June 2021

The Extended Parallel Processing Model (EPPM) and Risk Perceptions of Twitter messages related to COVID-19

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by

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A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Arts
with a concentration in Media Studies
Zimmerman School of Advertising and Mass Communications
College of Arts and Sciences
University of South Florida

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Date of Approval:
June 21, 2021

Keywords: Health Communication, Risk Communication, Infectious diseases, social media

Acknowledgements

This project would not have been possible without the support, kindness, and inspiration of Drs. Artemio Ramirez, Josh Scacco, and Janelle Applequist. They have contributed to my growth as a scholar and as a human being. They challenged me to think differently and expand on my ideas to develop robust arguments. By placing an emphasis on my voice, they allowed me to express my arguments with confidence. I am grateful to have their support and mentorship.

I would also like to thank Drs. Claes de Vreese, Lance Holbert, Philip Arceneaux, David Lydon-Staley, and Ashley Muddiman (in no order) for their support and motivation throughout this process. Their comments on earlier drafts of this document allowed me to think in novel ways to develop my ideas. I would also like to acknowledge Sreerupa Sanyal for her constant support and motivation, particularly towards the last phase of this process.

Lastly and most importantly, I am here because of the support of my parents and my siblings. Despite the numerous challenges and barriers that we faced as an immigrant family, my mother's confidence, resilience, and faith in me motivated me to rise and put forth my best work even on days when I was plagued with anxiety and depression. To baba, mama, Hassaan, Shehrzad, and Sarah, this is for you.

The words on this page do not do justice to the empathy and kindness I have received from the individuals mentioned above. Thank you. I appreciate you and will continue to work hard.

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Abstract

Since its genesis, the novel coronavirus or COVID-19 has claimed millions of lives across the world and has infected many more. The population in the US experienced one of the worst outbreaks of COVID-19 in the world, with the number of deaths rising monolithically at one point. Although the development and inoculation of a large number of the public has helped, newer variants threaten to revitalize the growth and spread of COVID-19. Scholars have extensively studied health messages related to COVID-19 in a variety of contexts. However, little attention has been paid to the risk perceptions of health messages related to COVID-19 on social media platforms. Hence, utilizing the EPPM, this study aimed to assess the risk perceptions of health messages related to COVID-19 on Twitter from the CDC, the WHO, and the White House. This study also sought to test the EPPM in the context of Twitter messages related to COVID-19. Using a survey experiment, this study tested the EPPM and assessed risk perceptions by measuring variables such as perceived threat, perceived efficacy, fear control responses, and danger control responses. Participants were exposed to conditions with varying levels of threat and efficacy (high/low/none). The results revealed little support for the EPPM but did find (1) a significant positive relationship perceived efficacy and danger control responses and (2) a significant negative perceived threat and fear control responses. The practical and theoretical implications of the study are discussed.

Chapter 1

Introduction

The emergence of the novel coronavirus (COVID-19) has wreaked havoc on countries all around the world. The first cluster of cases related to COVID-19 was identified in December 2019, in Wuhan, China (WHO, 2020). Since then, COVID-19 has continued its unabated growth globally and has caused many deaths and left many infected. As of June 25, 2021, the COVID-19 pandemic has caused 3,899,172 deaths worldwide and 597, 727 in the United States (WHO COVID-19 Dashboard, 2021). Millions of people are infected and suffer the short and long-term consequences of COVID-19. Although the development of vaccines has helped, the number of infections and deaths continue to rise globally and in the US. As a result, leaders worldwide have declared public health emergencies and have been forced to issue stay-at-home orders and lockdowns to control the spread of COVID-19.

As the number of deaths and cases increase, understanding risk perceptions of health-related messages to COVID-19 is critical to develop robust communication strategies (Dryhurst et al., 2020; Van Bavel et al., 2020). It is also important to understand how risk perception varies in a population during COVID-19 as it may positively or negatively affect compliance with safety measures from health agencies, which has implications for public health outcomes (Barrios and Hochberg, 2020). If an individual has a low risk perception of COVID-19 related health messages, they may impose negative externalities on the larger population which can thwart the efforts to flatten the curve (Barrios & Hochberg, 2020). Risk perception also may positively or negatively impact the credibility of health agencies and political institutions. Prior research in risk and crisis communication suggests that during a pandemic, health agencies seek to persuade audiences by presenting a threat and describing a set of behaviors which may alleviate the threat (Reynolds & Seeger, 2005). However, if the health agencies lose their credibility, the persuasive messages may not be effective. In the US, COVID-19 has been highly politicized. As a result, public opinion regarding COVID-19 among Americans has become increasingly polarized (Singal, 2020). This attitudinal polarization may negatively impact the persuasiveness of health messages related to COVID-19. Thus, assessing the risk perceptions in a highly politicized global pandemic such as COVID-19 is necessary.

A robust theoretical model is necessary to examine the risk perception of health messages related to COVID-19. One such model is Witte's (1992) extended parallel processing model (EPPM) which emphasizes fear as a central variable and specifies the relationship between threat and efficacy in propositional forms. Thus, utilizing the EPPM (Witte, 1992), this study aims to examine the risk perceptions of health messages related to COVID-19 on Twitter by the Centers for Disease Control and Prevention (CDC), the World Health Organization (WHO), and the White House between January 2020 and October 20, 2020. This study focuses on Twitter messages to assess the risk perceptions of health messages related to COVID-19 due to the increased salience of the internet and social media in the consumption of health news. A recent survey by Pew Research Center revealed that 53% of Americans found the Internet to be essential during COVID-19 (Vogels, Perrin, Rainie, & Anderson, 2020). Specifically, researchers have identified Twitter as a platform for integrating social networking, health news, and medical education (Forgie et al., 2013).

Risk perceptions of health messages have been studied comprehensively by scholars for decades. Although some studies (Ibuka et al., 2010; Barrios & Hochberg, 2020) assess risk perception of health messages, the nature of those studies focuses on economic outcomes or public health outcomes of influenza. Since its genesis, scholars have extensively studied the risk perceptions of COVID-19 through interdisciplinary theoretical lens and a variety of methods. Some studies have assessed risk perceptions of COVID-19 through exposure on television (Bursztyn et al., 2020; Jamieson & Albarracin, 2020), while some have utilized surveys to measure risk perceptions of COVID-19 (Brown et al., 2021, de Bruin, 2021; de Bruin & Bennett, 2020; Dryhurst et al., 2020; He et al., 2021; Honarvar et al., 2020; Karanseh et al., 2021; Lanciano et al., 2020; Olagoke & Olagoke, 2020; Shao & Hao, 2020). Scholars have also explored risk perceptions of COVID-19 through qualitative methods such as interviews, focus groups and content analyses (Banda et al., 2021; Lohiniva, 2020). However, there is little focus on the risk perceptions of health messages related to COVID-19 on social media platforms in an experimental setting in extant literature.

Hence, using an experiment embedded in a survey, this study focuses on assessing the risk perceptions of health-related messages on Twitter through the lens of the EPPM. Specifically, this study tests the EPPM on Twitter messages from the CDC, the WHO, and the White House. The findings from this study will contribute to the growing literature focused on risk perceptions of health messages on social media platforms such as Twitter. Lastly, this study extends the use of survey experiments as a robust methodology to study COVID-19. The paper begins with an overview of the EPPM and how it has been applied by scholars during COVID-19. Then, the focus shifts towards the importance of the risk perceptions of health messages and COVID-19, followed by a review of the politicization of COVID-19 and how it impacts risk perceptions. Later, the paper dives into the literature on political polarization and the importance of assessing risk perceptions on a contentious pandemic such as COVID-19. Lastly, the paper provides a review of the literature focused on the importance of health messages on Twitter during COVID-19, followed by the hypotheses, methods, results, and a discussion.

Chapter 2

Literature Review

The Extended Parallel Processing Model

The extended parallel processing model (EPPM) is adapted from Leventhal's (1970) danger control/fear control framework by filling in gaps regarding the fear control processes and what factors lead to message rejection (Witte, 1992, 1994). It integrates the danger control processes from Roger's (1975) Protection Motivation Theory (PMT) to help explicate factors which lead to message acceptance. The EPPM posits that exposure to a message leads an individual to attempt to control the danger by engaging in behavior which minimizes the danger or to control the fear via defensive avoidance or not adopting the recommended behavior (Witte, 1992, 1994). Individuals exposed to a message evaluate the perceive threat of the hazard. A low perceived threat does not induce motivation in an individual to process the message. However, a moderate or high perceived threat prompts an individual to appraise the efficacy of the recommended action in the message. If the perceived threat and the perceived efficacy of the forementioned action are high, the individual is prompted to follow the action. Likewise, a low perceived efficacy and a high perceived threat of the message lead to defensive mechanisms to avoid the fear (Witte, 1992, 1994). The forementioned description of the EPPM was a succinct explanation of what the theory entails. However, it is important to carefully define key variables which encompass the EPPM such as the fear and danger control processes and to outline literature which employs the EPPM.

According to Witte (1992), fear appeals are "persuasive messages designed to scare people by describing terrible things that will happen to them if they do not do what the message recommends". Although fear appeals are a central variable in many theories and models in health communication, many scholars and studies have shown that they are ineffective. Yet, there is mixed evidence for these claims. The utility of fear appeals will be discussed later in this section. Fear is characterized as a negative emotion which is signified by a high level of arousal and is induced by a threat which is perceived to be significant (Easterling & Leventhal, 1989; Lang, 1984; Ortony & Turner, 1990; Witte, 1992). Fear can be expressed physiologically, verbally, or via direct action (Lang, 1984). Additionally, fear is best captured through self-reported fear, which is measured by mood adjectives (Rogers 1983; Witte, 1992; Witte & Allen, 2000). However, fear is only one of the variables involved in the EPPM.

Perceived Threat. Witte (1992) defines threat as an "external stimulus variable", such as a message cue. If an individual cognitively acknowledges the existence of the threat, then they are *perceiving* a threat. Health messages focus on the severity of the threat and the target population's susceptibility to the threat (Rogers, 1975; 1983). As such, the *perceived severity* of a message refers to an individual's beliefs about the significance of the threat. Additionally, the *perceived susceptibility* is an individual's beliefs about their chances of being impacted by the threat (Witte, 1992).

Perceived Efficacy. Efficacy also exists as a message cue, and prompts to *perceived efficacy*, which indicates an individual's beliefs about efficacy. Message characterizations of efficacy focus on *response efficacy,* which refers to the effectiveness the recommended response and the target population's ability to conduct the response (Rogers, 1975, 1983; Witte, 1992; Witte & Allen; 2000). Moreover, the *perceived response efficacy* signifies an individual's cognitions regarding the effectiveness of a response in mitigating the threat (Witte, 1992).

Message Acceptance & Rejection. Witte (1992) defines *message acceptance* as, "an attitude, intention, or behavior change". On the other hand, *defensive avoidance* refers to a motivated resistance to the message, such as minimization or denial of the threat. Researchers have identified several ways in by which individuals defensively avoid a message, from not paying attention to the message to suppression of thoughts related to the message (Hovland, Janis, & Kelly, 1953; Janis & Feshbach, 1953; Janis & Mann, 1977; Witte, 1992, 1994). This avoidance then leads to a reaction towards the message. According to Brehm (1966, p. 94), when the perceived freedom of an individual is reduced and the individual feels that there is an effort to make them change, *reactance* occurs.

Overall, the EPPM outlines that when an individual first is presented with a fear appeal portraying components of a threat and the efficacy of the message (severity, susceptibility, response efficacy, and self-efficacy). Then, this prompts an individual to appraise the threat. A high appraisal of threat results in moderate to high perceived threat and elicits fear, which, then leads to the evaluation of the efficacy of the recommended response (Easterling & Leventhal, 1989; Lang, 1984; Witte, 1992, 1994). If the perceived threat is low, then there is no motivation to process the message and no response is initiated. However, when perceived threat and perceived efficacy are high, danger control processes are prompted and the individual moves to control the danger. This is also known as protection motivation. The individual then engages in adaptive behaviors to avoid the threat. It is important to note that when danger control processes are high, the individual responds to the threat, not the fear of the threat. Conversely, when the perceived threat is high and the perceived efficacy is low, fear control processes dominate. In the forementioned scenario, individuals believe that they cannot avert the threat and the fear of the threat is intensified. Hence, the individual is motivated to cope with the fear, and avoid the threat, by engaging in maladaptive behaviors. In the EPPM, this is referred to as defensive motivation. Lastly, the perceived threat of a message determines the intensity of the reaction to the message, while perceived efficacy influences the nature of reaction (Lazarus & Folkman, 1982; Witte, 1992, 1994). It is important to note that the EPPM acknowledges that there are individual differences in the appraisal of the threat and efficacy of a message. These differences are influenced by prior experiences, culture, and personality characteristics (Witte, 1992, 1994). Hence, the EPPM is apt to examine risk perceptions of COVID-19 messages and how political polarization affects these perceptions.

EPPM & Health Communication. The EPPM has been tested in numerous contexts and researchers have identified it to be an effective model in examining messages related to health issues such as influenza and HPV, smoking/vaping, and environmental issues such as coal mining, and anxiety/uncertainty management in interpersonal contexts (Barnett et al., 2009; Carcioppolo et al., 2013; Hong, 2011; Hullett & Witte, 2001; McMahan, Witte, & Meyer, 1998; Murray-Johnson et al., 2004; Witte, 1994). Scholars have also studied variables from the EPPM such as fear, perceived susceptibility, perceived severity, threat, response efficacy, self-efficacy, efficacy, danger control responses, and fear control responses individually. For example, Sheeran et al. (2014) explored perceived severity as a measure of risk appraisals and found that increased perceived severity was correlated with increased risk appraisals. The EPPM and its variables are often studied in the context of fear appeals. As mentioned earlier, some scholars have argued and found evidence that renders fear appeals ineffective as a means of persuasion (Janis & Feshbach, 1953; Kohn, Goodstadt, Cook, Sheppard, & Chan, 1982; Krisher, Darley, & Darley, 1973). However, Witte & Allen (2000) found that fear appeal messages significantly predicted changes in behavioral intentions and attention. Scholars have also found fear to be an important predictor or behavior with the assumption that an arousal of fear will motivate individuals to avoid the behavior that causes fear (Dillard, 1994; Donovan & Henley, 2003; Job, 1988; Lewis et al., 2013; Tay & Watson, 2002).

Despite evidence supporting the utility of fear appeals, they are still not always effective. For example, a study by Muthusamy et al. (2009) found that using fear appeals to persuade audiences with pre-existing fears is not effective. Similarly, Gore & Bracken (2005) concluded that messages that included threat without the efficacy component may cause more fear and lead individuals to engage in fear control processes. One of the criticisms of the EPPM overtime has been that emotions other than fear may be associated with components of the framework. As such, scholars have extended the EPPM to include other emotions. Nabi & Myrick (2019) found some evidence of hope in response to fear appeal messages rather than fear as a contributor to the effectiveness of persuasive messages. On the other hand, So (2013) suggests that along with fear, anxiety could play a meaningful role in the EPPM process. Even with the evidence supporting the role of emotions other than fear in the EPPM process, fear can still play an important role in the effectiveness of persuasive messages. There are numerous studies which argue and find support for the utility of the EPPM within the context of fear and fear appeals in health messages (Lewis et al., 2013; Maloney et al., 2011; Murray-Johnson et al., 2001; Smith et al., 2008; Stephenson & Witte, 1998; Witte & Morrison, 1995a, Witte & Morrison, 1995b).

Over the years, the EPPM has been applied to many contexts beyond emotional appeals as well. Scholars have argued that the EPPM's theoretical scope can be extended to a variety of messages. For example, some studies have utilized the EPPM to test messages about electromagnetic fields (McMahan et al., 1998), while some have argued that the model can be used as a motivational tool to perform a health behavior from one individual to others (Goei et al., 2010; Morrison, 2005). Also, traditionally, the EPPM has been utilized and tested on text-based messages. Wong & Capella (2009) identified that the EPPM can be an effective framework to analyze visual messages as well, further extending the EPPM's theoretical scope. Given the robustness of the EPPM through different contexts, it is an efficient model to examine risk perceptions of health messages related to COVID-19 on Twitter in a politically divided ecology. Not only does the EPPM examine how individuals perceive and react to messages, but it also differentiates between individuals and how they perceive and react to the messages.

EPPM & COVID-19 related health messages. Since its genesis, scholars have extensively studied COVID-19 in a variety of contexts. One of the areas of focus has been COVID-19 health messages. This study focuses on health messages related to COVID-19 on Twitter using the EPPM. Scholars have studied health messages related to COVID-19 using a variety of lenses such as moral traditions and collective action (Cruwys et al., 2020; Everett et al., 2020). As such, there has also been a focus by scholars on analyzing health messages related to COVID-19 using the EPPM or its constructs. For example, Khazaei et al. (2020) found favorable support for the EPPM in the risk perception process among health workers. Another study tested the EPPM on government issued health messages on Canadian adults and found that efficacy and threat play a significant role in predicting intentions, especially among older individuals (Lithopoulos et al., 2021). Interestingly, Rahn et al. (2021) did not find support for the EPPM among German participants on warning messages but did find that age plays an important role in in predicting intentions and compliance, with older adults more likely to comply. Focusing on health messages related to COVID-19 on young adults, Abbott et al. (2020) suggest that scholars need to focus on EPPM constructs, particularly efficacy, to overcome deficiencies in existing health messaging targeted towards younger adults. The need to focus on efficacy has been echoed by other scholars as well. For example, Yang et al. (2021) found that behavior intention was predicted by perceived efficacy. Some studies have sought to apply and extend the EPPM in the context of COVID-19 (Jahangiry et al., 2020). Yet, despite all the focus on the EPPM in the context of COVID-19, there is little to no focus on the role social media health messages. Rather, the existing literature focuses on traditional messaging systems.

Some have argued that the political nature of COVID-19 requires the conceptualization of novel theoretical frameworks that consider political elements along with health elements. For example, Young & Bleakley (2020) argue that current theoretical frameworks do not account for how media fragmentation, political polarization around COVID-19 influences in attitudinal, normative, and efficacy related beliefs, which are central to compliance with health behaviors. Hence, Young & Bleakley (2020) postulate that the ideological health spirals model (IHSM) bridges this gap. Although models such as the IHSM are useful, the EPPM is still a robust model to assess risk perceptions of health messages related to COVID-19. Despite the cross-pollination of political polarization and public health in the context of COVID-19, fear plays a central role in promoting compliance with recommended health behaviors. In fact, Harper et al. (2020) found that fear has positively impacted public health behavior compliance during COVID-19. Thus, the EPPM is apt to explore and assess the risk perceptions of health messages related to COVID-19 on Twitter.

The EPPM and Risk Perceptions of COVID-19

Risk perceptions can be defined as an individual's perceived susceptibility to a threat (Ferrer & Klein, 2015). Academics and policymakers have identified risk perceptions as a key element of behavioral change (Barrios & Hochberg, 2020; Ferrer & Klein, 2015). Often, health risks are a result of deliberate decisions made by individuals seeking the best information for them and their loved ones. Individuals may be adversely affected by these decisions if there are inaccuracies in their risk perceptions (Fischoff et al., 1993). Hence, it is essential for policymakers to enact interventions to which correct any inaccuracies in an individual's risk perception of a health crises. In fact, researchers have found evidence which suggests that interventions which successfully alter risk perceptions generate subsequent changes in health behavior (Ferrer & Klein, 2015; Sheeran et al., 2014, p. 511). Risk perceptions are influenced by the information that is available to an individual (Tversky & Kahneman, 1973). More, risk perceptions are impacted by an individual's existing beliefs, social, cultural, and contextual factors that are based on subjective attitudes (Brown et al., 2018; Godovykh et al., 2021; Pidgeon, 1998, Ropeik, 2011). So, even if the real risk is minimal, risk perceptions can influence behavioral and attitudinal changes (Cakar, 2020; Quintal et al., 2010; Reichel et al., 2007). In terms of health messages, scholars have argued that risk perception is a central construct associated with stopping a risky health behavior (McCoy et al., 1992).

Risk perceptions have been used as a central variable in studies across a myriad number of contexts. This paper is focused on assessing the risk perceptions of health messages related to COVID-19 on Twitter. Scholars have argued that an individual's risk perception directly affects how they perceive a message (Rothman & Salovey, 1997). This then leads the individual to make a judgement based on the perceived risk of the message. So, if the perceived risk of the message is high, individuals are more likely to take action to resolve the risk. This is consistent with the assumptions of the EPPM. Scholars have identified perceived risk to be the product of perceived severity and susceptibility, both constructs in the EPPM. (Rimal & Real, 2003). It can be argued that perceived severity and perceived risk are similar in nature and can be used interchangeably. This study uses perceived severity as an indicator of an individual's risk perceptions. Based on the overview of literature above, risk perceptions and the EPPM are related and effective in understanding the interaction between messages and behavioral change. As such, scholars have focused on risk perceptions by using the EPPM along with other frameworks.

So far, studies have explored how risk perceptions of COVID-19 impact knowledge and behaviors (Banda et al., 2020; Cori et al., 2020; Honarvar et al., 2020; Karanseh et al., 2020), compliance (Wong & Jensen, 2020; de Bruin & Bennett, 2020), emotional and psychological well-being (de Bruin, 2020; Lanciano et al., 2020; Sica et al., 2021), and public health policy (Chakraborty, 2020; Siegirst & Bearth, 2021), among many topics. Surprisingly, the literature focused on assessing the risk perceptions of messages related to COVID-19 using the EPPM is scant. Apart from a small number of studies (Birhanu et al., 2021; Jahangiry et al., 2020; Nazione & Perrault, 2020), there is little focus on the relationship between risk perceptions and the EPPM. Perhaps even more surprising, most of the abovementioned studies are focused on international populations, despite the US experiencing one of the worst COVID-19 outbreaks among a politicized public health response and a polarized citizenry. This study seeks to remedy this gap in the literature by focusing on the risk perceptions of Twitter messages related to COVID-19 using the EPPM.

An emerging area of focus of scholars has been the impact of politics on risk perceptions of COVID-19. In a highly polarized political climate such as that which surrounds COVID-19, the most salient information available to individuals is by the political and public health agencies such as the White House, the CDC, and the WHO. Recent studies have found that political polarization plays a role in shaping risk perceptions (Barrios & Hochberg, 2020; de Bruin et al., 2020; Shao & Hao, 2020). Blinded by a “partisan perceptual screen”, individuals’ perceptions and beliefs regarding public health guidelines, death counts, and infection counts may be interpreted differently based on the source's political leanings. In fact, using GPS data, researchers have discovered that areas with more Republicans practiced less social distancing than areas with a higher number of Democrats (Allcott, et al., 2020). Shao & Hao (2020) found that (1) conservatives show lower risk perceptions of COVID-19 than liberals and moderates, (2) confidence in political leaders can reduce risk perceptions and it mediates the effect of political ideology on risk perceptions, (3) perceived quality of coverage can lead to heightened risk perceptions of COVID-19. Similarly, de Bruin et al. (2020) discovered that Democrats were more likely to watch liberal news outlets such as MSNBC or CNN for COVID-19 related information while Republicans were more likely to watch Fox News. They also found that political ideology predicted policy preferences related to COVID-19 and risk perceptions. This sheds light on the importance of political variables such as polarization in the risk perceptions of COVID-19.

The Politicization of COVID-19

Politicization is characterized by the salience of political actors in the coverage (Bolsen et al., 2014; Chinn et al., 2020). Public health and COVID-19 have become highly politicized. Researchers have identified former President Trump's communication and that of leading conservative political commentators as a root of the politicization of COVID-19 (Franck, 2020; Hart et al., 2020; Peters & Grynbaum, 2020; Rupar, 2020). Furthermore, studies have shown that right-wing news outlets were more likely to spread misinformation regarding COVID-19 at the beginning of the pandemic and viewers of right-wing news were more likely to be misinformed about the pandemic (Hart et al., 2020; Motta et al., 2020). However, this is not the first instance of a health issue being politicized. Larson (2018) maintains that vaccine risk perceptions are also shaped by politics. This reveals that the interference of politics in health issues has a significant impact on risk perceptions. The effects of the politicization of COVID-19 have been confirmed by researchers. A study by Shao and Hao (2020) revealed that conservatives exhibit lower risk perceptions of COVID-19 due to lower confidence levels in political leaders. Additionally, a survey national survey of registered voters in the US by Civiqs revealed that 62% of Democrats were extremely concerned by COVID-19 while only 7% of Republicans expressed the same concerns (2020). In the same survey, only 2% of Democrats voiced no concern at all about COVID-19 whereas a surprising 44% of Republicans stated having no concern at all about the virus (Civiqs, 2020).

Hart et al. (2020) argue that although politicization is not inherently bad, politicization combined with a high degree of polarization is troubling. Additionally, the effects of politicized coverage are detrimental to health behaviors in a pandemic. Health and political communication scholars have argued that politicized coverage, combined with polarization, can affect motivated reasoning, and lead individuals to believe political elites over scientists (Hart et al., 2020; Taber, et al., 2009; Bolsen et al., 2014; Slothuus & de Vreese, 2010). This can lead to a polluted science environment (Kahan, 2012). It is critical for individuals to listen to scientists over the political elites in forming decisions regarding COVID-19-related health behavior. Hence, it is critical to understand how polarization affects the risk perceptions of COVID-19.

Political Polarization and COVID-19. Political communication researchers have argued that there is an increase in polarization over time, with political parties becoming homogenous in the political ideology of their members and exhibiting increased aggressiveness and hostility towards member of the opposite political party (Iyengar et al., 2012; Mason, 2013; Lott & Hassett, 2014; Mason, 2015; Gentzkow, 2016; Boxell et al., 2017). Due to the increased polarization, people have become selective about the information which they find credible. As a result, compliance with COVID-19 guidelines may be influenced by how the guidelines are interpreted by individuals. Extant research suggests that individuals tend to consume information from authority figures who align with their political beliefs (Barrios & Hochberg, 2020). Individuals may prefer such news due to their political dispositions or because they determine such sources to be credible (Mullainathan & Schleifer, 2005; Gentzkow & Shapiro, 2006). According to Pew Research Center, partisan gaps are pronounced in how individuals view COVID-19 related news in the media, with Republicans more likely to believe that the media has exaggerated the risks associated with COVID-19 (Gottfried et al., 2020). As a result, the increasing political divide in the US becomes important in the context of how messages related to COVID-19 are perceived by people. Hence, it is important to examine how and whether polarization and the political divide in the US impacts the risk perception of COVID-19 related health-messages.

The political divide and increased polarization among individuals in the US may affect how COVID-19 related messages from WHO, CDC, and the White House are perceived. Additionally, it may affect how individuals form health-related decisions and comply with stay-at-home orders and social distancing rules. Political communication scholars have long argued that individuals are socialized from an early age to view political elites as authoritative (Lane & Sears, 1964). Additionally, information has traditionally flowed from the authoritative political elites to the public (Schmidt, 2008; Zaller, 1992). The political elites then facilitate the ensuing debates among the public (Schmidt, 2008). In addition, the political elites shape public opinion by coining the terms of public discourse and by framing the issues for media and public (Zaller, 1992). In an increasingly hybrid and ubiquitous media environment, the communicative reach of public elites has increased drastically as content now flows through multiple media channels (Jenkins & Deuze, 2008; Scacco & Coe, 2016, 2021). In the case of COVID-19, political polarization can affect the perception of public health messages as the political elites, the White House and Trump in this case, shape public opinion about the pandemic. That is evident in the fact that 83% of Republicans rated Trump's response to COVID-19 as excellent, while only 18% of Democrats echoed that appraisal (Van Green & Tyson, 2020). Hence, it is critical to understand the role of political polarization in the perception of COVID-19.

Political polarization is characterized by the simultaneous presence of opposing or conflicting principles, tendencies, or points of view (Fiorina & Abrams, 2008). Most scholars explicate polarization as a bimodal distribution of observations on a liberal-conservative scale (DiMaggio, Evans, & Bryson, 1996; Fiorina & Abrams, 2008). Additionally, political polarization induces individuals to align themselves with certain views and opinions while organizing individuals and groups around identities, thus placing them in opposing factions (Baldassarri & Gelman, 2014). This creates a political divide among individuals and groups and leads to echo chambers, which are characterized by patterns of information sharing that reinforce preexisting beliefs by limiting exposure to opposing political views (Bakshy, Messing, & Adamic, 2015; Berry & Sobieraj, 2013; King, Schneer, & White, 2017; Prior, 2013; Sunstein. 2001). This political divide or polarization can be narrowed into subcategories or levels. Political scientists have identified elite polarization, mass polarization, partisan polarization, activist polarization, and affective polarization as the different categories where polarization exists (Abramowitz & Saunders, 2008; Baldassarri & Gelman, 2014; DiMaggio et al., 1996; Fiorina & Abrams, 2008; Iyengar et al., 2012). This represents an increase in political polarization in the US in recent times (Young & Bleakley, 2020). Additionally, it reflects how political polarization has permeated into political elite circles and the public by dividing people along social, ideological, and racial lines (Mason, 2018). In fact, a survey by Pew Research Center (2014) found that the average Democrat has become more liberal, and the average Republican has become ideologically more conservative during the last three decades in the US. The political divide in the US has been trending upward in recent times. A study by Iyengar et al. (2012) showed that Republicans and Democrats strongly dislike and "even loathe", their opponents. The forementioned studies reflect the sharp increase in political polarization among individuals in the US.

COVID-19 has only amplified the increase in political polarization. A recent study found that low confidence in the government is a major reason for the lack of compliance with public health messages which explains why the US has been unable to contain the virus despite being relatively well positioned to do so (Nuzzo et al., 2020). Additionally, Americans' credibility of medical scientists also varies by political affiliation. A survey conducted by Pew Research Center found that 53% of Democrats have a great deal of confidence in medical scientists while 31% of Republicans reported having the same level of confidence (Funk et al., 2020). Moreover, Hart et al. (2020) suggest that individuals in the US are polarized on the perceptions of scientists and the response to COVID-19. Scholars have also pointed out that Americans are experiencing a highly politicized pandemic in a polarized environment where groups are socially sorted along partisan lines (Iyengar et al., 2012; Mason, 2018; Stroud, 2011; Young & Bleakley, 2020). The high levels of political polarization and social sorting are enabled by a fragmented and hybrid media system, where social media algorithms micro-target individuals and present them with information based on their preferences (Chadwick, 2017; Settle, 2018; Young & Bleakley, 2020). This signifies the importance of political polarization and social media in assessing examining the risk perceptions of a highly politicized pandemic such as COVID-19.

Twitter, Health Communication, & COVID-19

Researchers have identified Twitter as a platform for integrating social networking, health news, and medical education (Forgie et al., 2013). Recent studies suggest that social media plays a significant role in health communication the consumption of news related to health. For example, Applequist et al. (2020) found that social media play important roles in recruiting participants with rare diseases for clinical studies through the development of patient-centered messages. In a study by Goodyear et al. (2018), 43% of young people reported that health-related content on social media had a positive impact on their health. Additionally, 46% of the people in the same sample reported changing their health-related behaviors as a direct result of accessing health-related content on social media (Goodyear et al., 2018). The forementioned study also found that social media users use followers and likes to determine the credibility of the information and which type of health-related content they should incorporate in their lives (Goodyear et al., 2018). The Twitter accounts of the White House, the CDC, and the WHO have 87.3 million, 3.2 million, and 8.4 million followers respectively. The large number of followers reveals that there is a sizeable audience who finds health-related content from these accounts credible, according to Goodyear et al. (2018). It must be noted that the forementioned study focuses on young people aged 13-18. However, public health experts have argued that although younger individuals are not affected by COVID-19 severely, they may be asymptomatic and can infect vulnerable populations (Boehmer et al., 2020).

Scholars from a variety of fields have recognized the importance of social media, particularly Twitter, as a messaging tool spurring meaningful change in political and health settings (Allington et al., 2020; Coe & Griffin, 2020; Sides et al., 2018; Tourjée & Ettachfini, 2018). For example, Scanfeld et al. (2010) conducted a content analysis of Twitter updates and found significant evidence of dissemination of health information and news on the platform. Researchers found that health information related to COVID-19 was shared widely on Twitter in South Korea (Park et al., 2020). The widespread heath information related to COVID-19 reveals the importance of the platform. Individuals may consume health news related to COVID-19 on Twitter and perceive it as threatening or non-threatening. Additionally, platforms such as Twitter encourage user-expression which may lead individuals to share their opinions regarding major health events such as COVID-19 (Paul & Dredze, 2011).

Although individual opinions are likely to not hold much weight, the aggregation of millions of messages can generate important knowledge and provide deep insights into public opinion in a population (Paul & Dredze, 2011). In fact, researchers from the University of Southern California's Information Sciences Institute have identified over 123 million tweets related to COVID-19 as of May 11, 2020, which signifies the enormity of communication regarding the pandemic on Twitter (Chen et al., 2020). Researchers have also identified Twitter as an effective source of COVID-19 related health news due to its concise and succinct messaging style (Chan, et al., 2020). However, even as COVID-19 related health messaging has circulated on Twitter, individuals in the US have not complied to public health guidelines completely. According to a recent Gallup poll, only 44% of Americans reported wearing a facemask outside their home (Brenan, 2020). Hence, Twitter is an important platform in the assessment of risk messages in health messages related to COVID-19. Some scholars have argued that social media, which includes Twitter, heightens a society's risk perceptions more than traditional mass mediums (Tsoy et al., 2021; Ng et al., 2018). Social media is known as an affordable, accessible, and easy way to obtain information. By focusing on Twitter, this study contributes important findings to an emerging area of interest among scholars.

Hypotheses

Following the traditional assumptions of the EPPM (Witte, 1992; 1996), the current study hypothesizes:

H1: High efficacy and high threat will influence danger control

H2: High threat and low efficacy will influence fear control)

H3: Low threat and low efficacy will influence fear control

H4: High efficacy will influence behavioral intentions

H5: High threat will influence reactance

H6: Perceived efficacy will mediate the relationship between efficacy and danger control

H7: Perceived threat will mediate the relationship between threat and fear control

Chapter 3

Methods

To assess the risk perceptions of health messages related to COVID-19 on Twitter, this study employs a between-subjects experiment embedded in a survey. The use of a population-based survey experiment is apt for the context of this study for several reasons. First, health communication scholars have used between-subjects designs effectively to reach robust conclusions and draw inferences (Smit et al., 2019). Secondly, compared to traditional surveys, experiments embedded in a survey allow for a more in-depth understanding of how variables interact with one another. This study was conducted using Qualtrics, an online survey tool. There are numerous benefits associated with using Qualtrics including lower cost, ease-of-use to participants, and the ability to recruit large samples (Wimmer & Dominick, 2013). A 2 (threat) X 2 (efficacy) between-groups experiment was employed to explore how the independent variables influence the dependent variables (danger control responses, fear control responses, behavioral intentions, reactance). Before the participants were recruited, approval for data collection and the study was obtained from the University of South Florida's (USF) Institutional Review Board (IRB). Post data collection, SPSS was used to streamline and analyze the data.

Participants

The participants for this study were recruited through Amazon Mechanical Turk service (MTurk). The experiment was conducted between March 2021 to early April 2021. Participants accessed the survey through CloudResearch platform, which is powered by MTurk. MTurk is an online crowdsourcing platform which has become a popular source for researchers due to its cheap cost. Although MTurk is an opt-in sample, it generates more representative samples of the population than most convenience samples, such as college students (Berinsky et al., 2012; Mullinix et al., 2016, Thorson, 2016). The experiment was restricted to participants only registered in the US over the age of 18 and active consumers of Twitter. Although MTurk also includes a non-US population, the platform allows researchers to screen out individuals not registered in the US through methods such as IP address matching (Thorson, 2016). The total number of participants that were recruited was 223.

The survey experiment was created in Qualtrics such that each participant was randomly placed in an experimental condition. The data were then screened to ensure that all surveys were completed fully to avoid erroneous submissions. The average time spent by participants on the survey was 7 minutes and 10 seconds. At the end of the survey, participants were asked to devise a custom code, which was used to approve payment for the participants as well as screen the data for quality. After data screening, 203 participants were selected for final data analysis.

Demographics & Twitter Use

A descriptive statistics analysis of the data revealed that 11.8% of the participants rarely used Twitter, 39.9% used it sometimes, 32.5% used it often, and 15.8% used it a lot. In terms of gender, 60.1% of the participants identified as female, 39.4% of the participants identified as male, and one person (0.5%) identified as non-binary/other gender. Participants between the ages of 18 to 30 years old comprised 44.3% of the sample, participants between the ages of 31-45 years old made up 36.9% of the sample, participants between the ages of 46-60 years old made up 15.8% of the sample, and 3% of the sample was comprised of participants over 60 years old. The sample was overwhelmingly White, with 71.9% of the sample identifying as such, 10.3% of the sample identified as Black or African American, 6.9% of the sample identified as Latino, 5.9% of the sample identified as Asian, American Indian or Alaska Natives comprised of 2% of the sample, while six (3%) participants identified as other. In terms of education, 46.3% of the participants held at least a bachelor's degree, 25.6% of the participants at least held an associate's degree, 15.8% of the sample held a graduate degree, 10.8% of the sample held an associate's degree, and three (1.5%) participants completed some high school. The majority of the participants reported an affiliation with the Democratic party (52.2) while 16.3% reported being affiliated with the Republican party. The percent of participants who reported affiliation with neither party was 26.6% while 4.9% of the participants reported being affiliated with another party.

Procedure

Prior to the start of the survey experiment, participants were asked to read the consent form and agree to participate. The consent form was approved by the IRB at USF. If the participants consented to participate, they were directed to the survey. Then, the participants were asked to answer a question focused on their Twitter use (Do you regularly use Twitter?) and the frequency of their Twitter use (How often do you use Twitter?). If they answered yes the Twitter use question and responded positively to frequency of Twitter use, they were randomly assigned to one of the three experimental conditions (high threat, high efficacy; high threat, low efficacy; low threat, low efficacy) or the control group, where participants were exposed to tweets from the @CDCgov, @WHO, and @realDonaldTrump accounts and were then asked to fill out a questionnaire. If they answered no, they were redirected to the end of the questionnaire. Levels of threat and efficacy in the experimental conditions were assessed by the researcher ostensibly using the conceptual and operational definitions provided by Witte (1992, 1996). After answering the initial screening question and exposure to tweets, participants were asked to answer questions of their perceived severity of threat, perceived susceptibility to the threat, perceived response efficacy, self-efficacy, danger control processes, fear control processes, and demographic questions. Upon the successful and full completion of the questionnaire, the participants were compensated for $1.00 and exited the survey experiment.

Stimuli Materials

The stimuli materials included one tweet each from the @CDCgov, @WHO, and @realDonaldTrump accounts. These accounts were selected due to their large following on Twitter. As mentioned earlier, studies have shown that a large following on social media platforms such as Twitter is associated with acceptance of a recommended health behavior (Goodyear et al., 2018). The tweets were not manipulated to maintain their ecological validity. Rather, they were selected based on the ostensible threat and efficacy that they reflected. The advanced search feature of Twitter was used to manually select Tweets from the @CDCgov and @WHO accounts which mentioned COVID-19, coronavirus, or pandemic along with the hashtag #COVID19. It is possible that there are other terms (for example, chinavirus) which encompass the description of COVID-19. However, the terms COVID-19, coronavirus, and pandemic have been widely used in the US to describe the virus whereas other terms are used by certain individuals. Tweets from the @realDonaldTrump account were selected using the Donald Trump Twitter Archive 2.0, an online tool which contains Trump’s tweets despite him being banned from Twitter (see appendix A for experimental stimuli).

Measures

Witte (1996) outlines that threat and efficacy are two distinct factors comprised of two dimensions each. In the threat factor, the two dimensions are severity and susceptibility. Efficacy is composed of response efficacy and self-efficacy. The following measures were all measured using a 5-point Likert type scale (strongly agree = 1 to strongly disagree = 5) on three unique items as conceptualized by Witte (1996).

Perceived Threat

The measure for perceived threat is calculated by averaging the scores from perceived severity and susceptibility as outlined by Witte (1996). Perceived severity captures how severe participant's perception of COVID-19 as a threat is. Participants were asked to respond to the following items:

1. I believe that COVID-19 is severe.
2. I believe that COVID-19 is seriously harmful.
3. I believe that COVID-19 is significant.

On the other hand, perceived susceptibility captures the participant's perception of how vulnerable they are to COVID-19. Participants were asked to respond to the following items:

1. I am at risk for getting COVID-19.
2. I am likely to contract COVID-19.
3. It is possible that I will contract COVID-19.

The items for perceived severity and susceptibility were combined to create a composite variable (α = 0.90, M = 1.99, SD = 0.77).

Perceived Efficacy

The measure for perceived efficacy is calculated by averaging the scores from response efficacy and self-efficacy (Witte, 1996). The response efficacy measure captures whether safety measures and guidelines issued by public health experts are perceived as efficient by individuals. For this study, social distancing, wearing masks, and disinfecting hands will be used as the main safety measures. Participants were asked to respond to the following:

1. Social distancing, wearing masks, and disinfecting hands works in preventing the contraction of COVID-19.
2. Social distancing, wearing masks, and disinfecting hands is effective in preventing COVID-19.
3. If I socially distance, wear a mask, and disinfecting my hands, I am less likely to get COVID-19.

On the other hand, the measure for self-efficacy captures how an individual perceives their ability to socially distance, wear a mask, and disinfect their hands. Participants were asked to respond to the following:

1. I am able to socially distance, wear a mask, and disinfect my hands to prevent the contraction of COVID-19.
2. Social distancing, wearing masks, and disinfecting hands is easy to do to prevent COVID-19.

The measures for response efficacy and self-efficacy were combined to create the composite variable for perceived efficacy (α = 0.94, M = 1.44, SD = 0.76).

Dependent Variables

Danger Control Responses

According to Witte (1996), danger control is a cognitive process that elicits protection motivation that occurs when a person has high perceived self and response efficacy to avert the relevant threat through “self-protective” changes. In this process, individuals think of strategies to avert the relevant threat. Danger control processes are measured through attitudes, behavioral intentions, and existing behaviors.

Attitudes toward social distancing, wearing face masks, and disinfecting hands were captured with three semantic differential scales: bad-good, desirable-undesirable, and unfavorable-favorable (e.g., "What are your attitudes regarding social distancing, wearing face masks, and disinfecting hands? bad-neutral-good).

Behavioral intention was measured through a question using a 5-poing Likert type scale (strongly agree = 1 to strongly disagree = 5). Participants will be asked to respond to the following item: I intend to socially distance, wear a mask, and disinfect my hands regularly.

Existing behaviors were also measured through two items using a 5-point Likert type scale (strongly agree = 1 to strongly disagree = 5). Participants were asked to respond to the following items:

1. I currently socially distance, wear a face mask, and disinfect my hands.
2. I consistently social distance, wear a face mask, and disinfect my hands.

The measures for attitudes, behavioral intention, and existing behaviors were combined to create a composite variable for danger control responses (α = 0.95, M = 1.51, SD = 0.93).

Fear Control Responses

Fear control is an emotional process which elicits defensive motivation. This occurs when individuals are exposed to a significant threat, but the perceived self and response efficacy is low. Moreover, this results in high levels of fear which cause coping responses designed to reduce fear and prevent danger control responses from occurring. Fear control processes are measured through defensive avoidance, denial, and reactance (this includes message derogation and perceived manipulative intent) (Witte, 1996).

Defensive avoidance was measured through the question: “When I first heard about COVID-19, my first instinct was to: (a) {want to/not want to} think about COVID-19 or (b) {want to/not want to} do something to keep myself from contracting COVID-19”.

Reactance was measured in two ways. First, the participant’s minimizing of COVID-19 was measured (e.g., how individuals felt about the health risk message regarding COVID-19). Then, the degree of perceived manipulation from the tweets was measured (Brehm, 1966, Witte, 1996). Participants were asked to respond to a question which examined whether the participants thought that the message in the tweets was “overblown, exaggerate, or overstated”. The degree of perceived manipulation was measured through a question which assessed whether the participants thought that the messages in the tweets was “manipulative, misleading, or distorted”.

The measures for defensive avoidance, reactance, and perceived manipulation were combined to create a composite variable for danger control responses (α = 0.90, M = 3.57, SD = 1.40).

Chapter 4

Results

Hypothesis 1

The first hypothesis predicts that high efficacy and high threat will influence danger control responses. A two-way ANOVA was conducted to test this hypothesis with high efficacy and high threat as independent variables and danger control responses as a dependent variable. The test was not significant: $F(3, 199) = 1.01$, $p = 0.39$, $\eta^2 = 0.02$, indicating no difference between high threat (M = 1.61, SD = 1.01) and high efficacy (M = 1.64, SD = 1). The Tukey HSD post hoc test did not indicate any significant differences.

Hypotheses 2 & 3

The second hypothesis predicted that high threat and low efficacy would influence fear control responses. Similarly, the third hypothesis predicted that low threat and low efficacy would also influence fear control responses. A two-way ANOVA was conducted to test this hypothesis with high efficacy and high threat as independent variables and fear control responses as a dependent variable. The test was not significant: $F(3, 199) = 0.86$, $p = 0.46$, $\eta^2 = 0.01$, indicating no difference between high threat (M = 3.44, SD = 1.44) and low efficacy (M = 3.76, SD = 1.33), low threat (M = 3.65, SD = 1.37) and low efficacy (M = 3.76, SD = 1.33). The Tukey HSD post hoc test did not indicate any significant differences.

Hypothesis 4

The fourth hypothesis predicted that high efficacy would influence behavioral intentions. A one-way ANOVA was conducted to test this hypothesis with high efficacy as the independent variable and behavioral intentions as a dependent variable. The test was not significant: $F(2, 200)$

= 0.91, p = 0.40, η^2 = 0.01, indicating no differences among the different levels of efficacy (M = 1.49, SD = 0.96). The Tukey HSD post hoc test did not indicate any significant differences.

Hypothesis 5

The fifth hypothesis predicted that high threat would influence reactance. A one-way ANOVA was conducted to test this hypothesis with high efficacy as the independent variable and behavioral intentions as a dependent variable. The test was not significant: $F(2, 200) = 0.97$, p = 0.32, η^2 = 0.01, indicating no differences among the different levels of threat (M = 3.57, SD = 1.40). The Tukey HSD post hoc test did not indicate any significant differences.

Hypothesis 6

The sixth hypothesis precited that perceived efficacy would function as a mediator between high/low efficacy and danger control. The total effect of high/low efficacy on danger control was not significant (p = 0.35). The direct effect of high/low efficacy on danger control was also not significant (p = 0.95). Finally, the indirect effect is also not significant. The bootstrapped unstandardized indirect effect was .07, and the 95% confidence interval ranged from -.06, 0.21. However, there was a statistically significant positive relationship between perceived efficacy and danger control responses (p < 0.001).

Hypothesis 7

Lastly, the seventh hypothesis postulated that perceived threat would function as a mediator between high/low threat and danger control. The total effect of high/low efficacy on fear control was not significant (p = 0.17). The direct effect of high/low efficacy on fear control was also not significant (p = 0.30). Finally, the indirect effect is also not significant. The bootstrapped unstandardized indirect effect was -.07, and the 95% confidence interval ranged from -0.22, 0.08. However, there was a statistically significant negative relationship between perceived threat and fear control responses ($p < 0.001$).

Chapter 5

Discussion

This study sought to assess the risk perceptions of health messages related to COVID-19 on Twitter messages from the CDC, the WHO, and the White House. Another focus of the current study was to test the EPPM on Twitter messages. The EPPM has been tested in various contexts and has proved to be a robust framework to test the interactions between messages and behavioral intentions and changes (Lewis et al., 2013; Murray-Johnson et al., 2001; Smith et al., 2008; Stephenson & Witte, 1998; Witte & Allen, 2000; Witte & Morrison, 1995a, Witte & Morrison, 1995b, Wong & Capella, 2009). Although all the hypotheses posed in the study were not supported, two interesting findings showed (1) a positive significant relationship between perceived efficacy and danger control responses, and (2) a negative significant relationship between perceived threat and fear control responses.

The results showed that the interactions among the constructs of the EPPM were not significant. This may lend support to the notion that fear appeals are not an effective means of persuasion (Janis & Feshbach, 1953; Kohn et al., 1982; Krisher, et al., 1973). Also, the results are not consistent with tests of the EPPM in existing literature which find it as an effective model to analyze risk and predict behavioral intentions in health messages (Lewis et al., 2013; Witte & Allen, 2000; Witte, 2009). Instead, the results from this study concur with literature that finds little to no support for the EPPM as an appropriate model to analyze messages. For example, one of the hypotheses predicted that high threat and efficacy would influence danger control responses, consistent with the assumptions of the EPPM (Witte, 1996). Yet, the analysis of the data revealed a small effect size and found no interaction between high threat, high efficacy, and danger control responses. Similarly, other hypotheses from this study predicted that (1) high threat and low efficacy would influence fear control responses and (2) low threat and low efficacy would influence fear control responses. These hypotheses were also not supported with small effect sizes and no interactions between threat, efficacy, and fear control responses. Ooms et al. (2015) found similar results in their test of the EPPM. Specifically, they found that threat, fear, and efficacy were not related to behavioral intentions, danger control responses, and fear control responses. Similarly, Popova (2012) also did not find empirical support for any of the propositions posed by the EPPM.

This study revealed that high levels of efficacy and threat did not influence behavioral intentions. This finding differs from the results of studies focused on the EPPM and the effects of efficacy and threat on persuasive messages (Lewis et al., 2013; Maloney et al., 2013; Shi & Smith, 2016; Witte & Allen, 2000, Witte, 1992; 1996; 2009; Yun et al., 2014). Interestingly, this finding is consistent with the findings from studies that do not show support for the EPPM (Ooms et al., 2015; Popova, 2012).

Another finding of the current study showed that perceived efficacy did not mediate the relationship between high/low efficacy and danger control responses. However, there was a significant positive relationship between perceived efficacy and danger control responses. Simply put, as levels of perceived efficacy rose, message acceptance and positive behavioral intentions, which compose danger control responses, also rose. Although the main mediation finding was inconsistent with the literature supporting the EPPM and its constructs (Witte, 1992, 1994,1996, 2009; Yun et al., 2014), the significant positive relationship between perceived efficacy and danger control responses is supported by many scholars (Abbott et al., 2020; Egbert et al., 2014; Maloney et al., 2013; Umphrey, 2004; Witte, 2009; Yang et al., 2020). Indeed, Krieger & Sarge (2013) found efficacy be a significant predictor of message acceptance and behavioral intention.

Lastly, the study found that perceived threat did not mediate the relationship between high/low threat and fear control responses but there was a significant negative relationship between perceived threat and fear control responses. Specifically, as levels of threat increased, fear control responses decreased and vice versa. Like the last finding, the main mediation finding differed from established literature supporting the utility of the EPPM. Surprisingly, the significant negative relationship between perceived threat and fear control responses reiterates the propositions posed by the EPPM (Witte, 1992, 1994,1996, 2009; Yun et al., 2014). This finding also validates Sheeran et al.'s (2014) argument that an increase in perceived threat leads to higher risk appraisals.

In the context of COVID-19, scholars have found mixed support for the EPPM as an effective model. Khazaei et al. (2020), Lithopoulos et al. (2021), along with other scholars found some support for the EPPM. Particularly, they found that efficacy plays a more important role than threat in the EPPM process when it comes to COVID-19 (Abbott et al., 2020, Jahangiry et al., 2020, Yang et al., 2021). These studies are consistent with some of the findings from the current study. On the other hand, Rahn et al. (2021) did not find empirical support for the EPPM.

One possible explanation for the insignificant results of this study could be the fact that emotions other than fear may play a more effective role in the EPPM process. This argument is supported by Nabi & Myrick (2019) and So (2013) who found support for hope and anxiety as better predictors of behavioral intentions than fear. The significant role of anxiety in the EPPM is further extended and supported by So et al. (2016) who found that perceived susceptibility was a better predictor of anxiety and that fear combined with anxiety lead to greater response efficacy than fear alone. Another explanation of the findings from this study could be that the participants may have been exposed to the Twitter messages before the study and thus did not appraise levels of threat and efficacy, which then lead to appraisals of risk perceptions. An argument can be made that people may not use Twitter as an immediate source for health news, especially related to COVID-19. Although there is no study backing these claims, this would mean that the participants were already exposed to messages with fear and efficacy. Scholars have argued that using fear appeals to persuade audiences with pre-existing fears is not effective and may lead to more fear about the health message (Gore & Bracken, 2005; Muthusamy et al., 2009). Also, only 15.8% of the participants in our sample reported using Twitter a lot, with the majority (39.9%) reporting rare use of Twitter. The use of Twitter is important to note because of the large number of messages disseminated on the platform. So, if individuals are not using Twitter regularly, they may miss health messages in the large traffic of other messages in their feed. Based on these findings, the importance of Twitter in health messaging, especially that related to COVID-19, is questionable.

Since most of the participants (44.3%) in the sample reported being between the ages of 18-30, age could have played a role in the results. Recent studies have found that older adults are more likely to comply with COVID-19 guidelines than younger adults and have stressed the need to develop robust messages to target younger audiences (Rahn et al., 2021; Yang et al., 2021). Utych & Fowler (2020) also found that older adults found health messages related to COVID-19 as a more serious threat. Similarly, in their analysis of compliance to COVID-19 guidelines, Moore et al. (2020) discovered that individuals between the ages of 18-31 had the lowest compliance rate compared to all other age groups. An argument can be made that the risk perceptions of COVID-19 were naturally lower among certain age groups which would have resulted in a ceiling effect. So, the risk perceptions would not have moved as much for certain age groups. Thus, the findings of this study highlight the potential importance of age for influencing health behaviors related to COVID-19.

The experimental stimuli used in this study were Tweets from public health and political institutions. To preserve the ecological validity of the Tweets, no manipulations were made. Although ecological validity was integrated in the actual messages, it created an environment of sources that people may not be exposed to regularly. That, combined with no manipulation, could have contributed to the null effects.

This study relied on the ostensible threat and efficacy reflected in the Twitter messages for the experimental manipulation to preserve the ecological validity of the messages. An argument could be made that manipulating threat and efficacy, followed by pilot testing of the manipulated messages, could have resulted in more significant results. For example, including a mixture of different sources in each condition with credible and less credible sources could have counteracted the effects. Including a mixture of sources is critical as information flows have increasingly become curated by more than one actor in a digital age. Thorson and Wells (2016) argue that an individual's personal network is flooded by a variety of actors. They further point out that it is essential to understand the intersection of these information flows to conduct exposure research. However, scholars such as O'Keefe (2003) argue that "when message variations are defined in terms of intrinsic features, message manipulation checks, under that description, are unnecessary" (p. 251). Threat and efficacy are not inherently obvious in messages but rather are latent and subject to perception. Based on this argument, although manipulation checks may be helpful, they are not necessary in this study.

Theoretical/Practical Contributions & Future Research

This study's primary theoretical objectives were focused on testing the EPPM on health messages related to COVID-19 on Twitter and assessing the risk perceptions of these messages. Although the EPPM has been tested and utilized in persuasive message research for decades, even during COVID-19, little attention has been paid to health messages on social media platforms such as Twitter (Abbott et al., 2020; Jahangiry et al., 2020; Yang et al., 2021). The lack of focus on health messages on social media platforms is interesting as scholars have repeatedly found them to be meaningful in prompting change in political and health behaviors (Allington et al., 2020; Coe & Griffin, 2020; Sides et al., 2018; Tourjée & Ettachfini, 2018). An attempt was made to bridge the forementioned gaps in the current scholarship in health communication. Also, this study sought to answer the longstanding question in existing literature focused on the effectiveness of the EPPM and fear appeals. An attempt was made to bridge the forementioned gaps in the current scholarship in health communication.

I found miniscule support for the EPPM but did find (1) a positive significant relationship between perceived efficacy and danger control responses and (2) a significant negative relationship between perceived fear and fear control responses. Despite the small findings, most of the propositions posited by the EPPM were not supported. These findings are consistent with studies that have found the EPPM, and fear appeals to be ineffective (Ooms et al., 2015; Popova, 2012, Rahn et al., 2021). Nevertheless, the significant relationship between efficacy and danger control responses highlights the need more emphasis on efficacy in literature focused on health messages related to COVID-19 (Abbott et al., 2020, Jahangiry et al., 2020, Yang et al., 2021). The findings of this study also question the appropriateness of using the EPPM to analyze health messages related to COVID-19 and find support for the literature arguing that emotions other than fear may play an important role (Nabi and Myrick, 2019; So, 2013; So et al., 2016). Yet, there are studies which find fear to be a significant predictor of behavioral intentions (Carey and Sarma, 2016; Lewis et al., 2013). The disparities in the findings of this study and extant literature suggest that more inquiry is needed into the effectiveness of the EPPM in analyzing health messages and assessing risk perceptions, especially in the context of COVID-19.

Another theoretical implication of this study is the need for a framework focused on political and health outcomes to explore health messages in a politicized pandemic such as COVID-19. As mentioned in the literature review, one such model is the IHSM, which correctly identifies that existing frameworks do not account for the polarization and media fragmentation around COVID-19 (Young & Bleakley, 2020). This argument has been supported by scholars who have found convergence between politics, COVID-19, and risk perceptions (Allcott, et al., 2020, Barrios & Hochberg; Coe & Griffin, 2020; de Bruin et al., 2020; Hart et al., 2020; Motta et al., 2020; Romer & Jamieson, 2020; Shao & Hao, 2020). This convergence of politics and COVID-19, supplemented with the findings of this study, reveal that health frameworks alone are not sufficient to assess the risk perceptions of health messages related to COVID-19. This argument is supported by Barrios & Hochberg (2020), who found that political partisanship plays a significant role in determining risk perceptions of COVID-19. This highlights the importance of applying frameworks that combine politics and health, such as the IHSM, to explore risk perceptions of COVID-19 on health messages (Young & Bleakley, 2020).

Finally, the findings of this study hold some important implications for health communication messages related to COVID-19 on social media and in general. First, health messages related to COVID-19 should focus on efficacy. Recent studies focused on COVID-19 have found support for efficacy as a robust predictor of behavior changes (Abbott et al., 2020, Jahangiry et al., 2020, Yang et al., 2020). Second, the importance of social media platforms such as Twitter should be explored further to assess whether it is indeed an effective way to disseminate important health messages related to COVID-19. Based on the results of this study, social media outlets such as Twitter are not effective and are only used by individuals belonging to a limited number of demographics. Thus, public health agencies and future should divert their focus towards outlets that are (1) consumed more by the public and (2) are more effective in eliciting risk appraisals and prompting recommended behavioral changes. Lastly, health messages related to COVID-19 should aim be concise, direct, and objective. Despite the convergence of politics and health surrounding COVID-19, health messages related to COVID-19 should aim to exclude any political or biased undertones and should stress the importance of following public health mitigation protocols for the benefit of humanity. Public health agencies should consider the convergence of politics and COVID-19 and develop robust messages that depoliticize COVID-19 and stress the importance of following public health guidelines to mitigate the risks posed by it. Similarly, future research should focus on developing and testing models that account for the health and political variables associated with COVID-19.

Limitations/Conclusion

Like any other scholarship, this study had several limitations. Although samples recruited from MTurk are widely used, the quality of the data and the representativeness of samples has been questioned. For example, Chandler et al. (2019) found that MTurk participants were less diverse across various demographics political variables compared to participants from other online research panels. Moreover, the number of workers on MTurk is low, which may affect the quality of the data produced. Although MTurk samples are considered to be more representative than traditional college samples, they still do not accurately represent the US population.

Another limitation of using MTurk is that the participants are used to participating in social scientific studies and hence, may be familiar with the study in question (Chandler et al., 2019).

Another limitation of the study was not accounting for a confounding variable such as familiarity to the stimuli used. The Twitter messages were on the platform before data collection and participants may have been exposed to them prior to the study and may have developed attitudes that did not change during the study. As mentioned earlier, this could point to a ceiling effect regarding risk perceptions and fear. In the context of the EPPM and COVID-19, scholars have argued that attempting to persuade audiences with pre-existing attitudes about fear is ineffective (Gore & Bracken, 2005; Muthusamy et al., 2009. Similarly, Retell et al. (2016) posit that familiarity plays an important role in how individuals react to a stimulus.

This study utilized self-reported measures from the EPPM which can result in measurement issues. Specifically, issues such as social desirability bias and acquiescence may have impacted participant responses. Social desirability bias refers to a response that is given based on the individual's perception of what is considered socially acceptable. On the other hand, acquiescence is defined as an attempt by participants to extrapolate the goals of the researchers and altering their responses accordingly (Wrench et al., 2008). Participants may have answered questions about following COVID-19 mitigation protocols to fit with the normative assumption that following the guidelines set by public health agencies is socially acceptable and desirable. Lastly, this study sought to assess the risk perceptions of health messages related to COVID-19 on Twitter. The limitation with this is that it is difficult to draw inferences from Twitter samples. Scarborough (2018) argues that Twitter is not representative and is limited to a certain audience and hence, it is difficult to draw conclusions. Indeed, the demographic data from this study found that only 15.8% of the sample reported using Twitter a lot while the majority (39.9%) reported using Twitter rarely. So, even if the findings from this study were significant, it would be difficult to draw robust conclusions.

To conclude, this study aimed to assess the risk perceptions of health messages related to COVID-19 on Twitter messages using the EPPM. We found very little support for the EPPM but did find significant relationships between (1) perceived efficacy and danger control responses and (2) perceived threat and fear control responses. The implications from this study point out the need to test and develop novel frameworks that account for health and political variables and outcomes to assess risk perceptions of health messages related to COVID-19. In the future, scholars should also test the utility of EPPM in different health settings with a wide range of emotions. Finally, the role of social media platforms such as Twitter in the dissemination and processing of health messages should be addressed in future scholarship.

References

Abbott, A., Askelson, N., Scherer, A. M., & Afifi, R. A. (2020). Critical reflections on COVID-19 communication efforts targeting adolescents and young adults. *Journal of Adolescent Health*, *67*(2), 159-160.

Abramowitz, A. I., & Saunders, K. L. (2008). Is polarization a myth?. *The Journal of Politics*, *70*(2), 542-555.

Adamic, L. A., and Glance, N. (2005). The political blogosphere and the 2004 US election: Divided they blog. Proceedings of the 3rd International Workshop on Link Discovery, LinkKDD ’05 (pp. 36–43). New York, NY, USA: ACM.

Allcott, H., Boxell, L., Conway, J. C., Gentzkow, M., Thaler, M., & Yang, D. Y. (2020). Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic (Working Paper No. 26946). National Bureau of Economic Research. https://doi.org/10.3386/w26946.

Allington, D., Duffy, B., Wessely, S., Dhavan, N., & Rubin, J. (2020). Health-protective behaviour, social media usage and conspiracy belief during the COVID-19 public health emergency. *Psychological medicine*, 1-7.

Applequist, J., Burroughs, C., Ramirez, A., Merkel, P. A., Rothenberg, M. E., Trapnell, B., ... & Krischer, J. P. (2020). A novel approach to conducting clinical trials in the community setting: utilizing patient-driven platforms and social media to drive web-based patient recruitment. *BMC medical research methodology*, *20*(1), 1-14.

Bakshy, E., Messing, S., & Adamic, L. A. (2015). Exposure to ideologically diverse news and opinion on Facebook. *Science*, *348*(6239), 1130-1132.

Baldassarri, D., & Gelman, A. (2008). Partisans without constraint: Political polarization and trends in American public opinion. *American Journal of Sociology*, *114*(2), 408-446.

Banda, J., Dube, A., Brumfield, S., Amoah, A., Crampin, A., Reniers, G., & Helleringer, S. (2021). Knowledge, risk perceptions, and behaviors related to the COVID-19 pandemic in Malawi. *Demographic Research*, *44*, 459-480.

Barnett, D. J., Balicer, R. D., Thompson, C. B., Storey, J. D., Omer, S. B., Semon, N. L., ... & Norbin, J. A. (2009). Assessment of local public health workers' willingness to respond to pandemic influenza through application of the extended parallel process model. *PloS one*, *4*(7), e6365

Barrios, J. M., & Hochberg, Y. (2020). *Risk perception through the lens of politics in the time of the covid-19 pandemic* (No. w27008). National Bureau of Economic Research.

Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2012). Evaluating online labor markets for experimental research: Amazon. com's Mechanical Turk. *Political analysis*, *20*(3), 351-368.

Berry, J. M., & Sobieraj, S. (2013). *The outrage industry: Political opinion media and the new incivility*. Oxford University Press.

Birhanu, Z., Ambelu, A., Fufa, D., Mecha, M., Zeynudin, A., Abafita, J., ... & Kebede, Y. (2021). Risk perceptions and attitudinal responses to COVID-19 pandemic: an online survey in Ethiopia. *BMC Public Health*, *21*(1), 1-17.

Bolsen, T., Druckman, J. N., & Cook, F. L. (2014). How frames can undermine support for scientific adaptations: Politicization and the status-quo bias. Public Opinion Quarterly, 78(1), 1-26. https://doi.org/10.1093/poq/nft044.

Boxell, L., M. Gentzkow, and J. M. Shapiro (2017). Greater internet use is not associated with faster growth in political polarization among us demographic groups. Proceedings of the National Academy of Sciences 114 (40), 10612–10617.

Brown, P., Daigneault, A. J., Tjernström, E., & Zou, W. (2018). Natural disasters, social protection, and risk perceptions. World Development, 104, 310-325.

Bruine de Bruin, W. (2021). Age differences in COVID-19 risk perceptions and mental health: Evidence from a national US survey conducted in March 2020. *The Journals of Gerontology: Series B*, *76*(2), e24-e29.

Bursztyn, L., Rao, A., Roth, C., & Yanagizawa-Drott, D. (2020). Misinformation during a pandemic (Working Paper No. 2020-44). Chicago, IL: Becker Friedman Institute. Retrieved from https://bfi.uchicago.edu/wp-content/uploads/BFI_WP_202044.pdf.

Cakar, K. (2020). Tourophobia: fear of travel resulting from man-made or natural disasters. Tourism Review. https://doi.org/10.1108/TR-06-2019-0231

Carcioppolo, N., Jensen, J. D., Wilson, S. R., Collins, W. B., Carrion, M., & Linnemeier, G. (2013). Examining HPV threat-to-efficacy ratios in the Extended Parallel Process Model. *Health communication*, *28*(1), 20-28

Carey, R. N., & Sarma, K. M. (2016). Threat appeals in health communication: messages that elicit fear and enhance perceived efficacy positively impact on young male drivers. *BMC public health*, *16*(1), 1-16.

Chadwick, A. (2017). *The hybrid media system: Politics and power*. Oxford University Press.

Chandler, J., Rosenzweig, C., Moss, A. J., Robinson, J., & Litman, L. (2019). Online panels in social science research: Expanding sampling methods beyond Mechanical Turk. *Behavior research methods*, *51*(5), 2022-2038.

Chakraborty, S. (2020). How risk perceptions, not evidence, have driven harmful policies on COVID-19. *European Journal of Risk Regulation*, *11*(2), 236-239.

Chan, A. K., Nickson, C. P., Rudolph, J. W., Lee, A., & Joynt, G. M. (2020). Social media for rapid knowledge dissemination: early experience from the COVID-19 pandemic. *Anaesthesia*.

Chen, E., Lerman, K., & Ferrara, E. (2020). Covid-19: The first public coronavirus twitter dataset. *arXiv preprint arXiv:2003.07372*.

Coe, K., & Griffin, R. A. (2020). Marginalized identity invocation online: The case of President Donald Trump on Twitter. *Social Media+ Society*, *6*(1), 2056305120913979.

Cori, L., Bianchi, F., Cadum, E., & Anthonj, C. (2020). Risk perception and COVID-19.

Coronavirus (COVID-19) Update: FDA Issues Emergency Use Authorization for Potential COVID-19 Treatment. (2020, May 1). US Food and Drug Administration. https://www.fda.gov/news-events/press-announcements/coronavirus-covid-19-update-fda-issues-emergency-use-authorization-potential-covid-19-treatment.

Coronavirus Disease 2019 (COVID-19). (n.d.). Retrieved November 08, 2020, from https://www.cdc.gov/coronavirus/2019-ncov/index.html.

Coronavirus: Outbreak concern. (2020, November 09). Retrieved November 10, 2020, from https://civiqs.com/results/coronavirus_concern?annotations=true&uncertainty=true&zoomIn=true.

de Bruin, W. B., & Bennett, D. (2020). Relationships between initial COVID-19 risk perceptions and protective health behaviors: A national survey. *American Journal of Preventive Medicine*, *59*(2), 157-167 de Bruin, W. B., Saw, H. W., & Goldman, D. P. (2020). Political polarization in US residents' COVID-19 risk perceptions, policy preferences, and protective behaviors. *Journal of risk and uncertainty*, *61*(2), 177-194.

Dillard, J. P. (1994). Rethinking the study of fear appeals: An emotional perspective. *Communication Theory*, *4*, 295–323.

Dryhurst, S., Schneider, C. R., Kerr, J., Freeman, A. L., Recchia, G., Van Der Bles, A. M., ... & van der Linden, S. (2020). Risk perceptions of COVID-19 around the world. *Journal of Risk Research*, *23*(7-8), 994-1006.

Easterling, D. V., & Leventhal, H. (1989). Contribution of concrete cognition to emotion: Neutral symptoms as elicitors of worry about cancer. *Journal of Applied Psychology*, *74*(5), 787

Egbert, N., Miraldi, L. B., & Murniadi, K. (2014). Friends don't let friends suffer from depression: How threat, efficacy, knowledge, and empathy relate to college students'; intentions to intervene on behalf of a depressed friend. *Journal of health communication*, *19*(4), 460-477.

Fiorina, M. P., Abrams, S. J., & Pope, J. C. (2005). Culture war. *The myth of a polarized America*, *3*.

Fiorina, M. P., & Abrams, S. J. (2008). Political polarization in the American public. *Annu. Rev. Polit. Sci.*, *11*, 563-588.

Fischhoff, B., Bostrom, A., & Quadrel, M. J. (1993). Risk perception and communication. *Annual review of public health*, *14*(1), 183-203.

Folkman, S., & Lazarus, R. S. (1984). *Stress, appraisal, and coping* (pp. 150-153). New York: Springer Publishing Company

Forgie, S. E., Duff, J. P., & Ross, S. (2013). Twelve tips for using Twitter as a learning tool in medical education. *Medical teacher*, *35*(1), 8-14.

Franck, T. (2020, February 29). Trump says the coronavirus is the Democrats' "new hoax." CNBC. https://www.cnbc.com/2020/02/28/trump-says-the-coronavirus- is-the-democrats-new-hoax.html

Funk, C., Kennedy, B., & Johnson, C. (2020, June 4). Trust in Medical Scientists Has Grown in US, but Mainly Among Democrats. Retrieved from https://www.pewresearch.org/science/2020/05/21/trust-in-medical-scientists-has-grown-in-u-s-but-mainly-among-democrats/?utm_content=bufferb005d&utm_medium=social&utm_source=linkedin.com&utm_campaign=buffer.

Gaines, B. J. and Mondak, J. J. (2009). Typing together? Clustering of ideological types in online social networks. Journal of Information Technology & Politics, 6(3-4), 216-231.

Gentzkow, M., and Shapiro, J. M. (2006). Media bias and reputation. Journal of Political Economy, 114(2), 280-316.

Gentzkow, M. (2016). Polarization in 2016. Toulouse Network for Information Technology Whitepaper, 1-23.

Gilbert, E. and Karahalios, K. (2009). Predicting tie strength with social media. Proceedings of the 27th international conference on Human Factors in Computing systems (CHI '09). ACM, New York, NY, USA, 211-220.

Godovykh, M., Pizam, A., & Bahja, F. (2021). Antecedents and outcomes of health risk perceptions in tourism, following the COVID-19 pandemic. *Tourism Review*.

Goei, R., Boyson, A. R., Lyon-Callo, S. K., Schott, C., Wasilevich, E., & Cannarile, S. (2010). An examination of EPPM predictions when threat is perceived externally: An asthma intervention with school workers. Health Communication, 25, 333–344.

Goodyear, V. A., Armour, K. M., & Wood, H. (2018). Young people and their engagement with health-related social media: New perspectives. *Sport, education and society*.

Gore, T. D., & Bracken, C. (2005). Testing the theoretical design of a health risk message: Reexamining the major tenets of the extended parallel process model. Health Education & Behavior, 32, 27–41.

Gottfried, J., Walker, M., & Mitchell, A. (2020, May 30). Americans' Views of the News Media During the Coronavirus Outbreak. Retrieved from https://www.journalism.org/2020/05/08/americans-views-of-the-news-media-during-the-covid-19-outbreak/.

Hargittai, E.; Gallo, J.; and Kane, M. 2007. Cross- ideological discussions among conservative and liberal bloggers. *Public Choice* 134(1):67–86.

Harper CA, Satchell LP, Fido D, Latzman RD. 2020. Functional fear predicts public health 473 compliance in the COVID-19 pandemic. Epub ahead of print 27 April 2020. International 474 Journal of Mental Health and Addiction.

Hart, P. S., Chinn, S., & Soroka, S. (2020). <? covid19?> Politicization and Polarization in COVID-19 News Coverage. *Science Communication*, 1075547020950735.

He, S., Chen, S., Kong, L., & Liu, W. (2021). Analysis of risk perceptions and related factors concerning COVID-19 epidemic in Chongqing, China. *Journal of Community Health*, *46*(2), 278-285.

Henley, N., & Donovan, R. J. (2002). Identifying appropriate motiva- tions to encourage people to adopt health nutrition and physical activity behaviours. *Journal of Research for Consumers*, *4*, 1–22.

Honarvar, B., Lankarani, K. B., Kharmandar, A., Shaygani, F., Zahedroozgar, M., Haghighi, M. R. R., ... & Zare, M. (2020). Knowledge, attitudes, risk perceptions, and practices of adults toward COVID-19: a population and field-based study from Iran. *International journal of public health*, *65*(6), 731-739.

Hong, H. (2011). An extension of the extended parallel process model (EPPM) in television health news: The influence of health consciousness on individual message processing and acceptance. *Health communication*, *26*(4), 343-353

Hovland, C. I., Janis, I. L., & Kelley, H. H. (1953). Communication and persuasion

Hullett, C. R., & Witte, K. (2001). Predicting intercultural adaptation and isolation: Using the extended parallel process model to test anxiety/uncertainty management theory. *International Journal of Intercultural Relations*, *25*(2), 125-139.

Ibuka, Y., Chapman, G. B., Meyers, L. A., Li, M., & Galvani, A. P. (2010). The dynamics of risk perceptions and precautionary behavior in response to 2009 (H1N1) pandemic influenza. *BMC infectious diseases*, *10*(1), 296

Iyengar, S., G. Sood, and Y. Lelkes (2012). Affect, not ideological social identity perspective on polarization. Public opinion quarterly 76(3), 405–431.

Jahangiry, L., Sarbakh, P., Reihani, P., Samei, S., Sohrabi, Z., Tavousi, M., & Montazeri, A. (2020). Developing and validating the risk perceptions questionnaire for COVID-19 (Risk Precept COVID-19): an application of the extended parallel process model.

Jamieson, K. H., & Albarracin, D. (2020, April 20). The relation between media consumption and misinformation at the outset of the SARS-CoV-2 pandemic in the US Retrieved from https://misinforeview.hks.harvard.edu/article/the-relation-between-media-consumption-and- misinformation-at-the-outset-of-the-sars-cov-2-pandemic-in-the-us/.

Janis, I. L., & Feshbach, S. (1953). Effects of fear-arousing communications. *The Journal of Abnormal and Social Psychology*, *48*(1), 78

Janis, I. L., & Mann, L. (1977). *Decision making: A psychological analysis of conflict, choice, and commitment*. Free press

Jenkins, H., & Deuze, M. (2008). Convergence culture.

Job, R. F. S. (1988). Effective and ineffective use of fear in health promotion campaigns. *American Journal of Public Health*, *78*, 163–167.

Johnston, A. C., & Warkentin, M. (2010). Fear appeals and information security behaviors: an empirical study. *MIS quarterly*, 549-566.

Karasneh, R., Al-Azzam, S., Muflih, S., Soudah, O., Hawamdeh, S., & Khader, Y. (2021). Media's effect on shaping knowledge, awareness risk perceptions and communication practices of pandemic COVID-19 among pharmacists. *Research in Social and Administrative Pharmacy*, *17*(1), 1897-1902.

Kempf, E. and M. Tsoutsoura (2018). Partisan professionals: Evidence from credit rating analysts. Technical report, National Bureau of Economic Research.

King, G., Schneer, B., & White, A. (2017). How the news media activate public expression and influence national agendas. *Science*, *358*(6364), 776-780.

Kohn, P. M., Goodstadt, M. S., Cook, G. M., Sheppard, M., & Chan, G. (1982). Ineffectiveness of threat appeals about drinking and driving. *Accident Analysis & Prevention*, *14*(6), 457-464

Krieger, J. L., & Sarge, M. A. (2013). A serial mediation model of message framing on intentions to receive the human papillomavirus (HPV) vaccine: revisiting the role of threat and efficacy perceptions. *Health communication*, *28*(1), 5-19.

Krisher, H. P., Darley, S. A., & Darley, J. M. (1973). Fear-provoking recommendations, intentions to take preventive actions, and actual preventive actions. *Journal of Personality and Social Psychology*, *26*(2), 301

Khazaei, S., Bashirian, S., Jenabi, E., Barati, M., Karimi-Shahanjarini, A., Moeini, B., ... & Fazli, Z. (2020). COVID-19 preventive behaviors and its related beliefs among health workers: The role of threat and coping appraisals. *J Educ Community Health*, *7*(3), 221-227.

Lang, P. J. (1984). Cognition in emotion: Concept and action. *Emotions, cognition, and behavior*, 192-226

Larson, H. J. (2018). Politics and public trust shape vaccine risk perceptions. *Nature human behaviour*, *2*(5), 316-316.

Larson, H. J. (2020). Blocking information on Covid-19 can fuel the spread of misinformation. Nature, 58, 306.

Lanciano, T., Graziano, G., Curci, A., Costadura, S., & Monaco, A. (2020). Risk perceptions and psychological effects during the Italian COVID-19 emergency. *Frontiers in psychology*, *11*, 2434.

Leventhal, H. (1970). Findings and theory in the study of fear communications. In *Advances in experimental social psychology* (Vol. 5, pp. 119-186). Academic Press.

Lewis, I., Watson, B., & White, K. M. (2013). Extending the explanatory utility of the EPPM beyond fear-based persuasion. *Health Communication*, *28*(1), 84-98.

Lithopoulos, A., Liu, S., Zhang, C. Q., & Rhodes, R. E. (2021). Predicting physical distancing in the context of COVID-19: A test of the extended parallel process model among Canadian adults. *Canadian Psychology/Psychologie Canadienne*.

Lohiniva, A. L., Sane, J., Sibenberg, K., Puumalainen, T., & Salminen, M. (2020). Understanding coronavirus disease (COVID-19) risk perceptions among the public to enhance risk communication efforts: a practical approach for outbreaks, Finland, February 2020. *Eurosurveillance*, *25*(13), 2000317.

Lott, J. R. and K. A. Hassett (2014). Is newspaper coverage of economic events politically biased? Public choice 160(1-2), 65–108.

Lovari, A. (2020). Spreading (dis) trust: Covid-19 misinformation and government intervention in Italy. *Media and Communication*, *8*(2), 458-461.

Mason, L. H. (2013). The polarizing effects of partisan sorting. In APSA 2013 Annual Meeting Paper.

Mason, L. (2015). “I disrespectfully agree”: The differential effects of partisan sorting on social and issue polarization. American Journal of Political Science, 59(1), 128-145.

Mason, L. (2018). Uncivil agreement: How politics became our identity. Chicago, IL: University of Chicago Press.

McCoy, S. B., Gibbons, F. X., Reis, T. J., Gerrard, M., Luus, C. E., & Sufka, A. V. W. (1992). Perceptions of smoking risk as a function of smoking status. *Journal of behavioral medicine*, *15*(5), 469-488.

McMahan, S., Witte, K., & Meyer, J. A. (1998). The perception of risk messages regarding electromagnetic fields: extending the extended parallel process model to an unknown risk. *Health communication*, *10*(3), 247-259

Morrison, K. (2005). Motivating women and men to take protective action against rape: Examining direct and indirect persuasive fear appeals. Health Communication, 18, 237–256.

Mullainathan, S. and A. Shleifer (2005). The Market for News. American Economic Review 95(4), 1031-1053.

Murray-Johnson, L., Witte, K., Liu, W., & Hubbel, A. P. (2001). Addressing cultural orientations in fear appeals: Promoting AIDS-protective behaviors among Mexican immigrant and African American adolescents and Ameri- can and Taiwanese college students. Journal of Health Communication, 6, 335–358.

Murray-Johnson, L., Witte, K., Patel, D., Orrego, V., Zuckerman, C., Maxfield, A. M., & Thimons, E. D. (2004). Using the extended parallel process model to prevent noise-induced hearing loss among coal miners in Appalachia. *Health Education & Behavior*, *31*(6), 741-755

Muthusamy, N., Levine, T. R., & Weber, R. (2009). Scaring the already scared: Some problems with HIV ⁄ AIDS fear appeals on Namibia. Journal of Communication, 59, 317–344.

Nabi, R. L., & Myrick, J. G. (2019). Uplifting fear appeals: Considering the role of hope in fear-based persuasive messages. *Health communication*, *34*(4), 463-474.

Ng, Y. J., Yang, Z. J., & Vishwanath, A. (2018). To fear or not to fear? Applying the social amplification of risk framework on two environmental health risks in Singapore. Journal of Risk Research, 21(12), 1487–1501.

Nuzzo, J. B., Bell, J. A., & Cameron, E. E. (2020). Suboptimal US response to COVID-19 despite robust capabilities and resources. *Jama*.

O'Keefe, D. J. (2003). Message properties, mediating states, and manipulation checks: Claims, evidence, and data analysis in experimental persuasive message effects research. *Communication Theory*, *13*(3), 251-274.

Olagoke, A. A., Olagoke, O. O., & Hughes, A. M. (2020). Exposure to coronavirus news on mainstream media: The role of risk perceptions and depression. *British journal of health psychology*, *25*(4), 865-874.

Ooms, J., Jansen, C., & Hoeks, J. (2015). The EPPM put to the test: evaluating four basic propositions. *Dutch Journal of Applied Linguistics*, *4*(2), 241-256.

Park, H. W., Park, S., & Chong, M. (2020). Conversations and medical news frames on twitter: Infodemiological study on covid-19 in south korea. *Journal of Medical Internet Research*, *22*(5), e18897.

Peters, J. W., & Grynbaum, M. M. (2020, March 11). How right-wing pundits are cov- ering coronavirus. The New York Times. https://www.nytimes.com/2020/03/11/ us/politics/coronavirus-conservative-media.html

Pew Research Center. (2014). Political polarization and media habits. Retrieved from http://www.journalism.org/2014/10/21/political-polarization-media-habits/.

Pidgeon, N. (1998). Risk assessment, risk values and the social science programme: why we do need risk perception research. Reliability Engineering & System Safety, 59(1), 5-15.

Prior, M. (2013). Media and political polarization. *Annual Review of Political Science*, *16*, 101-127.

Popova, L. (2012). The extended parallel process model: Illuminating the gaps in research. *Health Education & Behavior*, *39*(4), 455-473.

Quintal, V. A., Lee, J. A., & Soutar, G. N. (2010). Risk, uncertainty and the theory of planned behavior: A tourism example. Tourism Management, 31(6), 797-805.

Rahn, M., Tomczyk, S., Schopp, N., & Schmidt, S. (2021). Warning messages in crisis communication: risk appraisal and warning compliance in severe weather, violent acts, and the CoViD-19 pandemic. *Frontiers in psychology*, *12*, 891.

Reichel, A., Fuchs, G., & Uriely, N. (2007). Perceived risk and the non-institutionalized tourist role: The case of Israeli student ex-backpackers. Journal of Travel Research, 46(2), 217-226.

Retell, J. D., Becker, S. I., & Remington, R. W. (2016). Previously seen and expected stimuli elicit surprise in the context of visual search. *Attention, Perception, & Psychophysics*, *78*(3), 774-788.

Reynolds, B., & W. SEEGER, M. A. T. T. H. E. W. (2005). Crisis and emergency risk communication as an integrative model. *Journal of health communication*, *10*(1), 43-55.

Rimal, R. N., & Real, K. (2003). Perceived risk and efficacy beliefs as motivators of change: Use of the risk perception attitude (RPA) framework to understand health behaviors. *Human communication research*, *29*(3), 370-399.

Rogers, R. W. (1975). A protection motivation theory of fear appeals and attitude change1. *The journal of psychology*, *91*(1), 93-114.

Romer, D., & Jamieson, K. H. (2020). Conspiracy theories as barriers to controlling the spread of COVID-19 in the US. *Social Science & Medicine*, *263*, 113356.

Ropeik, D. (2011). The psychology of risk perception. Retrieved from: https://www.health.harvard.edu/newsletter_article/the-psychology-of-risk-perception

Rothman, A. J., & Salovey, P. (1997). Shaping perceptions to motivate healthy behavior: the role of message framing. *Psychological bulletin*, *121*(1), 3.

Rupar, A. (2020, March 20). Hannity claims he's "never called the virus a hoax" 9 days after decrying Democrats' "new hoax." Vox. https://www.vox.com/ 2020/3/20/21186727/hannity-coronavirus-coverage-fox-news

Scarborough, W. J. (2018). Feminist Twitter and Gender Attitudes: Opportunities and Limitations to Using Twitter in the Study of Public Opinion. *Socius*, *4*, 2378023118780760.

Settle, J. E. (2018). Frenemies: How social media polarizes America. Cambridge, UK: Cambridge University Press.

Shao, W., & Hao, F. (2020). Confidence in political leaders can slant risk perceptions of COVID–19 in a highly polarized environment. *Social Science & Medicine (1982)*, *261*, 113235.

Sheeran, P., Harris, P. R., & Epton, T. (2014). Does heightening risk appraisals change people's intentions and behavior? A meta-analysis of experimental studies. *Psychological bulletin*, *140*(2), 511.

Scacco, J. M., & Coe, K. (2016). The ubiquitous presidency: Toward a new paradigm for studying presidential communication. *International Journal of Communication*, *10*, 24.

Scacco, J. M., & Coe, K. (2021). *The Ubiquitous Presidency: Presidential Communication and Digital Democracy in Tumultuous Times*. Oxford University Press.

Scanfeld, D., Scanfeld, V., & Larson, E. L. (2010). Dissemination of health information through social networks: Twitter and antibiotics. *American journal of infection control*, *38*(3), 182-188.

Schmidt, V. A. (2008). Discursive institutionalism: The explanatory power of ideas and discourse. *Annual review of political science*, *1*.

Shao, W., & Hao, F. (2020). Confidence in political leaders can slant risk perceptions of COVID–19 in a highly polarized environment. *Social Science & Medicine (1982)*, *261*, 113235.

Shi, J., & Smith, S. W. (2016). The effects of fear appeal message repetition on perceived threat, perceived efficacy, and behavioral intention in the extended parallel process model. *Health communication*, *31*(3), 275-286.

Sides, J., Tesler, M., & Vavreck, L. (2018). Identity crisis: The 2016 presidential campaign and the battle for the meaning of America. Princeton University Press.

Siegrist, M., & Bearth, A. (2021). Worldviews, trust, and risk perceptions shape public acceptance of COVID-19 public health measures. *Proceedings of the National Academy of Sciences*, *118*(24).

Singal, J. (2020, May 8). *The Theory That Explains the Politicization of Coronavirus*. Intelligencer. https://nymag.com/intelligencer/2020/05/the-theory-that-explains-the-politicization-of-coronavirus.html.

Slothuus, R., & de Vreese, C. H. (2010). Political parties, motivated reasoning, and issue framing effects. Journal of Politics, 72(3), 630-645. https://doi.org/10.1017/ s002238161000006x.

Smit, E. S., Zeidler, C., Resnicow, K., & de Vries, H. (2019). Identifying the most autonomy-supportive message frame in digital health communication: a 2x2 between-subjects experiment. *Journal of medical Internet research*, *21*(10), e14074.

Smith, S. W., Rosenman, K., Kotowski, M. R., Glazer, E., McFeters, C., Keesecker, N. M. et al. (2008). Using the EPPM to create and evaluate the effectiveness of brochures to increase the use of hearing protection in farm-ers and landscape workers. Journal of Applied Communication Research, 36, 200–218.

So, J. (2013). A further extension of the extended parallel process model (E-EPPM): Implications of cognitive appraisal theory of emotion and dispositional coping style. *Health communication*, *28*(1), 72-83.

So, J., Kuang, K., & Cho, H. (2016). Reexamining fear appeal models from cognitive appraisal theory and functional emotion theory perspectives. *Communication Monographs*, *83*(1), 120-144.

Stephenson, J. (2020, August 04). CDC Revises Guidance on Isolation After Positive COVID-19 Test, Reports Prolonged COVID-19 Illness Among Nonhospitalized Patients. Retrieved November 07, 2020, from https://jamanetwork.com/channels/health-forum/fullarticle/2769188.

Stephenson, M., & Witte, K. (1998). Fear, threat, and perceptions of efficacy from frightening skin cancer messages. Public Health Review, 26, 147–174. Report on the Global HIV/AIDS epidemic (2002). United Nations Agency for International Development. New York.

Stroud, N. J. (2011). Niche news: The politics of news choice. Oxford, UK: Oxford University Press.

Sunstein, C., & Chambers, E. (2001). Bush v. Gore, Impeachment, and Beyond.

Tay, R., & Watson, B. (2002). Changing drivers' intentions and behaviours using fear-based driver fatigue advertisements. *Health Marketing Quarterly*, *19*, 55–68.

Thorson, E. (2016). Belief echoes: The persistent effects of corrected misinformation. *Political Communication*, *33*(3), 460-480.

Thorson, K., & Wells, C. (2016). Curated flows: A framework for mapping media exposure in the digital age. *Communication Theory*, *26*(3), 309-328.

Timeline: WHO's COVID-19 response. (n.d.). Retrieved November 08, 2020, from https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline.

Tourjée, D., & Ettachfini, L. (2018, November 7). Midterms 2018: Historic firsts for women, POC, and LGBT people. Vice. https://broadly.vice.com/en_us/article/7xypjz/midterms2018-historic-firsts-for-women-poc-and-lgbt-people.

Tsoy, D., Tirasawasdichai, T., & Kurpayanidi, K. I. (2021). Role of Social Media in Shaping Public Risk Perception during COVID-19 Pandemic: A Theoretical Review. *International Journal of Management Science and Business Administration*, *7*(2), 35-41.

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive psychology*, *5*(2), 207-232.

Umphrey, L. R. (2004). Message defensiveness, efficacy, and health-related behavioral intentions. *Communication Research Reports*, *21*(4), 329-337.

Utych, S. M., & Fowler, L. (2020). Age-based messaging strategies for communication about COVID-19. *Journal of Behavioral Public Administration*, *3*(1).

Van Bavel, J. J., P. Boggio, V. Capraro, A. Cichocka, M. Cikara, M. Crockett, … N. Ellemers. 2020. “Using Social and Behavioural Science to Support COVID-19 Pandemic Response.” Nature Human Behaviour

Van Green, T., & Tyson, A. (2020, April 2). 5 facts about partisan reactions to COVID-19 in the U.S. Pew Research Center. https://www.pewresearch.org/fact- tank/2020/04/02/5-facts-about-partisan-reactions-to-covid-19-in-the-u-s/.

Vogels, E. A., Perrin, A., Rainie, L., & Anderson, M. (2020, April 30). *53% of Americans Say the Internet Has Been Essential During the COVID-19 Outbreak*. Pew Research Center: Internet, Science & Tech. https://www.pewresearch.org/internet/2020/04/30/53-of-americans-say-the-internet-has-been-essential-during-the-covid-19-outbreak/.

WHO Coronavirus Disease (COVID-19) Dashboard. (2020, June 10). Retrieved from https://covid19.who.int/.

Wimmer, R. D., & Dominick, J. R. (2013). *Mass media research*. Cengage learning.

Witte, K. (1992). Putting the fear back into fear appeals: The extended parallel process model. *Communications Monographs*, *59*(4), 329-349.

Witte, K. (1994). Fear control and danger control: A test of the extended parallel process model (EPPM). *Communications Monographs*, *61*(2), 113-134.

Witte, K., & Morrison, K. (1995a). Intercultural and cross-cultural health communication: Understanding people and motivating healthy behaviors. And motivating healthy behaviors. International and Intercultural Communication Annual, 19, 216–246.

Witte, K., & Morrison, K. (1995b). The use of scare tactics in AIDS prevention: The case of juvenile detention and high school youth. Journal of Applied Communication Research, 23, 128–142.

Witte, K. (1996). Predicting risk behaviors: Development and validation of a diagnostic scale. *Journal of health communication*, *1*(4), 317-342.

Witte, K., & Allen, M. (2000). A meta-analysis of fear appeals: Implications for effective public health campaigns. *Health education & behavior*, *27*(5), 591-615

Wrench, J. S., Thomas-Maddox, C., Richmond, V. P., & McCroskey, J. C. (2008). *Quantitative research methods for communication: A hands-on approach*. Oxford University Press, Inc..

Yang, J., Wu, X., Sasaki, K., & Yamada, Y. (2021). Stage 2 registered report: Changing health compliance through message repetition based on the extended parallel process model in the COVID-19 pandemic.

Young, D. G., & Bleakley, A. (2020). Ideological Health Spirals: An Integrated Political and Health Communication Approach to COVID Interventions. *International Journal of Communication*, *14*, 17.

Yun, L., Kim, K., & Berry, T. R. (2014). Examining effective health messages to promote exercise: a test of Extended Parallel Process Model (EPPM). *European Health Psychologist*, *16*(S), 960.

Zaller, J. R. (1992). *The nature and origins of mass opinion*. Cambridge university press.

Appendices

Appendix A: Experimental Stimuli

Participants were exposed to one tweet each from the following accounts: @CDCgov, @WHO, and @realDonaldTrump. These tweets were selected based on the ostensible level of threat and efficacy that they reflected. The determination for the level of threat and efficacy in a tweet was derived from Witte's (1992, 1994, 1996) conceptualization of the constructs. For the control group, tweets were randomly selected about topics other than COVID-19.

Condition 1: High threat, High efficacy

WHO:

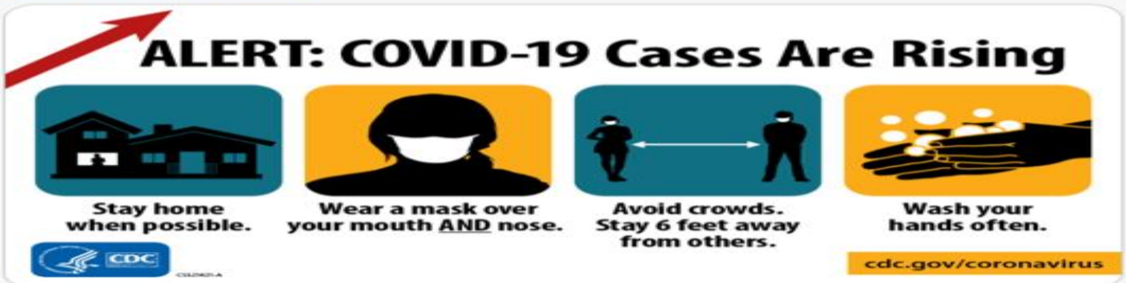
CDC:

CDC @CDCgov · Dec 16, 2020

URGENT. Many more people will get sick and die from #COVID19 unless we #SlowTheSpread.
300,000+ Americans already have died.

Protect yourself and others:
🏡 Stay home if you can.
😷 Wear a mask.
↔️ Stay 6 feet apart.
🚫 Avoid crowds.
👐 Wash your hands.

cdc.gov/coronavirus.



240 1.2K 1.9K

Donald Trump:

Donald J. Trump
@realdonaldtrump

There is a rise in Coronavirus cases because our testing is so massive and so good, far bigger and better than any other country. This is great news, but even better news is that death, and the death rate, is DOWN. Also, younger people, who get better much easier and faster!

Jul 2nd 2020 - 11:44:42 PM EST · Twitter for iPhone · View on Twitter

Condition 2: High threat, Low efficacy

WHO:


World Health Organization (WHO) @WHO · Jul 27, 2020

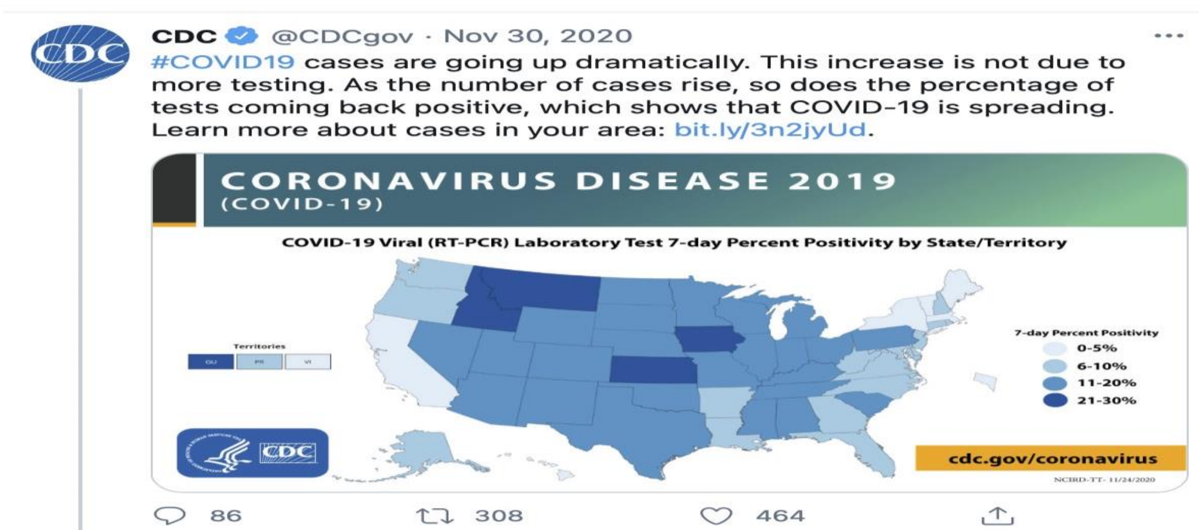
"Almost 16 million #COVID19 cases have now been reported to WHO, and more than 640,000 deaths.

And the **pandemic** continues to accelerate.

In the past 6 weeks, the total number of cases has roughly doubled"- @DrTedros

7 65 84

CDC:


CDC @CDCgov · Nov 30, 2020

#COVID19 cases are going up dramatically. This increase is not due to more testing. As the number of cases rise, so does the percentage of tests coming back positive, which shows that COVID-19 is spreading. Learn more about cases in your area: bit.ly/3n2jyUd.

86 308 464

Trump:

Donald J. Trump
@realdonaldtrump

The only reason the U.S. has reported one million cases of CoronaVirus is that our Testing is sooo much better than any other country in the World. Other countries are way behind us in Testing, and therefore show far fewer cases!

Apr 29th 2020 - 12:23:38 AM EST · Twitter for iPhone · View on Twitter

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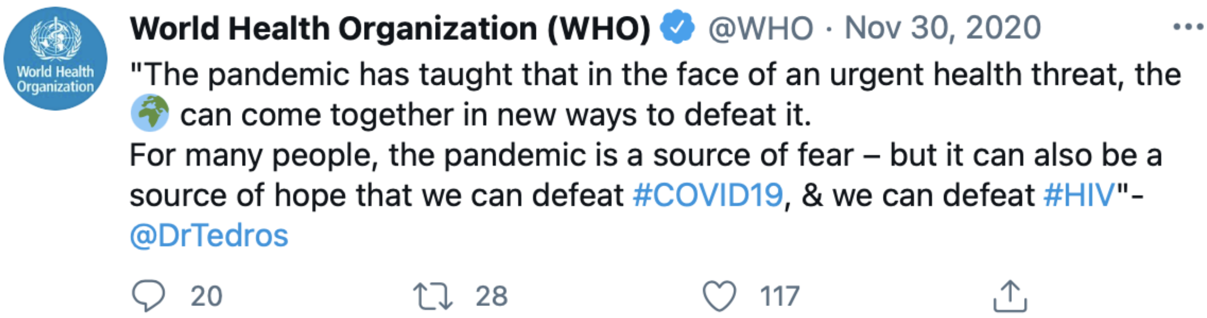
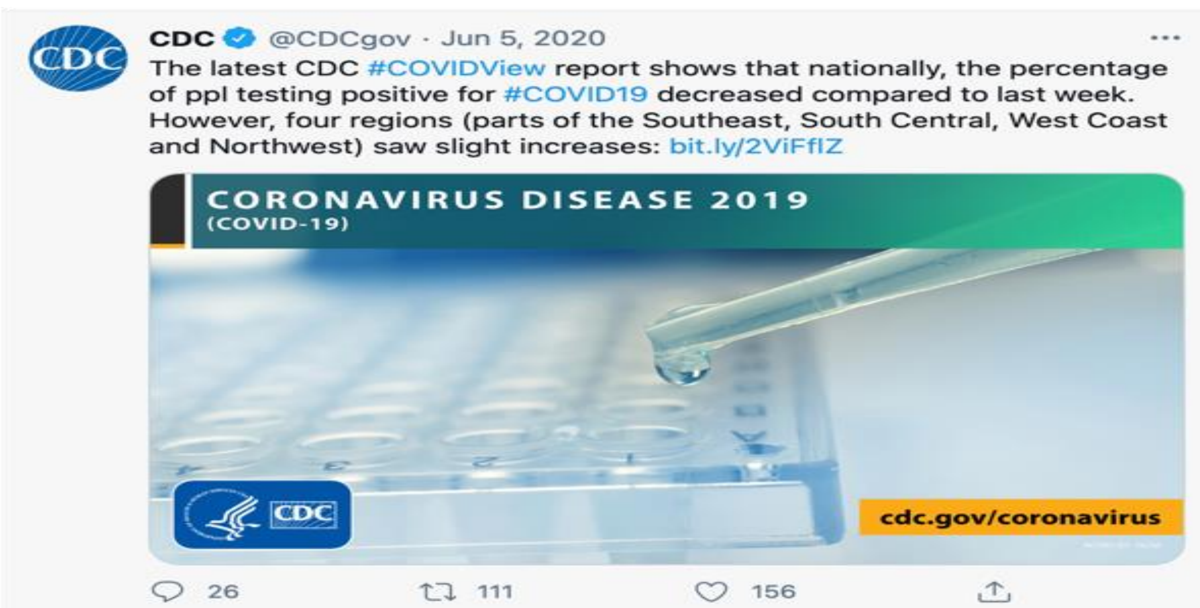
Condition 3: Low threat, Low efficacy

WHO:



CDC:



Trump:

Donald J. Trump
@realdonaldtrump

The Fake News Media and their partner, the Democrat Party, is doing everything within its semi-considerable power (it used to be greater!) to inflame the CoronaVirus situation, far beyond what the facts would warrant. Surgeon General, "The risk is low to the average American."

Mar 9th 2020 - 7:20:43 AM EST · Twitter for iPhone · View on Twitter

Condition 4: Control Group

WHO:

World Health Organization (WHO) @WHO · Nov 30, 2020

Malaria is a preventable & treatable disease that continues to claim hundreds of thousands of lives each year.

WHO is calling on countries & global health partners to step up the fight and #EndMalaria bit.ly/36j8o76

WHO/Europe and 7 others

32 268 897

CDC:


CDC @CDCgov · Sep 8, 2020

About 34 million adults in the United States currently smoke cigarettes. Evidence-based mass media campaigns like #CDCTips can help people quit smoking: CDC.gov/TipsImpact.

Trump:

> **Donald J. Trump**
> @realdonaldtrump
>
> *Mini Mike is now negotiating both to get on the Democrat Primary debate stage, and to have the right to stand on boxes, or a lift, during the debates. This is sometimes done, but really not fair!*
>
> Feb 2nd 2020 - 12:25:10 AM EST · Twitter for iPhone · View on Twitter