both Reddit and Twitter ('X'). Reddit is a platform where users are typically anonymous and are not required or expected to include personally identifying information on their account profile. Reddit has become one of the most prominent social media platforms with 52 million active users daily (Proferes et al., 2021). Discourse on Reddit is based on smaller subcommunities called "subreddits." A subreddit is based on a specific topic of conversation, which can either be very broad or specific and niche. Users choose to subscribe to subreddits, which then dictates the type of content that is promoted on their newsfeeds. Discourses on subreddits are typically moderated by other users, who also have power to dictate rules of discourse, and remove posts or users if they violate community guidelines. Previous work on information contagion typically focuses on Twitter or Facebook (Guilbeault et al., 2018; Mønsted et al., 2017) where posts are often addressed to wider audiences and associated with one's personal identity, however, contagion effects on sites such as Reddit where discourse is generated from closed communities using anonymous accounts are understudied. Due to the politicized nature of recent misinformation discourse as discussed in Chapter 1, subreddits focusing on political, scientific, and conspiratorial discourses were examined in the current chapter. The Reddit discourses collected for the present analysis were not focused on a specific topic based on keywords, but rather the most recent conversations found on each subreddit.

Twitter discourse collected for this study focused specifically on posts that contained keywords surrounding conspiracy theories claiming an association between 5G wireless technology and COVID-19 infections, which subsequently motivated the burning down of at least 80 mobile towers in the United Kingdom in early April 2020 (Hamilton, 2020). Previous work identified prominent 5G conspiracy theories such as claims stating that 5G reduces the ability of the human body to absorb oxygen, and that 5G is related to a complex agenda involving bioengineered viruses and deadly 5G-activated vaccines led by elite figures such as Bill Gates, George Soros, the World Health Organization (WHO), and secret-society organizations like the Illuminati (Bruns et al., 2020b). A study that used social network analysis found that influential accounts tweeting 5G-COVID conspiracies tended to form a broadcast network structure resembling the structure most typical for accounts from mainstream news outlets and celebrities that are frequently retweeted (Ahmed et al., 2020). Further, public figures and celebrities who, whether with deliberate malintent or not, share rumors and falsehoods to their large groups of followers (Arora et al., 2020; Bruns et al., 2021; Calac et al., 2022; I. Shin et al., 2022) were also involved in 5G-COVID conspiracy discourse, as shown in a study that identifies celebrities and religious leaders as 5G-COVID conspiracy propagators on Facebook (Bruns et al., 2020).

Methods

Data collection and analysis overview

On the platform Reddit, 500 of the most recent posts since April 2024 were collected from 4 subreddits that focus on scientific (r/science, r/EverythingScience) and conspiratorial (r/conspiracy, r/actualconspiracies) discourses, and 4 subreddits that focus on left-leaning (r/Liberal, r/democrats) and right-leaning (r/Conservative, r/Republican) discussions. These subreddits were chosen for analysis due to having a high number of subscribers and active involvement from users. See **Tables 6** and **7** for detailed descriptions (e.g., number of subscribers as of April 2024, timeframe of collected posts, affiliated communities) of each subreddit.

Table 6. Summary of Examined Political Subreddits (500 most recent posts collected on April, 2024)

	r/Liberal	**r/democrats**	**r/Conservative**	**r/Republican**
# of unique authors (% unique)	257 (51.4%)	145 (29.0%)	134 (26.8%)	71 (14.2%)
# of subscribers	116,831	437,104	1,086,234	190,861
# of posts with body text (%)	298 (59.6%)	78 (15.6%)	22 (4.4%)	20 (4.0%)
Collection Timeframe	11/2/2023 – 4/17/2024	3/30/2024 – 4/18/2024	4/14/2024 – 4/18/2024	3/25/2024 – 4/18/2024
Affiliated Subreddits	r/JoeBiden r/geopolitics r/democrats	r/JoeBiden r/environment r/women r/Liberal	r/dailywire r/AskThe_Donald r/ConservativeMemes r/Republican	r/CollegeRepublicans r/Capitalism r/ProGun r/Conservative

Table 7. Summary of Examined Scientific and Conspiratorial Subreddits (500 most recent posts collected on April, 2024)

	r/science	**r/Everything Science**	**r/conspiracy**	**r/actual conspiracies**
# of unique authors (% unique)	163 (32.6%)	132 (26.4%)	346 (69.2%)	190 (38.0%)
# of subscribers	31,836,939	523,128	2,093,158	82,135
# of posts with body text (%)	1 (<1%)	8 (1.6%)	277 (55.4%)	56 (11.2%)
Collection Timeframe	3/26/2024 – 4/18/2024	3/19/2024 – 4/18/2024	4/15/2024 – 4/18/2024	3/17/2017 – 2/22/2024
Affiliated Subreddits	r/askscience r/EverythingScience	Sister to r/science but with broader posting rules	r/Wikileaks r/911Truth r/NSALeaks r/UFOs	Claims more factual conspiracies than r/conspiracy

On Twitter, a total of 256,562 tweets (70,622 unique tweets) were collected from the public streaming API using keywords "5G" and covid-related words such as "coronavirus", "covid-19" between March 25th and April 3rd 2020. This time frame was chosen as it represents a period when the 5G conspiracy theory first became prominent, as shown in the spike in volume for "5G" posts in **Figure 6**. All personal identifiable information from tweets was removed in the reporting of the results to preserve anonymity. The author notes that due to the change in ownership, API policies, and name of the platform (Twitter has been renamed "X"), the terms and conditions of the streaming API used for data collection for this study are no longer applicable for current studies.

To analyze the relatively large volume of tweets collected in this study, biterm topic modeling (BTM) was applied to extract themes from text of tweets as used in prior studies examining COVID-19 topics on social media (Haupt, Jinich-Diamant, et al., 2021b; Haupt, Li, et al., 2021b; T. K. Mackey et al., 2020). The top 10 most retweeted tweets associated with each topic cluster were coded using a deductive coding scheme adapted from previous COVID-19 misinformation work (Haupt, Li, et al., 2021b; T. K. Mackey et al., 2021b) to classify posts on whether they contain misinformation, or factual (further discussed in Section 2.2).

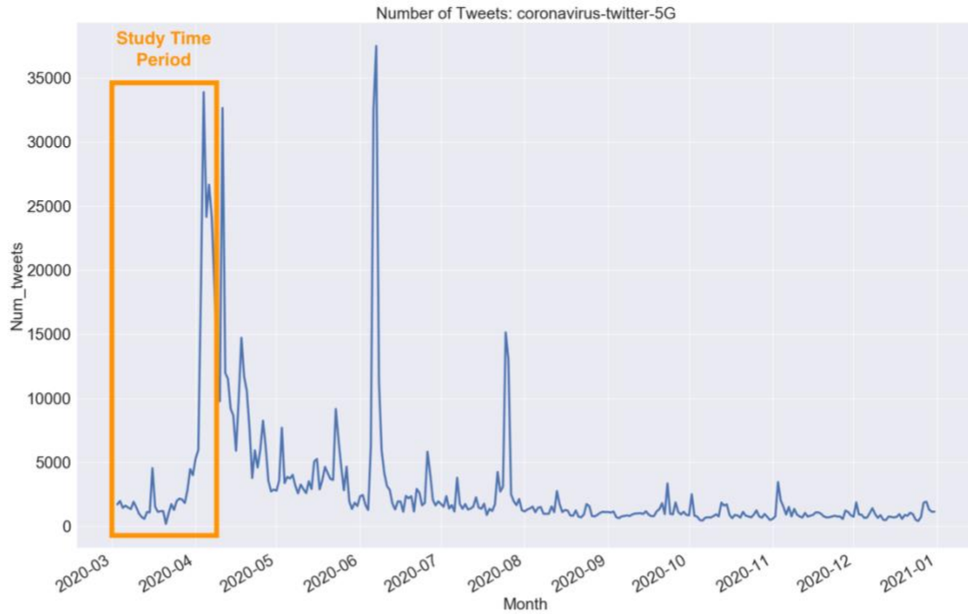

Figure 6. Number of 5G-related tweets from March 2020 to January 2021

Biterm Topic Model (BTM) on Twitter posts

In order to characterize highly prevalent misinformation and conspiratorial narratives in the corpus, the top 10 most retweeted tweets from all BTM topic outputs were extracted and manually coded for relevance first using a deductive coding scheme adapted from existing COVID-19 misinformation themes from the literature (Haupt, Li, et al., 2021b; Islam et al., 2020; T. K. Mackey et al., 2021b). Unsupervised topic modeling strategies, such as BTM, are methods particularly well suited for sorting short text (such as the 280-character limit for tweets) into highly prevalent themes without the need for predetermined coding or a training/labelled dataset to classify specific content. This is particularly useful in characterizing large volumes of unstructured data where predefined themes are unavailable, such as in the case of emerging social movements, novel disease outbreaks, and other emergency events where information changes rapidly (Blekanov et al., 2018; Haupt et al., 2023; Haupt, Jinich-Diamant, et al., 2021b; Haupt, Li, et al., 2021b; T. Mackey et al., 2018, 2020; T. K. Mackey et al., 2017, 2020; Schück et al., 2021).

The corpus of tweets containing the 5G keywords were categorized into highly correlated topic clusters using BTM based on splitting all text into a bag of words and then producing a discrete probability distribution for all words for each theme that places a larger weight on words that are most representative of a given theme (Kalyanam et al., 2017). While other NLP approaches use unigrams or bigrams for splitting text, BTM uses ‘biterms’, which is a combination of two words from a text (e.g., the text “go to school” has three biterms: ‘go to’, ‘go school’, ‘to school’) and models the generation of biterms in a collection rather than documents (Yan et al., 2013, p. 201). BTM was used for this study because biterms directly model the co-occurrence of words, which increases performance for sparse-text documents such as tweets. All data collection and processing were conducted using the programming language Python.

In total, 400 unique tweets were reviewed by human content coders. While misinformation and conspiracies are distinct concepts, the current study will refer to both as ‘misinformation’ within the analysis for brevity. Tweets were classified as 5G misinformation if they contained declarative statements claiming that 5G causes COVID-19. A tweet was considered factual information if it explicitly opposes 5G conspiracies or misinformation, and provided information countering the misinformation claims. See **Table 8** for examples of tweets in each category and the following studies for further description of how topic modeling was used to characterize 5G Twitter discourse (Haupt et al., 2023; Haupt, Li, et al., 2021b).

Table 8. Examples of Content Coded Tweets (paraphrased and redacted to retain anonymity).

5G Categories	*Misinformation:* 1. #5G produces the same symptoms as this supposed #coronavirus or #COVID19. Watch this video [LINK] 2. RT! 5G is the real silent killer, not the Corona Virus!!!
	Factual: 1. Scientists say any suggestion that coronavirus and 5G are linked is "complete rubbish" and biologically impossible 2. I can confirm that 5G is in no way giving people #coronavirus because that would require converting radio waves into organic molecules. This is pretty much God-level ability, and anyone capable of it would be running the planet already

Regression analysis - LIWC sentiment

Sentiment analysis was conducted to examine how cognitive, affective, and social conformity factors influence contagion effects of post content. Therefore, LIWC sentiment dictionaries were chosen for analysis if they corresponded language requiring greater cognitive effort for comprehension (i.e., word count, use of big words, analytic language), emotional affect (i.e.,, positive and negative emotion), and social processes (e.g., social behaviors, social references). These sentiments were tested as independent variables for multiple regression analysis with engagement behaviors at the dependent variables. On Reddit, engagement behaviors were count variables for the number of upvotes and comments received by a post. For Twitter, engagement was operationalized as counts for favorites, replies, and retweets. Multiple regression was used to assess which effects remain significant when controlled for each other. Due to potential multicollinearity between sentiment categories, a shapley regression was used to quantify the effect sizes between sentiments and engagement, as previously implemented in Chapter 1.

Results

Regression analysis – sentiment

Table 9 shows regression results between the tested LIWC sentiment variables and Reddit engagement behaviors for the political subreddits (r/Liberal, r/democrats, r/Conservative, r/Republican). Less than 30 posts included body text for r/Conservative and r/Republican, therefore only associations based on title text were examined for those subreddits.

When examining engagement effects in r/Liberal, upvoting was positively associated with higher word count (WC) in the title (.03, $p<.01$) when controlled for all tested variables. However, word count was negatively associated with upvoting for body text (-.00, $p<.05$). Based on the shapley results, WC explains the majority of the variance for both models ($78.1\%_{title}$, $49.9\%_{body}$). Use of analytic language was negatively associated with commenting on posts when used in both the title (-.01) and body text (-.01). These effects were highly significant ($p<.001$) and explain the majority of variance for commenting ($79.7\%_{title}$, $74.3\%_{body}$). Use of social references in the body text was also negatively associated with commenting (-.03, $p<.05$). For r/democrats, use of big words in the title was negatively associated with upvoting (-.01, $p<.01$) and commenting (-.01, $p<.01$) when controlling for covariates. Use of big words in the body text was also negatively associated with both types of engagement ($\beta_{Up} = -.03$, $p<.05$; $\beta_{Com} = -.04$, $p<.01$). Similar to r/Liberal, use of analytic language in the title and body text was negatively associated with commenting ($\beta_{Title} = -.01$, $p<.001$; $\beta_{Body} = -.02$, $p<.001$) and showed the strongest effect sizes among tested predictors (51.2%$_{title}$, 35.9%$_{body}$). Use of analytic language in the post title was also negatively associated with upvoting (-.00, $p<.05$) while higher word count in the body text was negatively associated with commenting (-0.0, $p<.05$).

For r/Conservative, title text containing analytic language was negatively associated with engagement (β_{Up} = -.01, $p<.01$; β_{Com} = -.01, $p<.001$) when controlled for all covariates. Higher word count in the title was also positively associated with upvoting (0.08) and commenting (0.05). These effects are highly significant ($p<.001$) and are the strongest predictors among tested variables (57%$_{Up}$, 37.9%$_{Com}$). Use of negative emotion words in the post title was negatively associated with both engagement behaviors (β_{Up} = -.06, $p<.05$; β_{Com} = -.05, $p<.05$) and use of big words was positively associated with upvoting (.01, $p<.05$). When assessing engagement in r/Republican, the use of social references in post titles was positively associated with upvoting (.02, $p<.05$) and showed the strongest effect size (31.6%) among tested variables. Use of analytic language was negatively associated with both types of engagement (β_{Up} = -.00, $p<.05$; β_{Com} = -.01, $p<.01$) while higher word count in the title was positively associated with commenting (0.03, $p<.01$) and explained the most variance (41.9%).

Table 9. Regression between LIWC Sentiment x Reddit Engagement (Upvote and Comment) – Political Subreddits by Title and Body Text

LIWC Sent	r/Liberal				r/democrats				r/Conservative		r/Republican	
	Title		Body *(n=298)*		Title		Body *(n=78)*		Title		Title	
	Up *Shap (Beta)*	***Com*** *Shap (Beta)*	***Up*** *Shap (Beta)*	***Com*** *Shap (Beta)*	***Up*** *Shap (Beta)*	***Com*** *Shap (Beta)*	***Up*** *Shap (Beta)*	***Com*** *Shap (Beta)*	***Up*** *Shap (Beta)*	***Com*** *Shap (Beta)*	***Up*** *Shap (Beta)*	***Com*** *Shap (Beta)*
WC	***78.1% (0.03)***	1.2% (0.01)	**49.9% (-0.0)**	0.3% (0.0)	3.6% (0.01)	0.6% (-0.01)	34.1% (-0.0)	**27.2% (-0.0)**	***57% (0.08)***	***37.9% (0.05)***	15.8% (0.02)	***41.9% (0.03)***
BigWord	1% (0.0)	11.9% (0.0)	4.8% (0.0)	13.8% (-0.01)	***48% (-0.01)***	***39.2% (-0.01)***	**33.3% (-0.03)**	***27.4% (-0.04)***	**4.3% (0.01)**	2.2% (0.01)	8.7% (0.01)	2.5% (0.0)
Analytic	0.3% (0.0)	***79.7% (-0.01)***	22.9% (0.0)	***74.3% (-0.01)***	**36.8% (-0.0)**	***51.2% (-0.01)***	17.3% (-0.01)	***35.9% (-0.02)***	***19.4% (-0.01)***	***31.4% (-0.01)***	**18.4% (-0.0)**	***30.7% (-0.01)***
emo_p	3.9% (-0.01)	1.2% (0.01)	10.9% (-0.04)	2.6% (-0.03)	0.3% (-0.01)	0.3% (-0.01)	1.6% (0.02)	0.6% (-0.02)	0.4% (0.03)	4.9% (0.06)	9.3% (0.04)	4.8% (0.03)
emo_n	1.9% (0.01)	0.1% (-0.01)	8% (0.01)	3% (-0.02)	5.5% (-0.02)	0.8% (0.01)	5.4% (0.06)	2.3% (0.06)	**8.2% (-0.06)**	**9.9% (-0.05)**	0.9% (0.01)	0.6% (-0.01)
socbehv	4.3% (0.01)	1.5% (0.0)	0.6% (0.0)	1.6% (0.01)	1.3% (0.0)	3.3% (0.01)	3% (0.02)	3.6% (0.02)	0.1% (-0.0)	0.9% (-0.01)	15.2% (0.01)	4.3% (0.01)
socrefs	10.5% (-0.01)	4.3% (0.0)	2.9% (0.0)	**4.3% (-0.03)**	4.4% (0.0)	4.6% (0.0)	5.2% (0.02)	2.9% (0.01)	10.6% (0.02)	12.8% (-0.02)	**31.6% (0.02)**	15.2% (0.01)
R-sq	*.026*	*.010*	*.033*	*.157*	*.037*	*.065*	*.286*	*.424*	*.080*	*.106*	*.044*	*.046*

Note: **bold** = p<.05, ***bold italic*** = p<.01, ***shaded cell*** = p<.001. Beta coefficients are rounded up to 2nd decimal place.

Table 10 shows regression results between the tested LIWC sentiment variables and Reddit engagement behaviors (i.e., upvoting and commenting) for the scientific (r/science and r/EverythingScience) and conspiratorial subreddits (r/conspiracy and r/actualconspiracies). The percentages show the results from the shapley regression, which corresponds to the proportion of variance attributed to each independent variable. The unstandardized beta coefficient from the multiple regression models are shown inside the parentheses "()". Cells that are **bolded** indicate statistical significance at p<.05 and ***bold italic*** indicate significance at p<.01. Less than 30 posts included body text for r/science and r/EverythingScience, therefore only associations based on title text were examined for those subreddits.

For post engagement on r/science, word count (WC) of the title was positively associated with upvoting (.04, p<.001) and commenting (.03, p<.001) when controlled for all tested covariates. Both effects are highly statistically significant (p<.001). Use of social references in the title was also associated with increased engagement (β_{Up} = .04, p<.05; β_{Com} = .04, p<.05). Use of big words (i.e., more than 6 letters) in post titles was negatively associated with both types of engagement (β_{Up} = -.03, p<.001; β_{Com} =- .03, p<.001) while use of analytic language was negatively associated with commenting (-.01, p<.05). Based on the shapley results, effects attributed to WC and use of big words account for the majority of the variance for both upvoting (83.3%) and commenting (65.5%). For the subreddit r/EverythingScience, longer word count in the title was positively associated with upvoting (.03, p<.01) and use of negative emotion words was associated with increased commenting (.08, p<.05) when controlled for all other variables. Use of big words in the title was negatively associated with both engagement behaviors (β_{Up} = -.01, p<.01; β_{Com} =- .01, p<.01) and was the strongest predictor among tested variables (40.4%$_{upvote}$, 40.6%$_{comment}$). Use of analytic language in the post titles was also negatively associate with commenting (-.01, p<.05).

When examining engagement for r/conspiracy, higher word count in the post title was positively associated with upvoting (.02, p<.01) when controlled for all other covariates. Use of analytic language in the title was negatively associated with both types of engagement (β_{Up} = -.01, p<.01; β_{Com} =- .01, p<.001) and explains the majority of variance for commenting (64.4%). Use of big words in the title was also negatively associated with commenting (-.01, p<.05). For the body text of posts, use of emotionally negative words was negatively associated with commenting (-.09, p<.05) and explains the majority of variance among tested predictors (41.8%). Within the subreddit r/actualconspiracies, titles with higher word count were positively associated with both types of engagements (β_{Up} = .02, p<.001; β_{Com} = .01, p<.01). Further, use of analytic language in the titles was negatively associated with upvoting (-.01, p<.01) and commenting (-.01, p<.01) when controlled for all tested variables. There were no statistically significant effects associated with the body text.

Table 10. Regression between LIWC Sentiment x Reddit Engagement (Upvote and Comment) – Scientific and Conspiratorial Subreddits by Title and Body Text

	r/science		**r/Everything Science**		**r/conspiracy**				**r/actualconspiracies**			
	Title		**Title**		**Title**		**Body** *(n=276)*		**Title**		**Body** *(n=56)*	
	Up	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***
LIWC Sent	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*
WC	***51.3% (0.04)***	***30.1% (0.03)***	***32% (0.03)***	2.2% (0.01)	***29.3% (0.02)***	3.9% (0.01)	3.7% (0.0)	1.4% (0.0)	***69.8% (0.02)***	***34.5% (0.01)***	1.3% (0.0)	16.1% (0.0)
BigWord	***32% (-0.03)***	***35.4% (-0.03)***	***40.4% (-0.01)***	***40.6% (-0.01)***	4.4% (0.01)	**23.9% (-0.01)**	26.4% (0.02)	2.1% (0.0)	3.7% (0.0)	4.5% (0.0)	31.4% (-0.04)	31.2% (-0.03)
Analytic	3.3% (-0.01)	**11.8% (-0.01)**	7.7% (0.0)	**23.8% (-0.01)**	***37.8% (-0.01)***	***64.4% (-0.01)***	21.9% (-0.01)	26% (0.0)	***20.2% (-0.01)***	***46.6% (-0.01)***	30.5% (0.01)	3.8% (0.0)
emo_p	0.3% (-0.01)	1.4% (0.06)	2.1% (0.05)	2.9% (0.05)	4.5% (0.05)	0.1% (0.0)	19% (-0.06)	14.3% (-0.06)	2.1% (-0.02)	12.3% (0.05)	5.4% (0.13)	17.4% (0.3)
emo_n	1.8% (0.05)	4.1% (0.07)	12.9% (0.07)	**22.7% (0.08)**	3.1% (-0.04)	0.2% (0.0)	2.1% (0.02)	**41.8% (-0.09)**	0.5% (0.01)	0.5% (-0.02)	19% (0.05)	17.7% (0.08)
socbehv	0.8% (0.01)	4.1% (0.04)	4.2% (0.02)	3.4% (0.01)	1.9% (-0.01)	0.4% (0.0)	25.1% (0.05)	13.3% (0.03)	0% (0.0)	0.8% (0.0)	7.9% (-0.03)	7.3% (-0.04)
socrefs	**10.5% (0.04)**	**13.1% (0.04)**	0.8% (-0.01)	4.4% (0.0)	19% (0.02)	7.1% (0.0)	1.9% (0.01)	1.1% (-0.01)	3.8% (0.01)	0.8% (0.0)	4.7% (0.0)	6.4% (-0.02)
R-sq	*.173*	*.161*	*.048*	*.054*	*.051*	*.079*	*.030*	*.050*	*.062*	*.042*	*.190*	*.156*

Note: **bold** = p<.05, ***bold italic*** = p<.01, ***shaded cell*** = p<.001. Beta coefficients are rounded up to 2nd decimal place.

Table 11 shows regression results between the tested LIWC sentiment variables and Twitter engagement behaviors (Favorite, Reply, Retweet) for 5G conspiracy discourse (factual and misinformation). Higher word count in the posts was positively associated with all examined types of engagement behaviors for both factual (β_{Fav} = .01, p<.001; β_{Reply} = .01,

$p<.001$; $\beta_{RT} = .01$, $p<.001$) and misinformation discourses ($\beta_{Fav} = .02$, $p<.001$; $\beta_{Reply} = .01$, $p<.001$; $\beta_{RT} = .02$, $p<.001$) when controlled for all tested covariates. Further, over 75% of the variance predicted by each model is attributed to word count. For factual 5G discourse, analytic language was positively associated with all types of engagement ($\beta_{Fav} = .00$, $p<.001$; $\beta_{Reply} = .00$, $p<.01$; $\beta_{RT} = .00$, $p<.001$) and was the second strongest predictor for each model. Use of negative emotional words was negatively associated with favoriting (-.00, $p<.05$) and replying (-.00, $p<.05$). Language referring to social behaviors was negative associated with favoriting (-.00, $p<.05$) while use of social references was positively associated (.00, $p<.01$). For 5G misinformation discourse, use of analytic language was negatively associated with all types of engagement ($\beta_{Fav} = -.00$, $p<.05$; $\beta_{Reply} = -.00$, $p<.05$; $\beta_{RT} = -.00$, $p<.05$) while use of negative emotion words was negatively associated with favoriting (-.00, $p<.05$). When assessing Twitter engagement overall, it is worth noting that the R-sq associated with most of the models examining Twitter discourse is consistently an order of magnitude lower compared to the models assessing Reddit engagement.

Table 11. Regression between LIWC Sentiment x Twitter Engagement (Favorite, Reply, and Retweet) –Factual and Misinformation 5G Discourse

LIWC Sent	***5G Factual (n=35,175 unique tweets)***			***5G Misinformation (n=8,947 unique tweets)***		
	Fav	***Reply***	***RT***	***Fav***	***Reply***	***RT***
	Shap (Beta)	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*
WC	***81.1% (0.012)***	***87.8% (0.007)***	***76.4% (0.009)***	***78.1% (0.024)***	***79.2% (0.012)***	***84.2% (0.021)***
BigWord	4.3% (0.001)	4.1% (0.0)	2.9% (0.001)	7.8% (0.002)	6.4% (0.001)	**6.7% (0.002)**
Analytic	***5.4% (0.001)***	***4.4% (0.0)***	***15.4% (0.001)***	**7.4% (-0.001)**	**9.7% (-0.001)**	**5.9% (-0.001)**
emo_p	0.1% (0.002)	0% (0.0)	0.1% (-0.001)	0.1% (-0.006)	0.7% (-0.006)	0.6% (-0.01)
emo_n	**1.1% (-0.004)**	**1.1% (-0.002)**	1.8% (0.0)	**4.9% (-0.009)**	2.5% (-0.003)	0.9% (-0.002)
socbehv	**2.8% (-0.002)**	0.1% (0.0)	1.8% (-0.002)	0.2% (-0.001)	0.2% (0.001)	0.4% (-0.001)
socrefs	***5.1% (0.003)***	2.4% (0.001)	1.7% (0.002)	1.6% (-0.001)	1.2% (-0.001)	1.4% (-0.001)
R-sq	.005	.005	.006	.014	.009	.013

Note: **bold** = p<.05, ***bold italic*** = p<.01, ***shaded cell*** = p<.001. Beta coefficients are rounded up to 3rd decimal place.

Analysis of Biterm Topic Clusters – 5G Twitter Discourse

Table 12 shows summary metrics of the 20 BTM topic clusters detected from the unsupervised machine learning approach. For each topic cluster, the table displays the total number of tweets, number of textually unique tweets, and the percentage of posts that are retweets of the top 10 most retweeted tweets. For the top 10 most retweeted tweets, the number of unique authors that were post authors and the percentage of top tweets that were classified as misinformation are also shown as columns. Topic clusters shaded in red indicate discourses with high percentage of misinformation based on content coding the top 10 retweeted tweets.

For most topic clusters, the majority of post volume is attributed to retweets of the top 10 retweeted tweets. This is most pronounced for topic clusters 11, 13, 15, 10, and 6 where over

80% of the post volume are from the top 10 most retweeted tweets. When averaged across all 20 topic clusters, the average percent of post volume attributed to the top 10 tweets is 64.8%. For the 4 clusters do not have a majority of posts attributed to the top 10 tweets, a sizable volume of posts are still attributed to these posts with 40.9% from the lowest cluster. Across all examined topic clusters high in misinformation, over 50% of post volume was attributed to the top 10 tweets.

Table 12. Summary Metrics of Biterm Topic Clusters – 5G Twitter Discourse

topic ID	Total Tweets	# unique Tweets	% Volume from top 10 tweets	# unique users of top 10 tweets	% Misinfo in Top 10 tweets
11	2358	345	89.1%	10	92.6%
13	10478	700	88.1%	9	92.7%
15	5866	770	86.5%	9	17.2%
10	2551	727	80.7%	7	60.6%
6	2217	703	80.5%	9	43.6%
19	10103	2625	76.3%	8	41.2%
8	2429	892	72.7%	6	69.9%
2	66434	15967	71.9%	9	11.2%
16	1523	628	68.0%	6	93.3%
5	5939	2023	63.6%	7	59.6%
14	4765	1510	61.2%	7	27.9%
0	5669	1617	58.2%	3	94.0%
4	9703	1988	57.2%	8	87.8%
1	14122	3529	54.7%	9	15.1%
17	18512	4788	54.2%	9	0.0%
7	1472	1358	50.3%	7	100.0%
3	14857	4490	48.7%	7	0.0%
12	20520	3594	47.0%	10	12.4%
9	7030	3219	46.6%	8	31.7%
18	50014	19149	40.9%	10	4.4%

Note: Cells shaded in red indicate topic clusters with high volume of misinformation tweets.

Discussion

When assessing properties of Reddit posts that elicit engagement from users, posts that were more cognitively demanding (i.e., containing complex words and analytic language) were less likely to receive upvotes and comments across all types of examined discourses. For all 8 subreddits, the use of analytic language was negatively associated with engagement when included in either title or body text. With the exception of r/Liberal, r/Republican, and r/actualconspiracies, all other subreddits showed lower engagement with the inclusion of big words (i.e., greater than 6 letters). Effects from post length, when controlled for covariates such as use of big words, were mixed on engagement. When title text was longer in word count, it was positively associated with either upvoting or commenting for all examined subreddits except for r/democrats. However, posts with longer body text were less likely to be upvoted on r/Liberal and receive comments on r/democrats. These findings suggest that lengthier post titles may be valued higher more generally across subreddit communities, as users may appreciate receiving more information on their newsfeed before deciding to view the body text. Body text with lengthier word counts, however, may strain user’s attention and willingness to engage. Posts that discuss more elaborated and complex ideas, as measured by the use of analytic language and big words, may also require a threshold of cognitive effort that is too high for users to be willing to engage with the content. As with many factors related to the cognitive component of contagion effects, it is important not to assume that potential message receivers will be willing to exert the cognitive effort required to read the post content, even if they have the ability to engage in the needed deliberative processes for comprehending the message.

On Twitter, posts with higher word counts were more likely to receive engagement within both factual and misinformation discourses, and these effects explained over 75% of the variance for all examined behaviors (favorite, reply, retweet). As tweets are in similar length to post titles on Reddit, this finding also suggests that online users may respond more to longer word counts in contexts where there are word limits, and the text is meant to provide high level thoughts and summaries, such as headlines, compared to detailed and elaborated posts. Use of analytic language was positively associated with engagement for factual discourse but showed negative associations for discourses containing misinformation. These findings may reflect differences in Twitter users involved in 5G discourse, as those engaging with factual discourse and participating in dispelling rumors may value analytic language more than those propagating 5G-related misinformation.

Effects on engagement from emotional affect words were limit across subreddits. Use of positive emotion words showed no statistically significant effects on either upvoting or commenting when controlled for all tested covariates. Use of negative emotion words were negatively associated with engagement on r/Conservative (both upvoting and commenting) and r/conspiracy (upvote only) while it had a positive effect on commenting when included in the title text for r/EverythingScience. On Twitter, use of negative emotion words was negatively associated with favoriting posts in both factual and misinformation 5G discourses, and negatively associated with replying within factual discourse. However, use of emotion words (both positive and negative) showed no significant associations with retweeting in any of the examined 5G discourse. These findings add to the current literature on information contagion. Previous work characterizes 5G-COVID conspiracies as having a higher degree of negative and emotional language (Gerts et al., 2021; Rains et al., 2021), however, the current analysis focuses on message properties that are associated with propagation and observes that the use of emotion words had an inhibitory effect on engagement behaviors. Therefore, these findings may indicate that conspiratorial discourse has a negative emotional signature, but that use of emotional words are less important for propagating messages. The present findings also suggest that information contagion effects on subreddits, which are closed discourse communities that are organized around a specific topic or purpose, may be influenced by emotional language differently compared to platforms that host more public conversations such as Twitter.

Language corresponding to social conformity factors were limited as predictors when examining information contagion. On Reddit, language reflecting social behaviors did not show statistically significant effects on upvoting or commenting. Use of social references in the title text was positively associated with engagement on r/science and r/Republican, and negatively associated with commenting when included in the body text for r/Liberal. All other subreddits did not show significant associations between social references and engagement. These findings suggest that mentions of social behaviors are not topics that evoke discourse, and that referencing other people can evoke discussion in some online conversations depending on the context of the user community. On Twitter, use of social behavior words was negatively associated with favoriting a tweet in 5G factual discourse while social references was positively associated with favoriting. There were no significant effects observed for use of social references and engagement with misinformation discourse. The higher engagement with tweets containing social-related words in factual discourse may reflect higher tendencies to make calls to authorities when confronting 5G conspiracies while misinformation spreaders may be less concerned about the source of information. This explanation would also be consistent with the analysis of the Biterm topic clusters detected in the 5G Twitter discourse. While the majority of post volume were retweets of the top 10 retweeted tweets for all types of examined conversation, this effect was particularly pronounced for topic clusters high in misinformation.

This study also observes that regressions explained greater variance of engagement behaviors on Reddit (R-sq range = .010-.424) compared to Twitter (R-sq range = .005-.014). These differences in predictor strength are likely due to features associated with each platform, as X has a 280-character limit, user profiles are typically public, and tweets are public to all user's followers. Conversely, Reddit does not contain word limits on posts, profiles are typically anonymous, and posts are sent to specific subreddits where those who see it share a common set of interests. Due to the lack of personal identity associated with Reddit accounts, it is possible that users on this platform place greater importance on textual features of posts while engagement with Twitter posts may be more impacted by whether a tweet was sent by an influential account. The impact of influential accounts is further observed in the analysis of Biterm topic clusters, where retweets from 10 users or less were able to account for the majority of post volume. It is also likely that people use platforms for different purposes. Previous work introduces a "Needs-Affordance-Features" framework (Karahanna et al., 2018), which posits that social media users are drawn towards certain sites based on their own specific psychological needs and the possible actions produced by platform features (e.g., posting anonymously vs posting with personal identity displayed). Differences in how platforms address psychological needs among users (e.g., seeking quick information vs detailed discussion) may further impact factors influencing contagion effects.

Limitations

There are other properties of posts related to propagation effects that were not examined in the current study, such as the influence of discourse topics on engagement levels. For instance, topics that are socially controversial and politically polarizing (e.g., gun control, abortion legality) are typically more likely to elicit engagement from users compared to mundane topics such as the weather (unless in cases of natural disasters that impact a group of people). Additionally, topics that are taboo or not considered socially acceptable often receive little attention or discussion in larger discourse, as well as topics that are unfamiliar to the general public or require knowledge from other cultural contexts. Future work is needed to compare effects from language use across polarizing and mundane discourse topics. Another limitation of this study is that the 5G discourse on Twitter is only 1 topic during a specified time frame. Effects from sentiment on propagation may differ in an analysis based on multiple topics during a wider time frame. Results from Reddit posts may also be influenced by the "karma" system implemented on the site, where accounts that are downvoted or do not post content often are not allowed to participate in certain subreddits. Differences in posting guidelines and discourse policies set by moderators, discourse norms established among long-term users, and number of subscribers in a subreddit are other factors that can influence engagement effects on subreddits not examined in the current study.

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Chapter 3 Adapting Semantic Networks to Investigate Information Contagion

Graph theory has increasingly been used in recent years to examine cognitive phenomena such as memory structure using semantic networks. Within a semantic network, concepts or words are represented as nodes and relationships between nodes are shown as ties. When constructed from textual sources, such as social media posts, ties between nodes are by based on the co-occurrence of words. However, ties between nodes can also be constructed using experimental measures where participants rate the similarity between concepts. Previous researchers proposed that ties between semantic nodes correspond to a spreading activation model of semantic priming, where concepts which are semantically related are located closer to each other in the network and have stronger links connecting them (Kenett et al., 2017). The processing of a concept leads to the activation of its mental representation, and this activation spreads to all other concepts connected to it and dissipates as the distance (i.e., the number of links) increases.

Overall, converging evidence suggest that network-based representations of semantic knowledge can correspond to cognitive processes that directly relate to how one would evaluate the content of a message. Work investigating how semantic networks relate to individual cognition has detected associations between semantic path length and working memory, where concepts with shorter lengths are recalled together at shorter times and more likely to be perceived as associated (Kenett et al., 2017). When investigating substance use behavior, for instance, individual differences in behavioral activation and inhibition tendencies were associated with differences in the organization of semantic networks and patterns of activation of expectancies (Simons et al., 2009). Kennet et al. (2016) compare semantic network generated between those with Asperger’s syndrome and matched-controls. Consistent with previous descriptions of autism as having hyper rigid and highly logical thought, Kenett et al. (2016) found that those with Asperger's had lower number of nodes and higher modularity in their semantic networks that were constructed from word association tasks. Another study using word association tasks found that semantic networks of high creative individuals had higher connectivity, shorter distances between concepts, and fewer subcommunities in their network than low creative individuals (Kenett et al., 2014). Semantic network structure can also indicate mental illness, as shown by Kelley & Gillan (2022) who found a positive association between depression and network density between depression-relevant linguistic features using 12 months of Twitter data.

In addition to representing cognitive processes on the individual level, semantic networks can be used to characterize views and thoughts aggregated from multiple users across large-scale social media discourse. Previous work that constructed semantic networks from Twitter data found that anti-vax discourse had a higher number of conceptual nodes and lower density compared to networks constructed from pro-vax conversations (Kang et al., 2017). Semantic networks from Twitter posts have also been used to identify frames concerning an emerging measles outbreak (Tang et al., 2018), examine meaning of a corporation's advocacy messages (Yang & Veil, 2017), and compare associations between climate change discussions (Shi et al., 2020). Other textual sources have been used to construct semantic networks as well. Networks based on news articles have been used to compare views towards disease-related policy decisions across stakeholder groups (Lim et al., 2016), and networks from interview transcripts were used to assess priorities in emergency response efforts to natural disasters (Tsuboyama-Kasaoka et al., 2021).

Ego network of words, a subset of semantic networks, are also effective at assessing how associations for a given topic may differ across people. Ego networks hone in on a selected node (ego) within the network and only show alter nodes that are within a specified degree of separation from the ego determined by the analyst (e.g., only nodes that are directly tied to the ego, nodes that are within 2 degrees of separation, etc…). Past work based on a corpus of tweets from professional writers and regular users shows that ego networks can capture how individuals organize their cognitive effort in language production and reveal structural invariants in how people organize their vocabulary (Ollivier et al., 2022). Other work has used ego networks to examine associations around the word "Feminism" (Xiong et al., 2019), and shows that ego networks can be adapted to improve performance of machine learning models (Lucia & Ferrari, 2014; Rong et al., 2016).

Despite the demonstrated utility of semantic networks in representing thought processes across large discourses, this approach is primarily applied to Twitter, where conversations are public, tied to one's personal identity, and posts have a character limit which makes conversations more telegraphic. However, semantic networks are underutilized for examining conversations on platforms such as Reddit, where the lack of word limits on posts and anonymity of the platform allow for elaborated discussions. To showcase the utility of semantic networks, this study applies centrality analysis to identify influential topics in political, scientific, and conspiratorial subreddit discourses, as previously examined in Chapter 2. This study will also use ego networks to characterize group opinions surrounding political candidates ("Trump" and "Biden") and views surrounding the word "health." Further, the current literature typically relies on centrality analysis from semantic networks to detect influential words (based on frequency of use among users) to identify discourse themes, however, there is no work that examines how the use of these influential words predict post engagement within their respective communities. In order to deepen understanding of online information sharing behavior, this work will conduct an exploratory analysis to examine how the use of words receive high use among community members (as operationalized using network centrality metrics) influence engagement behaviors towards social media posts.

Assessing influence of words based on group use

In addition to characterizing high volume discourse, semantic networks can identify words that receive high use among discourse communities using centrality metrics. Words that are used most often among groups tend to reflect topics, ideas, and concepts that are most influential among users. In fact, social theorists have long recognized the “symbolic function” of language, which states that language is more than a vehicle to express thoughts but also used to maintain and change levels of social cohesion between speakers and audiences (Carley & Kaufer, 1993). In other words, language can simultaneously signify group identity and create the group being signified. Within the field of sociolinguistics, it is well demonstrated that use of certain words can often signal identity and group membership. Words that are considered slang can identify individuals by age, region, and ethnicity. Use of jargon words can signify professional affiliations and regional dialects can hint at one’s geographic origin. Word use can also reveal ideological beliefs, as argued by semioticians who state that any sign in human communication, including words, can betray the ideology of its speaker (Noth, 2004). The use of group-related language not only signals membership, but it can also produce notable effects on behaviors and coordination efforts. One example of such effects is described in a story from the bible, where the inability to pronounce the term “shibboleth” was tied to one’s linguistic background, therefore identifying the speaker as an outsider. A less ancient example of a shibboleth is observed during WW2, where soldiers were able to identify the nationalities of others based on how they represented the number 3 on their fingers. The notion of a "password" (which is tied with modern definitions of shibboleth as well) further indicates that not everyone has equal knowledge of words, and that knowing certain words can provide access to specific social contexts.

Within the setting of social media discourse, the notion of group-related words is particularly relevant for platforms such as Reddit, where users gather on discussion forums focused on specific topics. Since users can regulate content by upvoting or downvoting content based on their attitudes and values, it is typical for social conventions and discourse rules to emerge on these forums. As suggested by the literature on language and group membership, it is likely that the norms and discourse expectations that develop within each community of users will be reflected in the words used most often in these conversations. For investigations on information contagion, understanding how use of group-specific language influences engagement can shed further light on how social conformity factors influences propagation effects of messages. The idea that some words can evoke further discussion among people has been previously examined in older work using semantic networks to examine symbolic properties of language. Carley & Kaufer (1993) identify the dimension of "conductivity" for words, which is defined as the "capacity of an expression to carry (or trigger) information in a two-directional flow." According to their definition, a word is conductive if it is able to initiate further trains of thoughts within a discourse by connecting multiple topics. A purely conductive word, such as a buzzword, notes a word that is neither the starting or stopping points for ideas being discussed but gateways to other ideas (Carley & Kaufer, 1993). Despite the existence of evidence suggesting that influential words, as determined by usage patterns within a group, can evoke social participation from members, there is currently no work that examines how using words that are used often by community members of online forums influences the likelihood of engagement. The present study will conduct an exploratory analysis to examine whether the use of influential words, as operationalized using network centrality metrics, are effective predictors of post engagement on Reddit. I hypothesize that posts containing words that correspond to highly central nodes in the semantic networks are more likely to evoke engagement.

Methods

Data Collection

The same datasets used in Chapter 2 are used again in the present analysis (i.e., r/Liberal, r/democrats, r/Conservative, r/Republican, r/science, r/EverythingScience, r/conspiracy, and r/actualconspiracies). See methods section in Chapter 2 for details about data collection from Reddit and **Tables 6** and **7** for further detail on the examined subreddit.

Generating Semantic Networks

Semantic networks were constructed for each subset by defining ties between words if they occur within 5 words of each other in the same post. Network measures were then run to identify the most influential concepts and identify network structures of the discourse using centrality measures (Hoser et al., 2006; Sadeghi et al., 2021). Types of centrality that can be calculated include: degree, eigenvector, and betweenness (Hoser et al., 2006). Degree centrality measures the total number of direct ties that a node has within a network and can indicate those concepts that are mentioned most often in the literature. Eigenvector centrality measures the extent a node is connected to other nodes who themselves are highly connected and can indicate concepts that are pillars or bedrock ideas within a field of research. Betweenness centrality measures the extent that a node bridges separate cluster groups within a network and can identify concepts that are more likely to bridge together ideas from separate research areas. The centralization of a network is also an important global property, where network that are highly centralized have most of their ties attributed to a handful of influential nodes compared to a non-centralized network where ties are evenly distributed across nodes. This metric can be used to further identify influential concepts within a group of users.

Correlation and Regression Analysis

After centrality measures were calculated for the semantic networks derived from the subreddits, new variables were created that count the number of high centrality words (top 10) were included in the title of the posts for each subreddit. Degree, eigenvector, and betweenness centrality measures were tested. Due to the non-normal distribution of social media engagement, Spearman’s Rho (non-parametric) was used to assess correlations between inclusion of high centrality words in the post titles with number of comments received. We further conducted multiple regression modeling to assess whether effects from bivariate correlations remain when controlled for other textual features examined in Chapter 2.

Results

Semantic Network Summary Metrics

Table 13 below shows summary metrics of the semantic networks generated for each subreddit based on both title and body text. Since there were less than 30 posts that contained body text for r/Conservative, r/Republican, r/science, and r/EverythingScience, semantic networks were created from title text only for these subreddits. The rows labeled "# of nodes" indicate the number of unique words used within all examined posts. Rows labeled "# of Ties" indicate how often the nodes were within 5 words from each other. Among the political subreddits, r/Republican had the highest number of nodes (2,121) and ties (18,718) in the title posts while r/Liberal had the lowest (nodes = 1,820, ties = 14,901). When comparing semantic networks created from body text, r/Liberal had over twice as many nodes (4,372) than r/democrats (1,852). This suggests that the content of posts in r/Liberal may cover a wider range of topics. The extent of centralization in the semantic networks also varies between left and right-leaning discourses: r/Liberal and r/democrats have higher centralization (.410, .503) in the title text compared to r/Conservative and r/Republican (.249, .334). These findings show that left-leaning discourse, as reflected in post titles, is more centralized (i.e., the same words are used more often across conversations) compared to right-leaning.

When examining semantic networks from scientific and conspiratorial online communities, r/science has the highest number of nodes (3,661) and ties (35,803) based on the title text while r/conspiracy has the lowest (nodes = 2,121, ties = 15,410). r/science also has a higher number of nodes compared to r/EverythingScience, indicating that r/science covers more unique topics. Among the conspiratorial subreddits, the body text semantic network from r/conspiracy has more than twice as many nodes (7,491) compared to r/actualconspiracies

(3,216) despite r/actualconspiracies having more nodes in the title text. This suggests that r/conspiracy may cover more topics when further elaborated on beyond the post title, however, the difference in node count may also be due to differences in posts with available body text (n=276 r/conspiracy, n = 56 r/actualconspiracies). The centralization score between r/conspiracy and r/actualconspiracies are both low (.148, .168 respectively), suggesting that conversations in the body of the posts are not dominated by the same topic or themes in either subreddit. However, r/actualconspiracies has the highest centralization (.426) from the post titles compared to r/conspiracy and scientific subreddits.

Table 13. Summary Metrics of Subreddit Semantic Networks by Title and Body Text

Political		**r/Liberal**	**r/democrats**	**r/Conservative**	**r/Republican**
# of Nodes	*Title*	1,820	1,838	1,994	2,121
	Body	4,372	1,852	*NA*	*NA*
# of Ties	*Title*	14,901	16,635	16,998	18,718
	Body	49,428	16,152	*NA*	*NA*
Density	*Title*	0.009	0.010	0.009	0.008
	Body	0.005	0.009	*NA*	*NA*
Centralization	*Title*	0.410	0.503	0.249	0.334
	Body	0.225	0.247	*NA*	*NA*
Scientific		**r/science**	**r/Everything Science**	**r/conspiracy**	**r/actual conspiracies**
# of Nodes	*Title*	3,661	2,325	2,121	2,869
	Body	*NA*	*NA*	7,491	3,216
# of Ties	*Title*	35,803	18,770	15,410	26,804
	Body	*NA*	*NA*	94148	30,395
Density	*Title*	0.005	0.007	0.007	0.007
	Body	*NA*	*NA*	0.003	0.006
Centralization	*Title*	0.261	0.140	0.103	0.426
	Body	*NA*	*NA*	0.148	0.168

Centrality Analysis

To assess prominent themes in each type of Reddit discourse, subreddits were grouped together based on the following categories: left-leaning (r/Liberal, r/democrats), right-leaning (r/Conservative, r/Republican), scientific (r/science, r/EverythingScience), and conspiratorial (r/conspiracy, r/actualconspiracies). Semantic networks were then generated for each group based on the text from post titles. The top 30 nodes based on eigenvector centrality were visualized below for each group of subreddits in **Figures 7** and **8**. Blue ties reflect networks from left-leaning subreddits, red ties correspond to right-leaning, gold ties for scientific, and purple for conspiratorial subreddits. Further, the width of the tie corresponds to the strength of ties between nodes (i.e., words that are most likely to co-occur with each other in a post). Larger node size indicates words with higher eigenvector centrality. See appendix Table A1 for list of top 30 nodes by degree and eigenvector centralities for the examined subreddits.

In the left-leaning network, “Trump” had the highest eigenvector centrality and was connected to the highest number of nodes (n = 1494) followed by “Biden”, which was co-mentioned with less than half as many nodes (n = 709). “Abortion” was third most influential based on eigenvector centrality (n=386) followed by “court” (n=357), “election” (n=303), “supreme” (n=261), “republicans” (n=344), and “gop” (n=349). Based on the strength of ties as depicted in the visualized network, “abortion” appears to be connected to nodes “ballot” and “ban” in addition to the states “florida” and “arizona.” Other strongly connected nodes appear to be “hush,” “money,” and “trial.” When examining the right-leaning group, “Biden” and “Trump” are top nodes in both eigenvector and degree centralities (n_{Biden} = 1099, n_{Trump} = 959), similar to left-leaning. However, “Trump” and “Biden” nodes are closer in influence within the right-leaning network compared to the left. Other influential nodes based on eigenvector centrality in the right-leaning network include: “israel” (n=385), “iran” (n=339), “attack” (n=233), “judge” (n=199), “america” (n=255), “war” (n=146), and “trial” (n=169). When assessing tie strength between nodes, the nodes “hush,” “money” and “trial” appear to cluster together while “attack” co-occurs often with “israel” and “iran.”

Within the scientific network, “study” is the most well connected node based on both eigenvector and degree centralities (n=1108). Other influential nodes include: “found” (n=566), “research” (n=591), “suggests” (n=199), “brain” (n=421), “risk” (n=348), “cancer” (n=307), “health” (n=304), “disease” (n=319), “aging” (n=166) and “discovered” (n=219). When assessing ties between nodes, “adhd” and “children” tend to co-occur often as well as “cancer” and “cells.” For the conspiratorial group, the word “reports” is the most influential node based on eigenvector centrality and is connected to the most nodes in the network by a large margin (n=1244 vs n=449 from the second most connected node “conspiracy”). Other top eigenvector nodes include “news” (n=319), “china” (n=276), “russia” (n=228), “trump” (n=372), “government” (n=382), “secret” (n=276), “history” (n=206), and “election” (n=225). It is also worth noting that names of news outlets are also influential nodes, such as “guardian” (n=143), “nbc” (n=40), “cnn” (n=61), “reuters” (n=72), “bbc” (n=83), and even the word “media” (n=164).

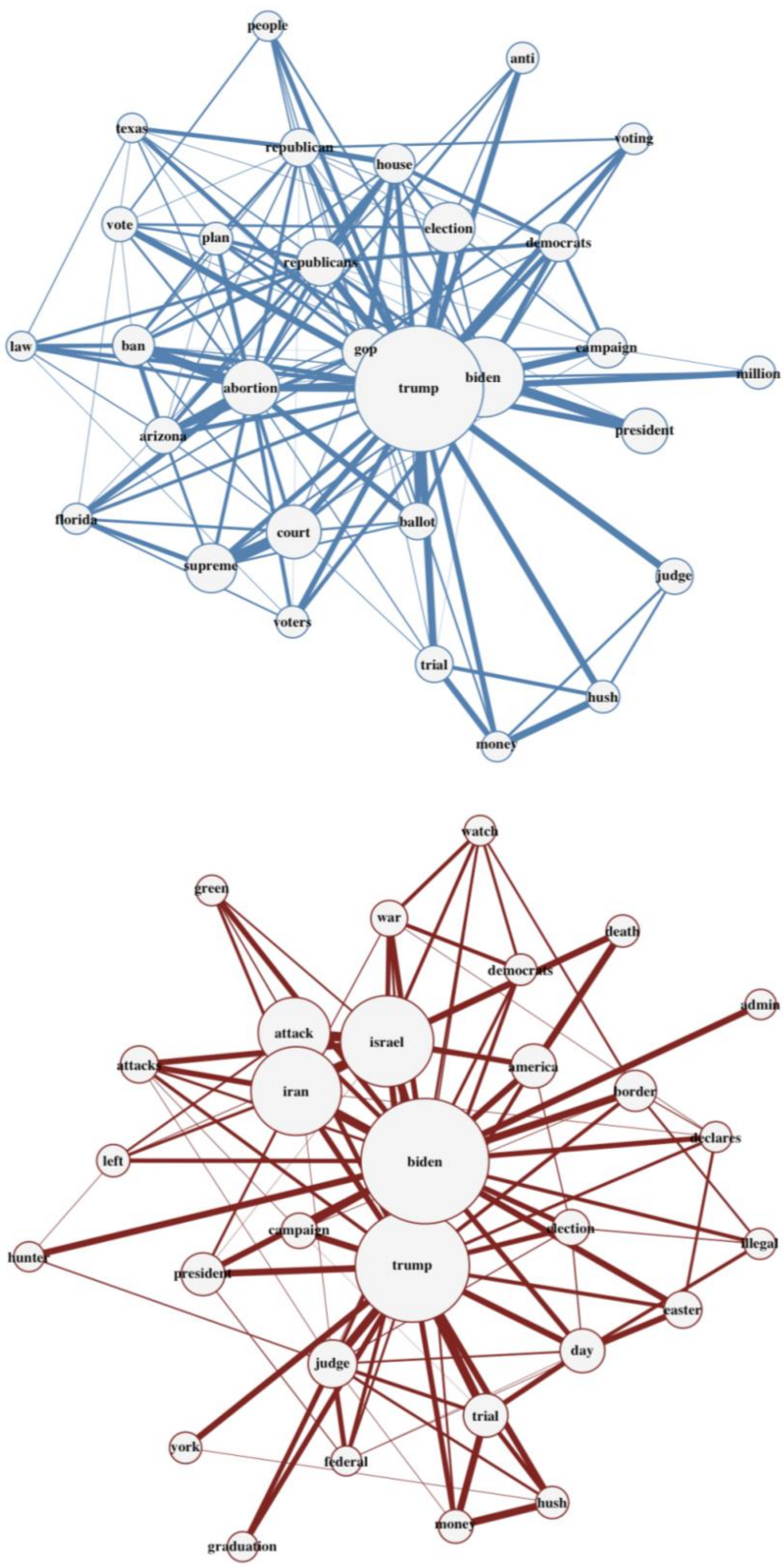


Figure 7. Subreddit Semantic Networks - Top 30 Nodes Based on Eigenvector Centrality. Left-Leaning (Blue), Right-Leaning (Red)

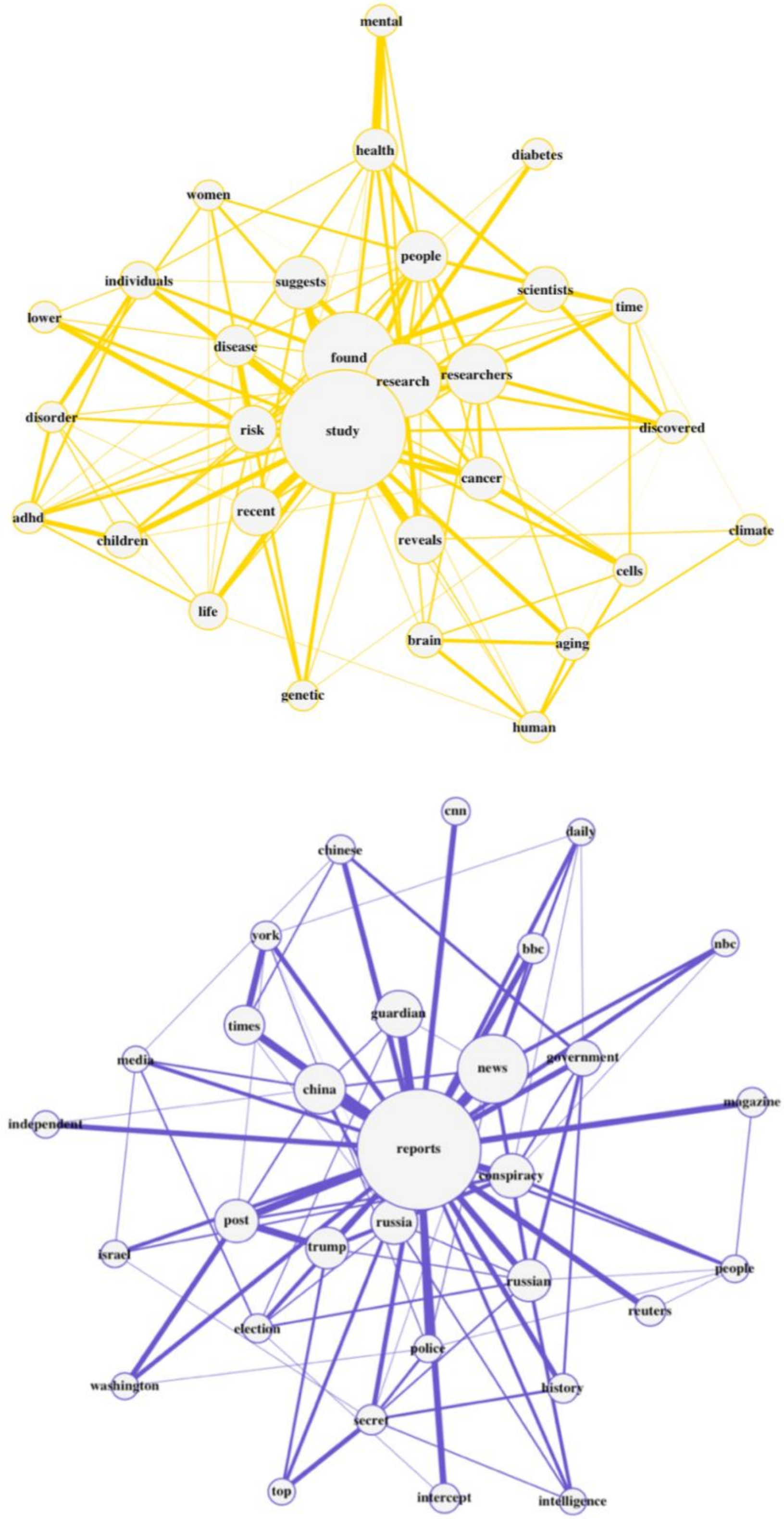


Figure 8. Subreddit Semantic Networks - Top 30 Nodes Based on Eigenvector Centrality. Scientific (Gold), Conspiratorial (Purple)

Ego Semantic Networks

Table 14 shows network metrics of the ego networks extracted from the semantic networks of the politically left-leaning (r/Liberal, r/democrats), right-leaning (r/Conservative, r/Republican), scientific (r/science, r/EverythingScience), and conspiratorial (r/conspiracy, r/actualconspiracies) subreddits. The column “Total Network” shows metrics for the full semantic network of each subreddit group. The columns “Trump & Biden” and “Health” show the network metrics for each ego network. Nodes were selected in the ego networks based on whether they were 1 degree of separation from the nodes “Trump” or “Biden,” or the node “Health.” For the political subreddits, metrics for separate “Trump” and “Biden” ego networks were calculated to assess differences in how each political figure is individually discussed between left and right leaning discourses. The metrics compared are the number of nodes (i.e., unique words) tied to each ego node and the number of ties (i.e., co-occurrences between words) between the ego node and its alter nodes. For the selected ego networks from each subreddit group, the proportion of nodes tied to the ego node that overlap with the number of nodes within the total group network was calculated and placed in () under the node count (e.g., in the “Trump Only” column, 1495 nodes / 3065 nodes from total network = 48.8%). The same procedure was conducted for ties as well.

There were similar number of nodes in both left (n=3065) and right leaning (n=3364) subreddit groups. Within the left-leaning group, the Trump only network has 1,495 nodes (48.8% of the total left-leaning network) that were either directly tied to Trump or 1 degree of separation. The Biden only network had less than half the connections to other nodes (n=710, 23.2% of total network) compared to the Trump ego network. When Trump and Biden ego networks are combined, they are connected to over half (58.0%) of the nodes in the left-leaning network. When examining the right-leaning group, the Trump only network is tied to 28.5% of the total nodes (n=960). While the Biden only network is connected to more ties compared to Trump (32.7%, n=1100), both Trump and Biden nodes are more evenly connected in the right-leaning network compared to the left-leaning group. When Trump and Biden ego networks are combined, they are connected to just less than half (48%, n=1614) of the nodes in the right-leaning network. For both Left and Right-leaning semantic networks, Health was connected to less than 2% of the total nodes (n_{left} = 56, n_{right} = 49).

Compared to the political networks, there was a greater number of unique nodes in both scientific (n = 4969) and conspiratorial (n = 4305) groups. Within the scientific group, the Trump and Biden nodes were connected to less than 1 percent (n=30) of the total nodes in the network while Health was connected to 6.1% (n=305). For the conspiratorial network, Trump and Biden were connected to a higher proportion of the total nodes (10.8%, n=464) while Health was connected to a lower proportion (1.9%, n=80) compared to scientific.

Table 14. Network Metrics of Semantic Ego Networks.

Subreddit Groups	Metrics	Total Network	Trump Only	Biden Only	Trump & Biden	Health
Left-leaning	*# of Nodes*	3,065	1495 (48.8%)	710 (23.2%)	1778 (58.0%)	56 (1.8%)
	# of Ties	30,919	15732 (50.9%)	7190 (23.3%)	18762 (60.7%)	330 (1.1%)
Right-leaning	*# of Nodes*	3,364	960 (28.5%)	1100 (32.7%)	1614 (48.0%)	49 (1.5%)
	# of Ties	34,193	9912 (29.0%)	11258 (32.9%)	17164 (50.2%)	239 (0.7%)
Scientific	*# of Nodes*	4,969	*NA*	*NA*	30 (0.6%)	305 (6.1%)
	# of Ties	53,319	*NA*	*NA*	151 (0.3%)	2542 (4.8%)
Conspiratorial	*# of Nodes*	4,305	*NA*	*NA*	464 (10.8%)	80 (1.9%)
	# of Ties	42,321	*NA*	*NA*	4150 (9.8%)	438 (1.0%)

Note: Percentages in () are based to Total Network column.

Figure 9 compares semantic ego networks generated from the title text in left-leaning (r/Liberal and r/democrats) and right-leaning subreddits (r/Conservative, r/Republican). Nodes were selected in the ego networks based on whether they were 1 degree of separation from the nodes "Trump" or "Biden." Since many nodes within the ego networks had exceptionally low eigenvector score, all visualizations in this section show the top 30 nodes based on degree centrality (i.e., word frequency) to better represent nodes that are more niche within the discourse (i.e., less connected to other groupings of nodes). The top graph shows the left-leaning semantic network where ties are colored blue and the bottom shows the right-leaning network with red ties. The tie width corresponds to the strength of ties between nodes (i.e., words that are most likely to co-occur with each other in a post). Larger node size indicates words with higher eigenvector centrality within its respective discourse.

The graph from the left-leaning subreddits show that the “Trump” node is connected to the highest number of alter nodes followed by “Biden”, which is connected to less than half the number of nodes (n=709 vs n=1494 Trump). Within the right-leaning network, mentions of “Biden” and “Trump” are more evenly disbursed (n=1,099 vs n=959 respectively). Nodes that are have the highest associations with “Trump” and “Biden” from left-leaning semantic networks include “abortion,” “ban,” “election,” “campaign,” “trial,” “supreme,” and “court.” There is 43.3% overlap in the top 30 nodes with the right-leaning network, as it also includes words such as “abortion,” “election,” and “trial.” However, top nodes unique to the right-leaning subreddits include “Israel,” “Iran,” “attack,” “war,” “border,” “illegal,” and “migrant.” Top nodes that were unique to the left-leaning network include “ban,” “ballot,” “Ukraine,” and “democracy.”

Figure 10 compares semantic ego networks generated from the title text in left-leaning (r/Liberal and r/democrats) and right-leaning subreddits (r/Conservative, r/Republican) based on whether they were directly tied to or within 1 degree of separation from the node “health.” The visualizations show that the nodes “Trump” and “Biden” have prominent associations with the term “health” in both left and right-leaning discourses. Despite the high degree of mentions for both politician nodes, overlap between the remaining top 30 terms between left and right-leaning networks is 16.7%. For the left-leaning network, other nodes associated with health include “abortion,” “plan,” “people,” “ban” and the states “Texas” and “Florida.” Within the right-leaning network, nodes associated with health include words such as “Israel,” “migrant,” “shelters,” “city,” and “departments.”

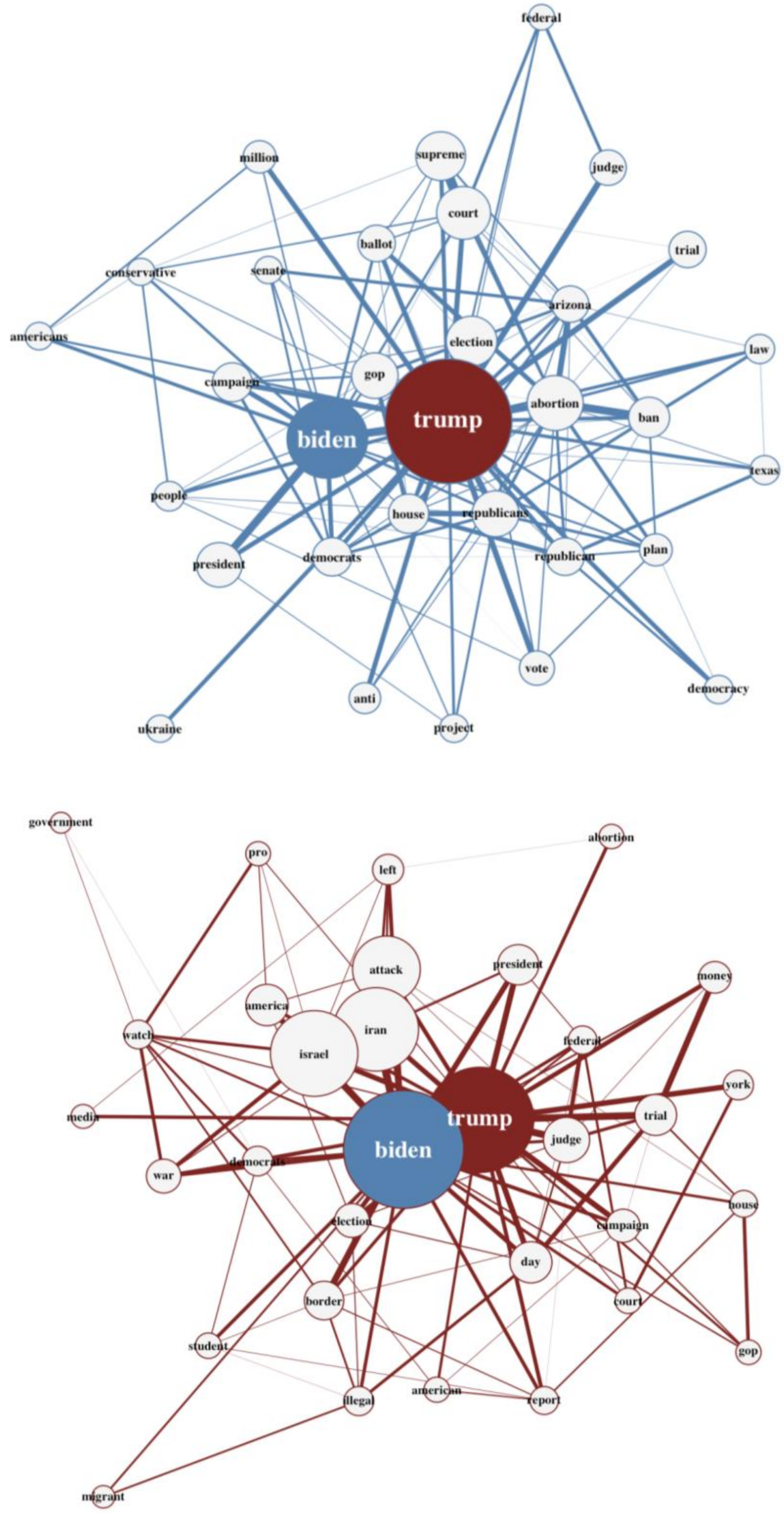


Figure 9. “Trump” & “Biden” Ego Networks – Top 30 Nodes Based on Eigenvector Centrality. Top (r/Liberal & r/democrats), Bottom (r/Conservative & r/Republican).

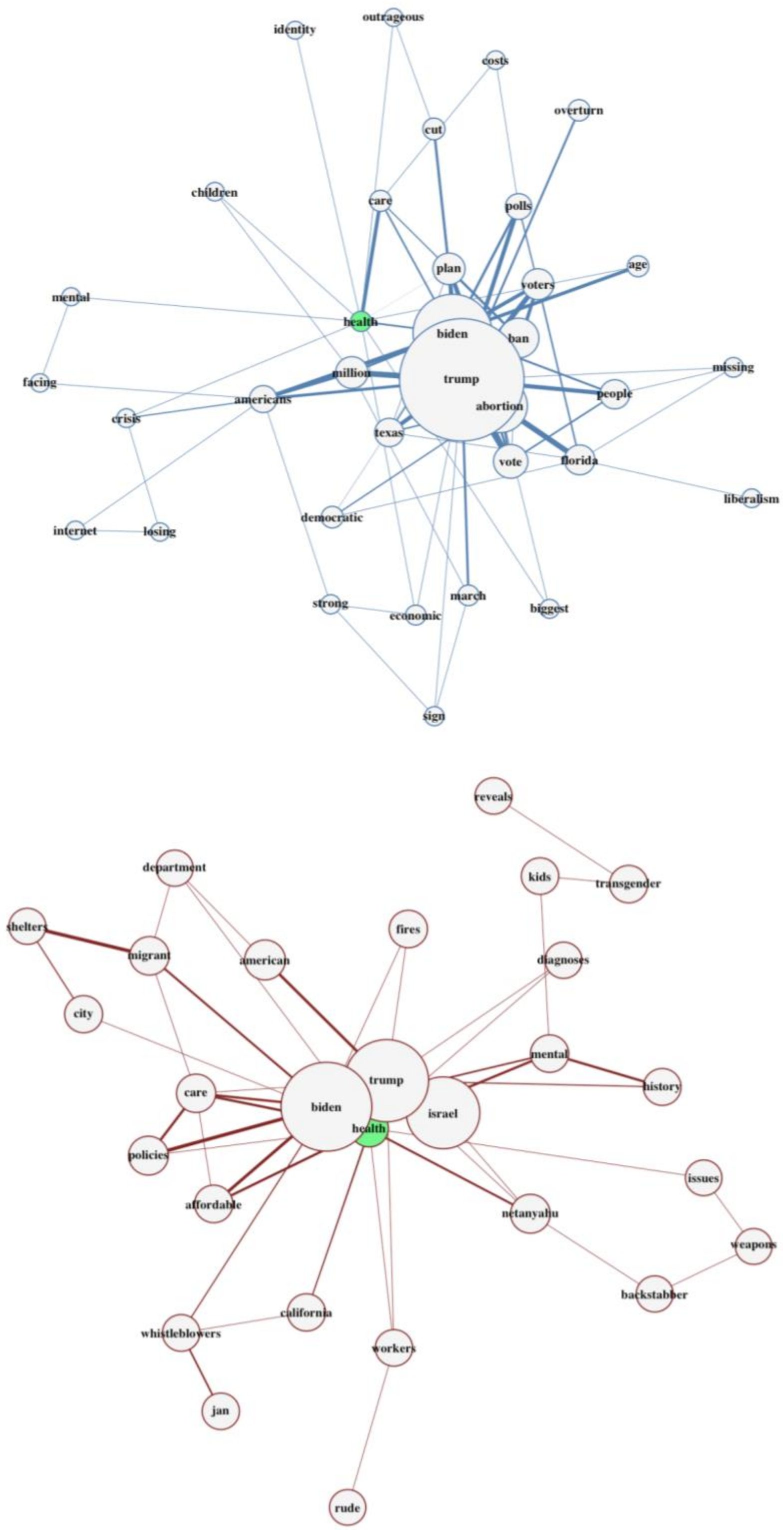
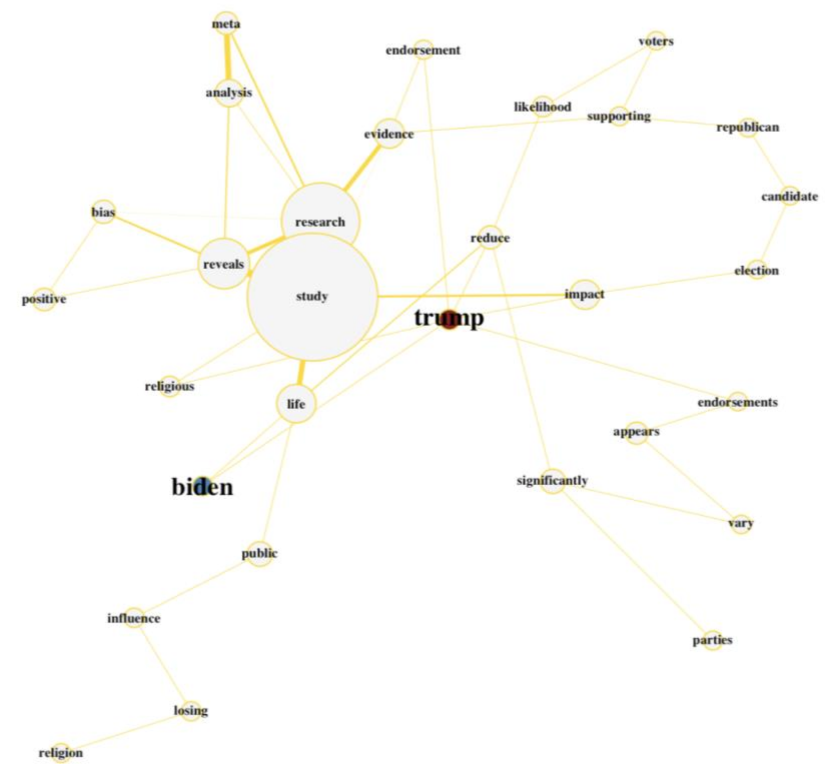


Figure 10. Health" Ego Networks – Top 30 Nodes Based on Eigenvector Centrality. Top (r/Liberal & r/democrats), Bottom (r/Conservative & r/Republican).

Figure 11 compares semantic ego networks generated from the title text in scientific (r/science and r/EverythingScience) and conspiratorial subreddits (r/conspiracy, r/actualconspiracies). Nodes were selected in the ego networks based on whether they were 1 degree of separation from the nodes “Trump” or “Biden”. The top graph shows the scientific semantic network (gold ties) while the bottom shows conspiratorial (purple ties). Within the scientific subreddits, the nodes “study,” “research,” and “reveals” are the most influential based on eigenvector centrality. Other words associated with the politicians include “impact,” “reduce,” and “endorsement.” For semantic networks from conspiratorial discourse, the nodes “reports,” “news,” “conspiracy,” and “government” are mentioned often as well as references to countries such as “Russia,” “China,” and “Iran.” Overall, “Trump” and “Biden” are mentioned more often in conspiratorial subreddits (Trump = 372, Biden = 117) compared to scientific discourses (Trump = 28, Biden = 10). Only 2 of the top 30 nodes (“election”, “public”) overlap between both scientific and conspiratorial subreddits.

Figure 12 compares semantic ego networks generated from the title text in scientific (r/science and r/EverythingScience) and conspiratorial subreddits (r/conspiracy, r/actualconspiracies) based on whether they were 1 degree of separation from the node “health.” The most influential nodes among the scientific subreddits based on eigenvector centrality are “study,” “research,” “found.” Top nodes that are mentioned in scientific and not conspiratorial subreddits include “mental,” “risk,” “disease,” “scientists,” “depression,” and “physical.” Nodes that are unique to conspiratorial discourse are “Trump,” “industry,” “secret,” “world,” “climate,” and “fraud.” Further, “health” is mentioned more often in scientific subreddits (n=304) than conspiratorial (n=79).



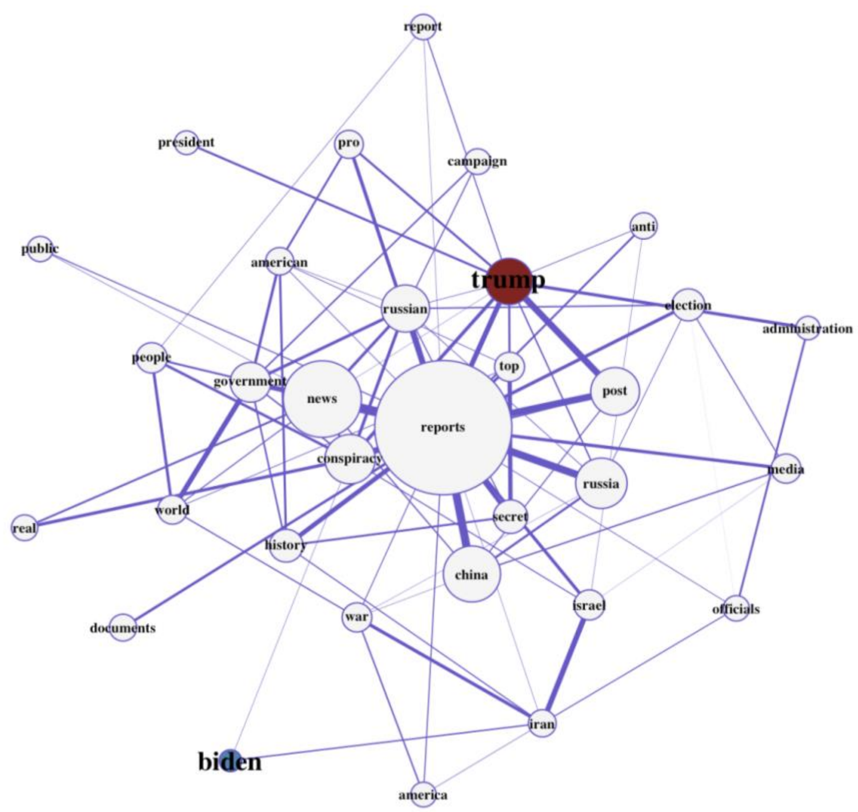


Figure 11. "Trump" & "Biden" Ego Networks – Top 30 Nodes Based on Eigenvector Centrality. Top (r/science & r/EverythingScience), Bottom (r/conspiracy & r/actualconspiracies).

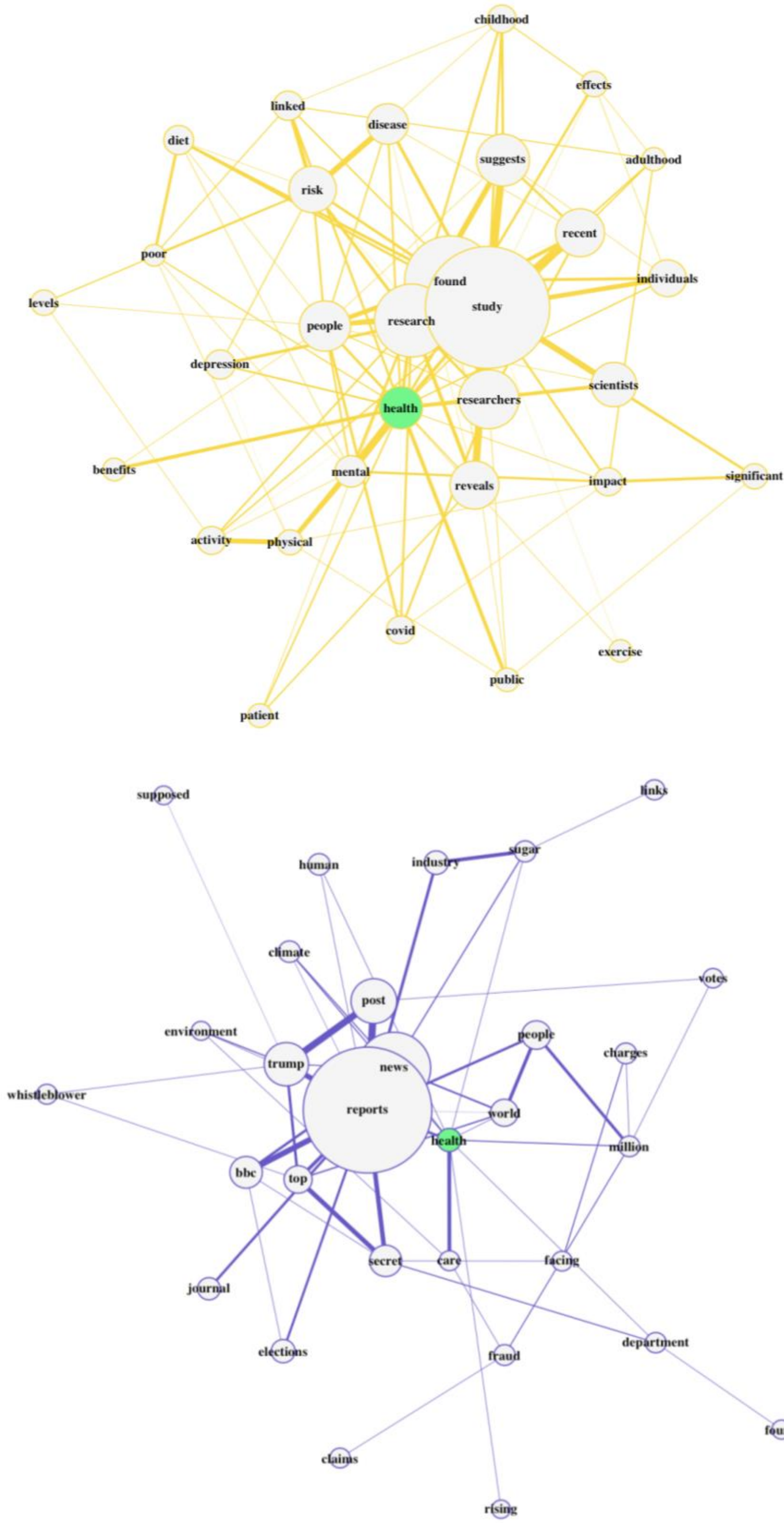


Figure 12. "Health" Ego Networks – Top 30 Nodes Based on Eigenvector Centrality. Top (r/science & r/EverythingScience), Bottom (r/conspiracy & r/actualconspiracies).

Correlation Analysis with Use of Centrality Words

Table 15 shows Spearman's Rho correlations between the use of centrality words and post engagement among the political subreddits. For r/Liberal, the use of centrality words in the title was positively correlated with both upvoting (rho_{Deg} = .10, $p<.05$; rho_{Eig} = .11, $p<.05$; rho_{Btwn} = .10, $p<.05$) and commenting (rho_{Deg} = .16, $p<.001$; rho_{Eig} = .15, $p<.01$; rho_{Btwn} = .16, $p<.001$). The inclusion of centrality words in the body text was also positively correlated with commenting (rho_{Deg} = .21, rho_{Eig} = .22, rho_{Btwn} = .19) and all tested effects were highly significant ($p<.001$). When examining r/democrats, the use of centrality words were negatively correlated with engagement: containing degree centrality words in the title was negatively correlated with commenting (-.10, $p<.05$) and the use of all tested centrality words in the body text was negatively correlated with upvoting (rho_{Deg} = -.28, $p<.05$; rho_{Eig} = -.22, $p<.05$; rho_{Btwn} = -.25, $p<.05$) and commenting (rho_{Deg} = -.32, $p<.01$; rho_{Eig} = -.28, $p<.05$; rho_{Btwn} = -.30, $p<.01$). Both right-leaning subreddits showed positive correlations with use of centrality words in the title text and engagement. For r/Conservative, all tested centrality words were positively correlated with upvoting (rho_{Deg} = .09, $p<.05$; rho_{Eig} = .10, $p<.05$; rho_{Btwn} = .09, $p<.05$) while the use of degree centrality words were positively correlated with commenting in r/Republican (.10, $p<.05$).

Table 15. Spearman's Rho Correlations between Use of Centrality Words (Degree, Eigenvector, Betweenness) x Engagement (Upvote and Comment) – Political Subreddits by Title and Body Text

	r/Liberal				**r/democrats**				**r/Conservative**		**r/Republican**	
	Title		**Body** *(n=298)*		**Title**		**Body** *(n=78)*		**Title**		**Title**	
	Up	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***
	Rho	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*
Degree	0.10 *	0.16 ***	0.07	0.21 ***	-0.08	-0.10 *	-0.28 *	-0.32 **	0.09 *	0.05	0.04	0.10 *
Eigen	0.11 *	0.15 **	0.11 *	0.22 ***	-0.05	-0.05	-0.22 *	-0.28 *	0.10 *	0.08	0.05	0.07
Btwness	0.10 *	0.16 ***	0.07	0.19 ***	-0.06	-0.06	-0.25 *	-0.30 **	0.09 *	0.05	0.02	0.09

Note: *=p<.05, **=p<.01, ***=p<.001

Table 16 shows Spearman's Rho correlations between the use of centrality words and post engagement among the scientific and conspiratorial subreddits. For r/science, the use of centrality words in the title text was positively correlated with both upvoting (rho_{Deg} = .35, rho_{Eig} = .35, rho_{Btwn} = .35) and commenting (rho_{Deg} = .27, rho_{Eig} = .28, rho_{Btwn} = .28). These effects were all highly significant (p<.001). Conversely, r/EverythingScience showed negative correlations between use of centrality words in the title text and commenting (rho_{Deg} = -.09, p<.05; rho_{Eig} = -.10, p<.05; rho_{Btwn} = -.09, p<.05). Conspiratorial subreddits also showed negative correlations with the use of centrality words in the body text and post engagement. Within r/conspiracy, the use of eigenvector words were negatively correlated with commenting (rho_{Eig} = -.21, p<.001) while use of eigenvector and betweenness words in posts from r/actualconspiracies were negatively correlated with commenting (rho_{Eig} = -.35, p<.01; rho_{Btwn} = -.31, p<.05).

Table 16. Spearman's Rho Correlations between Use of Centrality Words (Degree, Eigenvector, Betweenness) x Engagement (Upvote and Comment) – Scientific and Conspiratorial Subreddits by Title and Body Text

	r/science		**r/Everything Science**		**r/conspiracy**				**r/actualconspiracies**			
	Title		**Title**		**Title**		**Body** *(n=276)*		**Title**		**Body** *(n=56)*	
	Up	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***
	Rho	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*	*Rho*
Degree	.35 ***	.27 ***	-0.04	-0.09 *	0.04	0.06	-0.06	-0.10	0.01	-0.02	0.06	-0.23
Eigen	.35 ***	.28 ***	-0.05	-0.10 *	0.05	0.07	-0.11	-0.21 ***	0.00	-0.01	-0.08	-0.35 **
Btwnes s	.35 ***	.28 ***	-0.04	-0.09 *	0.04	0.06	-0.07	-0.08	0.04	-0.03	-0.02	-0.31 *

Note: *=p<.05, **=p<.01, ***=p<.001

Regression Analysis – Testing Centrality Word Effects Against LIWC Sentiment

Table 17 shows regression results examining Reddit engagement behaviors for the political subreddits (r/Liberal, r/democrats, r/Conservative, r/Republican) with the use of eigenvector centrality words and the previously tested LIWC sentiments as predictors (see Chapter 3). The percentages show the results from the shapley regression, which corresponds to the proportion of variance attributed to each independent variable. The unstandardized beta coefficient from the multiple regression models are shown inside the parentheses "()". Cells that are **bolded** indicate statistical significance at p<.05, ***bold italic*** indicate significance at p<.01, and grayed cells indicate p<.001. Less than 30 posts included body text for r/Conservative and r/Republican, therefore only associations based on title text were examined for those subreddits.

For post engagement on r/Liberal, word count (WC) was positively associated with upvoting for title (.03, p<.01) and body text (.00, p<.01) when controlled for all tested covariates.

Use of analytic words was negatively associated with commenting when included in title (-.01, $p<.001$) and body text (-.01, $p<.001$), and explained the majority of variance in both models (66.8%$_{title}$, 63.6%$_{body}$). The use of top eigenvector words was positively associated with commenting when included in the title (.46, $p<.01$) and body text (.10, $p<.01$). Inclusion of social references in the body text was negatively associated with commenting (-.03, $p<.05$). Within the subreddit r/democrats, use of big words in the title was negatively associated with upvoting (-.01, $p<.01$) and commenting (-.01, $p<.01$) when controlled for all other variables. Similar effects are observed when big words are included in the body text (β_{Up} = -.03, $p<.05$; β_{Com} = -.04, $p<.01$). Use of analytic language in the title was negatively associated with both types of engagement (β_{Up} = -.00, $p<.05$; β_{Com} = -.01, $p<.001$) and negatively associated with commenting when included in the body text (-.02, $p<.001$).

When examining engagement on r/Conservative, higher word count in the title was positively associated with upvoting (.08, $p<.001$) and commenting (.05, $p<.001$) when controlled for all other variables. Word count also explains the most variance for both engagement behaviors. Use of big words was also associated with higher upvote count (.01, $p<.05$). Further, use of analytic language in the post title was negatively associated with engagement (β_{Up} = -.01, $p<.01$; β_{Com} = -.01, $p<.001$) as well as use of negative emotional words (β_{Up} = -.06, $p<.05$; β_{Com} = -.05, $p<.05$). For r/Republican, title word count is positively associated with engagement () when controlled for tested covariates. Use of social references are positively associated with upvoting (.02, $p<.05$) while use of eigenvector words is associated with higher number of comments (.68, $p<.01$). Analytic language in post titles was negatively associated with upvoting (-.00, $p<.05$) and commenting (-.01, $p<.01$).

Table 17. Multiple Regression between LIWC Sentiment + Use of Eigenvector Centrality Words x Engagement (Upvote and Comment) – Political Subreddits by Title and Body Text

	r/Liberal				r/democrats				r/Conservative		r/Republican	
	Title		**Body** *(n=298)*		**Title**		**Body** *(n=78)*		**Title**		**Title**	
	Up	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***
	Shap (Beta)	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*
WC	***66.4% (0.03)***	0.6% (0.0)	***49.7% (0.0)***	1.3% (0.0)	3.9% (0.01)	0.5% (0.0)	32.2% (0.0)	25% (0.0)	***53.2% (0.08)***	***35.2% (0.05)***	**15% (0.02)**	***32.4% (0.03)***
BW	0.8% (0.0)	9.3% (0.0)	3.6% (0.0)	10.9% (-0.01)	***46.7% (-0.01)***	***38.4% (-0.01)***	**32.4% (-0.03)**	***26.6% (-0.04)***	**4.3% (0.01)**	2.2% (0.01)	8% (0.01)	1.7% (0.0)
Analytic	0.3% (0.0)	***66.8% (-0.01)***	18.7% (0.0)	***63.6% (-0.01)***	**35.5% (-0.0)**	***50% (-0.01)***	17.3% (-0.01)	***35.2% (-0.02)***	***19.1 (-0.01)***	***30.9 (-0.01)***	**17.8% (-0.0)**	***24.5% (-0.01)***
emo_p	3.6% (-0.01)	1% (0.01)	8.7% (-0.04)	2.1% (-0.02)	0.3% (-0.01)	0.3% (-0.01)	1.6% (0.02)	0.6% (-0.02)	0.4% (0.03)	4.7% (0.05)	8.9% (0.04)	3.8% (0.03)
emo_n	1.8% (0.01)	0.1% (-0.01)	6.8% (0.01)	2.4% (-0.02)	5.4% (-0.02)	0.8% (0.01)	5.2% (0.06)	2.3% (0.06)	**7.7% (-0.06)**	**9.4% (-0.05)**	0.9% (0.01)	0.4% (-0.01)
Soc behv	4.3% (0.01)	1.1% (0.0)	0.5% (0.0)	1.5% (0.01)	1.3% (0.0)	3.2% (0.01)	2.7% (0.02)	3.3% (0.02)	0.1% (-0.01)	1% (-0.01)	14.1% (0.01)	3.1% (0.01)
Soc refs	9% (-0.01)	3.9% (0.0)	2.4% (0.01)	**3.5% (-0.03)**	4.4% (0.0)	4.6% (0.0)	5.1% (0.02)	2.8% (0.01)	10.2% (0.02)	12.3% (0.02)	**28.3% (0.02)**	10% (0.01)
Eig	13.8% (0.16)	***17.1% (0.46)***	9.7% (0.06)	***14.6% (0.1)***	2.6% (-0.06)	2.3% (-0.05)	3.4% (0.01)	4.1% (0.0)	4.9% (0.46)	4.3% (0.34)	6.9% (0.29)	***24% (0.68)***
R-sq	*.028*	*.118*	*.040*	*.183*	*.038*	*.065*	*.292*	*.424*	*.082*	*.109*	*.047*	*.060*

Note: **bold** = p<.05, ***bold italic*** = p<.01, ***shaded cell*** = p<.001. Beta coefficients are rounded up to 2nd decimal place.

Table 18 shows regression results for Reddit engagement behaviors (i.e., upvoting and commenting) for the scientific (r/science and r/EverythingScience) and conspiratorial subreddits (r/conspiracy and r/actualconspiracies). Less than 30 posts included body text for r/science and r/EverythingScience, therefore only associations based on title text were examined for those subreddits.

For r/science, engagement is positively associated with higher word count (β_{Up} = .03, p<.001, β_{Com} = .02, p<.05), use of eigenvector words (β_{Up} = .31, p<.001, β_{Com} = .24, p<.01), and use of social references (β_{Up} =.04, p<.05, β_{Com} = .04, p<.05) when controlled for all other tested variables. Number of big words in the title was negatively associated with both types of engagement (β_{Up} =-.02, β_{Com} = -.03) and both effects were highly significant ($p<.001$). Use of analytic language was also negatively associated with commenting (-.01, $p<.05$). Based on the shapley results, word count explained the most variance for upvoting (36.2%) while use of big words explained the most for commenting (28.9%). Use of eigenvector words was the second strongest predictor in both upvoting (26.8%) and commenting (19.9%) models. Within the subreddit r/EverythingScience, higher word count in the title was associated with upvoting (.04, $p<.001$) while use of analytic language was negatively associated with commenting (-.01, $p<.05$) when controlled for all other variables. Both engagement behaviors were negatively associated with use of big words (β_{Up} =-.02, $p<.01$, β_{Com} = -.01, $p<.01$) as well as use of eigenvector words (β_{Up} =-.38, $p<.01$, β_{Com} = -.41, $p<.001$) in the title. Use of negative emotional language was positively associated with upvoting (.08, $p<.05$) and commenting (.09, $p<.01$). Similar to r/science, WC was the strongest predictor for upvoting (30.1%) while use of big words was the strongest for commenting (29.6%) among tested covariates.

When examining discourse on r/conspiracy, use of analytic language in the title was negatively associated with upvoting (-.01, $p<.01$) and commenting (-.01, $p<.001$) when controlled for all other variables and was the strongest predictor for both behaviors ($36.3\%_{upvote}$, $61.6\%_{comment}$). Post title word count was positively associated with upvoting (.02, $p<.05$) while use of big words was negatively associated with commenting (-.01, $p<.05$). For body text, use of negative emotional language was negatively associated with commenting (-.09, $p<.05$) and was the strongest predictor among tested variables (36.5%). Within r/actualconspiracies, word count of the title was positively associated with upvoting (.02, $p<.001$) and commenting (.01, $p<.01$) when controlled for all other covariates. Use of analytic language was negatively associated with both types of engagement (β_{Up} =-.01, p<.01, β_{Com} = -.01, p<.01). There was no statistically significant effects detected for word use in the body text.

Table 18. Multiple Regression between LIWC Sentiment + Use of Eigenvector Centrality Words x Engagement (Upvote and Comment) – Scientific and Conspiratorial Subreddits by Title and Body Text

	r/science		**r/Everything Science**		**r/conspiracy**				**r/actualconspiracies**			
	Title		**Title**		**Title**		**Body** *(n=276)*		**Title**		**Body** *(n=56)*	
	Up	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***	***Up***	***Com***
	Shap (Beta)	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*	*Shap (Beta)*
WC	***36.2% (0.03)***	**22% (0.02)**	***30.1% (0.04)***	4% (0.02)	**24.3% (0.02)**	2.8% (0.0)	1.6% (0.0)	0.8% (0.0)	***67.6% (0.02)***	***34.1% (0.01)***	0.8% (0.0)	12.7% (0.0)
BW	***24.3% (-0.02)***	***28.9% (-0.03)***	***32% (-0.02)***	***29.6% (-0.01)***	4.6% (0.01)	**22.1% (-0.01)**	19.9% (0.02)	1.9% (0.0)	3.8% (0.0)	4.5% (0.0)	31.1% (-0.04)	24.5% (-0.03)
Analytic	2.5% (0.0)	**10.1% (-0.01)**	5.9% (0.0)	**16.4% (-0.01)**	***36.3% (-0.01)***	***61.6% (-0.01)***	14.2% (0.0)	20.3% (0.0)	***20.4% (-0.01)***	***46.7% (-0.01)***	30.6% (0.01)	2.7% (0.0)
emo_p	0.2% (-0.01)	1.3% (0.06)	1.7% (0.05)	2.1% (0.06)	4.4% (0.05)	0.1% (0.0)	15.3% (-0.06)	12.8% (-0.06)	2% (-0.02)	12.3% (0.05)	5.3% (0.14)	12.8% (0.23)
emo_n	1.2% (0.04)	3.3% (0.06)	**10.8% (0.08)**	***17.1% (0.09)***	3% (-0.04)	0.2% (0.0)	1.7% (0.02)	**36.5% (-0.09)**	0.5% (0.01)	0.5% (-0.02)	18.8% (0.05)	15% (0.08)
Soc behv	0.6% (0.01)	3.5% (0.03)	3.7% (0.02)	2.9% (0.02)	1.9% (-0.01)	0.4% (0.0)	18.2% (0.05)	10.8% (0.03)	0% (0.0)	0.8% (0.0)	7.8% (-0.03)	6.2% (-0.04)
Soc refs	**8.1% (0.04)**	**11% (0.04)**	0.6% (0.0)	4% (0.01)	18.4% (0.02)	6.9% (0.01)	1% (0.0)	1.1% (-0.01)	4% (0.01)	0.8% (0.0)	4.6% (0.0)	6.3% (-0.03)
Eig	***26.8% (0.31)***	***19.9% (0.24)***	***15.3% (-0.38)***	***23.9% (-0.41)***	7% (0.18)	6% (0.16)	27.9% (0.0)	15.9% (-0.01)	1.6% (0.05)	0.2% (0.01)	0.9% (0.0)	19.7% (-0.03)
R-sq	*.195*	*.174*	*.063*	*.079*	*.053*	*.083*	*.037*	*.057*	*.063*	*.042*	*.191*	*.173*

Note: **bold** = p<.05, ***bold italic*** = p<.01, ***shaded cell*** = p<.001. Beta coefficients are rounded up to 2nd decimal place.

Discussion

These findings demonstrate multiple applications of semantic networks for investigating information contagion effects across social media discourses. Using centrality metrics based on graph theory, semantic networks were able to characterize political, scientific, and conspiratorial discourses by identifying influential words across user groups. Ego network analysis was able to further identify differences and overlap across user groups in associations surrounding specific topics (“Trump”, “Health”). To further examine the utility of identifying influential words, the current study revealed that count variables measuring the use of high centrality words in both title and body texts of posts were statistically significant predictors for both upvoting and commenting on Reddit, however, the direction and strength of these effects varied by subreddit communities. Effects on engagement from the use of centrality words continued to remain a statistically significant predictor when controlled for covariates such as word count in post and use of analytic and emotional language. The remainder of this section will further expand on these findings.

Properties of semantic networks, such as number of nodes, varied across the examined subreddits. Despite both being left-leaning, the subreddit r/Liberal had over twice as many nodes as r/democrat, and r/science had higher number of nodes based on title text than both conspiratorial subreddits and r/EverythingScience. Discourses with higher number of nodes within their semantic networks indicate a higher number of topics being covered, as reflected in the greater number of unique words found across posts. For instance, r/Liberal has over 2000 more unique words included in the body text of posts than r/democrats, despite both communities being similar in topic content. This difference is likely driven by differences in number of posts that included body text (n=298 for r/Liberal, n=78 for r/democrats). However, the lack of body text in posts still reflects a more limited scope of conversation when comparing discourse communities. When comparing number of nodes across title text, where the sample is consistent across subreddits (n=500), there are still large disparities in number of nodes, as seen with r/science that has over 1000 more nodes compared to multiple subreddits. There were also observed differences in centralization of semantic networks across discourses. Both left leaning subreddits showed higher centralization in the title text compared to right leaning subreddits, indicating that liberal-focused Reddit discourse consistently used the same set of words more often across conversations than conservative users. The subreddit r/actualconspiracies also showed the highest centralization in its network when comparing title text across subreddits, which may reflect a higher uniformity in topics within that community.

Analysis of top centrality words identified prominent topics within left leaning (r/Liberal, r/democrats), right leaning (r/Conservative, r/Republican), scientific (r/science, r/EverythingScience), and conspiratorial (r/conspiracy, r/actualconspiracies) discourses. In the left leaning network, "Trump" had the highest eigenvector score and was connected to the highest number of nodes. "Biden" was the second most influential node, however, it was connected to less than half the nodes as "Trump." Within the right leaning network, "Biden" is the most influential nodes followed by "Trump," however the difference in influence is much narrower compared to the left leaning group. Both groups of political subreddits shared 43.3% overlap in top 30 centrality nodes, which include terms such as "abortion," "election," "hush," "money," and "trial." Nodes unique to the right leaning network were "Israel," "Iran," "war," and "border" while unique terms for left leaning were "Ukraine," "ballot," and "ban." When comparing differences between scientific and conspiratorial networks, the term "study" was the most influential and well connected node within networks from scientific discourse while “reports” was the most influential node within conspiratorial networks. While these terms are related, the use in terminology may be reflective of differences in epistemological values between these groups. Studies are typically conducted by scientific institutions, but reports can have a covert connotation and be released by anyone, including those not affiliated with an institution or who needs to reveal information while preserving one’s identity. Conspiracy subreddits were also more likely to discuss terms referring to media outlets (e.g., “cnn”, “bbc”) and countries (e.g., “Russia”, “China”) while scientific discourses were more likely to mention health-related terms such as “disease,” “brain,” and “cancer.” The terms “Biden” and “Trump” are also mentioned more often in conspiratorial subreddits while “health” is mentioned more often in the scientific group, showing further differences in topic priorities between the groups.

In addition to characterizing message content in online discourse, the current study demonstrates that centrality analysis can be used to identify words in posts that are effective predictors of engagement behaviors (i.e., upvote and comment) on Reddit. Bivariate correlations showed that use of all 3 types of high centrality words (degree, eigenvector, betweenness) were positively correlated with engagement when included in text of posts on r/Liberal, r/Conservative, and r/science. For r/Liberal and r/science, these effects on engagement were highly significant ($p<.001$). However, the direction of effects varied across subreddits, even for groups that share topics. When examining effects for r/democrats and r/EverythingScience, use of centrality words was negatively correlated with engagement. Conspiratorial subreddits showed similar effects, as use of centrality words in the body text for r/conspiracy and r/actualconspiracies were negatively correlated with commenting. Multiple regression modeling was conducted to further examine whether effects from the use of centrality words persists when controlled for other factors associated with information contagion tested in the previous chapter.

Effects from the inclusion of eigenvector centrality words in either title or body text did not remain when controlled for covariates such as word count, use of analytic and emotional language within for subreddits r/democrat, r/Conservative, r/conspiracy, r/actualconspiracies. However, use of eigenvector centrality words in posts remained positive predictors of engagement when controlling for all tested variables for r/Liberal, r/Republican, and r/science and continued to show a negative effect on engagement for r/EverythingScience.

Implications of using Semantic Networks for Investigating Information Contagion

There are many potential advantages of assessing the extent to which variables derived from semantic networks are predictive of post engagement. As demonstrated in the present analysis, the use of high centrality words were shown to be significant predictors of post engagement even when controlled for other textual factors. These findings indicate that centrality-based measures can be used as data-driven sentiment variables which can complement existing sentiments available in software such as LIWC. While development of existing sentiment variables target topics and content that are more general and can be applied across a variety of discourses (e.g., anger, family, health), the present analysis introduces an approach to identify meaningful language that is context-specific to the examined discourse community. It is likely that models that account for both general sentiment predictors (e.g., from LIWC) and context-specific language as measured by centrality metrics can increase accuracy of classifier models and other machine learning approaches. These analyses can also inform messaging interventions by tailoring word use based on targeted audiences.

The current results also demonstrate the utility of semantic networks for identifying prevalent discourse topics in online discourse and comparing associations of topics between discourse communities. The indirect nature of generating semantic networks from text overcomes limitations in traditional self-report measures where factors such as social desirability bias may influence how participants disclose their beliefs. It is also possible and likely that traditional self-reported measures for political affiliation do not capture the political complexities and nuances of one's true political identity and stances. For example, conservatives who do not like Donald Trump and those who do still share the same political label, thus, classifying people based on self-reported label risks making assumptions of shared beliefs and values which not might be true. Conversely, creating representations of one's understanding on an issue based on previously written responses could assess implicit understandings that participants might not always be able to articulate explicitly. Overall, by applying semantic networks to social media posts, it is possible to gain a user-driven perspective of group beliefs which can inform more effective online moderation, counter-messaging strategies that inhibit the spread of false narratives, and guide policies addressing the regulation of virtual environments.

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CONCLUSION

In recent years, efforts in computational social science have developed simulation models accounting for cognitive mechanisms, emotional affect processes, and group conformity effects underlying information contagion effects on social networking sites (SNS). As mentioned in the introduction of this dissertation, the “Agent Zero” framework (Epstein, 2014) was proposed to computationally model a wide variety of behaviors such as vaccine uptake, mob violence, and political mobilizations on social media such as the 2011 Arab Spring. In this model, individual behavior is driven by cognitive, emotional, and social components, with each module represented as dispositional weights resulting in a behavioral outcome (e.g., voting, getting vaccinated, retweeting). Whether an agent node engages in a simulated behavior is dependent upon the sum of their cognitive and emotional evaluations, and agents are further influenced if their observe other agents engage in the simulated behavior, which is accounted for in the social component. The effects accounted for in the social component is particularly important when modeling online information contagion, as a recent review of network contagion effects note that social media sharing is often a complex contagion (Guilbeault et al., 2018), which states that sharing social media posts are often influenced by observing multiple instances of other users sharing on the platform.

As demonstrated in the current work and from research efforts of others, individual differences among users and posts can influence engagement behaviors on social media. These findings suggest that accounting for dispositional traits of agents as parameters may improve prediction accuracy of information contagion dynamics in future simulation models. While the agent zero approach improves on previous work by utilizing cognitively plausible agents not based on conceptualizing information as a disease, this model is still limited in that it does not account for dispositional traits of users that can influence susceptibility to information. Further, differences in textual properties of posts, such as linguistic complexity and use of group-specific words, have also been shown to influence contagion effects. Overall, empirical evidence indicates that for information contagion dynamics among humans, all humans are not equally susceptible to the same message and not all messages are equally contagious.

As shown in Chapter 1, grandiose narcissism and religiosity were significant predictors of social media engagement, including retweeting. Agent-based simulations aiming to model information contagion effects should parameterize these traits to improve accuracy of spreading dynamics. Motivated reasoning processes could also be captured by classifying information based on whether there is expected bias, and then set the simulation to account for scenarios where some nodes are more susceptible to information while others are immune. As shown in Chapter 2, posts that include big words and analytic language were less likely to receive engagement from users across different types of discourse. These findings indicate that regardless of the actual message content, the style in which the post is composed can also influence how contagious a post may become. In Chapter 3, the effects from textual features were further investigated by incorporating semantic network analysis. Semantic networks were able to characterize large scale discourse by identifying influential words based on centrality metrics and reveal differences in how ideas are associated with one another across groups of users. The inclusion of these influential words in posts was also shown to influence engagement across subreddits when controlled for previously examined covariates, revealing a novel predictor of contagion effects not previously identified in the literature.

Despite the existence of much work examining how characteristics of users and properties of posts influence message propagation, these are typically separate lines of investigation where effects rarely examine how other components of contagion influence each other (Chen et al., 2023). It is also worth mentioning that there are other factors associated with information contagion not explored in the present work. For instance, platform features such as including warning tags next to misinformation posts have been shown to have promising effects on influencing propagation effects (Clayton et al., 2020; Martel & Rand, 2023). While these prior research efforts have generated a vast amount of evidence identifying separate facets of information contagion dynamics, a holistic framework that accounts for all these components is lacking. Fortunately, it may be possible to build such a holistic framework that accounts for these complexities based on insights from computational models that are grounded in the cognitive realities of humans. To take inspiration from disease contagion models, as many researchers who examine social contagion effects typically do, SIR models are often extended to account for a wide range of factors associated with pathogen transmission that are not captured in the classic model. These extensions of the SIR model are able to parameterize multiple types of factors associated with disease outbreaks, such as effects from when an agent node dies from infection (and can no longer be a transmitter), vaccine immunity, possibilities of reinfection, whether agents were quarantined, or a potential exposure period between being infected vs being actively contagious (Lazebnik, 2023; Tang et al., 2020). When modeling information contagion dynamics using cognitively plausible agents, additional complexities related to engagement behaviors from characteristics of users and posts can be accounted for to improve insights generated from simulation models and develop more sophisticated and nuanced theoretical frameworks that explain complex social phenomenon. More specifically, user traits and post properties examined in the previous chapters of this dissertation and other factors identified in the literature can be used to inform what parameters are relevant when modeling the spread of different types of information (e.g., conspiracy, group-related talking points). See **Figures 13** and **14** for how variance among users and posts can be accounted for in agent-based simulation models of information contagion.

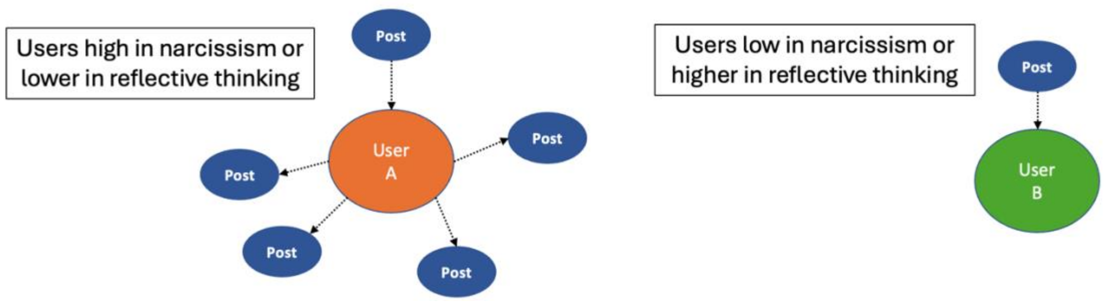

Figure 13. Accounting for Differences in Dispositional Traits among Agent Nodes when Modeling Information Contagion

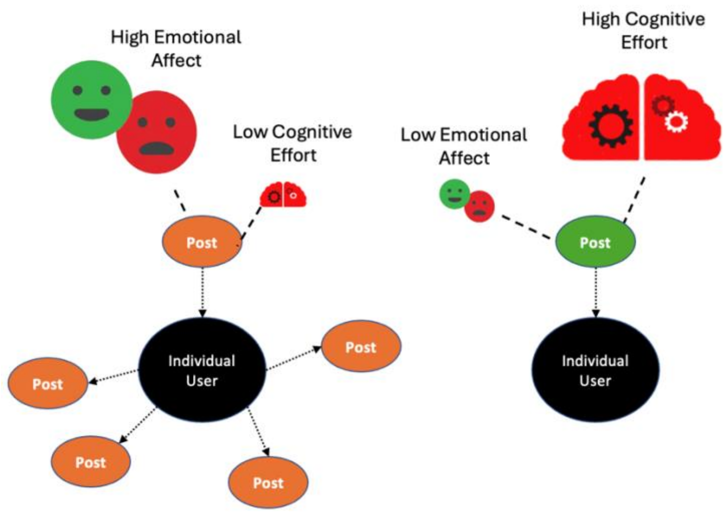

Figure 14. Accounting for Differences in Post Properties when Modeling Information Contagion

Benefits of improved models information contagion can improve assessments of public opinion and inform messaging campaigns. These models can also greatly benefit fields that rely on methodologies such as social listening, which evaluates public opinion towards specified topics by content coding social media posts across platforms. With more sophisticated information contagion models that account for contagion variance in posts (e.g., cognitive effort for comprehension, mentions group-relevant words) and users (e.g., narcissism, tendency for reflective thinking), it may be possible to forecast the duration and impact (e.g., share count) of given narratives. The ability to predict accurate timeframes that a narrative remains prevalent in user discussions can greatly inform political campaign strategies, public health communications, public relation efforts, and marketing and advertising campaigns. Online moderation and interventions for mitigating misinformation spread may also benefit from insights based on cognitively plausible simulation models. For instance, knowing the time period when a narrative will be most prevalent can inform response efforts from moderators or reveal when introducing a counter-message campaign would be most effective. Simulation models can also be used for message testing by predicting how variance in word use may influence the prevalence of a post. As observed in Chapter 3, inclusion of words that are used most often among a discourse community can either promote or inhibit engagement. Agent-based models that test the spread of messages can test the wording of a message that receives the greatest engagement. Since communities often respond to language differently, cognitively plausible models also have the potential to identify communities where a message will have the greatest and least amount of impact.

In sum, the age of social media is still relatively young. While information contagion has existed since the beginning of human civilization, recent years show the need to better understand the propagation dynamics in a new medium where people are able to interact with each other in an instant and information is more ubiquitous on a personal scale (e.g., the entire internet rests in our pockets). Greater insights into information contagion effects are crucial in order to improve how we regulate virtual environments and design platforms that promote healthy and informative information ecosystems. Fortunately, the sharp increase of available information coincides with ongoing advancements in artificial intelligence, computational modeling, and network analysis, which makes the possibility of investigating complex social phenomenon more obtainable than ever.

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