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Media Coverage of Collective Traumas: Implications for Cognitions, Affect, and Behaviors

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Media Coverage of Collective Traumas: Implications for Cognitions, Affect, and Behaviors

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Psychological Science

by

Kayley Danielle Estes

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2024

DEDICATION

A PhD is not earned in isolation. The past six years have been filled with so many people (and pets) who have made this journey possible and, at times, quite fun.

To my parents, thank you for everything. I am extremely privileged to have two caring, supportive, loving parents in my corner, no matter what. Thank you for supporting me while I worked towards grad school and barely made enough money to cover my gas. Thank you for supporting me when I said I needed to come home for a few weeks because the state was going to shut down as the pandemic began – and then letting River and myself live and do Zoom grad school from your house for the following six months. Thank you for always letting me call on my walks to and from the office, always listening to me ramble about my research, and always giving me a safe place to go when I needed a change of scenery. I genuinely could not have made it to this point in my life without your unwavering support. Thank you for everything you have done for me. I love you both with all my heart! For you, this dissertation is dedicated to your unwavering support, your devotion as parents, and always letting me ask "why?" as a kid.

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TABLE OF CONTENTS

	Page
LIST OF FIGURES	iv
LIST OF TABLES	v
ACKNOWLEDGEMENTS	vi
VITA	vii
ABSTRACT OF THE DISSERTATION	x
INTRODUCTION	1
References	11
CHAPTER 1: Abstract	16
Introduction	17
Methods	22
Results	25
Discussion	31
References	36
CHAPTER 2: Abstract	44
Introduction	45
Methods	55
Results	60
Discussion	71
References	80
CHAPTER 3: Abstract	90
Introduction	91
Methods	99
Results	106
Discussion	124
References	132
CHAPTER 4: Epilogue	141
References	149

LIST OF FIGURES

		Page
Figure 1.1	Association Between Amount of Hurricane Harvey-Related Media Exposure and Traumatic Stress Symptoms as Moderated by Perceived Trust in Media Sources at 2- and 6-Weeks After Hurricane Harvey Made Landfall	27
Figure 1.2	Association Between Amount of Hurricane Harvey-Related Media Exposure and Traumatic Stress Symptoms as Moderated by Perceived Trust in Media Sources at 2-Weeks, 6-Weeks, and 14-Months After Hurricane Harvey Made Landfall	28
Figure 2.1	Percent of Respondents' Self-Report and GIS-Based Evacuation Zone Status Using Population Weights	62
Figure 2.2	Reported Reasons for Deciding to Not Evacuate	63
Figure 2.3	Final GSEM Model Showing Significant Direct and Indirect Pathways for the Self-Report Subsample	70
Figure 3.1	Estimated Means of Latent Class Trajectories of Susceptibility Risk Perceptions Over Time with a Four-Class Solution	113
Figure 3.2	Estimated Means of Latent Class Trajectories of Severity Risk Perceptions Over Time with a Four-Class Solution	115

LIST OF TABLES

		Page
Table 1.1	Weighted Descriptive Statistics for All Variables of Interest	26
Table 1.2	Standardized, Weighted GEE Coefficients Examining the Relation Between Hours of Media Exposure and Trust in Hurricane-Related Media Exposure and Traumatic Stress Symptoms, Waves 1 and 2	29
Table 1.3	Standardized, Weighted GEE Coefficients Examining the Relationship Between Hours of Media Exposure and Trust in Hurricane-Related Media Exposure and Traumatic Stress Symptoms, Waves 1, 2, and 3	30
Table 2.1	Self-Report Model: GSEM Results Examining Risk Perceptions as a Mediator on Evacuation Behavior	67
Table 2.2	GIS-Based Model: GSEM Results Examining Risk Perceptions as a Mediator on Evacuation Behavior	69
Table 3.1	Descriptive Statistics of Variables Included in Final GSEM Models	108
Table 3.2	Bivariate Relationships for All Variables Included in the Models	110
Table 3.3	Growth Mixture Model Results for Susceptibility and Severity Risk Perception Trajectories	112
Table 3.4	GSEM Results Assessing Susceptibility Risk Perception Classes and Vaccine Uptake	118
Table 3.5	GSEM Results Assessing Severity Risk Perception Classes and Vaccine Uptake	122
Table 3.6	Frequency of Participants in Each GMM Class and Vaccine Uptake Group	124

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ABSTRACT OF THE DISSERTATION

Media Coverage of Collective Traumas: Implications for Cognitions, Affect, and Behaviors

by

Kayley Danielle Estes

Doctor of Philosophy in Psychological Science

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Distinguished Professor Roxane Cohen Silver, Chair

Technological advancements allow individuals to access news about collective traumas from multiple sources simultaneously, potentially increasing the amount of media consumed during a given crisis. While excessive media consumption during a collective trauma has been linked to negative psychological outcomes (e.g., posttraumatic stress symptoms), there are many situations in which it is impractical or even dangerous to advise the public to reduce media consumption. This dissertation examined the link between media exposure and emotional, cognitive, and behavioral responses during and following three collective traumas using large, probability-based samples and longitudinal designs. Among a sample of Texas residents following Hurricane Harvey ($N = 1{,}137$), Study 1 found that trust in media buffered against traumatic stress symptoms two weeks, six weeks, and 14 months post-landfall for people with high amounts of early media exposure to the disaster. Study 2 demonstrated that during Hurricane Irma, pre-landfall risk perceptions of injury and destruction, measured in the days *before* landfall, mediated the relationship between pre-landfall media exposure and evacuation behaviors measured one month after the hurricane among a sample of Florida residents ($N = 1{,}478$). This study underscored the importance of the media and emergency management personnel communicating transparent, non-sensationalized information for emergency decisions as a disaster unfolds.

Study 3 explored how early media consumption patterns during the COVID-19 pandemic were associated with long-term risk perception patterns among a national U.S. sample (N = 4,859). In addition, early media consumption and risk perception patterns were linked with vaccine uptake throughout the pandemic. These findings suggest that various aspects of early disaster media consumption (i.e., disaster-based media exposure, ideological focus of top news sources, perceived trust in media for specific disasters) are associated with traumatic stress symptoms, risk perceptions, evacuation behaviors, and vaccine uptake over time. Using large, probability-based samples with longitudinal data, this program of research provides insights for policymakers, media outlets, and emergency management personnel, advocating for trustworthy, direct communication to support appropriate risk perceptions, public health behaviors, and safety during disasters. This work also aids in understanding the nuanced relationships between media consumption and psychological outcomes and behaviors during collective traumas, contributing to the literature for updated communication strategies and interventions.

Introduction

According to the 24-hour media cycle, suffering and death have been the backdrop of daily life for the last few years. Even though most people have likely directly experienced a minimal number of collective traumas in the last decade, it seems like there is a new one to watch or read about in the media weekly. The pervasiveness of real-world traumatic events being reported through the news or on social media is a relatively new phenomenon, especially given the speed with which technology has progressed. Collective traumas are large-scale negative life events that impact the populace broadly, both by direct exposure and media coverage (Garfin et al., 2020). These can be either traumatic events as defined by the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5-TR; American Psychiatric Association, 2022) or major life stressors, but they will be referred to jointly as collective traumas for the remainder of this dissertation. Collective traumas can be found in many forms, including mass violence events, public health crises, or natural disasters, and they have been – and continue to be – extensively reported by the media and civilian journalists on social media. Despite extensive coverage of these types of events, there is much to understand about media coverage of collective traumas and its connection to several psychological outcomes. The purpose of this three-study dissertation is to examine the ways in which media coverage of collective traumas is connected to cognitions, affect, and behaviors using large, probability-based samples. First, I will introduce media coverage of collective traumas in general. Then, I will briefly discuss each psychological outcome and the role of media consumption in relation to risk perceptions as cognitions, traumatic stress as affect, and evacuation and vaccine uptake as behaviors. Finally, the plan for the dissertation will be presented.

Media

The media is a vital institution in the United States. During collective traumas, people turn to the media to receive updates about the current disaster (Silverblatt, 2004). Best practices suggest it is essential to obtain accurate information during a collective trauma in order to protect physical well-being and mental health (Garfin et al., 2023). Media coverage of collective traumas can be consumed through a variety of media outlets from traditional media (i.e., radio, newspaper, or television) to new media (i.e., social media and online news websites). Newspapers and television were typically used for this purpose for decades, and television remains the primary source of information for some people to this day (Backfried et al., 2016). However, the prolific rise of social media in the 21st century has shifted where affected individuals receive disaster information, especially as emergency managers increasingly use social media to update the public about threats (Young et al., 2020). During Superstorm Sandy, for example, 34% of the Twitter conversations about the storm included news organizations, government sources, and affected people sharing information about the storm (Drake, 2013).

Information about collective traumas is potentially communicated differently through various media outlets, depending on the gatekeepers who filter the information (e.g., television uses producers and editors to filter content; TikTok uses an algorithm to amplify filtered content from both news accounts and individual accounts). Social media is, by nature, a platform that empowers civilians to assume a more substantial participatory role in news dissemination (Young et al., 2020). The increased democratization of information dissemination on social media allows for a more diverse assortment of voices and perspectives to be heard about a larger variety of events.

Social media also allows for more real-time updates, especially at the beginning of an event when a news crew may have yet to arrive at the scene. The timeliness of information dissemination also differs between traditional and new media, with traditional media outlets being more accurate, on average, but slower than social media (Backfried et al., 2016). Despite concerns about information accuracy, individuals still tend to seek quick and unfiltered, often incorrect, information on social media (Young et al., 2020), especially when critical updates through official media channels are irregular or not reducing uncertainty (Jones et al., 2017). As the landscape of media consumption evolves, research must also attempt to quickly, but systematically, evolve with it. Research on social media from even two decades ago is largely outdated by now. A study on the September 11, 2001 (9/11) terrorist attacks showed that Americans mainly used television and the telephone for information, citing the Internet and e-mail less frequently (Carey, 2002). Meanwhile, recent Pew research demonstrates that 58% of U.S. adults prefer to receive their news from digital devices (i.e., smartphone, tablet) compared to only 27% who prefer television ("News Platform Fact Sheet," 2023). Therefore, it is imperative to examine media in a multifaceted manner in the context of collective trauma to deepen scientists' understanding of current media consumption in the U.S.

While examining the nuances of media consumption offers value by itself, delving into the relationships between media consumption and psychological outcomes is crucial for public benefit. There are numerous characteristics of the media and media coverage that can individually be associated with cognitions, affect, and behaviors in the context of a collective trauma. The number of media factors that are related to psychological outcomes is too great to list, but this dissertation will focus on a select few characteristics in three different studies. Study 1 examines the interaction between the amount of media exposure to a hurricane and the perceived trust that consumers have in that media and the interaction's association with traumatic stress symptoms. Study 2 focuses on the amount of media exposure and its connection to risk perceptions and evacuation behaviors in the context of an impending hurricane. Study 3 examines the amount of media exposure to a public health crisis, characteristics of the information sources, and perceived trust in that media in predicting health protective behaviors (vaccine uptake) over time. The three important outcomes under study will be discussed in turn.

Risk Perceptions

A risk perception is an individual's subjective judgment about the characteristics and severity of a risk (Brewer et al., 2004; Slovic, 2016). Risk perceptions differ from objective risk levels since perceptions are influenced by other psychological factors (e.g., affect, cognitions, context, and individual differences). Risks can be in any domain, from health to technology to safety to finances. Psychology can partially explain why subjective perceptions of risk differ between people. A series of gambling experiments created by Tversky and Kahneman (1974) examined how people evaluated probabilities. Their studies primarily discovered that people tend to use a variety of heuristics (e.g., representativeness, availability, anchoring) to evaluate the information given to them regarding a risk. Heuristics, though useful shortcuts for thinking quickly through new information, can be inaccurate in certain situations (Tversky & Kahneman, 1974); these can become cognitive biases. People can also use mental models to interpret novel events by drawing on past experiences, education, and other exposures (Gentner & Stevens, 1983).

Mental models can be accurate or may require more information to be helpful. Risk perceptions informed by heuristics and mental models serve an evolutionary purpose. Intuitive risk perception and risk judgments have helped humans survive throughout time. Prior to modern sophisticated analytic tools, humans had to rely on their intuition, honed by experience, to determine the threat level of safety risks (Slovic, 2010). Safety risks might have included a questionable smell from poisonous berries or threats from predators lurking in the nearby bushes. For the majority of human life, threats were almost always immediate and present in the small community in which one lived. In the modern world, however, safety risks sometimes look different and often have a larger magnitude. Some ancestral threats that were historically risky to humans are no longer fatal. For instance, modern medicine can help a person through a bout of food poisoning. Conversely, some things that historically posed a smaller risk now pose a much greater risk to life. For example, guns can now fire more bullets in a shorter amount of time than they ever could in history. Moreover, some modern threats have evolved slowly over time (e.g., climate change and the rise in frequency and intensity of natural disasters), while others have changed rapidly (e.g., exponentially advanced technology) and are at the forefront of public conversation (e.g., gun violence). These threats are discussed at different frequencies in the media, with a focus usually on the most immediate and prominent risk.

Nevertheless, Slovic (2010) argued that traditional news (i.e., print media, television news, and radio) in past decades was doing an inadequate job of attending to mass atrocities around the globe. However, modern technology, trends within social media (e.g., Instagram, X/Twitter, Facebook), and the globalization of news now allow the general public to have a hand in deciding what is discussed. The large news companies are no longer the only gatekeepers of newsworthy events, and more is now seen and discussed. Grassroots efforts to spread a story on social media often then fuel the official news coverage of the story after the fact. While it is an improvement in that there are fewer gatekeepers to withhold stories about topics focused on minoritized populations such as police brutality, sexism, queerphobia, etc., internet users are potentially being bombarded with negative news from all over the world at an increased frequency. This potential for ceaseless exposure to world news can shape risk perceptions, as risk perceptions are at least partially influenced by how frequently risk information is represented in the media (Slovic, 1987). Smartphones allow users to search for specific news at all hours of the day or enable push notifications to alert them to breaking news as it unfolds, unlike in prior decades when breaking news was primarily shown at set times each day (e.g., the morning news). It is essential to understand how risk perceptions are related to different aspects of media consumption, including the amount of time individuals spend consuming news about tragedies. Two studies in this dissertation examine this topic. Study 2 tests risk perceptions as a mediator between media exposure regarding an impending hurricane and evacuation behaviors. Study 3 examines whether characteristics of early media containing information about the COVID-19 pandemic are related to risk perceptions over time and are linked with vaccine uptake behaviors years later.

Affect

A key concern is not simply that breaking news is available at all times of the day, but the same information is frequently repeated. In general, when a video or a story goes viral on social media, users may be exposed to identical content dozens of times as it is shared and re-posted thousands of times by different users. In contrast, some collective traumas happen suddenly and without warning (e.g., earthquake), so there may be little video or photo content of the event and its immediate aftermath. Often, television news stations will repeat the same few pieces of visual content (e.g., a 10-second video recorded by someone at the event site) they have received on a loop while discussing the event, increasing the frequency with which viewers receive the same content. This repeated exposure has been studied in relation to its link with negative mental health consequences such as acute stress and posttraumatic stress symptoms (Ahern et al., 2004; Holman et al., 2014; Hopwood & Schutte, 2017). It is also linked to a cycle of distress in which repeated media exposure to a collective trauma event is associated with a fear of future negative events and increased consumption of media following subsequent collective traumas (Thompson et al., 2019). Given the improbability of avoiding the media altogether during crises characterized by uncertainty, however, it is necessary to determine if there are any protective factors against the established negative psychological outcomes typically associated with media exposure. Indeed, recent research suggests that a high level of trust in the media one consumes regarding stressful events may buffer against psychological distress (Lee, 2022; Patwary et al., 2021). Study 1, conducted in the aftermath of a devastating hurricane, examines the interaction between the amount of media consumed and trust in that media in predicting psychological symptomatology over time.

Behavioral Outcomes

Evacuation Behaviors

When individuals have the potential to be exposed to an impending disaster (e.g., hurricane or other natural disaster), they may need to make decisions, often with incomplete or ambiguous information collected from media exposure, about whether or not they will evacuate their place of residence. Understanding when people choose to evacuate, or even *if* they choose to evacuate at all, is an important area of study that has profound implications on emergency messaging and general risk to life during natural disasters. The research on factors that are associated with evacuation behaviors, especially for hurricanes, is highly contested (Thompson et al., 2017). However, most of the research relies on retrospective, cross-sectional data from non-representative samples, which may have contributed to the mixed results in the literature. In order to protect lives and property, it is vital to understand why people do not evacuate from a disaster while under evacuation orders, especially in areas where disasters are highly probable and regularly a threat. Although there is limited research on media, one question of interest is what role media might play in understanding evacuation behaviors. Some researchers have studied it as a warning source along with other types of warning sources (e.g., neighbors; Thompson et al., 2017), but does it possibly play a more central role in the decision-making process? In order to do that, high-quality data must be collected using large, probability-based samples with real-time data assessed as a disaster approaches participants. Study 2 focuses on the factors associated with evacuation behaviors in advance of a hurricane making landfall including media characteristics and risk perceptions.

Vaccine Uptake

Unlike evacuation behaviors, the umbrella of vaccine behavior research has been studied extensively. One of the main areas of research focuses on the concern around misinformation and disinformation disseminated in the media. Misinformation includes information that is accidentally false and is shared without the intent to cause harm. In contrast, disinformation includes false information that is knowingly being created and shared with the intent to cause harm (Wang et al., 2019). In a pre-COVID-19 systematic review of the spread of health-related misinformation on social media, Wang and colleagues (2019) noted that misinformation tends to be more popular online, even though there are often fewer misinformation messages compared to factual ones. A highly concerning misinformation topic – even before the COVID-19 pandemic – is that of immunizations and the spread of the “anti-vax movement” (also known as the anti-vaccine movement; Nuwarda et al., 2022). Though misinformation about vaccines was rampant as the COVID-19 vaccines were rapidly produced and became publicly available, a previous seminal moment in the field was the publication of false research linking the MMR vaccine to autism (Wang et al., 2019). Decades later, this retracted article is still discussed in some anti-vax online forums, contributing to a growing mistrust in government and science when discussing vaccines (Basch et al., 2017). Vaccine hesitancy was even noted as one of the World Health Organization's top 10 global health threats in 2019, prior to COVID-19 vaccine hesitancy (Nuwarda et al., 2022). Despite this being an area extensively studied, there is still a limited understanding of why some people are more susceptible to health misinformation than others.

A detailed examination of media factors that may be linked with vaccine uptake for infectious diseases (e.g., influenza viruses, SARS-CoV-2) is likely a fruitful endeavor, as media is a crucial source for information during uncertainty. For instance, a team of researchers found that individuals seeking information about the flu vaccine who placed more value in medical journals and newspaper articles were more likely to perceive the vaccine as effective and receive the vaccine compared to those who placed more value in social media and advertisements (Hwang, 2020). Following the development of COVID-19 vaccines and the extensive public discourse on vaccine hesitancy in mainstream media, this field of study has rapidly expanded in recent years. Given the speed with which rigorous science moves, it will take time to sort through the wealth of information from the pandemic to establish a consensus in the research. A deeper discussion of this topic in the context of the COVID-19 pandemic will be considered in Study 3, in which I examine the early media characteristics and longitudinal factors linked with vaccine uptake years into a public health crisis.

Plan for the Dissertation

The overarching aim of this dissertation is to understand how a variety of aspects of media coverage of traumatic events are connected to cognitions, affect, and behaviors. Considering the fact that human brains have been consuming such vast amounts of information about a broad array of collective traumas for only a few decades, research regarding the psychological consequences of this increase in media consumption is still grossly incomplete. In order to effectively help the public and policymakers navigate through the multitude of crises that the world experiences – and collectively consumes – at an increased rate, scientists need to better understand the relation between media and risk perceptions – along with behavioral and affective outcomes – in a variety of modern collective traumas contexts (e.g., public health crises, natural disasters). This dissertation expands the established research on media and risk perceptions by examining the relationship using new models, contexts, and with multiple media factors. It uses three different samples in three contexts with several overarching goals. Primarily, the dissertation seeks to expand and refine research on media coverage in the context of collective traumas. Through this effort, it provides theoretically rich and methodological rigorous data to inform policymakers, media companies, and the public at large as they navigate access to and delivery of the multitude of collective traumas people experience and consume across traditional and new media in their daily lives. Study 1 uses a probability-based, representative sample of Texas residents in the aftermath of a major hurricane to test the relationship between hours of media exposure and perceived trust in that media and traumatic stress responses over time. Study 2 employs a large, probability-based sample of Florida residents, assessed in the days prior to a major hurricane making landfall, to assess risk perceptions as a mediator between theoretically derived variables including hours of media exposure and evacuation behaviors. Study 3 uses a large, probability-based sample of the U.S., first measured at the start of the COVID-19 pandemic, to study longitudinal patterns of risk perceptions and the relationships between early media characteristics with vaccine uptake after the pandemic was downgraded to an endemic stage.

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CHAPTER 1

Consuming Hurricane-Related Media: The Protective Role of Perceived Trust

Abstract

We examined whether perceived trust in media was associated with post-Hurricane Harvey traumatic stress symptoms and tested whether it buffered the association between hurricane-related media exposure and post-Hurricane Harvey traumatic stress symptoms. A probability-based, representative sample of Texas residents, drawn from the GfK KnowledgePanel, were surveyed online three times: two weeks (N = 1,137), six weeks (N = 1,023), and 14 months (N = 748) after Hurricane Harvey (a Category 4 storm) made landfall in 2017. Measures included traumatic stress symptoms, Hurricane Harvey-related media exposure, perceived trust in that media, Hurricane Harvey direct exposures, and demographics. Generalized Estimating Equations (GEE) were used to evaluate longitudinal relationships. Among participants reporting high perceived trust in the early Hurricane Harvey-related media they consumed, the relationship between average daily hours of hurricane-related media exposure (reported two weeks post-landfall) and posttraumatic stress symptoms (reported at each wave of data collection) was weaker than for those who perceived low trust in hurricane-related media at both six weeks (β = -0.35, 95%CI [-0.58, -0.13], p = .002) and 14 months (β = -0.45, 95%CI [-0.70, -0.19], p = .001) post-landfall. Findings suggest that perceived trust in media may protect against traumatic stress symptoms associated with early media exposure when disaster strikes. Longitudinally, we show that these findings are consistent over time: trust in disaster-related media coverage was associated with lower traumatic stress symptoms up to 14 months later among Texans who consumed high daily amounts of Hurricane Harvey-related news.

Introduction

Advancements in technology in the 21st century have revolutionized the way people gather information about natural disasters and other collective traumas, providing people with minute-by-minute updates and live blogs before, during, and after the disaster (Tanaka, 2021). These advancements allow people to receive news about a disaster through multiple formats (i.e., traditional media, internet news, and social media) simultaneously, potentially increasing the amount of media a person is exposed to in a given timeframe, as people often use several information sources to remain current on natural disasters (Simon et al., 2015). After Hurricane Ike in 2008, television and interpersonal exchanges were the most commonly used sources for hurricane-related information for people who evacuated (Burke et al., 2010). Since then, exploding social media use has significantly expanded access to news with unfiltered stories available 24/7 to millions of people who use it for news about events occurring in their communities. Importantly, this media access creates a direct line of communication between the public and emergency management personnel, allowing valuable information about disasters to be disseminated to the public before, during, and after the event. When this communication is effective and is trusted by the consumer, it can strengthen mitigation efforts, enhance early warning systems, and promote timely evacuations (Monahan & Ettinger, 2018).

A small but growing body of research suggests that institutional trust, specifically trust in social and traditional media, may be psychologically protective during traumatic events filled with uncertainty (Lee, 2022; Patwary et al., 2021). More broadly, trust in institutions is a potential protective factor that mitigates traumatic stress responses. The relationship between institutional trust and traumatic stress has recently centered around the COVID-19 pandemic, during which changes in institutional trust were mixed as trust in many institutions decreased

(Kennedy et al., 2022), while trust in others retroactively increased only after seeing the health benefits of lockdown measures (Bol et al., 2021). Moreover, studies consistently showed that when there was higher trust in institutions (e.g., government), it was associated with lower negative affect as well as high subjective well-being during the pandemic (Li et al., 2022; Roccato et al., 2021). While most research has concentrated on the pandemic and its aftermath, prior studies also addressed institutional trust in the context of mass violence. Gelkopf and colleagues (2012) found that confidence in the army and government among people who were repeatedly bombed in Israel was associated with lower posttraumatic stress symptoms (PTSS) and global distress, such that participants who exhibited more confidence in these institutions reported less PTSS and global distress. These findings collectively underscore the potential that institutional trust may buffer against traumatic stress after events characterized by uncertainty (e.g., war, terrorism, natural disasters).

The media is one of the most important American institutions. During crises, people turn to it to learn about the current disaster, the predicted trajectories of events (Silverblatt, 2004), and to establish order (Houston et al., 2012). Best practices in disaster psychology routinely note the importance of obtaining information during a disaster for maintaining physical well-being and mental health (Garfin et al., 2023). Yet such information may only protect against psychological distress if the individuals receiving it believe it to be trustworthy. Although there is no universally agreed-upon definition of trust in media in the communications literature, it is often defined as a combination of several factors including medium, source, and message credibility (Fischer, 2018; Van Der Meer et al., 2023). However, most prior literature on trust in the media seeks to objectively define trustworthiness rather than evaluating respondents' subjective perceptions of trust (Knudsen et al., 2021). Considering trust in media from this person-based perspective – as an individual's *perceived trust* in media independent of the objective media trustworthiness or credibility – could contribute to our understanding of the relationship between trust in media as an institution and PTSS.

While our modern technology-driven information network transmits urgent updates (e.g., evacuation orders) during crises, a robust body of research also demonstrates a positive association between post-disaster PTSS and increased media consumption about the disaster (Pfefferbaum et al., 2014; Thompson et al., 2019). Indeed, in a representative sample collected in the immediate aftermath of the Boston Marathon bombings, extensive disaster-related media exposure was associated with *higher* acute stress symptoms than was direct exposure (Holman et al., 2014). Similarly, media exposure to news about the COVID-19 pandemic also exacerbated stress responses, especially when it was spreading conflicting information (Holman, Thompson et al., 2020). Moreover, a meta-analysis revealed that media exposure to disasters and other large-scale violence events was strongly linked to subsequent poor short-term psychological outcomes, possibly through sensitization to media-based exposure in communities that have experienced a similar threat (Hopwood & Schutte, 2017). Prolonged exposure to media coverage of trauma may amplify anxiety and fear (Holman et al., 2014), which could, in turn, activate attentional bias and make it difficult for people to disengage (Fox et al., 2001).

During a crisis, exposure to media that contain rumors (Jones et al., 2017) or conflicting information (Holman, Thompson et al., 2020) is associated with more distress. In this scenario, trust in the media may be important because if people do not trust the media being consumed, they may lack the knowledge necessary to prepare for, adapt to, and mitigate the threat, which could exacerbate stress responses. Indeed, a hallmark of effective disaster-related mental health intervention involves ensuring those affected have the information they need to make the decisions to stay safe during a crisis and recover in its aftermath (Garfin et al., 2023). This may create a sense of adaptive control and efficacy (Henselmans et al., 2010) or promote problem-focused coping (Park & Folkman, 1997), both of which can alleviate stress and increase well-being during difficult circumstances such as natural disasters (Guo et al., 2013). Together these studies show that while media plays a crucial role in information dissemination, viewing extensive coverage of disaster is often correlated with poor mental health in a variety of disaster contexts.

Yet it may be counterproductive to simply advise against media exposure during a disaster, such as a hurricane, as it is a conduit by which people access critical updates on storm trajectories and evacuation orders (Ball-Rokeach & DeFleur, 1976; Jung, 2017). Moreover, media exposure during prior public health crises, such as COVID-19 (Garfin et al., 2021) and in response to hurricanes (Garfin, Thompson et al., 2022), has been associated with health protective and preparation behaviors, respectively. Trust in the media may also serve to mitigate anxiety, fostering confidence in the information being shared. Thus, it is critical to examine whether the individual-level features of media exposure and media trust are differentially associated with distress, so that disaster-related updates can be conveyed in a manner that minimizes the potential for psychological distress.

Current Study

According to the National Weather Service (Metz, 2017), Hurricane Harvey formed in the Gulf on August 18, 2017, and, like many hurricanes, caused uncertainty about where it would make landfall, how strong it would be, and how quickly it would dissipate. On August 21st, long range model guidance clarified that it would make landfall in Texas, a substantial change from the original mapping suggesting the hurricane would largely miss the United States. The hurricane intensified to a Category 4 hurricane on August 24th at 6 PM CDT with maximum sustained winds of 130 mph (215 km/m) before making landfall on August 25, 2017 along the Middle Texas Coast near Corpus Christi and Port Aransas. This was the first major hurricane (Category 3 or above on the Saffir-Simpson Hurricane Wind Scale; Tropical Cyclone Climatology, nd) to make landfall on the Middle Texas Coast since 1961 and the first major hurricane to hit the US since 2005 (Hurricane Research Division, 2023, April). The storm then stalled over Texas for four days, dropping historic amounts of rainfall of more than 60 inches over southeastern Texas, flooding an estimated 155,000 structures (Metz, 2017). The devastation and disruption were extensive between the quick rise from a tropical storm to a Category 4 hurricane and the relentless rainfall.

Here, based on the aforementioned evidence, we explored the relationship between hours of media exposure and perceived trust in that media and traumatic stress responses in a representative sample of 1,137 Texas residents, assessed in the early aftermath of Hurricane Harvey and followed over time. We measured a common outcome of hurricane exposure: traumatic stress symptoms (Galea et al., 2007; Thompson et al., 2019). We controlled for factors commonly associated with post-disaster distress: demographic factors that are commonly associated with post-disaster outcomes (see Galea et al., 2005) and amount of Hurricane Harvey-related exposure (e.g., disaster-related loss and injury; Garfin et al., 2023). We had three hypotheses:

1) Amount of Hurricane Harvey-related media exposure during and following the hurricane would be positively associated with traumatic stress symptoms;

2) Individuals' perceived trust in their media sources regarding information about the hurricane would be negatively associated with traumatic stress symptoms;

3) Perceived trust in media sources would buffer the negative effect of media exposure on PTSS.

Methods

Participants were drawn from the GfK (now Ipsos) KnowledgePanel. GfK used address-based probability sampling methods to randomly recruit individuals into their research panel, which was designed to be representative of the United States. Households without an Internet connection were provided a web-enabled device and free Internet services. Panelists were invited to complete confidential surveys online in exchange for compensation or points for merchandise. Once recruited to the KnowledgePanel, panelists were assigned to the sample for our study and notified electronically of the opportunity to take part in each wave of data collection through an email link or their online panel member page.

Our Wave 1 survey was fielded to all GfK panelists living in Texas (*N*=3067) starting at 5 pm CDT on 9/8/17, two weeks after Hurricane Harvey made landfall in Texas. The survey was closed to new participants 15 hours later after reaching the prearranged target sample size; participants who had already begun the survey were allowed to finish it within the three-day fielding period, during which *N*=1137 participants completed the survey. The Wave 2 survey was fielded 10/12/2017 to 10/29/17, and 1023 completed it (90.00% retention rate). The Wave 3 survey was fielded 10/22/18 to 11/6/18; the final sample size was 748 participants (65.79% participation rate). Participants received a cash equivalent of $15-$20 for completing the surveys. The Institutional Review Board at University of California, Irvine approved all procedures. Informed consent was obtained upon entry into the GfK panel.

All descriptive and inferential statistics were weighted using post-stratification weights (provided by GfK) specific to the Texas population, unless otherwise specified. These weights were calculated to adjust the final sample to the demographic composition of Texas for adults 18 and older based on several demographics including gender, age, race/ethnicity, household income, metro/non-metro areas, and education. Weights also account for survey non-response and attrition over time, allowing for population-based inferences at each wave and over time.

Measures

Traumatic Stress Symptoms

Respondents reported hurricane-related traumatic stress symptoms at Waves 1, 2, and 3 using a modified version of the PTSD-PC, a five-item measure validated in primary-care settings as a screener for PTSD (Calhoun et al., 2010; Prins et al., 2016). Items contained questions such as "Have you had nightmares about the hurricane or thought about it when you did not want to?" Response options included a 5-point scale from 1=*never* to 5=*all the time*. Items were averaged for an acute stress score at Wave 1 (α = .84) and a PTSS score at Waves 2 (α = .87) and 3 (α = .78).

Hurricane Harvey-Related Media Exposure

At Wave 1, participants were asked "In the days during and following Hurricane Harvey, how many hours per day, on average, did you spend watching and/or listening to media coverage about it?" for each of three media source groups 1) television, radio, and print; 2) online news sources (CNN, Yahoo, NYTimes.com); and 3) social media (e.g., Facebook, Twitter, Reddit, etc.) in the days during and following Hurricane Harvey. Responses were summed for a total daily amount of media exposure score. Since it is possible for participants to have used two or three of the media source groups at one time, the daily average score can be higher than the 24 hours in a day with the final range of media exposure scores being 0 – 33 hours of media consumption per day.

Perceived Trust in Media for Hurricane Harvey-Related Information ("Trust in Media")

At Wave 1, immediately after being asked about media exposure, participants were asked, "How much do you trust the news you have been receiving regarding Hurricane Harvey?" to assess individual-level perceived trust in media (referred to here as "trust in media"). Respondents used a 5-point scale from 1=*strongly distrust* to 5=*strongly trust* to answer the question. Due to skewness and low numbers of respondents in the lowest groups ($n_{weighted}$ = 32 for response option 1 and $n_{weighted}$ = 97 for response option 2), the variable was dichotomized into low trust (1-3) and high trust (4-5). (All analyses were also conducted with the continuous variable. All results were consistent with those reported in this paper using the dichotomized variable.)

Exposure to Hurricane Harvey-Related Loss or Injury

Respondents reported the degree to which they experienced injury or loss due to Hurricane Harvey at Wave 1. There were six possible exposures that included losing property, the participant's home being destroyed, losing a pet, sustaining personal injury, and knowing someone who was injured or killed in the hurricane or its aftermath. Exposures were summed and ranged from 0-6.

Demographics

Demographics were collected by GfK upon entry into the Knowledge Panel and updated regularly. Education was dichotomized (less than Bachelor's degree = 0; Bachelor's degree or higher = 1). Age was continuous and ranged from 18 to 90 years old. Gender was dichotomized (male = 0; female = 1). Ethnicity was categorized into four categories: White/non-Hispanic, Black/non-Hispanic, other/non-Hispanic or 2+ races, and Hispanic, with White/non-Hispanic as the reference group. Income was measured as a continuous variable, grouped in 21 bins and further grouped into six categories: less than $10,000, $10,000 – $24,999, $25,000 – $49,999, $50,000 – $74,999, $75,000 – $99,999, and $100,000+.

Analytic Strategy

All statistics were conducted in Stata 18.0 (StataCorp, 2023) using Generalized Estimating Equations (GEE, Ballinger, 2004), a repeated measures approach. GEE coefficients represent the average population-level effect of predictors on outcome variables over time, accounting for the correlation between observations at different time points. Robust standard errors were estimated as appropriate for complex survey data. We conducted one GEE with Waves 1 and 2 and a second GEE with Waves 1, 2, and 3. Both were conducted using an identical analytic strategy. In Model 1, we examined the relationship between hours of hurricane-related media exposure and trust in that media and traumatic stress symptoms over time. In Model 2, we added an interaction term (hours of media exposure X trust in media exposure). All analyses controlled for demographic covariates, exposure to Hurricane Harvey, and time. Continuous variables were standardized to provide comparable effect sizes across predictors.

Results

See Table 1.1 for all weighted descriptive statistics. Adjusting for time, demographics, and Hurricane Harvey-related exposure to loss and injury, both hours of hurricane-related media exposure and trust in that media exposure were associated with traumatic stress responses (see Table 1.2, Model 1) over Waves 1 and 2. The interaction term between the amount of hurricane-related media exposure and trust in media was a statistically significant predictor of traumatic stress symptoms (β = -0.35, 95%CI [-0.58, -0.13], p = .002; see Table 1.2, Model 2), suggesting that trust in media exposure moderates the association between hours of media exposure and traumatic stress symptoms. As the amount of media exposure increased, respondents with higher trust in the media reported fewer traumatic stress symptoms than respondents reporting low trust in media (see Figure 1.1). At the lowest level of media exposure, trust did not appear to explain variability in the relationship between hours of hurricane-related media exposure and PTSS.

Table 1.1

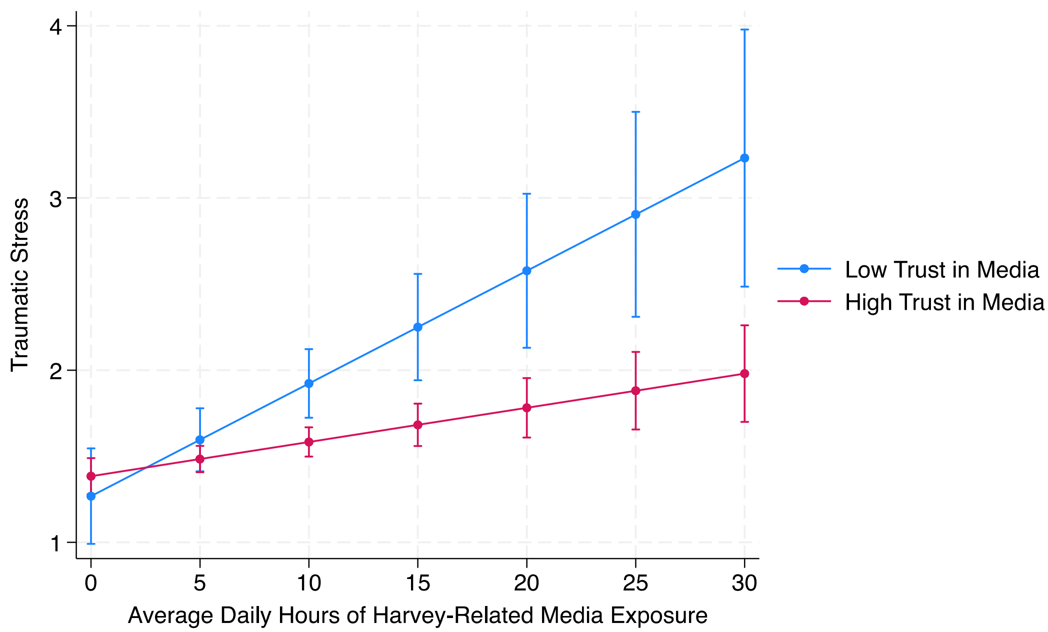
Weighted Descriptive Statistics for All Variables of Interest (N = 1,137)

Variable	***n***	**%**	**Mean (*SD*)**
Traumatic Stress Symptoms (Wave 1)			1.74 (0.82)
Traumatic Stress Symptoms (Wave 2)[a]			1.50 (0.74)
Traumatic Stress Symptoms (Wave 3)[b]			1.46 (0.72)
Media Exposure			8.43 (7.80)
Trust In Media			
Low Trust In Media	295	26.00	
High Trust In Media	842	74.00	
Harvey-Based Loss and Injury			0.30 (0.64)
Age			46.90 (16.77)
Income[c]			4.10 (1.57)
Education			
Less Than a Bachelor's Degree	819	72.00	
Bachelor's Degree or Higher	318	28.0	
Gender			
Male	529	46.50	
Female	608	53.50	
Race/Ethnicity			
White, non-Hispanic	556	48.90	
Black, non-Hispanic	136	12.00	
Other, non-Hispanic	58	5.10	
Hispanic	372	32.70	
2+ Races, non-Hispanic	15	1.30	

Note. [a]*N* = 1008. [b]*N = 748.* [c]Income measured as six incremental categories; a mean of 4.1 corresponds to $50,000-$74,999. All data were weighted to allow for population-based inferences.

Figure 1.1

Association Between Amount of Hurricane Harvey-Related Media Exposure and Traumatic Stress Symptoms as Moderated by Perceived Trust in Media Sources at 2- and 6-Weeks After Hurricane Harvey Made Landfall (N = 1,005)



To test if the pattern remained over time, we extended the GEE analyses to include the Wave 3 data (14 months after Hurricane Harvey's landfall, $N = 743$). These results replicated the early response findings adjusting for time, demographics, and Hurricane Harvey-related loss and injury. Both Wave 1 hours of hurricane-related media exposure and trust in that media exposure were associated with PTSS (see Table 1.3, Model 1) over time. The interaction between the amount of media exposure and trust in media on traumatic stress symptoms was also statistically significant ($\beta = -0.45$, 95%CI [-0.70, -0.19], $p = .001$; see Table 1.3, Model 2). These results indicate that the association between the amount of media exposure and PTSS is stronger when trust in media is low, even when assessing PTSS as far out as 14 months post-disaster event (see Figure 1.2).

Figure 1.2

Association Between Amount of Hurricane Harvey-Related Media Exposure and Traumatic Stress Symptoms as Moderated by Perceived Trust in Media Sources at 2-Weeks, 6-Weeks, and 14-Months After Hurricane Harvey Made Landfall (N = 743)

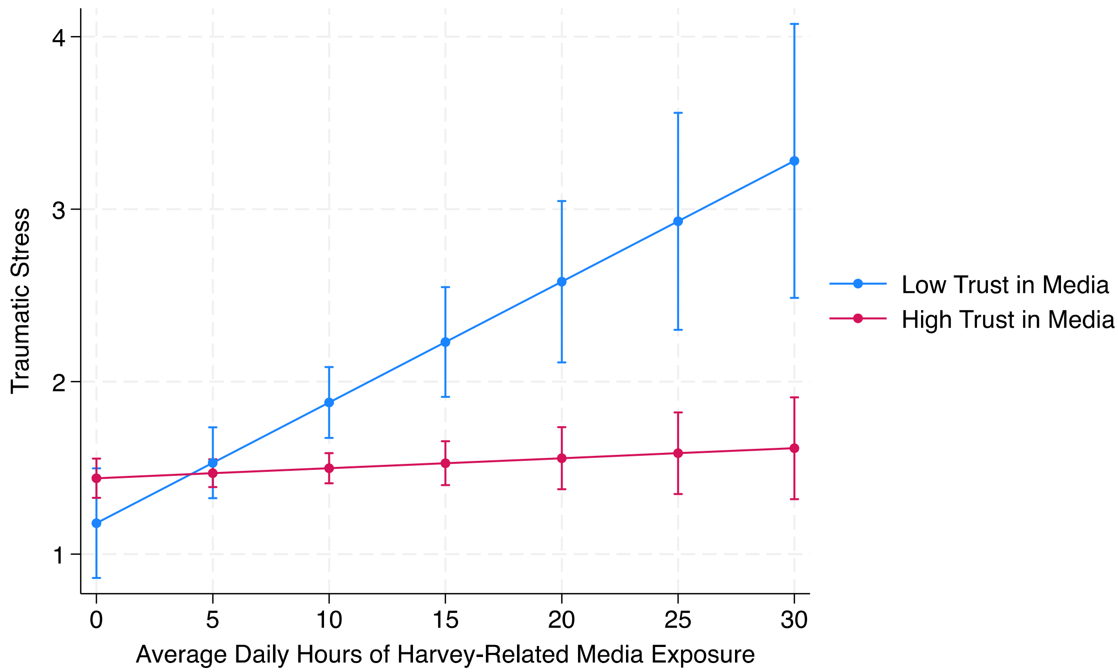


Table 1.2

Standardized, Weighted GEE Coefficients Examining the Relation Between Hours of Media Exposure and Trust in Hurricane-Related Media Exposure and Traumatic Stress Symptoms, Waves 1 and 2 (N = 1,005)

Variable	Model 1				Model 2			
	ß	***SE***	***p***	**95% CI**	***ß***	***SE***	***p***	**95% CI**
Media Exposure	0.34	0.06	0.000	0.23, 0.45	0.59	0.11	0.000	0.37, 0.82
Trust in Media[a]	-0.21	0.10	0.035	-0.40, -0.01	-0.20	0.09	0.027	-0.37, -0.02
Media Exposure X Trust in Media[a]	-	-	-	- -	-0.35	0.12	0.002	-0.58, -0.13
Harvey-Based Loss and Injury	0.32	0.04	0.000	0.24, 0.40	0.30	0.04	0.000	0.22, 0.39
Education[b]	-0.04	0.08	0.633	-0.19, 0.12	-0.04	0.08	0.580	-0.19, 0.11
Age	0.01	0.04	0.836	-0.06, 0.08	0.01	0.04	0.880	-0.07, 0.08
Income[c]	-0.05	0.04	0.242	-0.14, 0.03	-0.06	0.04	0.113	-0.14, 0.01
Gender[d]	0.09	0.08	0.293	-0.08, 0.25	0.10	0.08	0.206	-0.06, 0.26
Race/Ethnicity								
Black, non-Hispanic	0.03	0.12	0.787	-0.20, 0.27	0.05	0.12	0.677	-0.18, 0.28
Other, non-Hispanic, 2+ races	0.38	0.27	0.163	-0.15, 0.90	0.37	0.27	0.181	-0.17, 0.90
Hispanic	0.17	0.10	0.075	-0.02, 0.36	0.15	0.09	0.120	-0.04, 0.33
Time	0.00	0.04	0.985	-0.09, 0.09	0.00	0.04	0.985	-0.09, 0.09
Constant	0.08	0.34	0.821	-0.59, 0.75	0.08	0.34	0.812	-0.59, 0.75
Model Statistics	Wald $\chi^2(11) = 225.65$; $p < .001$				Wald $\chi^2(12) = 283.92$; $p < .001$			

[a]Low trust in media = 0, high trust in media = 1. [b]Reference group = less than a college degree. [c]Reference group = male. [d]Reference group = White, non-Hispanic. For graphing purposes, trust in media was dichotomized, but the interaction was also significant when conducted with trust in media as a continuous variable from 1-5.

Table 1.3

Standardized, Weighted GEE Coefficients Examining the Relationship Between Hours of Media Exposure and Trust in Hurricane-Related Media Exposure and Traumatic Stress Symptoms, Waves 1, 2, and 3 (N = 743)

Variable	Model 1				Model 2			
	ß	*SE*	*p*	95% CI	*ß*	*SE*	*p*	95% CI
Media Exposure	0.30	0.08	0.000	0.15, 0.45	0.60	0.14	0.000	0.33, 0.86
Trust in Media[a]	-0.25	0.12	0.035	-0.48, -0.02	-0.22	0.10	0.035	-0.42, -0.02
Media Exposure X Trust in Media[a]	-	-	-	- -	-0.45	0.13	0.001	-0.70, -0.19
Harvey-Based Loss and Injury	0.33	0.05	0.000	0.23, 0.42	0.31	0.05	0.000	0.21, 0.40
Education[b]	-0.10	0.08	0.191	-0.26, 0.05	-0.12	0.07	0.121	-0.26, 0.03
Age	-0.03	0.05	0.510	-0.12, 0.06	-0.03	0.04	0.452	-0.12, 0.05
Income[c]	-0.11	0.05	0.040	-0.22, -0.01	-0.13	0.04	0.005	-0.21, -0.04
Gender[d]	0.04	0.10	0.696	-0.15, 0.23	0.09	0.09	0.328	-0.09, 0.26
Race/Ethnicity								
Black, non-Hispanic	0.00	0.13	0.988	-0.26, 0.26	0.03	0.13	0.842	-0.23, 0.28
Other, non-Hispanic, 2+ races	0.16	0.18	0.379	-0.19, 0.51	0.15	0.17	0.387	-0.19, 0.49
Hispanic	0.11	0.12	0.344	-0.12, 0.34	0.07	0.11	0.511	-0.15, 0.29
Time	0.03	0.03	0.279	-0.03, 0.10	0.03	0.03	0.277	-0.03, 0.10
Constant	-0.07	0.28	0.814	-0.62, 0.48	-0.11	0.27	0.697	-0.64, 0.43
Model Statistics	Wald $\chi^2(11)$ =160.62; $p < .001$				Wald $\chi^2(12)$ = 261.16; $p < .001$			

Note. [a]Low trust in media = 0, high trust in media = 1. [b]Reference group = less than a college degree. [c]Reference group = male. [d]Reference group = White, non-Hispanic. For graphing purposes, trust in media was dichotomized, but the interaction was also significant when conducted with trust in media as a continuous variable from 1-5.

Discussion

Using a representative sample of Texas residents first assessed in the early aftermath of Hurricane Harvey, the relationship between disaster-related media exposure and traumatic stress responses over time is documented. These findings expand prior work on media exposure following disasters by highlighting the potentially protective role that perceived trust in media may play by buffering the association between disaster-related media exposure and traumatic stress symptoms. For participants with high trust in the Hurricane Harvey-related media they consumed, the relationship between average daily hours of Hurricane Harvey-related media exposure and traumatic stress symptoms was weaker than for those who reported low trust in their Hurricane Harvey-related media. These relationships were evident in the early aftermath of Hurricane Harvey and persisted over time. This suggests that in the context of coping with a disaster, both the amount (i.e., hours), as well as how much one trusts the media being consumed, are important considerations.

Understanding how to effectively communicate with the populace during natural disasters like hurricanes is critical, particularly in the context of the escalating climate crisis. Not only have hurricanes been increasing in frequency, intensity, and duration since the 1980s, but hurricane-associated storm intensity and rainfall rates are anticipated to continue increasing in the future (Walsh et al., 2014; Ting et al., 2019), exposing people to more potentially traumatic events annually. The rise in hurricane frequency may lead to repeated exposure to multiple hurricanes over time, raising concerns about their cumulative effects. Cumulative direct and indirect (i.e., through media) exposure to prior collective traumas, including mass violence and natural disaster events, is associated with stronger acute stress responses after a subsequent collective trauma (Garfin et al., 2015). It is possible that cumulative exposure to major hurricanes either multiple times within one hurricane season or over multiple seasons could follow a similar pattern such that experiencing multiple hurricanes may sensitize the individual to react more negatively to future hurricanes. How to communicate with the populace during these crises without instilling panic or increasing distress has been an increasing topic of interest in the public health sphere (Garfin et al., 2020).

Hurricane Harvey, like many major hurricanes, also created significant uncertainty for those in Texas. This may explain the relatively high average hours of media exposure (8.43 hours) reported by our sample at Wave 1. In the days prior to landfall, the probability of Hurricane Harvey hitting Texas went from low to near certain, and the category of the hurricane intensified to a Category 4 the evening before landfall (Metz, 2017). Even after the hurricane made landfall, it stalled over Texas, leading to relentless rains for days. In the context of disaster events where the situation often rapidly evolves, staying apprised of the disaster and its aftermath requires attention to the media. Thus, while limiting the amount of news consumed about a single event is typically a good idea (Holman et al., 2014; Hopwood & Schutte, 2017; Pfefferbaum et al., 2014), in the face of a severe hurricane and flooding, limiting news consumption is difficult and potentially dangerous. As previously demonstrated in other contexts and shown in this study, trust in media may serve a psychologically protective function (Lee, 2022; Patwary et al., 2021). In cases like this, it is vital that any news that is consumed, regardless of amount, can be strongly trusted by the individual. This study demonstrated that the trust an individual places in their news may be protective against traumatic stress symptoms; the emphasis in this study is on the individual trust, not the objective trustworthiness of the news source. However, guiding people toward validated and credible news sources that are trustworthy not only ensures their access to accurate, corroborated information but also promotes a sense of individual trust in their media in the midst of uncertainty and crisis. Prior research shows that when people are given honest, accurate information about their risk levels, even if the information is worrying, people can understand their risk well (Fischhoff et al., 2018). Within the framework of rapidly updated information and a changing risk landscape, these results suggest that trust in the information that is being given, even if it is at a high frequency, may be protective long term and may therefore be a key factor to preventing sustained psychological distress well after the event.

To increase people's trust in their disaster-related news, there needs to be an emphasis placed in trustworthy and verified news online. Trust in media has declined in the past two decades, with social media being reported as one of the lowest trusted institutions among a nationally representative sample even before the pandemic (Kavanagh et al., 2020). The inundation of mis- and disinformation, particularly within the online news sphere and on social media, has reached unprecedented levels during the COVID-19 pandemic (Chowdhury et al., 2023). Misinformation has specifically been shown to be an issue during and immediately after disasters on social media. Several factors seem to be associated with misinformation during a disaster, including anxiety in the absence of reliable information or an overload of information at one time (Muhammed & Mathew, 2022). To address this issue during a natural disaster, it is vital to emphasize the availability of reliable and verified news content.

In addition to highlighting reliable news sources, it is equally vital to educate the public on how to discern trustworthy sources for disaster-related information and identify mis- and disinformation for themselves. There has been a renewed interest in increasing media literacy, or the ability to critically analyze information from the media to determine its credibility, since the 2016 election in the United States (Bulger & Davison, 2018; Hobbs, 2019) and the rise of deepfakes (i.e., hyper-realistic videos that use artificial intelligence or AI to show someone saying or doing things that never happened; Westerlund, 2019). Drawing inspiration from the success of some northern European countries in teaching their citizens to navigate the complexities of information credibility online and, thus, increase media literacy (Bulger & Davison, 2018; Lessenski, 2019), it is apparent that this approach could empower individuals to make more informed choices when seeking information about a disaster. Not only would increasing media literacy and fostering trust in news sources contribute to a better-informed public in general, but it would likely help reduce traumatic stress following disasters as indicated by the present study. Investing in media literacy, promoting trust in credible news sources, and empowering individuals to recognize misinformation during natural disasters is not merely a matter of information access but crucial steps towards protecting against traumatic stress in the face of increasing rates of disaster events.

Limitations and Future Directions. Although this study has many strengths, notably its longitudinal design and representative sample, it is not without potential limitations. One is that our perceived trust in media variable is a single-item measure. Though the pattern of this single-item's relation with traumatic stress holds in our longitudinal analyses, future research should use a more robust assessment of trust in the media. This would allow future research to focus on the nuances of trust in media to understand how trust in distinct types of media (e.g., social media, television, radio) may impact psychological distress following a disaster. Moreover, future research should also assess the accuracy of the information being given about an event to quantify the objective trustworthiness of the media source, as objective trustworthiness could be differentially associated with traumatic stress when compared to subjective trustworthiness. As highlighted previously, this study focused on American media with an ostensibly free press, and therefore the results may not be relevant in the context of countries with different media operating conditions and regulatory environments. Future research outside the U.S. context might further investigate this issue. Additionally, this study utilized survey data over time, and therefore cannot make any causal inferences. Studies extending these findings using experimental designs for causal inference could be another fruitful area for future research.

Conclusion

This study highlights that perceived trust in disaster-related media moderates the relationship between media exposure and disaster-related traumatic stress symptoms in the short-term and over a year later. These findings suggest that trusting the media sources one uses may help mitigate the potential negative consequences of high-frequency media exposure to a natural disaster. Therefore, it is important to promote objectively trustworthy media sources by increasing media literacy and the ability to recognize misinformation to protect individuals from long-lasting psychological distress as natural disasters, such as hurricanes, become increasingly frequent and destructive.

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CHAPTER 2

Responding to an Imminent Threat: Risk Perceptions and Evacuation Decisions Before and After Hurricane Irma

Abstract

Existing research on decisions surrounding evacuation behaviors in advance of natural disasters typically rely on retrospective data and non-representative samples. Additionally, the literature presents inconsistent findings regarding the factors associated with evacuation behaviors. The current study surveyed a probability-based sample from Florida about several potential factors linked with evacuation behaviors in the days leading up to Hurricane Irma's landfall (N =1,478). Two Generalized Structural Equation Model mediation analyses (one with only participants who self-reported being in an evacuation zone, n = 706, and one with only those under evacuation orders based on residential address, n = 371) were conducted with binary evacuation behaviors (yes/no) as the endogenous outcome variable and real-time risk perceptions as the mediator. Nearly 40% of participants incorrectly reported being under evacuation orders. Though results are similar for both models, the Self-Report model has stronger ecological validity because it accounts for participants who were incorrect but still evacuated. In the Self-Report model, more pre-landfall Irma media exposure, lower income, and prior loss or injury due to a hurricane were directly associated with greater perceptions of risk about the hurricane. Higher risk perceptions, being younger, and having prior experience in an evacuation zone were directly linked with evacuating, while media, prior loss or injury, and income were indirectly associated with evacuating through risk perceptions. The use of a probability-based sample with real-time data collection bypasses the issue of recall bias, especially for subjective variables such as risk perceptions. Implications for the literature include an update to the models predicting evacuation behavior to include risk perceptions as a mediator, with media exposure in advance of a disaster being indirectly linked with evacuation behaviors. It is important that media depicting hurricane coverage conveys information that is transparent about the accuracy of current modeling

techniques, and this information is conveyed in a non-sensationalized manner to help people know when -- or when not -- to evacuate.

Introduction

Approaching hurricanes provide local populations with a limited but critical timeframe in which to prepare and respond, often with only a day or two of advanced warning. However, this urgency poses a significant barrier for researchers studying the decision-making processes relevant to evacuation behaviors. The relatively minimal time between hurricane formation and landfall creates logistical complications when attempting to secure funding, obtain Institutional Review Board (IRB) approval, and launch data collection in the potentially affected areas before landfall. Therefore, while communities may have the opportunity to enact emergency management plans, researchers often miss the opportunity to capture real-time pre-event data. In Thompson and colleagues' (2017) systematic review of 83 studies published between 1961 and 2016 regarding evacuation likelihood and behaviors surrounding natural disasters, only four studies were longitudinal and only two collected data prospectively. All other event-based studies that focused on a real hurricane instead of a hypothetical one were cross-sectional and measured responses within a few months to a year post-disaster event, potentially introducing substantial amounts of recall or memory bias into the data collected. Understanding pre-event factors that contribute to evacuating when under orders to do so is essential as proper adherence to evacuation orders can protect civilian and first responder lives (Karaye et al., 2022). This is especially true as severe natural disasters, such as hurricanes, have increased in frequency over time (NOAA National Centers for Environmental Information (NCEI), 2024).

Demographic Correlates

Much of the research on evacuations focuses on hypothetical future hurricane events, assessing the perceived likelihood (i.e., intention) of evacuating if that event were to occur, and most of the rest focuses on a real hurricane that has occurred. Though few studies have successfully captured pre-event data (see Kang et al., 2007; Murray-Tuite et al., 2012), most studies focusing on a real hurricane have examined evacuation behavior factors assessed only after the events. Several factors have been studied as potential correlates of evacuation decisions, though much of the findings in the literature are mixed (Thompson et al., 2017). Black participants tend to report a greater intent to evacuate during hypothetical future hurricanes, but they are less likely actually to evacuate during a real disaster (Thompson et al., 2017), marking an important distinction between intention and behavior in the evacuation literature. Moreover, many factors have mainly been studied in the context of either intention or behavior, not both. Therefore, the literature assessing both intention for future disasters and actual behaviors from past disasters must be used simultaneously when examining the current state of research. Being female or White is consistently associated with increased evacuation behaviors during an active threat (Thompson et al., 2017). Being younger is typically linked with a higher intention of evacuation (Lazo et al., 2015), though not always. For example, a study examining evacuation intentions in Florida found that older age was associated with higher intentions of evacuating in a hypothetical future hurricane in a high-risk county (Morss et al., 2016). Age seems to be associated, both positively and negatively, with evacuation intentions and behaviors. Some studies have found a positive link between higher education and evacuation intentions and behaviors (see Lachlan et al., 2009), while others reported a negative link (Thompson et al., 2017). Similarly, the associations between higher income and evacuation intentions and behaviors are positive in some studies (Elliott & Pais, 2006), negative in others (Dixit et al., 2008), or null (see Murray-Tuite et al., 2012).

Prior Experiences with Disasters

Results linking prior experience with a similar disaster and subsequent evacuation behaviors or intentions are also inconsistent. Many studies have found prior experiences with disasters to be negatively, positively, or not associated with future evacuation intentions and behaviors (Thompson et al., 2017). One reason for these inconsistent results may be due to the broad definition of prior disaster experiences. For example, Sharma and Patt (2012) identified three categories of past experiences that may play a role in individuals' evacuation decisions: severity of the past experience, past experiences with false alarms, and number of past evacuation behaviors. Assessing these factors may be more fruitful in determining if there is a robust association between evacuation behaviors and past evacuation experiences. Similarly, research on the role of prior property damage from a previous disaster and evacuation intentions and behaviors during another disaster is mixed (Thompson et al., 2017). One study found a link between property damage from prior wildfires and increased intentions to evacuate during hypothetical future wildfires (Mozumder et al., 2008). Another study found previous experience with property damage from hurricanes to be associated with decreased belief in the effectiveness of evacuation, ultimately resulting in lower intentions to evacuate in the future (Demuth et al., 2016). Previous evacuation behaviors themselves, however, are a robust predictor of future evacuations throughout the literature (see Murray-Tuite et al., 2012; Riad & Norris, 1998; Riad et al., 1999).

Media Characteristics

The connection between media exposure to information about an impending natural disaster and evacuation behaviors has yet to be well established. As part of a hypothetical hurricane study, viewing pictures of hurricane damage increased respondents' reports that they would be likely to evacuate (Burnside et al., 2007). The media (including both traditional and social media) has been reported to be a potential disaster warning source, and warning sources are linked with evacuation behaviors (Thompson et al., 2017). However, the content and amount of exposure to the media as a warning source have not been established as predictors of evacuation behaviors. Recent research on social media has found social media sites to play an essential role in the evacuation decision-making process. A study of New Jersey residents following Hurricane Sandy marked a change in the sources people reported using for information seeking during a natural disaster to include an increased use per participant of Twitter (now X) and Instagram during the evacuation period compared to normal conditions (Ferris et al., 2016). The limited literature suggests that media factors may be important as more minute-by-minute news updates become readily available through a variety of media sources in advance of a disaster. A robust connection between media use as the disaster unfolds and evacuation behaviors has yet to be established, however.

Media (both traditional and new media) has long played a role in educating members of the public about their risks within the context of all types of disasters (Paul & Dutt, 2010; Romo-Murphy & Vos, 2014). Historically, the media has served the role of informing community residents of impending collective traumas and educating the community about the resources available to them before and after an event (Lubens & Holman, 2017). Public health research shows that the public strongly endorses wanting honest, accurate information about collective events, even if the information worries them (Fischhoff et al., 2018). With accurate information being broadcasted as an event unfolds, people have a better chance to make relatively accurate risk assessments (Fischhoff et al., 2018). However, media coverage of hurricanes and other tropical cyclones has been criticized for a tendency to provide sensationalized stories, giving inaccurate information to community members (Anderson-Berry & King, 2005). A study conducted with the sample used in the present study found that a high amount of media exposure before Hurricane Irma made landfall was significantly related with psychological adjustment after the hurricane, suggesting that excessive media exposure may be associated with undue levels of stress before the storm (Thompson et al., 2019). The authors suggest that sensationalized reporting could be countered by ensuring appropriate levels of risk are communicated, which may address the significant relationship between media exposure and psychological adjustment over time (Thompson et al., 2019). Notably, hurricane landfall is notoriously difficult to predict, though (Mohanty & Gupta, 2008). Media that updates the public about impending hurricanes must be clear about the limitations of current hurricane modeling. In order for the media to function efficiently and provide the most benefit to the public in the context of natural disasters, information provided must inform, educate, and prepare the community without instigating unnecessary panic (Lubens & Holman, 2017). Moreover, media exposure has been shown to be correlated with risk perceptions in other collective trauma contexts such as public health (see Garfin et al., 2022), but this connection has not been established in the context of impending hurricanes. Nonetheless, the same relationship would likely be present.

Risk Perceptions

Perceptions of risk regarding natural disasters, however, have been frequently assessed as a potential predictor of evacuation behaviors (Thompson et al., 2017). Risks must be perceived for warnings about impending natural disasters and potential evacuation orders to be effective. That is, higher risk perceptions tend to be associated with more evacuation intentions and behaviors (Dash & Gladwin, 2007). Subjective perceptions of risk have been robustly correlated with evacuation intentions and behaviors regarding future or past hurricanes (see Carnegie & Deka, 2010; R. Stein et al., 2013; R. M. Stein et al., 2010). Risk perceptions are rarely studied as a mediator of evacuation behaviors and any of the established or debated factors previously discussed; though in their review of the evacuation literature, Thompson and colleagues (2017) suggest this be tested empirically. The predictors of hurricane-based risk perceptions are similarly uncertain. Among the limited research that has examined risk perceptions as a mediator of evacuations, factors such as the hurricane's category at landfall (Villegas et al., 2013) and gender, with women evacuating more than men (Bateman & Edwards, 2002), have been found to predict risk perceptions that, in turn, predict evacuation behaviors. Demuth and colleagues (2016) conducted a study that used a hypothetical hurricane scenario and surveyed coastal residents in one Florida county outside of hurricane season. In this study, researchers tested the mediation effect of two aspects of risk perceptions (cognitive and affective) on evacuation intentions and found a significant indirect effect between past hurricane experiences (i.e., severity of impacts, financial loss, and prior evacuation behaviors) and evacuation intentions through risk perceptions. While these studies provide a strong foundation to the research examining risk perceptions as a possible mechanism to explain the relationships between evacuation behaviors and the predictors previously discussed in the evacuation literature, it is imperative that risk perceptions be studied in the context of a real, impending natural disaster.

Evacuation Decision Making

Many people choose to stay in their home and not evacuate while under evacuation orders, and several studies have examined this phenomenon. In multiple studies, the presence of pets in the house or livestock under a participant's care was cited as a top reason for not evacuating (Heath et al., 2001; Thompson et al., 2017). Another common reason was the presence of a household member with a disability (Van Willigen et al., 2002). Other reasons for not evacuating that have been established include concern for the safety of one's belongings (Aguirre, 1991) or a need to protect one's home (Riad et al., 1999), concerns about traffic issues (Dow & Cutter, 1998), and a belief that the participant could "ride out the storm" (Smith & McCarty, 2009). We need to continue exploring why people do not evacuate using representative samples since understanding decision-making can help the media inform and educate people who are resistant.

Limitations of Prior Research

A prevailing limitation in the natural disaster literature is the reliance on retrospective data collection. Most natural disaster studies, as described by Thompson and colleagues (2017), collect data weeks, months, or even years post-disaster, relying on participants to recall their emotions and thought processes prior to an evacuation decision. For example, Goodie and colleagues (2019) studied Hurricane Irma, but the researchers utilized an online, non-representative sample and assessed the participants three months post-landfall. Retrospective reports are susceptible to biases due to situational factors (Loftus et al., 1978) and the deterioration of recall accuracy over time (Schmolck et al., 2000). This methodological flaw raises concerns about the reliability of findings derived from such studies and may contribute to some of the mixed findings prevalent in the literature. While there are a handful of studies (see Kang et al., 2007) that collected data prior to a disaster, these studies largely lack generalizability due to the absence of the use of representative samples (Thompson et al., 2017). These two limitations restrict efforts to formulate universally effective evacuation strategies or suggestions for policymakers. The present study addresses these limitations by surveying a probability-based sample of Floridians in the period between the formation and landfall of Hurricane Irma, allowing for real-time pre-event data collection.

The Present Study

In September 2017, Hurricane Irma, classified as a Category 5 hurricane initially, made its way toward Florida's mainland. Before landfall, it reached maximum sustained winds higher than any Atlantic hurricane recorded in over a decade (Feng & Lin, 2021). By the time Hurricane Irma made landfall in Florida, it had weakened to a Category 3 storm, but it triggered one of the largest evacuation efforts in the state's history (Wong et al., 2018). Mandatory evacuation orders were issued for 6.5 million people, with numerous others recommended for voluntary evacuation, resulting in approximately 4 million vehicles being used in the evacuation process (Feng & Lin, 2021). This study used real time pre-landfall data collected as Hurricane Irma was approaching Florida residents to understand the factors associated with their decision to evacuate or not when under real or perceived evacuation orders. Specifically, we sought to understand theoretically and empirically derived factors (e.g., prior experiences, media exposure, demographics) that were associated with pre-landfall hurricane-specific risk perceptions. We also sought to examine risk perceptions as a mediator between pre-landfall survey responses and evacuation behaviors measured after the hurricane passed. We had four hypotheses based on these aims.

Hypotheses Regarding Direct Associations

Hypothesis 1. Identifying as female, prior loss or injury due to a hurricane, and consuming higher amounts of Hurricane Irma-based media in advance of landfall would be directly associated with higher pre-hurricane risk perceptions.

Hypothesis 2. Identifying as female or White, non-Hispanic, being younger, having evacuation zone experience during prior disasters, and having higher risk perceptions would be associated with evacuating. We expected that media exposure prior to landfall would be associated with evacuation behaviors, but the direction was not hypothesized.

Hypotheses Regarding Indirect Associations

Hypothesis 3: Risk perceptions were expected to mediate pre-hurricane media exposure and evacuation behaviors, such that higher media exposure was expected to be associated with greater odds of evacuating, and this was expected to be mediated by higher risk perceptions.

Hypothesis 4: Risk perceptions were expected to mediate both demographics and prior hurricane experiences with evacuation behaviors, but the direction was not hypothesized.

Methods

Sampling and Design

Respondents for this study were drawn from the GfK KnowledgePanel. At the time of data collection, GfK was a survey research organization that used address-based probability sampling methods to randomly recruit people into their online research panel, which was designed to be representative of the United States. Households without Internet connection were provided with Internet access; those who were web-enabled received points for merchandise. Upon entry to the KnowledgePanel, respondents completed a baseline survey that assessed demographic information. Once recruited, panelists were periodically assigned to a sample and were electronically notified of opportunities to take part in confidential online surveys through an email link or their online panel member page. All eligible GfK panelists who resided in Florida were invited to participate in Wave 1 of this study as Hurricane Irma was projected to make landfall in the United States within days (N = 2,873). In total, 1,637 Florida residents (56.98% participation rate) completed the survey in the 60 hours between when the survey began (9/8/17 at 6PM EDT) and closed (9/11/17 at 6PM). (Hurricane Irma first made landfall in the Florida Keys on 9/10/17 around 3PM EDT.) A majority of the participants (95%) completed the Wave 1 survey within the first 48 hours. Panelists who completed the first online survey (Wave

1) received the equivalent of $20 in compensation.

The Wave 2 survey was fielded to all Wave 1 participants along with 40 additional Florida residents who were involved in a prior longitudinal study conducted by the research team (*n* = 1,723; Holman et al., 2014). In total, 1,518 respondents completed the survey during the fielding period one month later (10/12/17 – 10/29/17; 87.90% participation rate; 90.23% retention from Wave 1). The Institutional Review Board of the University of California, Irvine, approved all procedures prior to Wave 1 data collection and all participants provided informed consent.

Measures

Post-Irma Evacuation Behavior. At Wave 2, participants were asked if they had evacuated their home during Hurricane Irma. If they did not evacuate, they had the option to indicate that they did not reside in an evacuation zone. Responses were then coded as follows: 0 equaled not in an evacuation zone; 1 equaled in an evacuation zone and evacuated; 2 equaled in an evacuation zone but did not evacuate.

Geographic Information System (GIS)-Based Evacuation Zones. Residential latitude and longitude were collected on each participant, which were then randomly shifted 100-2000 feet to protect respondent privacy. The shifted latitude and longitude were then entered in ArcGIS (a spatial software) and were mapped onto Florida's evacuation zones (*ArcGIS Online*, 2019; *Know Your Zone*, n.d.). Based off this map, participants were then assigned a dummy code for objective, GIS-based evacuation zones (0 equaled not under evacuation orders, 1 equaled under evacuation orders).

Risk Perceptions. Participants indicated the percent chance that four events would occur (where 0% equaled the event will absolutely not happen and 100% equaled the event is certain to happen) at Wave 1: (1) “your home will be severely damaged or destroyed because of the hurricane or its aftermath,” (2) “you will never be able to return to your current home as a result of the hurricane or its aftermath,” (3) “you will be seriously injured by the hurricane or its aftermath,” and (4) “someone close to you will be seriously injured by the hurricane or its aftermath.” A composite risk perception score was calculated as the mean of the four responses, with Cronbach’s $\alpha = .76$ (Fischhoff et al., 2018).

Prior Hurricane Experiences: At Wave 1, participants’ prior hurricane experiences were assessed by asking “Which of the following describes your experiences with previous hurricanes and their aftermath?” From the responses, we created two variables:

Prior Hurricane Evacuation Experiences. Four response options comprised the prior evacuation experiences variable. Participants could mark all that applied from (1) “I was in an evacuation zone and evacuated,” (2) “I was in an evacuation zone, but chose not to evacuate,” (3) “I was in an evacuation zone, but was unable to evacuate,” and (4) “None of these describe my experiences with previous hurricane(s).” These responses were recoded and dichotomized such that 0 indicated no prior experiences and 1 indicated at least one prior experience.

Prior Loss or Injury from a Hurricane. Six response options comprised the prior loss or injury variable. Participants would mark all that applied. The response options included (1) “I lost property in a hurricane or its aftermath,” (2) “My home was totally destroyed in a hurricane or its aftermath,” (3) “I was injured in a hurricane or its aftermath,” (4) “I lost a pet in a hurricane or its aftermath,” (5) “I knew someone who was injured in a hurricane or its aftermath,” and (6) “I knew someone who was killed in a hurricane or its aftermath.” Responses were recoded and dichotomized as 1 if participants indicated they had experienced any prior loss or injury, and with a 0 if they did not.

Hurricane Irma Media Exposure. At Wave 1, participants indicated how many hours per day, on average, since coverage of Hurricane Irma began that they had spent watching and/or listening to coverage on three media types: (1) traditional media (TV, radio, print news), (2) online news source (CNN, Yahoo, NYTimes.com, etc.), and (3) social media (Facebook, Twitter, Reddit, etc.). For each media type, they could select between 0 and 11+ hours per day. The sum was taken for all three media types for a total daily average exposure score. The range is 0 – 33 hours; the daily average exposure can be beyond the 24 hours in a day since participants could have been consuming media on one device (e.g., through online news or social media) while simultaneously watching, reading or listening to news on another device.

Demographics. GfK collected participant demographic information upon entry to the KnowledgePanel (age, gender, race/ethnicity, income, education) and updated it regularly. Due to small sample sizes of minoritized races and ethnicities in the sample, race and ethnicity were combined and dichotomized (0 = White, non-Hispanic; 1 = People of Color).

Reasons for Not Evacuating. At Wave 2, participants who reported not evacuating were asked to indicate their reasoning for their decision. They could mark all that applied from the following response options: "Because I didn't live in an evacuation zone," "Because I didn't have anywhere to go," "Because I had pets I couldn't take with me," "Because I wanted to take care of my home," "Because I – or someone else I live with – is disabled," "I didn't leave my home for another reason," and "I didn't evacuate but wish I had done so." Frequencies were reported for individual response options.

Population Weights. At Wave 2, post-stratification weights were iteratively constructed from respondents' design weights using probability estimates based on multiple demographic characteristics (gender, age, race/ethnicity, household income, metro/non-metro area, and education), region of residence, and Internet access. These weights adjusted for sample attrition as well as discrepancies between the final obtained sample and U.S. Census benchmarks for Florida, to enable population-based inferences. The final weighted sample closely matched the 2015 U.S. Census data for Florida.

Analytic Strategy. Descriptive statistics were conducted on the full sample using Wave 2 population weights, when appropriate. All analyses were conducted using STATA 18 software (StataCorp, 2023). A multinomial logistic regression was conducted to examine if Wave 1 variables were associated with correctly or incorrectly reporting one's evacuation zone status. Standardized results were reported in which all continuous variables were standardized before being entered into the model.

Two identical Generalized Structural Equation Model (GSEM) analyses were then conducted on two sub-samples without population weights as weights were provided for the full sample only. Model 1 used the subsample of people who, when assessed at Wave 2, self-reported being in an evacuation zone during the Hurricane Irma weekend. Participants who answered "did not evacuate" were removed to create the subsample; the reference group included participants who did not evacuate, and the group of interest in the model was participants who did evacuate. This model will be referred to as the "Self-Report" evacuation zone model throughout this paper. Model 2 used the subsample of people who were objectively in an evacuation zone by the time Hurricane Irma made landfall using shifted latitude and longitude data in conjunction with the official Florida evacuation zones (*Know Your Zone*, n.d.). This model only relied on participants' residential latitude and longitude, so participants who were not objectively in an evacuation zone during the emergency were removed from the sample to create the subsample. This model will be referred to as the "GIS" evacuation zone model throughout this paper. Both models tested the direct, indirect, and total effects of the mediation of risk perceptions on the exogenous predictors (i.e., demographics, past hurricane experiences, and media exposure) and evacuation behavior as the endogenous outcome variable**.** The outcome variable was dichotomous (i.e., did not evacuate or did evacuate), so the model was estimated using generalized structural equation modeling to allow for a binary endogenous variable. Due to the dichotomous nature of the evacuation behaviors variable and the continuous nature of the risk perceptions composite, the appropriate family and link were defined for each equation in the models. This method allowed for multiple equations (e.g., testing the direct associations of the predictors with risk perceptions for the first equation and the direct associations of the predictors and risk perceptions with evacuation behavior for the second equation) while also allowing for indirect pathways to be examined using risk perceptions as the mediator. GSEM results were reported as unstandardized and standardized in which all continuous variables were standardized before being entered into the model. Attrition analyses were conducted for the analyses in which population weights were not used due to the subsample chosen. Population weights accounted for sample attrition for statistics provided on the full sample.

Results

Descriptive Statistics

The final weighted sample (*N* = 1,478) was majority female (55.36%), majority white (62.06%) and Hispanic (21.64%); 11.50% of the sample was Black, non-Hispanic, and the remaining 4.80% of the sample reported being a different non-Hispanic race or multiracial. A minority (29.32%) of the sample had a Bachelor’s degree or higher. The average age was 51.70 (*SE* = .69, range = 18-91) with an average income between $25,000 and $49,999 (income was measured on a 1-6 ordinal scale beginning with less than $10,000, followed by $10,000 –

$24,999, then increasing by $24,999 for each category; response option 6 was $100,000+; mean income using this scale was 3.92, *SE* = .06). At Wave 1, participants reported spending an average of 7.88 (SE = .30) hours daily consuming Hurricane Irma media and reported on average a 16% chance of experiencing damage or personal injury due to the hurricane. A majority of the sample did not have prior experience living in an evacuation zone during a hurricane (76.08%) nor had they experienced hurricane-related loss or injury (81.40%). Only a portion of the weighted sample was ever under evacuation orders during Hurricane Irma based on GIS data (21.87%; $n_{unweighted}$ = 398 participants), while half of the weighted sample reported being under evacuation orders during Hurricane Irma (49.93%; $n_{unweighted}$ = 746 participants).

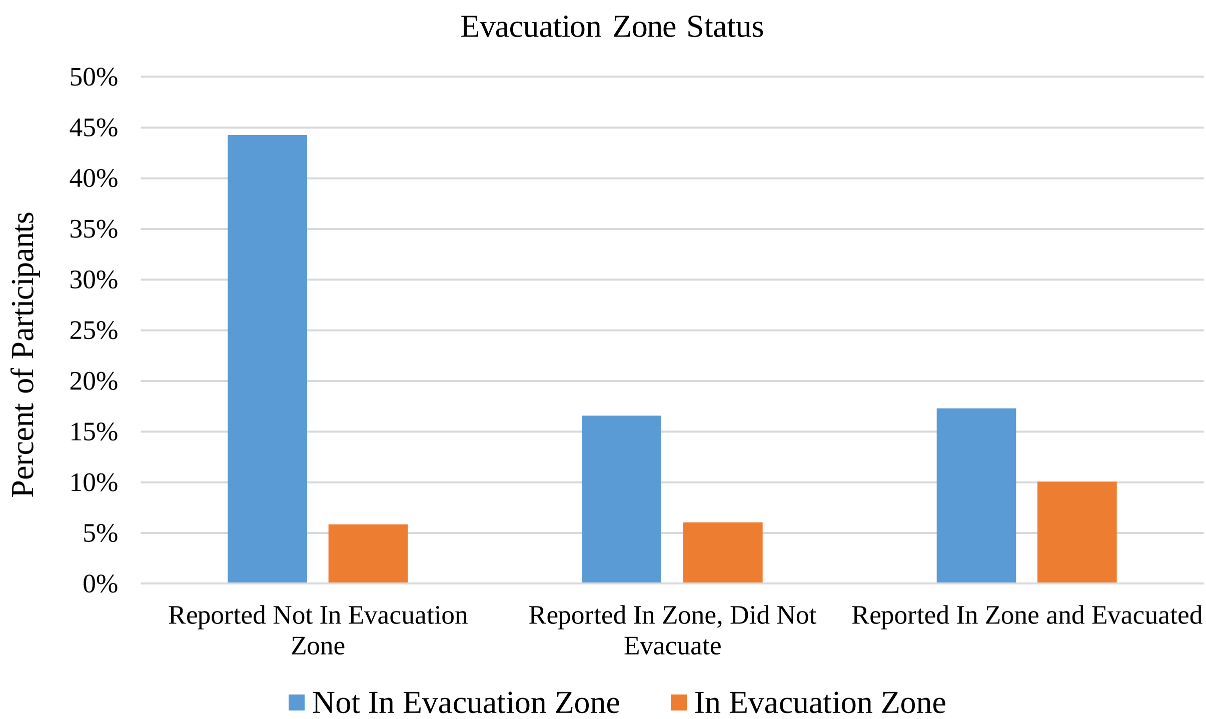
Between Waves 1 and 2, 159 participants left the study (retention rate = 90.23%). Attrition analyses found that younger people were more likely to drop out than older people ($t(1635) = 5.79$, $p < .001$). Additionally, race and ethnicity differed such that People of Color were more likely to leave the study than White people ($t(1635) = -2.38$, $p = .02$). No other variable of interest was significantly different between participants who participated in both waves of data collection and those who did not, including risk perceptions, media exposure, and prior experiences with hurricanes.

Evacuation Status Accuracy and Reasons for Staying Behind

Weighted percentages were examined of the Wave 2 sample that incorrectly reported their evacuation zone status (i.e., if they were under orders to evacuate at any time during the Hurricane Irma emergency) and compared these responses to the GIS-based data (see Figure 2.1). A total of 5.84% of participants reported not being under evacuation orders but actually were (i.e., unaware), while 33.85% of the sample reported being under evacuation orders while but never were (e.g., false alarm). Of these participants who incorrectly reported being under evacuation orders, just over half (51.07%) evacuated their homes (i.e., shadow evacuation). Participants who self-reported not evacuating when asked at Wave 2 indicated their reasoning for deciding to stay at their residence (Figure 2.2).

Figure 2.1

Percent of Respondents' Self-Report and GIS-Based Evacuation Zone Status Using Population Weights (N = 1,475)

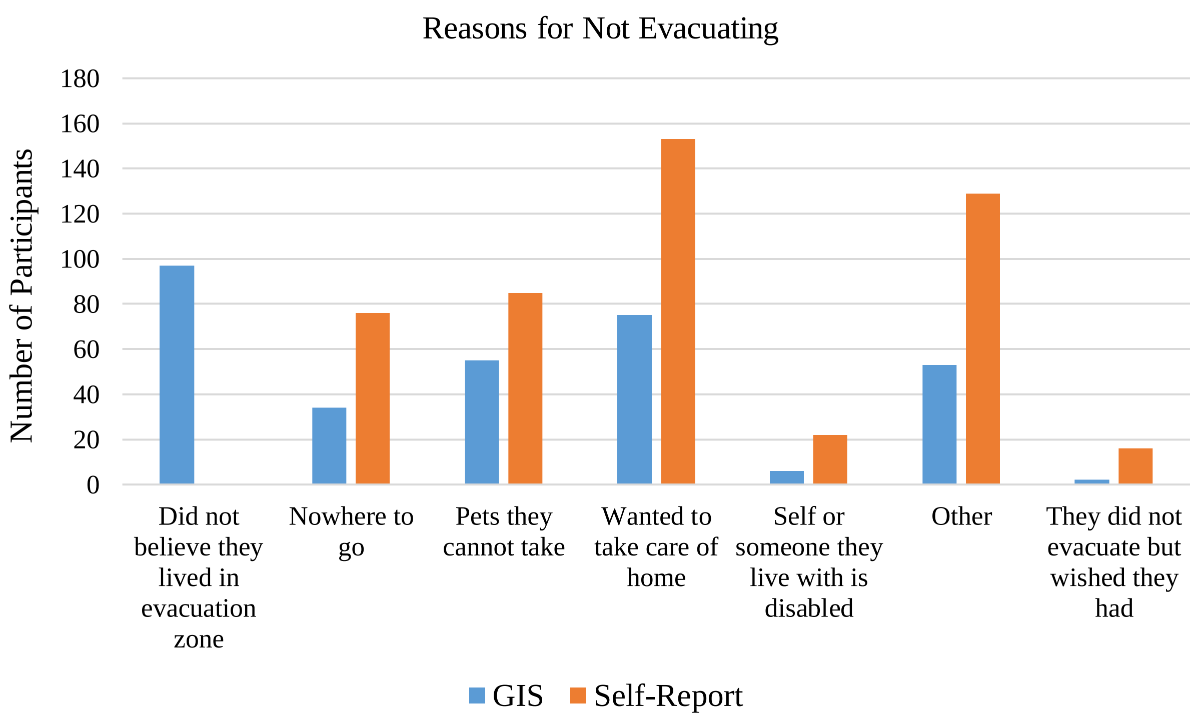


Note. GIS-based evacuation zone status is indicated by the color of the bars. Self-reported evacuation status is indicated on the x-axis.

A multinomial logistic regression analysis was conducted to determine if any variables were associated with correctly or incorrectly reporting one's evacuation zone status in one of three ways (i.e., unaware of being under evacuation orders, false alarm but did not evacuate, and shadow evacuations). Compared to the group of participants who correctly assessed their evacuation orders as a whole, participants in the group that incorrectly reported being under evacuation orders and evacuated (i.e., shadow evacuations) had higher risk perceptions (OR = 1.27, p = .001, 95%CI [1.09, 1.45]). The same group was also significantly more likely to be younger (OR = .84, p = .03, 95%CI [.71, .97]). No other statistically significant results for this model were found.

Figure 2.2

Reported Reasons for Deciding to Not Evacuate (Measured at Wave 2; n_{GIS} = 197; $n_{self\text{-}report}$ = 323)



Note. Only participants who did not evacuate when asked at Wave 2 were included in this figure. The GIS subsample, indicated by the color of the bars, included only participants who were under evacuation orders based on residential addresses and self-reported that they did not evacuate. The Self-Report subsample, indicated on the x-axis, included only participants who self-reported being in an evacuation zone and not evacuating.

GSEM Results with Self-Reported Evacuation Status Subsample

The Self-Report evacuation zone GSEM model tested the potential mediation of risk perceptions on the relationships between prior experiences, media exposure, and demographics (as exogenous predictors) and evacuation behavior (as a dichotomous endogenous outcome), using all participants who self-reported being under evacuation orders during the Hurricane Irma event when measured at Wave 2, regardless of if they actually had evacuation orders. There were two equations analyzed simultaneously: First, the predictors of risk perception were measured. Results indicated that prior loss or injury due to a similar disaster ($\beta = .26$, $p = .003$, 95% CI [.09, .43]), higher amounts of Hurricane Irma-based media ($\beta = .22$, $p = .01$, 95% CI [.15, .29]), and reporting lower income ($\beta = -.11$, $p = .005$, 95% CI[-.19, -.03]) were associated with higher Wave 1 risk perceptions (see Table 2.2). Second, the predictors of being in the group that evacuated were analyzed including the exogenous predictor and mediator variables. Higher risk perceptions were again associated with a higher likelihood of being in the group that evacuated (OR = 1.46, $p < .001$, 95% CI [1.22, 1.73]), as well as among those who had previously experienced evacuation orders during a previous storm (OR = 1.62, $p = .004$, 95% CI [1.17, 2.24]). Older participants were less likely to be in the group that evacuated (OR = .79, $p = .008$, 95% CI [.67, .94]).

Risk perceptions acted as a mediator between three pre-landfall variables and evacuation behaviors. Specifically, having experienced a prior loss or injury due to a previous hurricane or its aftermath (OR = 1.10, $p = .02$, 95% CI [1.02, 1.19]) and higher amounts of media consumed before the storm (OR = 1.09, $p = .001$, 95% CI [1.03, 1.14]) were associated with a higher odds of being in the group that evacuated, mediated through risk perceptions. In addition, higher income was indirectly associated with evacuating such that the higher income participants reported, the less likely they were to be in the group that evacuated, mediated through lower risk perceptions (OR = .96, p = .02, 95% CI [.93, .99]).

Stata 18 only provides Akaike Information Criterion (AIC; Akaike, 1974) and Bayesian Information Criterion (BIC; Raftery, 1995) values as model fit statistics when conducting GSEM analyses. For this model, AIC = 2,889.69 and BIC = 2,980.88. In an attempt to gain an imperfect sense of variance explained by the model, I ran the model using the regular *sem* command, which assumes linearity of the outcome variable, to estimate the coefficient of determination (CD). The CD is essentially the percentage of variance in the outcome explained by the model. In this model, the CD equaled 0.12, so the variance explained in evacuation behavior by this model is about 12%.

GSEM Results with GIS-Based Subsample

The GIS-based GSEM model tested the potential mediation of risk perceptions on prior experiences, media exposure, and demographics as exogenous predictors and evacuation behavior as a dichotomous endogenous outcome, using the GIS-based subsample of participants that truly resided in an evacuation zone. There were two equations analyzed simultaneously: First, the predictors of risk perception were analyzed. Results showed that consuming more Hurricane Irma-based media (β = .14, p = .01, 95% CI [.04, .24]) and reporting lower income (β = -.11, p = .04, 95% CI [-.22, -.01]) were associated with increased risk perceptions (see Table 2.2 for all results). Second, the predictors of being in the group that evacuated were analyzed including the exogenous predictor and mediator variables. Higher risk perceptions were also significantly associated with being in the group that evacuated (OR = 1.75, p < .001, 95% CI [1.35, 2.26]), as was having prior experience being in an evacuation zone (OR = 2.63, p <.001, 95% CI [1.66, 4.17]). There was one significant indirect effect between more media exposure to the hurricane coverage and evacuating, mediated through higher risk perceptions (OR = 1.08, p =

.02, 95% CI [1.01, 1.15]). In other words, more media exposure was associated with higher risk perceptions and higher odds of evacuating, making media exposure indirectly associated with evacuation behavior. Again, Stata 18 only provided AIC and BIC values for this model (AIC = 1495.03; BIC = 1573.35). The imperfect CD = 0.13, so the variance explained in evacuation behavior by this model is about 13%.

Table 2.1

Self-Report Model: GSEM Results Examining Risk Perceptions as a Mediator on Evacuation Behavior (N = 706; n_{no_evac} = 323, n_{yes_evac} = 423)

Direct Associations with Risk Perceptions	b^a	β	*SE*	*p*	95% CI
Prior Evacuation Zone Experience	1.95	0.12	0.08	0.11	-0.03, 0.27
Prior Loss or Injury	4.29	0.26	0.09	0.00	0.09, 0.43
Irma Media Exposure	0.54	0.22	0.04	0.00	0.15, 0.29
Gender	1.01	0.06	0.08	0.41	-0.09, 0.21
Race/Ethnicity	-1.18	-0.07	0.10	0.46	-0.26, 0.12
Education	-0.54	-0.03	0.08	0.68	-0.19, 0.12
Age	-0.01	-0.01	0.04	0.82	-0.09, 0.07
Income	-1.23	-0.11	0.04	0.01	-0.19, -0.03
Constant	17.27	-0.11	0.08	0.18	-0.26, 0.05
Direct Associations with Evacuation Behavior	OR[a]	OR	*SE*	*p*	95% CI
Risk Perceptions *(mediator)*	1.02	1.46	0.13	0.00	1.22, 1.73
Prior Evacuation Zone Experience	1.62	1.62	0.27	0.00	1.17, 2.24
Prior Loss or Injury	0.97	0.97	0.19	0.87	0.66, 1.42
Irma Media Exposure	1.01	1.03	0.09	0.69	0.88, 1.22
Gender	1.25	1.25	0.21	0.17	0.91, 1.73
Race/Ethnicity	0.67	0.67	0.14	0.06	0.44, 1.02
Education	1.10	1.10	0.19	0.60	0.78, 1.54
Age	0.99	0.79	0.07	0.01	0.67, 0.94
Income	0.95	0.93	0.08	0.43	0.79, 1.11
Constant	1.88	1.01	0.18	0.98	0.71, 1.42
Variance (e.Risk Perception)	241.30	0.90	0.05		0.81, 1.00
Indirect Associations	OR[a]	OR	*SE*	*p*	95% CI
Prior Loss → Risk Perception → Evacuation Behavior	1.10	1.10	0.04	0.02	1.02, 1.19
Irma Media → Risk Perceptions → Evacuation Behavior	1.01	1.09	0.03	0.00	1.03, 1.14
Income → Risk Perceptions → Evacuation Behavior	0.97	0.96	0.02	0.02	0.93, 0.99

Note. [a]Unstandardized results column. Evacuation behavior reference group = did not evacuate.

Prior evacuation zone experience reference group = no experience. Prior loss or injury reference group = no loss or injury. Gender reference group = male. Race/Ethnicity reference group = White, non-Hispanic. Education reference group = less than a Bachelor's degree.

Table 2.2

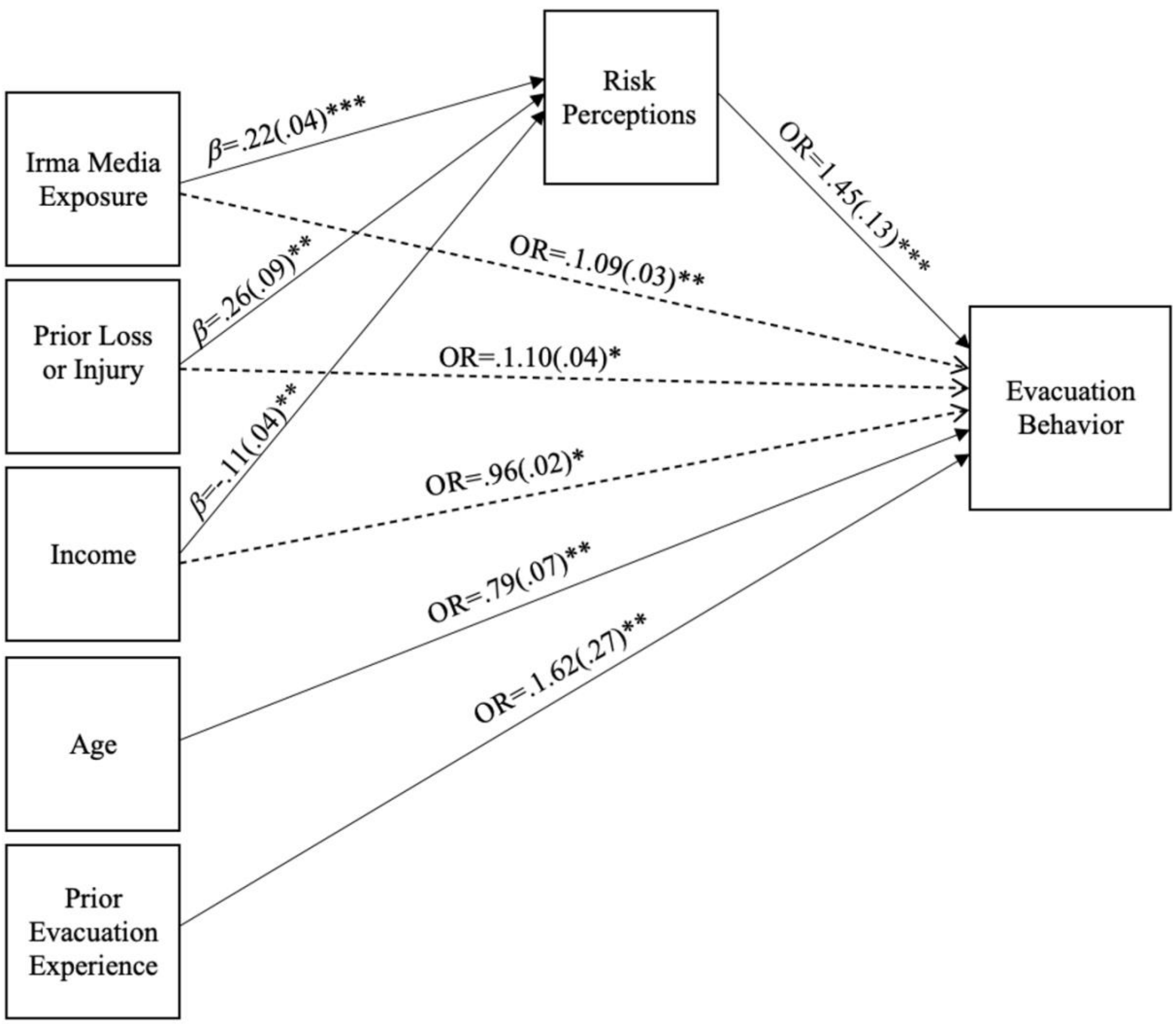
GIS-Based Model: GSEM Results Examining Risk Perceptions as a Mediator on Evacuation Behavior (N = 349; n_{no_evac} *= 197;* n_{yes_evac} *= 175)*

Direct Associations with Risk Perceptions	*b*[a]	*β*	*SE*	*p*	95% CI
Prior Evacuation Zone Experience	1.68	0.10	0.10	0.31	-0.10, 0.30
Prior Loss or Injury	4.04	0.25	0.13	0.07	-0.02, 0.51
Irma Media Exposure	0.38	0.14	0.05	0.01	0.04, 0.24
Gender	3.25	0.20	0.11	0.06	-0.01, 0.40
Race/Ethnicity	-0.41	-0.03	0.15	0.86	-0.31, 0.26
Education	-2.69	-0.16	0.11	0.14	-0.38, 0.05
Age	0.01	0.00	0.05	0.93	-0.10, 0.11
Income	-1.27	-0.11	0.06	0.04	-0.22, -0.01
Constant	17.79	-0.12	0.12	0.30	-0.35, 0.11
Direct Associations with Evacuation Behavior	OR[a]	OR	*SE*	*p*	95% CI
Risk Perceptions *(mediator)*	1.03	1.75	0.23	0.00	1.35, 2.26
Prior Evacuation Zone Experience	2.63	2.63	0.62	0.00	1.66, 4.17
Prior Loss or Injury	0.86	0.86	0.27	0.64	0.47, 1.59
Irma Media Exposure	1.01	1.04	0.12	0.75	0.82, 1.31
Gender	1.53	1.53	0.38	0.08	0.95, 2.48
Race/Ethnicity	0.78	0.78	0.27	0.47	0.39, 1.54
Education	1.31	1.31	0.34	0.30	0.79, 2.18
Age	0.99	0.84	0.10	0.17	0.66, 1.07
Income	0.93	0.90	0.12	0.43	0.70, 1.17
Constant	0.59	0.41	0.11	0.00	0.24, 0.70
Variance (e.Risk Perception)	248.87	0.92	0.07		0.80, 1.06
Indirect Associations	OR[a]	OR	*SE*	*p*	95% CI
Irma Media → Risk Perceptions → Evacuation Behavior	1.01	1.08	0.04	0.02	1.01, 1.15

Note. [a]Unstandardized results column. Evacuation behavior reference group = did not evacuate. Prior evacuation zone experience reference group = no experience. Prior loss or injury reference group = no prior loss or injury. Gender reference group = male. Race/Ethnicity reference group = White, non-Hispanic. Education reference group = less than a Bachelor’s degree.

Figure 2.3

Final GSEM Model Showing Significant Direct and Indirect Pathways for the Self-Report Subsample (N = 706)



Note. Only significant pathways shown. Solid lines represent direct associations; doted lines represent indirect associations. All odds ratios are standardized. Prior evacuation experience reference group = no experience. Prior loss or injury reference group = no loss or injury. Evacuation behavior reference group = did not evacuate.

Discussion

Using a probability-based sample of Florida residents in conjunction with location-based data, we assessed the percentage of the population that correctly reported their evacuation zone status as a major hurricane was approaching the state. About 6% of the weighted sample were unaware of being under evacuation orders. Though this is a relatively small proportion, it is nonetheless concerning, especially when applied to the total population of the state. Perhaps more concerning, almost 34% of the sample incorrectly reported being under evacuation orders. While these participants were erring on the side of caution, the 17% of the full sample who inappropriately evacuated their homes undoubtedly contributed to traffic and may have consumed valuable resources (Feng & Lin, 2021). Individuals in this group reported statistically significant higher risk perceptions compared to those who correctly reported their evacuation order status. Therefore, it is possible that instilling appropriate risk perception levels could help reduce incorrect evacuations during future hurricane events (cf. Garfin et al., 2022).

Direct Associations

Given the percentage of incorrect self-reported evacuation orders (about 40%), the Self-Report model may be most useful for interpretation due to its stronger ecological validity compared to the GIS-based model. People make decisions based on what they perceive to be true, not necessarily what is objectively true (Thompson et al., 2024). Since nearly 40% of participants in the current study did not accurately know their evacuation zones, the Self-Report model remains the most appropriate for evacuation research until this issue is resolved. The design of this study enabled pre-landfall factors and real-time risk perceptions to be measured and examined, several of our hypotheses were partially supported by the data. Specifically, higher amounts of Hurricane Irma-based media coverage consumed in advance of the storm making landfall were associated with higher risk perceptions, which partially supports Hypothesis 1 and is consistent with other collective trauma literature such as research in the context of a public health emergency (see Garfin et al., 2022). Having experienced prior loss or injury in a hurricane was associated with higher risk perceptions, which supported Hypothesis 1 and extended Demuth and colleagues' (2016) findings in which property damage from a previous hurricane was linked to lower evacuation intentions to include other types of loss (e.g., pet loss, personal injury, loss of a close friend or family member). Gender was not significantly associated with risk perceptions, though, contrary to Bateman and Edwards' (2002) findings. Income was not hypothesized to be associated with risk perceptions due to the mixed findings in the evacuation literature about income in general (Thompson et al., 2017), but in this study, income was significantly associated with risk perceptions such that higher income was linked with lower risk perceptions.

Hypothesis 2 was partially supported as well. Participants who evacuated reported significantly higher risk perceptions, were more likely to have experienced at least one prior hurricane evacuation order, and were younger compared to participants who did not evacuate. This is consistent with some prior evacuation literature (Thompson et al., 2017). Participants who had experienced an evacuation order before, regardless of if they evacuated or not, were 62% more likely to be in the group that evacuated during Hurricane Irma if they believed they were under evacuation orders. Moreover, for every one percent increase in risk perceptions on a 0 -100% scale, there was a 2.32% increase in odds of evacuating. Gender was not associated with evacuating, contrary to our hypothesis. The amount of media consumed prior to the hurricane making landfall in Florida was also not directly associated with evacuation behaviors.

Indirect Associations

Nonetheless, media consumption in advance of the storm making landfall was indirectly associated with evacuation behaviors, supporting Hypothesis 3. Specifically, the amount of Hurricane Irma-based media consumed was indirectly associated with evacuating through increased risk perceptions. There were also significant indirect links between having experienced a prior hurricane-related loss or injury with evacuating from Hurricane Irma through increased perceptions of risk about the impending disaster. Additionally, having higher income was indirectly associated with evacuation behaviors such that the higher the income reported, the lower the risk perceptions, which was linked with lower odds of evacuating. Both of these results support Hypothesis 4.

Similar results were found for the group of participants who were under evacuation orders based on their residential latitude and longitude. More pre-landfall media exposure and lower income were associated with risk perceptions. Higher risk perceptions, having experienced a prior hurricane-related evacuation order, and being younger were associated with evacuating, while higher media exposure was indirectly associated with evacuating through higher risk perceptions. For people who were objectively in an evacuation zone based on their residential address, the most common reason reported for not evacuating was that they did not believe they were in an evacuation zone. Alternatively, the top reason reported for not evacuating from the participants who self-reported being in an evacuation zone and not evacuating was wanting to take care of their homes. Notably, there was very little regret reported from either subsample.

Theoretical Implications

Based on these results, factors associated with real-time risk perceptions of an approaching hurricane, evacuation behaviors, and risk perceptions as a potential mechanism for the relationships between established and debated predictors and evacuation behaviors may differ based on how evacuation behaviors are measured (i.e., objective versus subjective measures). Both GSEM models have some overlapping factors: higher media and lower income were directly linked to risk perceptions, risk perceptions and prior evacuation experiences were directly associated with evacuations, and media was indirectly associated with evacuations through risk perceptions. In addition, the Self-Report model included additional variables to each section of the model (i.e., prior loss or injury was directly linked with risk perceptions, lower age was directly associated with evacuating, and lower income and prior loss or injury were indirectly associated with evacuating). These discrepancies between the sub-samples (i.e., Self-Report and GIS-based subsamples) could explain some of the mixed findings in the existing literature (Thompson et al., 2017), so future studies regarding evacuations need to be transparent about how they measure evacuation behavior. Furthermore, the unique nature of our design, which enabled us to collect data as the hurricane was approaching, allowed for increased confidence in the accuracy of participants' responses, especially for the variables that are more susceptible to recall bias such as risk perceptions and daily average amount of media consumed on the topic (Loftus et al., 1978; Schmolck et al., 2000). This unique design may also explain why some prior results (e.g., identifying as female being associated with evacuating; Thompson et al., 2017) were not found in the present study.

In addition to the benefits of collecting subjective data in the crucial few days' warning between a hurricane's creation and landfall, our models were able to examine real-time risk perceptions as a mediator between pre-landfall factors and evacuation behavior measured post-landfall. Risk perceptions partially explained the relationship between the amount of media consumed and evacuation behaviors which suggest that media is important to include in the evacuation literature, though not directly. Media exposure and other measures of media that may be associated with risk perceptions and evacuation behaviors (e.g., receiving disaster information from social media compared to online news websites) should be added to future models to delve into the nuances of media in this context. In addition, the results suggest that the established models for examining evacuation behaviors need to be updated to consider risk perceptions as a mediator of evacuation behavior and media as an indirect link with evacuation behaviors.

Practical Implications

Due to the lack of established research connecting media consumption to evacuation behaviors, it is important to draw on other disaster and collective trauma literature to suggest implications regarding media in this context given the novel nature of these findings. Media, both traditional and new, have a critical role to play in the delivery of emergency information (Romo-Murphy & Vos, 2014), but that delivery must be accurate and fact-based in a non-sensationalized manner, prioritizing facts over clickbait (Anderson-Berry & King, 2005; Fischhoff et al., 2018) in an effort to avoid spreading indiscriminate hysteria about the situation (Lubens & Holman, 2017). With accurate information, people are more likely to form accurate risk perceptions, which are associated with rational decision making (Fischhoff et al., 2018; Renn, 1999). Media personnel have a responsibility to provide the facts, so individuals can make educated, informed decisions for the best course of action for themselves (Renn, 1999). Non-sensationalized, accurate information being distributed through the media coupled with a better knowledge of community evacuation zones would likely help reduce the confusion among civilians during hurricanes. Accurate information is notoriously difficult to derive during a hurricane, though.

Modeling and predicting hurricane pathways with relative accuracy is a notoriously complex and challenging task (Mohanty & Gupta, 2008). Even when public awareness of the inherent uncertainty in forecasts is present, there is a tendency for increased anger towards scientists when hurricanes deviate from projected pathways, especially if these projections were already a modification from the original projected pathway (Klima et al., 2012). Overall, these pathways are still relatively accurate, though. The accuracy of predicting hurricane pathways has improved significantly over the past several decades, with the National Hurricane Center typically providing the most precise forecasts, especially in the 24-48 hours before landfall (Masters, 2022). Advances in artificial intelligence and recurrent neural networks hold promising potential for further enhancing the accuracy of these models in the near future (Alemany et al., 2018). Until pathway models are further improved, enhancing public understanding of hurricane pathway forecasts and their limitations is essential. Recommendations include enhancing the design elements of forecast graphics to minimize misinterpretation (Evans et al., 2022) and incorporating both words and numbers in forecasts rather than relying solely on verbal descriptions (Rosen et al., 2021). It is crucial that the public is not given unrealistic expectations about the capabilities of predictive modeling, and communicating the uncertainty inherent in hurricane forecasts is necessary. While scientists must ensure their models are well understood, it is ultimately the responsibility of the media and emergency management personnel to convey this information accurately and comprehensibly, avoiding jargon to ensure transparency.

Policymakers could help make strides towards better knowledge of evacuation zones and orders if the evacuation zones were standardized across counties and states. Although there are arguments for evacuation zones and orders to be set by regional governments such as the city or county (local governments know the infrastructure that has been put in place to counter life-threatening disasters such as storm surges; Lowry, 2022), the variability in protocols across counties is likely to contribute to confusion during events that affect multiple cities across a state or multiple states. Creating a comprehensive alert system for hurricane-based evacuation notifications that would serve as the primary information source for people across counties and states might remove much of the confusion around the evacuation zone systems currently in place. There are some national emergency alert systems in place, like the NOAA Weather Radio All Hazards system, but this requires a special weather radio receiver in order to receive the alerts, while most local systems are opt-in systems where locals must know where and how to sign up for them (National Weather Service, n.d.-b). An opt-out, national system would be especially helpful in the case of unstable pathways for landfall predictions, which was an issue with Hurricane Irma and most other hurricanes.

As mentioned previously, Hurricane Irma triggered the largest evacuation effort in Florida's history. The public's heightened response to Hurricane Irma may be partially explained by the availability heuristic since it was only two weeks after Harvey caused devastation in Texas and Louisiana (Tversky & Kahneman, 1973). With nearly 40% of our sample incorrectly reporting their evacuation order status *during a major hurricane event*, which made landfall just two weeks after Hurricane Harvey slammed into Texas and Louisiana (National Weather Service, n.d.-a), a novel approach to the problem is needed, and accurate, real-time data collection can help support policymakers in this endeavor.

Limitations and Future Directions

This study, while contributing valuable real-time insights into evacuation behaviors during a major hurricane, is not without its limitations. One of the main limitations was the lack of representativeness of the GSEM statistical approach used. The chosen models were largely unable to apply population weights to the statistical estimates because they were conducted on subsamples from the larger study. This limits the ability to make generalizable statements about the entire population who were actually or perceived to be under evacuation orders. Additionally, younger participants and People of Color were more likely to drop out of the study between Waves 1 and 2, though attrition was low at less than 10%. Future studies should enhance the generalizability of their findings by incorporating population weights and other mechanisms to allow for a representative sample that accounts for attrition over time. A third limitation of the study was the relatively small sample size of the GIS-based model. The GIS-based model utilized in this study was characterized by a relatively small sample size (n = 371). The GSEM model may have been underpowered for detecting small effects, potentially explaining the minimal findings observed, compared to the Self-Report model. It is recommended that future hurricane evacuation researchers oversample coastal residents to detect small effect sizes. Such an approach would increase the statistical power of the study and potentially uncover more nuanced relationships. Though, even in the GIS-based model with a smaller sample size, it is noteworthy that the results showed an indirect association between media exposure and evacuation behaviors in both models. This consistency suggests that, despite the limitations mentioned, the link between media exposure and evacuation behaviors is an important area for further investigation. Future research should also use similar methodology with a broader set of communities to test if the pattern of results can be repeated across the Gulf region or in other regions of the United States that are impacted by different types of natural disasters.

Conclusion

Using a prospective design, this study demonstrated the associations between prior hurricane experiences and media exposure with evacuation behaviors during Hurricane Irma, emphasizing the potential mechanism of real-time risk perceptions measured as the hurricane was imminent. The discrepancy between self-reported and objective evacuation zone statuses underscores a communication gap, pointing to areas for improvement in disaster management and public information dissemination, as well as a need for continued progress in hurricane pathway modeling. This research underlines the complexity of evacuation decision-making and the need for further investigation with real-time data collection that does not rely on retrospective reporting to help communities make the safest decisions surrounding imminent natural disasters.

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CHAPTER 3

Examining Early Media and Longitudinal Risk Perceptions Across the COVID-19 Pandemic

Abstract

Beginning at the onset of the COVID-19 pandemic in March/April 2020, this study used a national U.S. sample from the NORC AmeriSpeak Panel to evaluate risk perceptions related to infection susceptibility and severity (measured as death from COVID-19) longitudinally at three time points throughout the pandemic. Through growth mixture modeling (GMM), risk perception trajectories were identified and classified into four distinct groups for each type of risk perception. These classes were then incorporated as potential categorical mediators in two generalized structural equation models (GSEM) to examine the relationship between early COVID-19 media characteristics (measured in the beginning of the pandemic) and vaccine uptake over the pandemic. Findings showed that most individuals maintained low risk perceptions over time, but subsets of the sample exhibited higher risk perceptions at different pandemic stages, which was linked to their media consumption. While many factors contribute to risk perception trajectories, this study concentrated on media characteristics to explore their unique impact on risk perceptions and vaccine uptake during the pandemic. Notably, specific risk perception trajectories and media characteristics measured in the pandemic's first month (e.g., liberal-leaning news sources, increased COVID-related media exposure, and trust in COVID-related media) were linked to engaging in more vaccine behaviors by the pandemic's end. This research highlights the connection between early crisis media consumption, long-term risk perceptions, and vaccine behaviors, providing insights for communication and public health professionals who wish to leverage media during future infectious disease outbreaks.

Introduction

Few collective traumas in recent history affected the entire world for such a long period of time as the COVID-19 pandemic. The pandemic shared several key characteristics with other categories of collective traumas (e.g., terrorism, wildfires, bombings). It was an unexpected cataclysmic event that challenged the basic structure of society (Hirschberger, 2018). Additionally, for many, it shattered their world assumptions (i.e., that the world is benevolent and meaningful; Janoff-Bulman, 1992) in that people were confronted with the darker sides of human nature (e.g., leaders suggesting prematurely lifting lockdown measures in a state for the sake of the economy, knowing that vulnerable people would be more likely to die; Togoh, 2020). Mitigation strategies to prevent the transmission of the virus resulted in a scarcity of resources, especially in grocery stores, resulting in some people "panic buying" essentials. As the virus rapidly spread, the death count increased exponentially and overwhelmed the health system and burdened healthcare workers. Thousands of families grieved alone, unable to say goodbye in person or even hold funerals. The dominos quickly fell as the pandemic rapidly engrossed the world.

From a research perspective, the pandemic allowed for a unique opportunity to study collective trauma as it evolved in real time. Most crisis-specific research uses retrospective surveys, asking people to remember how they felt or what they did weeks, months, or even years prior to answering researchers' questions. Our research team conducted a study that began data collection in the very early stages of the pandemic (Holman et al., 2020) and has continued to follow the same people as the pandemic progressed to the endemic stage. In the beginning, little was known about the novel coronavirus rapidly spreading throughout the world, uncontrollably. Battlefield language was quickly adopted into common vernacular (e.g., frontline), and the science was not established yet (e.g., could transmission occur through the air or only on surfaces?). The first month of the pandemic in the U.S. marked a collective acute stress period for the country.

Collective Acute Stress Phase

Research has demonstrated that Americans tend to perceive novel viral health risks as higher in risk compared to common threats such as the annual influenza (Hong & Collins, 2006). The novel coronavirus, as it was called in the beginning, was known to be fatal in many cases, was hard to protect against as science did not yet know how it was spread, exposure was often involuntary with asymptomatic spreading and no mask mandates, and authorities were not in control of the situation. This uncontrollable, invisible novelty that could infect a person or their loved ones was, psychologically, a perfect storm for anxiety (Slovic, 1987). However, not all novel health threats are perceived in this way. During a prior media-amplified public health crisis (i.e., Ebola), the American public largely understood the relatively low rates of transmission of Ebola over time (Fischhoff et al., 2018). This was achieved despite the media dramatizing the health threat (Sell et al., 2017) and spreading misinformation (Beall et al., 2016). The difference between the communication of information regarding Ebola and COVID-19, however, is that COVID-19 information was very inconsistent, especially in the beginning stages; as the scientific information evolved, the messaging changed over time.

COVID-19 was declared a pandemic by the WHO on March 11, 2020 (Center for Disease Control and Prevention [CDC], 2023a). In the beginning, before COVID-19 was heavily politicized, information regarding COVID-19 was seemingly unreliable as scientists rushed to understand the novel virus. The inconsistency only became worse as the pandemic became politicized, and political leaders repeated contradictory reports from health officials (e.g., CDC).

These contradictory reports resulted in ambiguity. For instance, there were several conflicting reports about the severity of the virus in the beginning (e.g., one group said it was no worse than the annual flu, and the other group said it was much more serious than the flu). Ambiguity about a threat, especially an invisible threat, is one of the main factors that can lead to heightened risk perception (Renn et al., 2011). American society had experienced this ambiguity phenomenon before with the H1N1 (i.e., "swine flu") outbreak in 2009 when there was a general increase in anxiety over the virus due to ambiguity and feelings of uncontrollability (Taha et al., 2014). To manage uncomfortable feelings of ambiguity and heightened levels of uncertainty surrounding the pandemic when it first began, evidence suggests that individuals may have increased their information-seeking behaviors through media, new media especially, to obtain as much information as possible, regardless of how accurate the information was (Bento et al., 2020; Mangono et al., 2021).

Chronic Stressor Phase

A chronic stressor is a subgroup of stressors (e.g., environmental events) that are ongoing and often daily, having the potential to affect a person's body, mind, family, or community (Mclean & Link, 1994). COVID-19 itself became a collective chronic stressor, impacting daily life for most of the U.S. for multiple years. During that time, however, several key characteristics of the perceived risk surrounding the COVID-19 virus changed. First, the novelty of the virus wore off. Science largely solidified its understanding of the virus, how to protect oneself from getting sick, and how to treat those who did become ill. The traditional news, social media, and even organizational newsletters were saturated with COVID-related information periodically throughout the course of the pandemic, with peaks in the acute stress phase and as new variants emerged (Jurkowitz, 2021). Authorities put a series of mandates and procedures in place to protect the public against the virus, though procedures were not uniform across the country (Thompson et al., 2022). Production advanced so that masks became more readily available. Home test kits and drive through testing became normal and relatively easy to access for most. Vaccines – initial courses and, later, boosters – were created and widely available for free over time. While the core threat (i.e., the virus) was still invisible, it became relatively known. The pandemic, though, was still a collective trauma impacting a majority of society, either directly by illness or death or through secondary exposures and higher-order impacts for several years.

Collective Stressor Context

While the pandemic was a chronic stressor, it was also punctuated by acute stress peaks at times. The objective risks of the pandemic waxed and waned as the seasons changed, vaccines were made available to the public, high-quality masks were mass-produced, the anti-vax movement gained traction, and more. The major source of periods of acute stress, however, were new waves of the pandemic generated by variants of the original virus (CDC, 2023a). The Delta variant largely infected unvaccinated people, but the media was filled with stories of "breakthrough cases" in which fully vaccinated people were infected and fell ill with the new variant. The Delta variant was also the first major variant to spread in the U.S. in the summer of 2021 (Katella, 2022). Following the Delta variant, vaccine companies sought Food and Drug Administration (FDA) approval for booster vaccines for those who were already fully vaccinated with the initial courses, and they received initial approval in the fall of 2021 (CDC, 2023a). For some, this may have triggered some anxiety or uneasiness surrounding the efficacy of the vaccines, since the effects appeared not to last long enough to see the end of the pandemic. Next, the Omicron variant rapidly spread through the country, infecting both unvaccinated and vaccinated people more easily than Delta, with a 1.6 times higher transmissibility rate (CDC, 2023a). Many people saw the creation of the first round of vaccines as the way to end the pandemic (CDC, 2023a), but variants undermined that effort as a large portion of the country refused, and continues to refuse, vaccinations. With each new wave spearheaded by a new variant of the virus, the rules and risks of the pandemic and the slow progress towards "returning to normal" (i.e., pre-pandemic society) changed.

Risk Perceptions

Risk perceptions in the health field can be parsed into different types. This paper focuses on susceptibility to and severity of a health risk. Susceptibility is the possibility of experiencing or contracting the health risk, and severity is the seriousness or harm that could come from experiencing the health risk (Brewer et al., 2007; El-Toukhy, 2015). Research consistently shows that risk perceptions, including both susceptibility and severity, are significantly associated with vaccine uptake. Renner and Reuter (2012) found that when people were more worried or felt more threatened by a health crisis, they intended to get vaccinated more. Similarly, Schmitz and colleagues (2021) found a positive link between risk perceptions about getting infected with COVID-19 (i.e., susceptibility) and vaccination intentions and behaviors. Prior to the COVID-19 pandemic, a meta-analysis found that the pooled effect size of perceived susceptibility on vaccine uptake was moderate such that those who perceived themselves to be more susceptible to an illness were more likely to be vaccinated against it (Brewer et al., 2007). The authors also reported a pooled effect size of perceived severity on vaccine uptake of small to moderate size (Brewer et al., 2007). However, it is crucial to recognize that risk perceptions are not static and likely change over time, particularly in the dynamic context of a public health crisis like the COVID-19 pandemic. As vaccines were developed and new variants emerged, individuals' perceived susceptibility and severity likely changed, which may have been linked to vaccine behaviors. In fact, the multi-year COVID-19 pandemic provided an opportunity to understand how risk perceptions changed in this highly volatile environment, particularly as multiple variants spread and secondary vaccines (i.e., boosters) were developed over time. Therefore, studying risk perceptions longitudinally across the pandemic is essential for better understanding vaccine behavior as multiple vaccines (i.e., boosters) were distributed.

Considering the fluctuations that defined the COVID-19 pandemic, as variants spread and boosters were created, risk perceptions likely fluctuated and differed between groups of people. For instance, some people may not have believed the COVID-19 virus was dangerous throughout the entirety of the pandemic, while others may have felt at high risk of death if sick due to underlying conditions or of falling ill due to a job on the frontlines. Moreover, people may have felt a high level of threat during the beginning of the pandemic while there was extreme uncertainty and ambiguity, but their risk perceptions may have decreased as science began to understand the nature of the virus and vaccines were made widely available. Conversely, some people may have thought the threat levels of the virus at the beginning of the pandemic were overstated, but as the pandemic continued, they or someone close to them fell ill or passed away from the virus, increasing their risk perceptions of personal susceptibility or severity. The volatility of the pandemic likely differentially affected individuals' risk perceptions over time. However, because the pandemic was highly politicized and impacted nearly every aspect of daily life, these impacts may still be consistent across subgroups of Americans with similar demographics, political party affiliations, or media habits.

Media Exposure

During times of uncertainty, such as when faced with an invisible and novel health threat, people tend to integrate risk information from trusted sources (e.g., the media) that either amplify or weaken their individual risk perceptions (Kasperson et al., 1988). Several major public health crises have been studied previously in conjunction with media exposure and risk perceptions theories. For example, while studying the Severe Acute Respiratory Syndrome (SARS) epidemic, Berry and colleagues (2007) examined news media reports for message repetition, context, source, and grammar. They found that throughout the year in which the epidemic ensued, a considerably large portion of the content of media reports about SARS used strong grammar (i.e., use of warrants or the establishment of a relation between data and claims, as well as the use of connectives or qualifiers explaining the conditions under which the claim is true as opposed to weak grammar of rhetorical questions). Similarly, Sell and colleagues (2017) studied media messages in U.S. news reports about the Ebola virus outbreak in 2014 and discovered the frequent use of risk-elevating messaging in the news reports and subsequent discussions. These studies demonstrate a trend in which media report on new viruses with strong, risk-amplifying language that has the potential to permeate the public discourse about the threat.

Additionally, as technology has rapidly evolved over time, recent research has tried to separate the function of new media (i.e., social media and online news) and traditional media (i.e., television, print media, and radio) in the context of public health threats. For example, Ng and colleagues (2018) found that, among college students in Singapore, exposure through social media to two environmental health risks predicted increased risk perceptions, while exposure to the health threats via traditional media was not significantly related to risk perception. In the context of COVID-19, though, the messaging from the news was inconsistent in that some messaging directly contradicted other messaging, especially during the beginning of the pandemic when information was still being gathered and the crisis became rapidly politicized. Gathering accurate health-specific news on social media presents unique challenges.

Misinformation and speculation are pervasive across social media platforms, which effectively bypass traditional news gatekeepers (i.e., official news agencies and editors). Platforms such as YouTube are often inundated with numerous posts, comments, and videos containing false information, especially regarding health outbreaks that pose community-wide concerns (Pandey et al., 2010). A systematic literature review conducted prior to the COVID-19 pandemic established that misinformation about health topics was routinely present on social media, frequently inducing strong negative emotions such as fear (Y. Wang et al., 2019). The early days of the COVID-19 pandemic were characterized by the media sphere being saturated with pandemic information, conflicting – potentially outright incorrect – messaging, and the politicization of the crisis. Therefore, it is vital to investigate the patterns of news consumption and other media consumption behaviors that were popular in the beginning of the pandemic in order to develop a better understanding of the relationship between a person's early media habits and their risk perceptions over time. Moreover, examining early media habits and subsequent risk perceptions during a novel, engrossing public health crisis may offer insights into long-term behavioral patterns, including vaccine uptake.

Current Study and Hypotheses

This study uses longitudinal patterns of risk perceptions assessed at three time points (i.e., risk perception trajectories) to predict vaccine uptake. To better understand who is and is not likely to comply with vaccine guidelines during future public health crises, it is vital to understand the function of risk perception trajectories through the course of the pandemic into the endemic stage. Vaccine uptake is a proven health protective behavior (CDC, 2023b). While this study focuses on risk perceptions over time and media consumed in the acute phase of the pandemic, advancing scientists' understanding of characteristics of individuals with antivaccination attitudes may help public health officials better target risk messaging for those never or no longer vaccinated against the COVID-19 virus. This may also help mitigate some vaccination issues during future public health crises.

Using a five-wave longitudinal survey design, this study aims to answer two research questions. First, are there patterns of risk perceptions over time that can be classified across a large sample of individuals? As noted above, it is expected that there will be four main trajectories: group 1 will have consistent high-risk perceptions over time, group 2 will have consistent low risk perceptions over time, group 3 will start with low-risk perceptions in the acute phase and increase over time, potentially as death rates increase, and group 4 will demonstrate high risk perceptions in the acute phase and decrease over time as the novelty of the virus declines. Second, this study will assess if consumption of media with different media characteristics such as ideological foci (Jones et al., 2023), as well as different amounts of exposure in the acute phase of the pandemic, will interact with classes of risk perception trajectories to predict vaccine uptake three years later, controlling for demographics, global distress. It is hypothesized that a high frequency of media consumption with a conservative-leaning ideological focus will be associated with lower vaccine uptake, mediated through low-risk perception trajectories.

Methods

Participants and Sample Design

This longitudinal study consists of five waves of data collection using a probability-based national sample. Respondents for this study were drawn from the NORC AmeriSpeak Panel, a probability-based panel of 35,000 U.S. households that was created using random door-to-door recruitment via U.S. mail, telephone, and field interviews. Panelists are then randomly assigned to participate in AmeriSpeak surveys. A key feature of the AmeriSpeak Panel's recruitment methods is that no one can volunteer to participate; everyone in the sample is randomly selected and invited to the panel and assigned to individual surveys.

The Wave 1 survey was fielded to a sample of 11,139 panelists from 3/18/2020 to 4/18/2020. After participants received an email stating that the survey was available, they completed it online. Surveys were confidential, self-administered, and accessible any time for a designated period (10 days for each of three cohorts who were surveyed separately); participants could complete the survey only once. NORC compensated AmeriSpeak panelists with points, exchangeable for merchandise, worth a cash equivalent (for Wave 1, $4). When the fielding period ended, 6,598 had completed surveys (59.2% completion rate); 84 cases (1.3%) were removed from the final sample due to unreliable survey completion times (under 6.5 min) or extensive missing data (>50% of questions), leaving N = 6,514 panelists (58.5% participation rate).

The Wave 2 survey was fielded about six months later (9/26/20 to 10/16/20) to all available Wave 1 panelists (6,501 panelists). Panelists received the equivalent of $6 for completing the Wave 2 survey. The incentive was increased to the cash equivalent of $10 towards the end of the field period to boost cooperation. Of these, 5,722 completed the Wave 2 survey, but 61 responses (1.10%) were removed due to extensive missing data or unreliable survey completion time. The final sample size was 5,661 (87.08% participation rate). Most respondents (80.1%) completed the survey within the first four days of data collection.

The Wave 3 survey was fielded approximately one year later (11/8/21 – 11/24/21) to all available remaining Wave 1 panelists (6,486 panelists). Participants were offered the equivalent of $8 for completing the Wave 3 survey. In total, 4,984 panelists completed the Wave 3 survey, but 103 (2.10%) respondents were removed due to extensive missing data or unreliable survey completion time. The final sample was 4,881 participants (75.25% participation rate).

The Wave 4 survey was fielded about six months later (5/19/22 – 6/16/-22) to all available remaining Wave 1 panelists (6,473 panelists). Participants were offered the equivalent of $5 for completing the survey. In total, 4,987 panelists completed the Wave 4 survey, but 128 (2.57%) respondents were removed due to extensive missing data or unreliable survey completion time. The final sample was 4,859 participants (75.07% participation rate).

The Wave 5 survey was fielded 14 months later (8/14/23 – 9/29/23) to all available panelists who completed Wave 1. Participants were offered the equivalent of $3 for completing the survey. 4,623 panelists completed the Wave 5 survey, but 53 (1.15%) respondents were removed due to extensive missing data or unreliable survey completion time. The final sample was 4,570 participants. Wave 5 was collected outside of the ongoing longitudinal study and focused exclusively on health data but used the same panel of participants. For ease of interpretation within these analyses, this wave will be referred to as Wave 5.

Participants provided informed consent when they joined the NORC panel and were informed that their identities would remain confidential. All procedures for this study were approved by the Institutional Review Board of the University of California, Irvine.

Measures

Demographics

Demographic information was collected upon entry to the AmeriSpeak panel and is updated regularly. Gender was measured as a dichotomous variable with two options: male and female. Age was measured as a continuous variable. The range in Wave 1 was from 18 to 97. Race and ethnicity were measured with six options: “white, non-Hispanic,” “Black, non-

Hispanic," "other, non-Hispanic," "Hispanic," "2+, non-Hispanic," and "Asian, non-Hispanic." These were recoded to the following four categories: "white, non-Hispanic," "Black, non-Hispanic," "other/2+, non-Hispanic," and "Hispanic." Education was coded into two categories: less than a Bachelor's degree and Bachelor's degree or above. There were seven response options for employment status. These were dichotomized to include unemployed and employed. Income was divided into eight ranges of income with each response option being a $25,000 income range anchored by "less than $24,999" and "$175,000 or more." NORC also assessed political party affiliation on a majority of the sample (n = 6,492) prior to the start of Wave 1. Participants were asked to place themselves on a scale of 1 ("Strong Democrat") to 7 ("Strong Republican") with "Don't lean/independent/none" as the midpoint to assess political party affiliation.

Global Distress

Global distress was assessed at Wave 1 using the Brief Symptom Inventory (BSI-18 measuring depression, anxiety, and somatization; Derogatis, 2001). Symptoms were measured on a 0 (not at all) to 4 (extremely) Likert-type scale and were summed to form an overall index of global distress (α = .92).

Media Variables

Media Exposure. At Wave 1, media exposure was assessed by asking respondents to report the average number of hours of COVID-19-related news they consumed per day over the previous seven days across three possible sources: television, radio, and print news; online news sources (e.g., CNN, Yahoo, NYTimes.com); and social media (e.g., Facebook, Reddit, Twitter). These variables were recoded such that the values corresponded to the number of hours of each type of COVID-19-related media that participants consumed in the prior week (i.e., 0-11+).

“Less than one hour” was coded as 0.5 hours. The three media sources were summed. The possible range was 0-33 hours to account for the possibility that participants were using multiple media sources at once.

Ideological Focus of News Media Sources. At Wave 1, participants were asked to indicate the top three information channels (i.e., news channels) out of 31 options that they used for COVID-related news in the week prior to completing the survey. If a channel was not listed, participants had the option to type it into a textbox. These text responses were coded and grouped based on eight commonly reported information channels. A majority of participants indicated using common news sources including Fox News (n = 2,255; 34.6%), ABC News (n = 2,173; 33.3%), CNN (n = 2,116; 32.4%), CBS News (n = 1,646; 25.2%), MSNBC (n = 1,158; 17.7%), The New York Times (n = 790; 12.1%), NPR (n = 705; 10.8%), and The Washington Post (n = 600; 9.2%). The remaining channels were used by less than 9% of participants. Latent patterns of information channel use were created through a multiple correspondence analysis (MCA). The MCA results had four dimensions: journalistic complexity, ideological focus, domestic focus, and non-news (Jones et al., 2023), but this study only used the ideological focus dimension. Each participant was given a score for the ideological focus of their joint top three endorsed news sources for COVID-19 information. If they endorsed fewer than three, then those that they endorsed were used to give them a score. Non-news sources (e.g., social media) were analyzed on a separate dimension and not included in these analyses. A negative ideological focus score indicated a liberal-leaning to their combined top three news sources, while a positive score indicated a conservative-leaning to their top three news sources. Scores could range from -1 to +1, and the range in this sample was from -0.39 to 0.85.

Risk Perceptions

Across the waves of data, two items were repeatedly assessed across the first four waves of data collection (during the pandemic stage). Participants were asked to report the percent chance that an event would happen using a sliding thermometer anchored by 0 – 100% (Garfin et al., 2021). Participants indicated the percent chance they would get sick with COVID-19 in the next three months, which assessed susceptibility risk perceptions. Then, severity risk perceptions were assessed by asking participants to indicate the percent chance they would die if they got sick with COVID-19. Similar questions have been used in prior research on other disease outbreaks (Bruine De Bruin et al., 2006). Predictive and construct validity have been established in previous longitudinal research, indicating that individuals can provide relatively accurate probability judgments of future life events (Fischhoff et al., 2018).

Vaccine Uptake

At Wave 5, participants were asked if they had been vaccinated against COVID-19 with dichotomous response options: yes and no. If they answered yes, participants were asked how many COVID-19 vaccinations they had in total; response options included 1, 2, 3, and more than 3. These two items were combined such that participants who answered no in the first question were coded as a 0 in the second question. These response options were further combined to create a three-category ordinal variable: 0 ("no vaccines"), 1 ("initial course only;" 1-2 vaccines), and 2 ("boosters;" 3+ vaccines).

Analytic Plan

Before assessing models, descriptive statistics were calculated for each variable, and bivariate relationships were examined.

Growth Mixture Modeling

To address the first research question regarding the presence of risk perception trajectories over time, growth mixture modeling (GMM; Muthén, 2001; Muthén & Shedden, 1999) was used to examine latent classes of linear trajectories. Two models, one for the risk of falling ill with COVID-19 (susceptibility) and one for the risk of dying if ill with COVID-19 (severity), were created. Since the results from the GMM were used as mediators between Wave 1 and Wave 5 variables in subsequent GSEM models, only risk perceptions from Waves 2-4 were used for these analyses. A GMM was used over a latent class growth model (LCGA) because GMM allowed for within-class variation (Nagin & Odgers, 2010). The GMMs were conducted using MPlus software (Muthén & Muthén, 2017).

First, a no growth (i.e., flat line / no slope) versus growth model (significant slope over time) was tested to confirm that there were trajectories over time rather than no change, on average, over time. Then, the best fitting model was determined in a holistic way, assessing the best fit through the loglikelihood value, number of parameters, Bayesian Information Criterion (BIC; Raftery, 1995), Akaike Information Criterion (AIC; Akaike, 1974), entropy, and the *p*-value of the likelihood ratio test of k-1 classes. Entropy is how cleanly a participant is classified into one trajectory over another with a perfect score being 1. The objective was to find the number of classes that was the most parsimonious (least number of parameters) with the lowest log-likelihood value, BIC, and AIC, the highest entropy, a significant improvement (*p*-value) from GMMs with fewer classes, and classes with meaningful amount of participants in each class. Once the best-fitting models were determined, each participant was assigned the number that corresponds to the class in which they best fit for each GMM, creating two categorical variables. These variables were then exported to be used in other models.

Generalized Structural Equation Model

Once the appropriate number of GMM trajectories were identified and participants were assigned to a trajectory classification number for each type of risk perception (one for susceptibility and one for severity), the trajectory classifications were added to a path model as latent variable mediators using a generalized structural equation model (GSEM) framework in Stata 18 (Stata Corp, 2023). This path model focused on testing the direct, indirect, and total effects of the mediation of risk perception trajectories on media characteristics and behavioral outcomes (i.e., endogenous variable: vaccine uptake), adjusting for covariates. Demographics were included based on bivariate relationships. Since the model had several mediation groups (hypothesized four+ trajectories for each type of risk perception), there were potential power concerns. Two models – one for each type of risk perception – were used to ensure model integrity. Given the ordinal nature of the endogenous variable assessing vaccine uptake, the equations for the vaccine uptake portion of the models were treated as such, requiring the use of GSEM to allow for a categorical endogenous variable. Using GSEM with an ordinal outcome variable did not provide the usual fit statistics typical for SEM to evaluate the model. The software provided some fit statistics like Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC), along with effect sizes for equations. Nonetheless, this method was chosen because the path model allowed multiple equations to be assessed at the same time, accounting for any artificially inflated type 1 error.

Results

Only participants that had a response to the vaccine uptake question in Wave 5 were included in the analyses. See Table 3.1 for the descriptive statistics of all included variables. Only demographics with significant associations with vaccine uptake were included in the final models. Race and ethnicity variables were removed from the model due to small sample sizes when separated by GMM classifications (e.g., the 4^{th} severity class only included 23 Black, non-

Hispanic participants). See Table 3.2 for all statistically significant bivariate relationships. Additionally, these analyses were pre-registered with hypotheses for media exposure and ideological focus as the only media variables. Due to the importance of trust in media in Chapter 1 of this dissertation, I decided to test trust in media in this context, and it was pre-registered as an exploratory variable.[1]

[1] All results were tested with and without trust in media included in the model. The results were largely the same, and the models had better model fit indices when trust in media was included. Therefore, all results present in this chapter include trust in media.

Table 3.1

Descriptive Statistics of Variables Included in Final GSEM Models

Continuous Variable	*N*	*M*	SD	Min	Max
Media Exposure	4,511	6.18	6.06	0	33
Ideological Leaning of Media	4,515	0.00	0.19	-0.39	0.85
Trust in Media	4,501	3.08	1.25	1	5
Global Distress	4,512	0.50	0.54	0	4
Political Party	4,484	3.86	1.98	1	7
Income	4,515	4.33	1.84	1	8
Age	4,515	51.32	15.92	18	97
Categorical Variable	**Frequency**				
Education					
Less than a Bachelor's Degree	2,383				
Bachelor's Degree+	2,132				
Vaccine Uptake					
No Vaccines	930				
Initial Course Only	1,124				
Boosters	2,487				

Note. A positive score on ideological leaning indicates a more conservative leaning to the top three media sources consumed by a participant. A higher political party score corresponds to a stronger Republican identification.

Growth Mixture Models

Susceptibility Risk Perceptions GMM

First, a growth mixture model (GMM) was fit to the data to test if there were patterns of risk perceptions over time that could be classified. After testing a no-growth model and determining that there was a significant slope over time for a one-class model due to marginally improved model fit statistics ($\text{Loglikelihood}_{\text{nogrowth}}$ = -53131.26; $\text{Loglikelihood}_{\text{growth}}$ = -53123.30; $\text{AIC}_{\text{nogrowth}}$ = 106276.53, $\text{AIC}_{\text{growth}}$ = 106262.60; $\text{BIC}_{\text{nogrowth}}$ = 106320.98; $\text{BIC}_{\text{growth}}$ = 106313.40), the best-fitting model was determined holistically. There were four classes of susceptibility risk perceptions (i.e., percent change of falling ill with COVID-19). The entropy for a four-class solution equaled 0.953. Class 1 was defined by an intercept of 6.61 and a slope of -1.92 ($p < .000$; see Figure 3.1). See Table 3.3 for standard errors and estimated means for all classes. 3,244 participants (76.62%) were categorized into Class 1. It was characterized by a low, slightly declining slope and will be referred to as the Consistent Low susceptibility risk perception class. Class 2 was defined by an intercept of 60.09 and a slope of 23.05 ($p < .000$; see Figure 3.1). 26 participants (0.61%) were categorized into Class 2, however, and therefore will not be interpreted or included in future analyses due to a small sample size. This class will be referred to as the High Increase susceptibility risk perception class. Class 3 was defined by an intercept of 21.04 and a slope of 2.29 ($p = .001$; see Figure 3.1). It was characterized by a moderately low slope that slightly increased over time. 569 participants (13.44%) were classified into Class 3, which will be referred to as the Moderate susceptibility risk perception class. Class 4 had an intercept of 38.05 and a slope of 10.18 ($p < .000$; see Figure 3.1). 395 participants (9.33%) were categorized into Class 4. It was characterized by a medium slope that increased over time. Class 4 will be referred to as the Medium Increase susceptibility risk perception class.

Table 3.2

Bivariate Relationships for All Variables Included in the Models

Vaccine Uptake			Susceptibility Class			Severity Class		
Variable	OR	95% CI	Variable	RRR	95% CI	Variable	RRR	95% CI
Media Exposure			*Media Exposure*			*Media Exposure*		
	0.99	0.98, 1.00	Moderate	1.02*	1.00, 1.03	Decrease	1.03***	1.02, 1.05
			Medium Increase	1.04***	1.03, 1.06	Consistent High	1.07***	1.05, 1.09
						Increase	1.06***	1.04, 1.08
Ideological Leaning of Media			*Ideological Leaning of Media*			*Ideological Leaning of Media*		
	0.08***	0.06, 0.10	Moderate	0.50**	0.31, 0.81	Decrease	0.18***	0.11, 0.30
			Medium Increase	0.62	0.36, 1.08	Consistent High	0.17***	0.08, 0.35
						Increase	0.43*	0.22, 0.86
Trust in Media			*Trust in Media*			*Trust in Media*		
	1.76***	1.67, 1.84	Moderate	1.06	0.99, 1.14	Decrease	1.25***	1.17, 1.35
			Medium Increase	0.90*	0.83, 0.98	Consistent High	1.25***	1.12, 1.40
						Increase	0.98	0.88, 1.08
Global Distress			*Global Distress*			*Global Distress*		
	1.12*	1.01, 1.24	Moderate	1.72***	1.47, 2.01	Decrease	1.99***	1.71, 2.32
			Medium Increase	2.11***	1.79, 2.50	Consistent High	2.94***	2.42, 3.58
						Increase	2.20***	1.79, 2.71
Education†			*Education*†			*Education*†		
	2.65***	2.36, 2.97	Moderate	0.86	0.72, 1.02	Decrease	0.75**	0.63, 0.89
			Medium Increase	0.64***	0.51, 0.79	Consistent High	0.32***	0.24, 0.43
						Increase	0.47***	0.36, 0.62
Political Party			*Political Party*			*Political Party*		
	0.71***	0.69, 0.73	Moderate	0.93**	0.89, 0.98	Decrease	0.86***	0.83, 0.90

Variable	OR	95% CI	Variable	RRR	95% CI	Variable	RRR	95% CI
			Medium Increase	0.99	0.94, 1.04	Consistent High	0.84***	0.78, 0.90
						Increase	0.99	0.93, 1.06
Income			*Income*			*Income*		
	1.25***	1.21, 1.29	Moderate	1.00	0.95, 1.05	Decrease	0.88***	0.84, 0.92
			Medium Increase	0.88***	0.83, 0.93	Consistent High	0.71***	0.65, 0.77
						Increase	0.87***	0.81, 0.94
Age			*Age*			*Age*		
	1.03***	1.03, 1.03	Moderate	0.98***	0.97, 0.98	Decrease	1.03***	1.03, 1.04
			Medium Increase	0.96***	0.95, 0.97	Consistent High	1.01**	1.01, 1.02
						Increase	0.99**	0.98, 0.99
Susceptibility[a]								
Moderate	1.09	0.91, 1.29						
Medium Increase	0.57***	0.47, 0.69						
Severity Class[b]								
Decrease	2.00***	1.67, 2.40						
Consistent High	1.52**	1.16, 1.98						
Increase	0.72***	0.57, 0.92						

Note. [†]Reference group is less than a Bachelor's degree. [a]Reference group is Consistent Low susceptibility class. [b]Reference group is Consistent Low severity class. *p < .05, **p < .01, ***p < .001.

Table 3.3

Growth Mixture Model Results for Susceptibility (N = 4,234) and Severity (N = 4,231) Risk Perception Trajectories

				Susceptibility						
Class	α_0	SE	95% CI	*ß*	SE	95% CI	Estimated Means			*n*
							W2	W3	W4	
Consistent Low	6.61	0.26	6.1, 7.13	-1.92	0.23	-2.37, -1.48	6.61	4.5	3.54	3,244
High Increase	60.09	5.39	49.52, 70.66	23.05	6.04	11.21, 34.89	60.09	85.45	96.97	26
Moderate	21.04	0.77	19.53, 22.56	2.29	0.68	0.96, 3.63	21.04	23.56	24.07	569
Medium Increase	38.05	1.12	35.85, 40.25	10.18	1.02	8.18, 12.18	38.05	49.25	54.34	395
Model Fit		Loglikelihood = -50572.04		AIC = 101178.08		BIC = 101286.04		Entropy = 0.971		
				Severity						
Class	α_0	SE	95% CI	*ß*	SE	95% CI	Estimated Means			*n*
							W2	W3	W4	
Consistent Low	5.44	0.16	5.13, 5.74	-0.76	0.11	-0.97, -0.55	5.44	4.6	4.22	3,136
Decrease	60.46	0.88	58.74, 62.56	-33.01	0.58	-34.14, -31.9	60.46	24.15	7.64	613
Consistent High	69.91	1.69	66.59, 73.23	-7.21	1.69	-9.75, -4.67	69.91	61.98	58.37	231
Increase	6.94	0.82	5.35, 8.54	28.04	0.99	26.09, 29.98	6.94	37.78	51.8	251
Model Fit		Loglikelihood = -50572.04		AIC = 101178.08		BIC = 101286.04		Entropy = 0.971		

Note. α_0 = intercept. *ß* = slope. Additional model fit statistics include LRT *p*-value of k – 1 classes (Susceptibility < .001; Severity < .001) and Vuong-Lo-Mendell-Rubin loglikelihood (Susceptibility = -51847.10; Severity = -51021.56).

Figure 3.1

Estimated Means of Latent Class Trajectories of Susceptibility Risk Perceptions Over Time with a Four-Class Solution (N = 4,234)

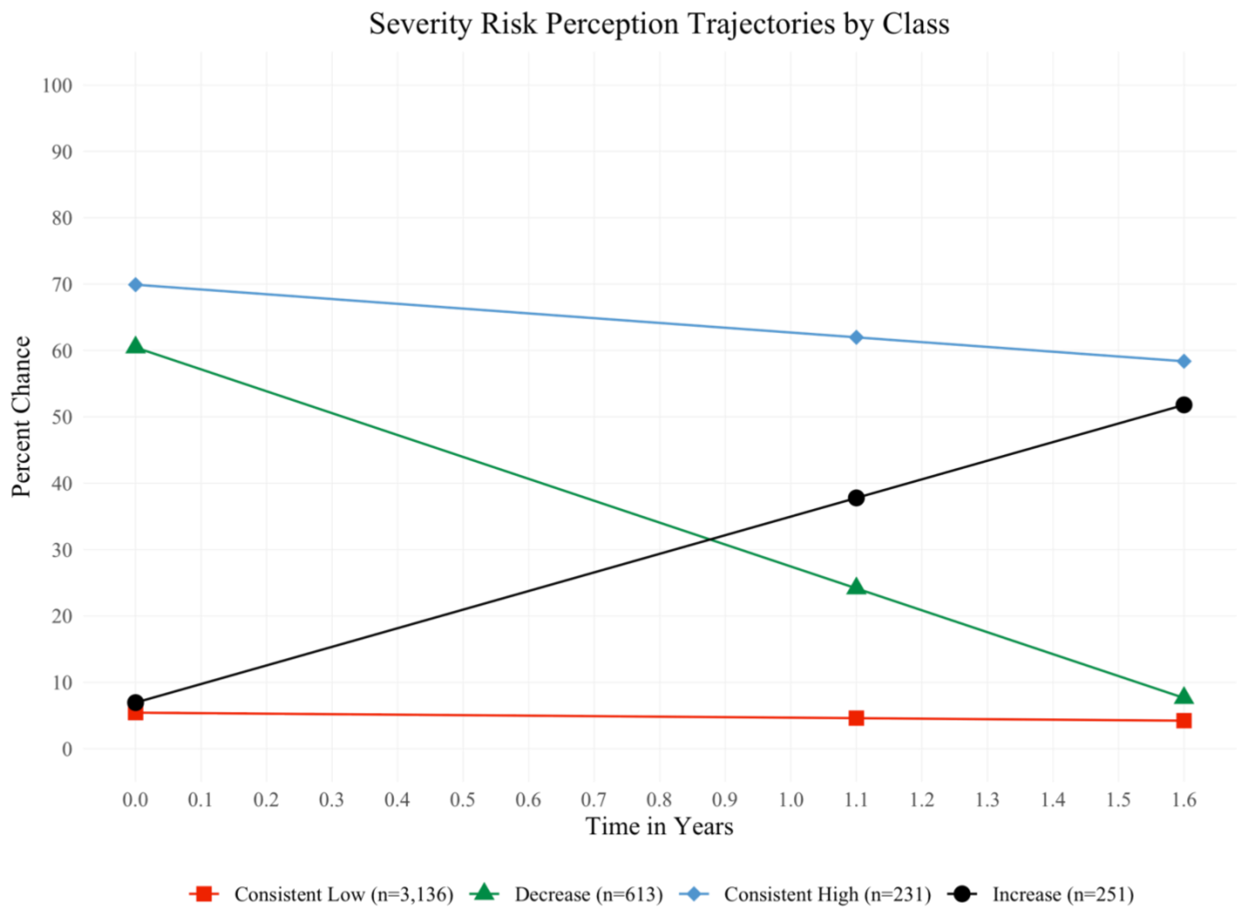
Note. Time in years begins with Wave 2 at 0 (Sept/Oct 2020), Wave 3 at 1.1 (November 2021), and Wave 4 at 1.6 (May/June 2022).

Severity Risk Perceptions GMM

Repeating the process from the susceptibility GMM, a separate GMM was fit to the data to test if there were patterns of severity risk perceptions over time that could be classified. After determining that there were significant slopes over time for a one-class model due to slightly improved loglikelihood ($\text{Loglikelihood}_{\text{nogrowth}}$ = -54417.54; $\text{Loglikelihood}_{\text{growth}}$ = -54279.82), AIC ($AIC_{nogrowth}$ = 106849.08, AIC_{growth} = 106575.64), and BIC ($BIC_{nogrowth}$ = 106893.53; BIC_{growth} = 106626.44), the best-fitting model was determined holistically. Again, there were four classes of severity risk perceptions (i.e., percent change of dying if sick with COVID-19). The entropy for a four-class solution equaled 0.971 (see Table 3.3 for model fit statistics). Class 1 was the majority class (3,136 participants; 74.12% of the samples), beginning with an intercept of 5.44 and had a slope of -0.76 ($p < .001$; see Figure 3.2). This class was defined by a low beginning and end of the trajectory and will be referred to as the Consistent Low severity class. Class 2 had 613 participants (14.49% of the sample). Class 2 was defined by a high intercept of 60.46 and a slope of -33.01 ($p < .001$; see Figure 3.2). This class was characterized by a strong decline in risk perceptions over time and will be referred to as the Decrease severity class. Class 3 had the smallest number of participants with 231 participants (5.46% of the sample). Class 3 was defined by relatively high risk perceptions over time with an intercept of 69.91 and a slope of -7.21 ($p < .001$; see Figure 3.2). This class will be referred to as the Consistent High severity class. Class 4 included 251 participants (5.93% of the sample). Class 4 was defined by low average risk perceptions with an intercept of 6.94 and increased over time with a slope of 28.04 ($p < .001$; see Figure 3.2). This class will be referred to as the Increase severity class.

Figure 3.2

Estimated Means of Latent Class Trajectories of Severity Risk Perceptions Over Time with a Four-Class Solution (N = 4,231)



Note. Time in years begins with Wave 2 at 0 (Sept/Oct 2020), Wave 3 at 1.1 (November 2021), and Wave 4 at 1.6 (May/June 2022).

Generalized Structural Equation Models

Susceptibility Risk Perception GSEM

Moderate Class. Demographics included in the model were first determined by examining bivariate relationships (see Table 3.2). Compared to the Consistent Low class, the Moderate class was defined by higher global distress (RRR = 1.49, $p < .001$, 95%CI [1.26, 1.76]), less education (RRR = 0.80, p = .02, 95%CI [0.65, 0.97]), and being younger (RRR = 0.98, p < .001, 95%CI [0.97, 0.99]), adjusting for over covariates. Functionally, this means that a one-unit increase in participants' global distress at Wave 1 increased the risk of being in the Moderate class by 49%, compared to the Consistent Low class. Compared to participants without a Bachelor's degree, those with a Bachelor's degree had a 20% lower risk of being in the Moderate class compared to the Consistent Low class. Therefore, participants without a Bachelor's degree had a 20% higher relative risk of being in the Moderate class compared to the Consistent Low class. For every one-year increase in age, there was a 2% risk reduction of being in the Moderate class compared to the Consistent Low class.

Medium Increase Class. Media was significantly associated with being categorized into the Medium Increase class. Compared to the Consistent Low class, participants categorized into the Medium Increase class watched more COVID-based media at Wave 1 (RRR = 1.03, p = .002, 95%CI [1.01, 1.04]), watched early pandemic media that had a more liberal leaning (RRR = 0.41, p = .01, 95%CI [0.21, 0.80]), and reported lower trust in their early pandemic media (RRR = 0.90, p = 0.03, 95%CI [0.81, 0.99]), adjusting for other covariates. Being classified into the Medium Increase class compared to the Consistent Low class was also associated with higher global distress, lower education, and lower age (see Table 3.4).

Vaccine Uptake with Susceptibility Risk Perception Classes

Vaccine uptake across the pandemic had many significant direct associations. The odds ratios are understood in the context of increasing in categories from one vaccine group to the next (i.e., "No Vaccines" group to the "Initial Course Only" group or the "Initial Course Only" group to the "Boosters" group). Ordinal logistic regressions with more than two categories in the ordinal variable assume proportional odds, so only one odds ratio is given, which is used for the increase from one category to the next. For instance, the OR of Wave 1 trust in media for COVID news was 1.38 (OR = 1.38, $p < .001$, 95%CI [1.30, 1.47]), adjusting for other covariates. This can be interpreted as follows: for a one-unit increase in trust in media, there were 38% increased odds of engaging in vaccination behavior (meaning getting the initial course of vaccines or getting boosted if already vaccinated). Moreover, as the ideological leaning of participants' early pandemic media sources became less conservative (thus, more liberal), the odds of engaging in vaccination behaviors increased by 64% (OR = 0.36, $p < .001$, 95%CI [0.25, 0.53]). Additionally, being categorized into the Medium Increase risk perception group was associated with a 26% decreased odds of engaging in vaccination behaviors compared to being in the Consistent Low class (OR = 0.74, $p = .006$, 95%CI [0.60, 0.92]). Covariates significantly associated with engaging in vaccination behaviors can be found in Table 3.4. No indirect effects were found.

Table 3.4

GSEM Results Assessing Susceptibility Risk Perception Classes and Vaccine Uptake (N = 4,234)

Direct Associations with Class	Simplified Model				Complete Model			
	RRR	*SE*	*p*	95% CI	RRR	*SE*	*p*	95% CI
Consistent Low Class	Base Outcome				Base Outcome			
Moderate Class								
Media Exposure	1.01	0.01	0.07	1.00, 1.03	1.00	0.01	0.83	0.99, 1.02
Ideological Leaning of Media	0.55	0.15	0.03	0.32, 0.93	0.61	0.17	0.08	0.35, 1.06
Trust in Media	1.01	0.04	0.75	0.94, 1.10	1.04	0.05	0.38	0.95, 1.13
Global Distress					1.49	0.13	0.00	1.26, 1.76
Education†					0.80	0.08	0.02	0.65, 0.97
Political Party					0.98	0.03	0.55	0.93, 1.04
Income					1.05	0.03	0.06	1.00, 1.11
Age					0.98	0.00	0.00	0.97, 0.99
Constant	0.15	0.02	0.00	0.12, 0.20	0.34	0.09	0.00	0.20, 0.57
Medium Increase Class								
Media Exposure	1.05	0.01	0.00	1.03, 1.06	1.03	0.01	0.00	1.01, 1.04
Ideological Leaning of Media	0.44	0.14	0.01	0.24, 0.82	0.41	0.14	0.01	0.21, 0.80
Trust in Media	0.83	0.04	0.00	0.76, 0.91	0.90	0.05	0.03	0.81, 0.99
Global Distress					1.62	0.15	0.00	1.35, 1.94
Education†					0.73	0.09	0.01	0.58, 0.92
Political Party					1.05	0.03	0.15	0.98, 1.12
Income					0.97	0.03	0.37	0.91, 1.04
Age					0.96	0.00	0.00	0.96, 0.97
Constant	0.16	0.02	0.00	0.12, 0.21	0.68	0.21	0.21	0.38, 1.24
Direct Associations with Vaccine Uptake	OR	*SE*	*p*	95% CI	OR	*SE*	*p*	95% CI
Class								
Moderate	1.00	0.09	0.98	0.84, 1.20	1.16	0.11	0.13	0.96, 1.41
Medium Increase	0.57	0.06	0.00	0.47, 0.70	0.74	0.08	0.01	0.60, 0.92
Media Exposure	0.98	0.01	0.00	0.97, 0.99	0.99	0.01	0.07	0.98, 1.00
Ideological Leaning	0.21	0.04	0.00	0.15, 0.29	0.36	0.07	0.00	0.25, 0.53

of Media								
Trust in Media	1.63	0.05	0.00	1.54, 1.72	1.38	0.04	0.00	1.30, 1.47
Global Distress					1.38	0.09	0.00	1.21, 1.58
Education†					2.01	0.14	0.00	1.75, 2.31
Political Party					0.73	0.01	0.00	0.70, 0.76
Income					1.21	0.02	0.00	1.16, 1.26
Age					1.04	0.00	0.00	1.03, 1.04

Note. †Reference group = Less than a Bachelor's degree. "Simplified Model" was conducted with only the variables of interest (i.e., class and media variables). "Complete Model" was conducted with covariates included. These models were run separately to ensure the models were appropriately powered.

Severity GSEM Results

Severity Risk Perception GSEM

Decrease Class. The Consistent Low Severity Class was used as the base outcome (i.e., reference group) for all GSEM analyses. Compared to the Consistent Low class, the risk of being categorized into the Decrease class was significantly associated with a more liberal-leaning of early COVID-19 media sources (RRR = 0.53, $p = .03$, 95%CI [0.30, 0.94]), adjusting for covariates. Therefore, as the ideological leaning of the media sources became more conservative by one unit, there was a 47% lower risk of being in the Decrease class. Other demographic factors significantly associated with a higher risk of being in the Decrease class compared to the Consistent Low class included a lower education attainment level, leaning more strongly Democrat as a political party identifier, reporting a lower income, and being older (see Table 3.5).

Consistent High Class. Compared to being classified in the Consistent Low class, the Consistent High class was associated with significantly more hours of daily COVID-based media consumption on average (RRR = 1.04, $p < .001$, 95%CI [1.02, 1.04]), controlling for covariates.

In other words, for every one-hour increase of average COVID-based media consumed at Wave 1, there was a 4% increased risk of being in the Consistent High class of severity risk perceptions across Waves 2 through 4. Covariates that were significantly associated with increased risk of being in the Consistent High class included higher global distress, a lower education attainment level, identifying more strongly as a Democrat as a political party identifier, reporting a lower income, and being older (see Table 3.5).

Increase Class. Being in the Increase class was associated with reporting more daily hours of COVID-based media exposure (RRR = 1.04, $p < .001$, 95%CI [1.02, 1.06]) and consuming COVID news from more liberal-leaning sources (RRR = 0.40, $p < .001$, 95%CI [0.18, 0.91]). Therefore, for every one-hour increase in early pandemic COVID-based media exposure, there was a 4% increased risk of being in the Increase class. Additionally, for every one-unit increase towards conservative leaning in news sources' ideological leaning, there was a 60% decreased risk of being categorized into the Increase class. The only covariates that were significantly associated with being in the Increase class included global distress and lower education (see Table 3.5).

Vaccine Uptake with Severity Risk Perception Classes

Using the Consistent Low class as the reference group, the Decrease and Consistent High classes were significantly associated with engaging in vaccination behaviors (meaning getting vaccinated or getting boosted if already vaccinated). The Increase class had a 49% increase in odds, and the Consistently High class had a 41% increase in odds of engaging in vaccination behaviors, compared to the Consistent Low class (see Table 3.5). Media variables were also significantly linked with vaccine behaviors, adjusting for covariates. A one-hour increase in average daily hours of COVID-based media exposure in the beginning of the pandemic was associated with a 1% decrease in engaging in vaccination behaviors (OR = 0.99, $p = .03$, 95%CI [0.977, 0.999]). As the ideological leaning of the news sources used in the beginning of the pandemic scored more conservative, there were 62% decreased odds of engaging in vaccination behaviors (OR = 0.38, $p < .001$, 95%CI [0.26, 0.56]). Moreover, people who reported more trust in their news media for COVID-related information early in the pandemic had 38% increased odds of engaging in vaccination behaviors (OR = 1.38, $p < .001$, 95%CI [1.30, 1.46]). Additionally, participants with higher global distress, higher educational attainment levels, who identified as a Democrat more strongly, reported higher income, and were older were associated with increased odds of engaging in vaccination behaviors (see Table 3.5). No indirect effects were found when bootstrapped with 1000 repetitions.

Table 3.5

GSEM Results Assessing Severity Risk Perception Classes and Vaccine Uptake (*N = 4,231*)

Direct Associations with Class	Simplified Model				Complete Model			
	RRR	*SE*	*p*	95% CI	RRR	*SE*	*p*	95% CI
Consistent Low	Base Condition				Base Condition			
Decrease								
Media Exposure	1.02	0.01	0.00	1.01, 1.04	1.02	0.01	0.06	1.00, 1.03
Ideological Leaning of Media	0.30	0.08	0.00	0.17, 0.51	0.53	0.15	0.03	0.30, 0.94
Trust in Media	1.15	0.05	0.00	1.06, 1.24	1.08	0.05	0.10	0.99, 1.18
Global Distress					2.38	0.21	0.00	2.00, 2.82
Education†					0.77	0.08	0.01	0.63, 0.94
Political Party					0.91	0.03	0.00	0.86, 0.96
Income					0.90	0.03	0.00	0.86, 0.95
Age					1.04	0.00	0.00	1.04, 1.05
Constant	0.11	0.02	0.00	0.08, 0.14	0.02	0.01	0.00	0.01, 0.04
Consistent High								
Media Exposure	1.07	0.01	0.00	1.05, 1.08	1.04	0.01	0.00	1.02, 1.06
Ideological Leaning of Media	0.31	0.13	0.01	0.13, 0.70	0.54	0.25	0.18	0.22, 1.32
Trust in Media	1.13	0.07	0.06	1.00, 1.27	1.10	0.08	0.16	0.96, 1.26
Global Distress					2.83	0.32	0.00	2.27, 3.54
Education†					0.41	0.07	0.00	0.29, 0.57
Political Party					0.89	0.04	0.01	0.82, 0.97
Income					0.79	0.04	0.00	0.72, 0.87
Age					1.03	0.01	0.00	1.02, 1.04
Constant	0.03	0.01	0.00	0.02, 0.05	0.02	0.01	0.00	0.01, 0.05
Increase								
Media Exposure	1.06	0.01	0.00	1.04, 1.08	1.04	0.01	0.00	1.02, 1.06
Ideological Leaning of Media	0.39	0.15	0.02	0.18, 0.83	0.40	0.17	0.03	0.18, 0.91
Trust in Media	0.89	0.05	0.05	0.80, 1.00	0.96	0.06	0.48	0.85, 1.08
Global Distress					1.88	0.22	0.00	1.50, 2.37
Education†					0.55	0.08	0.00	0.41, 0.74
Political Party					1.05	0.04	0.22	0.97, 1.14
Income					0.96	0.04	0.29	0.88, 1.04

Age					0.99	0.00	0.07	0.98, 1.00
Constant	0.08	0.01	0.00	0.05, 0.11	0.09	0.04	0.00	0.05, 0.20
Direct Associations with Vaccine Uptake	OR	*SE*	*p*	95% CI	OR	*SE*	*p*	95% CI
Class								
Decrease	1.73	0.17	0.00	1.43, 2.10	1.49	0.16	0.00	1.20, 1.83
Consistent High	1.29	0.18	0.08	0.97, 1.70	1.41	0.22	0.03	1.04, 1.91
Increase	0.72	0.09	0.01	0.56, 0.92	0.88	0.12	0.37	0.68, 1.15
Media Exposure	0.98	0.01	0.00	0.97, 0.99	0.99	0.01	0.03	0.98, 1.00
Ideological Leaning of Media	0.23	0.04	0.00	0.16, 0.33	0.38	0.07	0.00	0.26, 0.56
Trust in Media	1.62	0.04	0.00	1.53, 1.71	1.38	0.04	0.00	1.30, 1.46
Global Distress					1.31	0.09	0.00	1.14, 1.50
Education†					2.04	0.15	0.00	1.77, 2.35
Political Party					0.73	0.01	0.00	0.71, 0.76
Income					1.22	0.02	0.00	1.17, 1.27
Age					1.04	0.00	0.00	1.03, 1.04

Note. †Reference group = Less than a Bachelor's degree. "Simplified Model" was conducted with only the variables of interest (i.e., class and media variables). "Complete Model" was conducted with covariates included. These models were run separately to ensure the models were appropriately powered.

Table 3.6 included the number of participants within each GMM class solution and the vaccine uptake group in which they fell.

Table 3.6

Frequency of Participants in Each GMM Class and Vaccine Uptake Group

GMM Class	Vaccine Uptake Group		
	No Vaccine	Initial Course Only	Booster
Susceptibility			
Consistent Low	633	742	1,869
High Increase	9	11	6
Moderate	90	147	332
Medium Increase	103	131	161
Severity			
Consistent Low	666	786	1,648
Decrease	73	112	428
Consistent High	30	56	145
Increase	62	79	110
Total Across Models	930	1,124	2,487

Note. Totals are slightly different than susceptibility and severity risk perception subsamples because participants were removed from the GMMs if they were missing two or three risk perception data points.

Discussion

Using a large, national sample of residents of the United States over the course of the pandemic, this study highlighted the relationship between media characteristics, risk perceptions, and vaccine behaviors. Having greater COVID-based media exposure, liberal leanings to the top news sources used, and greater trust in COVID-19 media one consumed at the beginning of the pandemic were significantly associated with the probability of being in specific, less common risk perception classes – both for the susceptibility and severity models – as well as engaging in vaccination behaviors. These findings expand the existing research on media and vaccine behaviors (for example, Chen & Stoecker, 2020; Meyer et al., 2016), highlighting that early crisis media habits could be used to help predict vaccine behaviors over the course of the pandemic. Moreover, early crisis media characteristics were linked with certain classes of risk perceptions in both the susceptibility and severity models, demonstrating a correlation between characteristics of early media exposure and less common but distinct risk perception trajectories over the course of the crisis. This research also provided valuable insights into how different aspects of early crisis media were associated with risk perception patterns and vaccine behaviors, helping public health officials better understand potential areas for messaging interventions so as to improve vaccine uptake during future public health crises. These results were significant while accounting for demographics such as individual political party identification, education, income, and age, as well as global distress at the beginning of the pandemic. Overall, this study offered a comprehensive view of how early media characteristics were related to public cognitions about COVID-19 and vaccinations over the course of the pandemic, providing a nuanced perspective on the interplay between media characteristics, health-based risk perceptions, and public health behaviors.

Though there are many other studies on vaccine behavior and its relationship with either media or risk perceptions, this study is unique in its methodology, quality of data, and specific focus. Not only did this study use a large, probability-based, national sample, but the timing of the longitudinal data collection allowed for a comprehensive overview of the entire pandemic. Wave 1 was collected in the first month of the formal declaration of the pandemic in the U.S. (CDC, 2023a), collecting media and global distress data in real-time, which circumvented recall bias concerns (Loftus et al., 1978). Moreover, the risk perception items assessed in-the-moment cognitions multiple times throughout the pandemic as the conditions of the pandemic changed, more accurately capturing cognitions at they occurred. Lastly, the vaccine uptake items were measured after the pandemic had officially ended (Sarker et al., 2023) and were measured outside the context of the pandemic, as they were part of a survey that was solely focused on updating participants' health profiles. By measuring vaccinations in the context of a general health survey instead of a pandemic-focused survey, participants may have felt less pressure to answer in alignment with any political or conspiratorial beliefs they may have endorsed (Winter et al., 2022). Much of the existing COVID-19 research was cross-sectional or focused on only a piece of the pandemic (for examples, see De Figueiredo et al., 2023; Jia et al., 2020; X. Wang et al., 2020). While cross-sectional research is critical for developing a collective scientific understanding of the pandemic, the timing of the five waves of data collection in this study allows us to understand the process of our key variables over the course of the entire pandemic.

Risk Perceptions

As established in previous research (see Brewer et al., 2007; El-Toukhy, 2015), perceptions of susceptibility and severity are two distinct risk constructs. However, this study demonstrated that these constructs can be further classified longitudinally. While a majority of participants had low risk perceptions (Consistent Low class) for both susceptibility and severity risk perceptions, there were distinct groupings for people who had higher risk perceptions at different times during the pandemic, although these classes had varying sample sizes. Understanding who those were that had less common risk perception patterns, even as health protective behaviors were widely used, lockdown measures were in place, and vaccines were widely available, can aid public health officials in predicting vaccine behaviors in the future (Brewer et al., 2007). Current CDC guidance for Americans is to continue to be vaccinated with boosters or "updated COVID-19 vaccines", which are quickly becoming an annual recommendation akin to the flu vaccine (Katella, 2024). Understanding risk perceptions over the course of the pandemic provides insights into vaccine messaging to target those less likely to receive updated vaccines as COVID-19 continues to be present in our society as a stable, prevalent virus in the endemic stage (Mendoza et al., 2022).

Media Characteristics

Across both GSEM models, media characteristics were significantly and directly linked not only with risk perception classifications but with vaccine uptake as well. Though indirect associations were not found to be significant in either model, these direct associations partially supported the hypotheses. Both the ideological focus of the top news sources reportedly used at the beginning of the pandemic and the trust participants placed in their news media were significantly associated with engaging in more vaccine behaviors. In both models, as the ideological focus of the news sources leaned towards conservative ideology, it was associated with 62% decreased odds of receiving more vaccines. Therefore, people who consumed news from sources leaning more liberal engaged in more vaccine behaviors. Additionally, the odds of receiving more vaccines increased by 38% for people with more trust in their media. Importantly, this study only measured the perceived trust an individual reported having in their chosen news media; the accuracy of the information that was being shared from these media sources was not examined. Partially supporting the hypothesis, the amount of media consumed on average was significantly associated with vaccine uptake only for the severity risk perception model. However, consuming high amounts of media was associated with a higher probability of being in certain classes for both types of risk perceptions. This study demonstrated that many characteristics of media, including its ideological focus, the perceived trust consumers have in the source, and amount of media exposure were significantly associated with infection-based risk perceptions and vaccine uptake, highlighting the complex relationship between media and public health cognitions and behaviors.

In most of the results, a conservative-leaning to the news sources reportedly used by participants at the beginning of the pandemic was associated with a reduced risk of being in a non-majority risk perception class and lower odds of engaging in vaccination behaviors. Therefore, participants with more conservative-leaning news sources had a higher probability of being in the Consistent Low risk perception classes and engaging in less vaccine behavior, controlling for the amount of media consumed and how much they trusted it. Notably, these results also held while accounting for individual-level political party identification. In the original analyses conducted by Jones and colleagues (2023), many participants from across the political party spectrum had ideological focus scores that did not align well with their political party identity; many participants used a combination of news sources to get information about the COVID-19 pandemic. Therefore, it is not enough to target risk and vaccine messaging along party lines and assume it is reaching the intended audience; specific news sources should be targeted as well.

While the results from this study suggest that increasing individual-level trust in people's public health-related news in the outset of a public health crisis is one key to increasing vaccine uptake for years to come, it is vital to place that trust in accurate, verified information. The COVID-19 pandemic was marked by a rapid increase in mis- and disinformation, especially on social media (Chowdhury et al., 2023). Two key factors that increase the risk of misinformation being shared as a crisis unfolds is the absence of reliable information or a burden of too much information being rapidly shared (Jones et al., 2017; Muhammed & Mathew, 2022). Unfortunately, both of these factors were highly prevalent at the beginning of the pandemic. In the early days of the pandemic, information was ceaselessly being provided about numbers of confirmed cases, a steadily rising death toll, and state-wide shutdowns, along with secondary consequences of the pandemic (Newman et al., 2020). The information being shared may not have always been perceived as reliable, as information was inconsistent from government and scientific leaders, as well as citizen journalists (Jaiswal et al., 2020). Moreover, the beginning of the pandemic was a rapidly evolving crisis with scientists swiftly publishing new research, potentially shifting the public's perceived risk with every new finding (Estes & Thompson, 2020). The evolving science, mixed with the inundation of information, likely provided the perfect foundation for the infodemic (i.e., too much information including mis- and disinformation during a disease outbreak) experienced during the pandemic (*Infodemic*, n.d.). In light of this, it is naturally advised not to trust just any media consumed. There are several agencies and private companies actively attempting to combat mis- and disinformation, especially for health information (see WHO for example; *Infodemic*, n.d.). For the purpose of this study, however, an emphasis should be placed on the availability of reliable and verified health news. Furthermore, the content needs to be simple so consumers can determine accurate information, both through the use of verified accounts with credentials and by increasing media and scientific literacy.

Limitations and Future Directions

Despite its strengths, this study was not without its limitations. Though the study employed a large sample size, the GMM results revealed imbalanced class sizes of risk perception trajectories, severely limiting the number of variables that could be included in the GSEM models. Some of the current models may have minor power issues, which is why both the simplified models with only the key media variables included along with the complete models with the covariates were provided simultaneously for comparison. While the uneven class sizes created statistical challenges, it was also a product of real-life risk perceptions, and cannot be corrected by simply collecting a larger sample. Instead, alternative forms of classifications may be more appropriate to find nuances among the large classes (Consistent Low classes) to create more even class sizes. In addition, some of the trajectories may not have been linear. For instance, the smallest susceptibility class that was removed from the GSEM model due to small sample size had a sample mean at Wave 3 that was much higher than Waves 2 or 4; it appeared to be quadratic. However, with only three time points, a quadratic growth mixture model would not be identified and could not be used; a minimum of four time points are needed for such an analysis. Future research should collect more waves of data specifically asking about susceptibility and severity risk perceptions.

Aside from the classifications, important COVID-19-related variables, such as COVID-19 exposure, were not included in the models because they were not assessed at each time point and, therefore, could not be accounted for longitudinally. Though this study had a specific focus on understanding the relationship between media variables and risk perceptions with vaccine uptake, future research should incorporate a broader set of social and epidemiological variables to gain a more comprehensive understanding of the factors associated with vaccine uptake. Moreover, vaccines were made available to the public between Waves 2 and 3. Thus, vaccine uptake was distributed across the multiple waves of data, rather than exclusively at Wave 5 when vaccine uptake across the pandemic was assessed. Accounting for vaccine uptake at each wave of data collection could provide more context for the differing risk perception trajectories. Finally, the vaccination rates measured in this study do not fully align with the CDC's estimations (CDC, 2024b). This discrepancy could be due to differences in data collection or estimation methods. In addition to this discrepancy, the current study did not use population weights for the analyses, and appropriate caution should be taken when attempting to generalize the results to the population as a whole. Despite these limitations, this study provides a valuable contribution to the field by identifying significant relationships between media variables, risk perceptions, and vaccination behaviors. The findings offer essential insights that can guide the design of more effective public health communications in the early days of new public health crises in the future.

Conclusion

Experts have warned that COVID-19 may not be the last pandemic many of us experience in our lifetimes (Williams et al., 2023). Certainly, it will not be the last public health emergency the world will experience even in this decade (Marani et al., 2021). During the COVID-19 pandemic itself, Mpox (formerly known as monkeypox) spread quickly among certain sub-populations, especially within the LGBTQIA+ community (Pasquini & Funk, 2022), compounding the need for health protective behaviors and vaccine uptake. Although this study was situated in the context of the COVID-19 pandemic, the findings provide valuable insight for future public health crises. As the world continues to fight ongoing infectious disease outbreaks, including the resurgence of nearly eradicated diseases such as measles (CDC, 2024a), understanding how the characteristics of early media may be leveraged by scientists, public health personnel, and policymakers to effectively target risk messaging may help reduce the timeline of future pandemics or prevent them from escalating to that level entirely.

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CHAPTER 4

Epilogue

Advances in technology allow individuals to access news about collective traumas from a variety of sources simultaneously, including traditional media, online news platforms, and social media. This accessibility can increase the amount of media consumed in a given timeframe, as people often use multiple information sources to stay updated on current and recent disasters (Simon et al., 2015). While media is essential for disseminating information, studies show that consuming extensive coverage is frequently associated with negative psychological outcomes (Hopwood & Schutte, 2017). Prolonged exposure to disaster coverage can amplify anxiety and fear (Holman et al., 2014) , leading to attentional bias towards these stimuli and making disengagement difficult (Fox et al., 2001). However, in many collective trauma contexts, advising the public to disengage from media is unrealistic and potentially dangerous as emergency management personnel increasingly use social media to share urgent updates about a crisis (Drake, 2013; Young et al., 2020). Given these challenges, it is critical to understand and improve the ways in which these crises are studied in order to know when it is more important to limit media consumption for psychological well-being and when staying informed for safety and physical well-being is more essential. A significant limitation of collective trauma research is the reliance on retrospective data collection and non-representative samples in studies on collective traumas such as natural disasters and public health crises (Thompson et al., 2017). To effectively prepare for and adapt to future incidents, it is crucial to measure subjective variables in real-time using representative, probability-based samples to ensure unbiased data collection. This dissertation addresses these issues by using large, probability-based samples – applying population weights when appropriate – and collecting data as collective traumas unfold.

Study 1 investigated the relationship between hurricane-based media exposure, trust in that media, and traumatic stress responses in Texans soon after Hurricane Harvey made landfall in 2017. The study utilized a representative sample and evaluated longitudinal relationships using generalized estimating equations (GEE) analyses. Results showed that individuals who reported low trust in hurricane-related media had stronger positive relationships between media exposure and traumatic stress symptoms compared to those with high trust at 2 weeks, 6 weeks, and 14 months post-landfall. Additional factors such as income and Hurricane Harvey-related loss and injury were found to be significant predictors of traumatic stress symptoms. The study highlighted the importance of trustworthy media coverage in potentially mitigating negative effects of media exposure after a natural disaster, emphasizing the need for accurate and honest information dissemination during and immediately after such events.

Study 2 utilized real-time online data collection to examine how risk perceptions mediate the relationship between certain theoretical predictors, like income and prior hurricane-based experiences, and evacuation behaviors among almost 1,500 Florida residents as Hurricane Irma approached the state in 2017. Using mediation generalized structural equation modeling (GSEM), results indicated that risk perceptions played a crucial role in relation to evacuation behaviors and that the amount of hurricane-based media exposure was indirectly linked with evacuation decisions through higher risk perceptions. By incorporating real-time data collection methods and considering a range of predictors, this study contributed to the existing literature on evacuation behaviors (see Thompson et al., 2017) by providing an updated model and offered valuable insights for emergency management personnel regarding knowledge of evacuation zones and communicating orders during an emergency.

Study 3 began at the start of the COVID-19 pandemic in March/April 2020 and followed a national U.S. sample drawn from the NORC AmeriSpeak Panel. Longitudinal patterns of risk perceptions regarding infection susceptibility and severity (in the form of death from COVID-19) were assessed at multiple points over the pandemic period. Patterns of risk perception trajectories were identified and classified into four groups for each type of risk perception using growth mixture modeling (GMM). These classes were then entered into two generalized structural equation models (GSEM) as potential categorical mediators, with a focus on the relationship between early COVID-19 media characteristics and vaccine uptake three years later. Results indicated that while the majority of individuals had low risk perceptions over time, a subset of the sample had higher risk perceptions at either the beginning or end of the pandemic, depending on which risk perception trajectory they were classified into, potentially due in part to the characteristics of the media they consumed. Although there are undoubtedly many factors that play a role in risk perception trajectories, this study focused on media characteristics and habits in an attempt to understand the unique link early media might play in risk perceptions and vaccine uptake over the course of the pandemic. Specifically, some of the risk perception trajectories over the pandemic and media characteristics measured in the first month of the pandemic (i.e., liberal leanings to the top news sources used, more COVID-based media exposure, and trust in one's COVID-based media) were associated with receiving more COVID vaccines by the end of the pandemic. This research shed light on the connection between early crisis media consumption, long-term risk perceptions, and health-protective behaviors over the course of the public health emergency, offering valuable insights for communication and public health professionals on how to leverage media at the beginning of future infectious disease outbreaks.

This dissertation explored the relationship between media exposure and affect, cognitions, and behaviors in the context of collective traumas. The findings suggest that various aspects of media consumption are associated with traumatic stress symptoms, risk perceptions, evacuation behaviors, and vaccine uptake, and these findings hold over time. By utilizing representative samples and real-time data collection, this program of research offers valuable insights for other crisis researchers, emergency management personnel, media outlets, and the public. The results highlight the importance of informed decision-making in policy development and transparent, non-sensationalized communication strategies to address the collective traumas experienced through traditional and new media platforms.

Limitations

Despite the valuable insights gained from this dissertation from large, ecologically valid surveys, some overarching limitations must be acknowledged. First, all three studies used correlational survey designs rather than experimental methods. While this approach was more contextually relevant and highlighted associations between media characteristics, risk perceptions, and the affective and behavioral outcomes of interest, this methodology does not allow for causal inferences. Next, although large, probability-based samples were utilized from Texas, Florida, and the U.S. as a whole, challenges were faced when attempting to apply population weights to all the analyses. Weights were only appropriate to use in Study 1 with the Texas sample. Analyses conducted for Studies 2 and 3 involved the use of several subsamples, which precluded the use of weights as they were only available for the full sample in a given wave for each study. This limitation affected the ability to draw population estimates for the broader population. Additionally, the research was confined to specific regions and disaster contexts. Each study focused on a single disaster at a time (i.e., individual hurricanes or the COVID-19 pandemic) without examining repeated events or other types of natural disasters (e.g., wildland fires) or other infectious disease outbreaks (e.g., Mpox). This individual focus may limit the applicability of the findings to other contexts and types of collective traumas.

Future Directions

To address the limitations outlined above and build upon the findings of these studies, several future research directions are offered. First, future research should incorporate more longitudinal designs to capture the dynamics of psychological responses over time and across multiple disasters. Although each study in this dissertation had an element of longitudinal analyses, more comprehensive and complex analyses would require additional time points (e.g., a quadratic growth mixture model requires at least four time points of repeated data; Muthén, 1999), which would have been a more flexible option for the pandemic risk perception trajectory analyses). I propose a multi-year study, spanning several years, conducted in a community or region repeatedly impacted by multiple natural disasters such as wildland fires, drought, and extreme heat. Tracking individuals' media consumption, risk perceptions, psychological outcomes, and behaviors over time as these events occur would provide a more comprehensive understanding of how these variables may evolve as a natural disaster continues to impact a community. This approach would also allow researchers to study the cumulative effects of exposure and potential vulnerabilities that may accumulate through repeated exposures to several types of collective traumas.

Moreover, expanding the scope of the research to include multiple regions or diverse types of collective trauma contexts would enhance the generalizability of the findings. Much of natural disaster research is studied in the context of one type of collective trauma only. It is vital that we as researchers move to understand which findings are applicable to other types of collective trauma contexts and which findings are unique to the present context. For example, we know that media exposure during a mass violence event (e.g., a mass shooting) is linked to negative health outcomes including posttraumatic stress symptoms (Hopwood & Schutte, 2017) .

The findings from Study 1 examining the interaction of trust in one's media about the disaster and traumatic stress symptoms over time could be applicable to the mass violence context, broadening the findings to another unfortunately common collective trauma context that has the potential to affect even more people. To compare across collective trauma contexts, well-funded future research should focus on following a panel of participants over the course of several years, collecting data immediately after a variety of collective traumas. Then, analyses could be conducted comparing the role of media and risk perceptions as a mechanism through which media and other variables of interest might be associated with affective and behavioral outcomes within a single sample to compare and contrast the collective traumas experienced.

Finally, supplementing survey data with experimental studies is necessary to determine causation and to understand the underlying mechanisms behind any observed associations between media characteristics, risk perceptions, and other responses such as behaviors. Though experimental studies in the lab would provide the most internally valid results (McDermott, 2011), to promote good external validity, I recommend future research meld experimental methods into established methodology of the sort used in this dissertation (for example, see Turcotte et al., 2015). Targeted experiments that manipulate trust in media about a current disaster participants would be experiencing through vignettes or manipulated news articles could prove useful to begin to understand the effect perceived trust in media has on traumatic stress symptoms or evacuation behaviors. Manipulating news articles or modifying which sources present the news are methods that have been repeatedly used in communication and journalism research to understand trust in specific types of media (see Karlsen & Aalberg, 2023). This methodology could be repeated for infectious disease outbreaks with articles about the effectiveness of a new vaccine, but the articles would be manipulated to appear as if they are from different common news sources. Manipulating news about current collective traumas would need to be carefully crafted and a clear and strong debriefing would be required to ensure participants are not harmed by potentially false information, especially if combined with an anonymous survey that prohibits face-to-face interactions to ensure the debrief is fully understood.

In summary, future research should focus on incorporating experimental designs into longitudinal survey methodology to establish causation and capture the potential temporal dynamics of participants' responses to multiple types of collective traumas. Expanding the research to include multiple regions or types of disasters and using analyses that lend themselves to the use of population weights will further enhance the validity and applicability of the present findings.

Conclusion

This dissertation highlights the critical need for policies ensuring media integrity and trustworthiness during crises, underscoring the connection between several media factors (e.g., amount of exposure, perceived trust, the ideological focus of the information source) and evacuation and health behaviors. It demonstrates that rigorous research with real-time data collection regarding a variety of aspects of media should be incorporated into emergency preparedness and public health communication strategies. The findings, drawn from large, probability-based samples offer essential insights for policymakers and media companies to enhance public awareness and promote informed decision-making during collective traumas. Ultimately, this research calls for a collaborative approach between public policymakers, media industry personnel, emergency management personnel, and scientists to foster a media environment that supports public well-being and effective crisis response.

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