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ORIGINAL ARTICLE

Media exposure, threat processing, and mitigation behaviors in Gulf Coast residents facing the co-occurring threats of COVID-19 and hurricanes

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Abstract
The 2020 hurricane season threatened millions of Americans concurrently grappling with COVID-19. Processes guiding individual-level mitigation for these conceptually distinct threats, one novel and chronic (COVID-19), the other familiar and episodic (hurricanes), are unknown. Theories of health protective behaviors suggest that inputs from external stimuli (e.g., traditional and social media) lead to threat processing, including perceived efficacy (self- and response) and perceived threat (susceptibility and severity), guiding mitigation behavior. We surveyed a representative sample of Florida and Texas residents (N = 1846) between April 14, 2020 and April 27, 2020; many had previous hurricane exposure; all were previously assessed between September 8, 2017 and September 11, 2017. Using preregistered analyses, two generalized structural equation models tested direct and indirect effects of media exposure (traditional media, social media) on self-reported (1) COVID-19 mitigation (handwashing, mask-wearing, social distancing) and (2) hurricane mitigation (preparation behaviors), as mediated through perceived efficacy (self- and response) and perceived threat (susceptibility and severity). Self-efficacy and response efficacy were associated with social distancing (p = .002), handwashing, mask-wearing, and hurricane preparation ($ps < 0.001$). Perceived susceptibility was positively associated with social distancing ($p = 0.017$) and hurricane preparation ($p < 0.001$). Perceived severity was positively associated with social distancing ($p < 0.001$). Traditional media exhibited indirect effects on COVID-19 mitigation through increased response efficacy ($ps < 0.05$), and to a lesser extent self-efficacy ($p < 0.05$), and on hurricane preparation through increased self-efficacy and response efficacy and perceived susceptibility ($ps < 0.05$). Social media did not exhibit indirect effects on COVID-19 or hurricane mitigation. Communications targeting efficacy and susceptibility may encourage mitigation behavior; research should explore how social media campaigns can more effectively target threat processing, guiding protective actions.

KEYWORDS
COVID-19, health protective behaviors, hurricanes, media, mitigation

1 | INTRODUCTION

The 2020 Atlantic and Gulf Coast hurricane season posed a critical threat to millions of Americans concurrently grappling with the ongoing threat of COVID-19. During the spring of 2020, most states, including Florida and Texas, had issued "stay at home" orders and other restrictions on activity in an effort to curb the spread of COVID-19 (National Academy for State Health Policy, 2021). Despite early reports downplaying their importance (Lyu & Wehby, 2020), by April 2020 facemasks emerged as an important mitigation strategy to reduce COVID-19 transmission (World Health Organization, 2020). Yet, as residents sought to cope with the novel threat of COVID-19, they faced a more familiar threat:

the annual Atlantic/Gulf Coast hurricane season, which runs from June 1 to November 30 (National Hurricane Center & Central Pacific Hurricane Center, 2021).

The threats of COVID-19 and the 2020 hurricane season required divergent mitigation strategies, communicated primarily through the media. Early COVID-19 mitigation heavily relied on movement restrictions, social distancing, and the performance of ongoing actions (e.g., wearing a mask in public). In contrast, potential hurricane evacuation orders would require residents vacate their homes and seek safe shelter with friends and family inland, at hotels, or at other designated public evacuation sites; many forms of hurricane mitigation rely on advance planning efforts and discrete actions such as securing supplies and having an evacuation plan (Centers for Disease Control & Prevention, 2021). How did residents perceive and respond to the simultaneously occurring yet conceptually and practically distinct threats of COVID-19 and the 2020 hurricane season? Given that the media is the primary mechanism by which information about threats is conveyed to the public, how did varying sources of input (e.g., social vs. traditional media) predict responses including mitigation? Were threat processing mechanisms the same for both threats? Or did divergent processes occur, resulting in threat-specific mitigation decisions?

Herein, we draw from key theories of health protective behaviors to explore these questions, leveraging a longitudinal, representative, probability-based sample of Florida and Texas residents, assessed in late May 2020, who had been dealing with the novel COVID-19 pandemic for several months and were facing the start of the annual hurricane season. In preregistered analyses, we examined the relationships between threat-specific media inputs (with a focus on contrasting social vs. traditional media sources), threat processing variables (perceived susceptibility and perceived severity), efficacy (self- and response), and performance of mitigation behaviors. We evaluated the threats of COVID-19 and the 2020 hurricane season separately, allowing for a comparison of these co-occurring, yet distinct threats.

1.1 | Threat mitigation

Despite the economic, physical, and psychological benefits of engaging in individual-level threat mitigation, it is well-established that the current level of household disaster mitigation (e.g., buying supplies in advance, putting up removable storm shutters) is far from what is needed to offer meaningful protective benefits (Meyer et al., 2014; Rivera, 2020). For example, in a sample of Atlantic coast residents, only a minority of residents reported taking protective action before the immediate hours leading up to a storm (Meyer et al., 2014). A study of North Carolina residents repeatedly exposed to hurricanes found that nearly a third of home owners had never thought about insurance or options to strengthen their homes and 44% had never engaged in any protective actions at all (Stock et al., 2021). Similarly, while research suggests that there was widespread compliance with early social distancing orders and masking recommendations (Garfin et al., 2021), it was well documented that a substantial minority of Americans did not adhere to COVID-19 public health recommendations over time (Folmer et al., 2021).

Individual-level mitigation behaviors are critical components of promoting public health in response to both COVID-19 and hurricanes. Compliance with masking recommendations is key to improving efficacy for preventing infectious disease spread (Lyu & Wehby, 2020; MacIntyre et al., 2009); early social distancing policies were effective at slowing the spread of COVID-19 (Delen et al., 2020). Analyses from the Centers for Disease Control and Prevention estimated the majority of deaths following Hurricane Sandy (e.g., drowning in homes) could have been prevented with better disaster preparation plans (Centers for Disease Control & Prevention, 2013). This lack of preparation exacerbates the consequences of these threats, leading to additional psychological distress (Kessler et al., 2012), with potential downstream impacts on physical health (Garfin et al., 2019). As COVID-19 becomes endemic (Kofman et al., 2021) and climate-related threats such as severe hurricanes continue to increase (Emanuel, 2017; Moftakhari et al., 2017), understanding the inputs and mechanisms that encourage individual-level mitigation are essential for protecting public health.

1.2 | Type of threat

Although both climate-related weather events (Emanuel, 2017; Moftakhari et al., 2017) and infectious disease outbreaks (Rogalski et al., 2017) are expected to increase in the future, the threat of hurricanes and COVID-19, particularly in the Spring of 2020, differs in important ways. For Atlantic/Gulf Coast residents, hurricanes are a familiar threat faced annually; thus, those exposed may exhibit habituation, as noted in prior studies on threat exposure (Bodas et al., 2017; Reser & Swim, 2011), potentially leading to lower mitigation behavior (Bodas et al., 2017). Such processes may help explain the relatively low levels of individual-level mitigation despite annual threat (Meyer et al., 2014; Rivera, 2020). Yet, hurricanes are also episodic, acute events, with a demarcated beginning and end; and prior research shows hurricane-related mitigation behaviors tend to exhibit an uptick in the time immediately preceding an event (Meyer et al., 2014) as well as immediately after an event (Beatty et al., 2019). Given the history of repeated exposure to extreme hurricanes on the Gulf Coast over the past several years (e.g., Michael, Irma, Harvey), it is plausible that these experiences may have resulted in the performance of individual mitigation behaviors in response to these threats.

In contrast, COVID-19 was a novel threat in spring of 2020; Americans had not faced a viral epidemic of such magnitude since the 1918 Spanish Flu (Cori et al., 2020; Parmet & Rothstein, 2018). Prior to COVID-19, experts were already warning of a lack of preparedness and distrust of science that would likely make mitigation for a future pandemic exceedingly difficult, correctly prophesizing that governments would need to resort to draconian interventions in response to an overall lack of preparation, with a substantial proportion of skeptical citizens likely rejecting public health interventions (Parmet & Rothstein, 2018). Yet, prior localized epidemics demonstrated a pattern of panic in response to emerging viral threats, sometimes disproportionate to the actual threat (Garfin et al., 2020). Theoretical models from decision science suggest that mitigation behavior is guided by a confluence of factors, particularly dread and uncertainty (Fox-Glassman & Weber, 2016), with threats viewed as more severe and unfamiliar typically associated with higher risk perceptions and decisions to act (Slovic, 1987). This dread and uncertainty may be in response to unfamiliar threats as well as unfamiliar interventions (Bond & Nolan, 2011). Thus, individuals may have had greater perceptions of risk with respect to COVID-19 infection because it was a novel threat, or greater aversion to unfamiliar interventions such mask-wearing in the United States, social distancing, and adult vaccinations (Bond & Nolan, 2011). However, evidence from the earliest phase of the COVID-19 outbreak demonstrated that psychological distress (Holman et al., 2020) and perceptions of risk of infection susceptibility and severity increased (Garfin et al., 2021), particularly as the novel pandemic shifted from an acute to a chronic event. By May of 2020, the novel COVID-19 pandemic and its associated mitigation had dragged on for over 3 months, creating a chronic, but unfamiliar stressor. Threat processing mechanisms and their relationship to mitigation in this context have been underexplored.

1.3 | Media exposure to hazards

The media is a primary input by which the populace learns about threats including hurricanes and COVID-19, likely impacting threat processing mechanisms that guide mitigation behaviors. Media dependency theory states that during times of crisis, individuals rely on the media for critical updates (Ball-Rokeach & DeFleur, 1976; Jung, 2017). A recent review of media use during hurricanes found that people used both traditional and social media during hurricanes, although the link between exposure to this information and performance of mitigation behaviors is unknown (Ulvi et al., 2019). During the early phase of COVID-19, media use increased dramatically (Koetsier, 2020), with many reporting substantial consumption of COVID-19-related content. While some evidence exists that threat-related media exposure can encourage information seeking and sharing between governments and citizens (Ulvi et al., 2019), such exposure can be a double-edged sword. Although media exposure can encourage mitigation behaviors, it can also spread misinformation (Allington et al., 2020; Kahn & Barondess, 2008; Zarocostas, 2020) and increase distress (Garfin et al., 2020; Holman et al., 2020). During COVID-19, increased media consumption had a positive relationship with protective behaviors, such as hand-washing (Akdeniz et al., 2020). Yet, research from the Netherlands suggests that social media both undermined and enhanced public trust in scientific expertise during COVID-19, although the effect of these dynamics on health protective behaviors was not evaluated (van Dijck & Alinead, 2020).

Type of media input may also matter for encouraging mitigation behaviors, although findings have been mixed about the directionality. In contrast to the majority of findings, research from a survey of 327 earthquake survivors found that media exposure (both traditional and new [including social] media) to earthquakes was *negatively* associated with risk perceptions (Xu et al., 2020). The authors speculate that this could be because they assessed and contrasted media type (traditional and new [social]) or because of the demographic composition of their sample (predominantly rural). These relationships, in turn, could impact mitigation action (Bubeck et al., 2012). Social media in particular (Cool et al., 2015; Ulvi et al., 2019) may be an effective conduit for disseminating rapid, real time information (Freberg et al., 2013), yet high levels of misinformation available on social media may be problematic for public health communications (Zarocostas, 2020). For example, research during COVID-19 found that misinformation was higher on social media compared to news media, which in turn was linked with lower compliance with COVID-19 mitigation (Bridgman et al., 2020). Traditional media can also spread inaccurate information (1) during hurricanes as information evolves rapidly during and in the immediate aftermath of a storm (Kahn & Barondess, 2008), and (2) during COVID-19, particularly with respect to scientific uncertainty as new data come in (Aven & Bouder, 2020; Fischhoff, 2020; Fischhoff & Davis, 2014). Despite the potential benefits and pitfalls of information dissemination via traditional and social media, the relationship between type of media exposure and actual mitigation is largely unknown.

1.4 | Threat processing

How media exposure translates to mitigation behavior in response to a threat is likely a function of the threat processing mechanisms related to those behaviors. Such processes have been hypothesized by prior theories of health protective behavior including the extended parallel process model (EPPM; Witte, 1992). The EPPM provides a framework by which decisions to engage in mitigation behaviors can be explained. In this model, inputs from external stimuli (e.g., threat messaging from media exposure) lead to threat processing mechanisms including perceived efficacy (i.e., self-efficacy and response efficacy) and perceived threat (i.e., susceptibility and severity), which in turn elicit motivation to engage in mitigation (Cho & Witte, 2005). Perceptions of a given threat should be high enough to warrant an attempt to reduce fearful circumstances, and efficacy should be high enough to motivate action (Cho & Witte, 2005). Indeed, prior research suggests that people reporting higher levels of perceived risk, perceived severity, and self-efficacy tend to adopt more protective behaviors in response to infectious disease threats (Chong et al., 2020; Cui et al., 2017; S. C. Kim & Hawkins, 2020; Lee & You, 2020; Lim et al., 2020), including COVID-19 (Guidry et al., 2021), and are more likely to evacuate during a hurricane (Burnside et al., 2007; Stein et al., 2010). However, as detailed below, other research conducted during the early phase of the COVID-19 pandemic found mixed support for EPPM threat processing constructs as guides for protective behavior (Sarrina Li & Huang, 2020; Yang et al., 2021), suggesting the need for continued inquiry.

1.4.1 | Perceived threat

There has been mixed support of the threat processing component of the EPPM during COVID-19 (Roberto et al., 2021). Data from a nonrepresentative sample did not find evidence of an association between COVID-19 risk perception and mitigation behaviors (Fullerton et al., 2021). Relatedly, perception of COVID-19 severity was associated with social distancing, although not with other forms of threat mitigation (e.g., hygiene behaviors); perceived susceptibility was not associated with protective behaviors (Magnan et al., 2021). Yet, the link between perceived threat and mitigation has been supported in analyses from two distinct, large, nationally representative samples of Americans (Bruine de Bruin & Bennett, 2020; Garfin et al., 2021), which both found positive associations between COVID-19-related risk perceptions (both severity and susceptibility) and threat mitigation behaviors (including mask wearing and social distancing). Research conducted with samples at-risk for hurricanes also supports the association between perceived threat and mitigation behaviors: a small random sample ($N = 234$) of coastal residents in North Carolina found that thinking about hurricane risk and perceptions of severity were associated with greater hurricane mitigation (Stock et al., 2021). Similarly, in the immediate advance of Hurricanes Isaac and Sandy ($N = 385$), subjective perceptions of hurricane risk (assessed via mental models) were generally inaccurate, with misconstrued warnings and relatively poor mental models of the intensity and impact of potential storms (Meyer et al., 2014). In turn, this led to lower hurricane mitigation behaviors including preparation and evacuation (Meyer et al., 2014). Yet, these studies did not incorporate efficacy or different types of media exposure into the models, and different types of threat (e.g., episodic vs. chronic; novel vs. familiar) were not compared.

1.4.2 | Perceived efficacy

Some research has evaluated efficacy as a predictor of mitigation during COVID-19, including social distancing (Chong et al., 2020; Guidry et al., 2021; Roberto et al., 2021) and hand washing. An online survey of 514 Hong Kong residents found that self-efficacy was associated with COVID-19 mitigation behavior (e.g., physical distancing, washing hands) (Chong et al., 2020); in other survey research both self-efficacy and response efficacy emerged as critical predictors of COVID-19 mitigation (Scholz & Freund, 2021). Research on disaster preparation more generally evaluated the relationship between self-efficacy and threat mitigation behavior (Rivera, 2020), finding that those with higher reported self-efficacy were more likely to have an emergency preparation plan. Other research indicates that lower response efficacy was associated with lower mitigation intentions with respect to hurricanes (Demuth et al., 2016). However, with respect to hurricane mitigation (e.g., flooding and wind damage), in a random sample of coastal homeowners ($N = 2500$), out of eight behaviors assessed only intention to install hurricane shutters was associated with self-efficacy (Slotter et al., 2020), suggesting that perceived efficacy may not uniformly predict mitigation behavior.

1.5 | The present study

Using a longitudinal, representative sample of Gulf Coast residents from Florida and Texas previously exposed to hurricanes (including Harvey, Michael, and Irma), we draw from key EPPM constructs for a theoretically derived exploration of mitigation behavior in response to COVID-19 and the impending 2020 hurricane season. We have several aims as follows:

1. Test whether threat processing constructs (i.e., perceived threat, perceived efficacy) explain engagement in self-reported threat mitigation behaviors (handwashing, mask wearing, social distancing) in response to COVID-19.
2. Test whether threat processing constructs (i.e., perceived threat, perceived efficacy) explain engagement in self-reported threat mitigation behavior (hurricane preparation) in response to hurricanes.
3. Examine whether there are differential effects of media inputs (collected during an actual threat) from social compared to traditional media sources.

2 | METHOD

2.1 | Procedure

Data collection was part of a longitudinal cohort study, of which data from multiple waves of the survey were used for the analyses presented herein. Four waves of data had been collected; three waves will be discussed in this report, henceforward referred to as wave 1 (collected September 8-11, 2017), wave 2 (collected October 22-November 6, 2018), and wave 3 (collected May 14–27, 2020). Data from wave 2 are presented in Supporting Information. The remaining wave was not relevant to the present analyses and will not be discussed further. Study aims and analytic strategy were preregistered on the Open Science Framework (https://osf.io/k632z/?view_only=79bd39b85b024c5aa8b3b6d531e22f9f).

Participants were drawn from the Ipsos KnowledgePanel. Ipsos (formerly GfK) uses address-based sampling to randomly recruit panelists using probability-based sampling methods; the panel is designed to be representative of the United States. Households without internet connection are provided a web-enabled device and free internet services. Once household members are recruited for the panel and assigned to a study sample, they are notified electronically of the opportunity. They can then take the survey through their email link or by visiting their online member page.

A total of 2507 current and former panelists who were surveyed in tandem to major extreme weather events (e.g., Hurricanes Harvey, Irma, and Michael) since 2017 were contacted to participate in wave 3 ; the wave 3 survey was completed by 1846 panelists in May 2020 (pre-2020 Atlantic Hurricane season, during the COVID-19 pandemic) for a response rate of 73.6% from eligible wave 1 respondents. In the initial wave 1 survey, 5940 residents of Florida and Texas were invited to complete a survey on responses to the threat of Hurricane Irma as it approached the Florida mainland: 2774 completed the survey in the 60-h data collection period (46.7% response rate); 1879 completed the survey in 2018 (wave 2) with a 70.2% response rate from all eligible wave 1 respondents. Unless otherwise noted, all variables were assessed during the May 2020 (wave 3) data collection.

2.2 | Measures

All measures were collected in 2020 (wave 3) except for hurricane-related media exposure. Hurricane-related media exposure was collected in 2017 (wave 1), during and in the immediate aftermath of a Category 5 (Irma in Florida) and a Category 4 (Harvey in Texas) hurricane, respectively. Media exposure was also collected in 2018 (wave 2), immediately following Hurricane Michael. Media-exposure from 2017 is presented in the main text as many respondents were directly exposed to either Hurricane Harvey or Hurricane Irma. Thus, the 2017 measure provides a more direct comparison with media exposure to COVID-19, as participants were also directly exposed to that hazard in real time. Although Hurricane Michael was also a catastrophic hurricane, it made landfall in Florida in an area of the state with relatively low population density; thus, most of our sample was exposed to Hurricane Michael and other 2018 hurricanes via the media or indirectly (e.g., knowing someone exposed) (Garfin et al., 2022). See Supporting Information for exact items from the survey and full results using the 2018 media exposure data.

2.2.1 | Mitigation behavior

Hurricane mitigation behaviors

Participants completed a checklist derived from prior research (Wong-Parodi & Feygina, 2018). This checklist asked participants: "please check all those that you have done to prepare for the 2020 hurricane season" with the following options: (1) learn about the risks from hurricanes and how to prepare for them; (2) make a plan for safe places to move vehicle(s) in the event of a hurricane; (3) put together an emergency kit (e.g., food, medical supplies, flashlight); (4) develop and practice an emergency plan; (5) identify shelter locations in the event of an evacuation; (6) copy important documents (e.g., birth certificates, driver's licenses); (7) get a row boat or inflatable raft; (8) make my home more hurricane proof (e.g., install hurricane shutters, sand bags); (9) have flood insurance; (10) consider hurricane forecasts when making travel plans; and 11) other. Responses were summed to create a count of participants' hurricane mitigation behaviors.

COVID-19 mitigation behaviors

Participants reported their frequency of engaging in 10 individual-level mitigation behaviors in response to the coronavirus outbreak using a Likert-type scale from 1 (never) to 5 (all the time): (1) wash my hands for at least 20 s; (2) wash my hands and/or use hand sanitizer after touching surfaces outside my home; (3) avoid touching my face when in public; (4) wear a face mask and/or gloves in public; (5) avoid socializing in groups > 10 with people outside my household; (6) avoid socializing with any people outside my household; (7) avoid public transportation (e.g., buses, subways, Uber, Lyft); (8) minimize trips outside the home; (9) cancel or reschedule travel plans; and (10) other. Items 1–3 constituted *hand hygiene* ($\alpha = 0.77$), item 4 assessed *mask wearing*, and items 5–9 assessed *social distancing behaviors* ($\alpha = 0.81$). Item 10 (other) was omitted due to high missingness. A similar approach was used in prior research using a distinct sample. Mean scores were calculated for each type of mitigation behavior to generate a frequency score.

2.2.2 | External stimuli

Hurricane media exposure

Traditional media exposure (including online news from traditional news outlets) was assessed using the average of two questions: "In the past week, how many hours per day, on average, have you spent watching, reading, and/or listening to media coverage about (Hurricane Harvey [for Texas] or Hurricane Irma [for Florida])? Please estimate your average daily use for each of the media categories described below" with stems: (1) TV, radio, print news, and (2) online news sources (CNN, Yahoo, NYTimes.com, etc.) and response options 0–11+.[1]

Social media exposure was assessed using the item "In the past week, how many hours per day, on average, have you spent watching, reading, and/or listening to media coverage about [Hurricane Harvey (for Texas) or Hurricane Irma (for Florida)]? Please estimate your average daily use for each of the media categories described below" with stem: social media (Facebook, Twitter, Reddit, etc.) and response options 0–11+. Media exposure items were based off prior research (Holman et al., 2014).

[1] Exact response options for hours of traditional and social media exposure were none, <1, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11+.

COVID-19 media exposure

Traditional media exposure (including online news from traditional news outlets) was assessed using the average of two questions: "In the past week, how many hours per day, on average, have you spent watching, reading, and/or listening to media coverage about the COVID-19 outbreak? Please estimate your average daily use for each of the media categories described below" with stems: (1) TV, radio, print news and (2) online news sources (CNN, Yahoo, NYTimes.com, etc.) and response options 0–11+.

Social media exposure was assessed using the item "In the past week, how many hours per day, on average, have you spent watching, reading, and/or listening to media coverage about the COVID-19 outbreak? Please estimate your average daily use for each of the media categories described below" with stem: social media (Facebook, Twitter, Reddit, etc.) and response options 0–11+.

2.2.3 | Threat processing

Perceived efficacy

Hurricane self-efficacy was assessed by asking: "Of the actions listed above, how well do you think you could perform them to prepare for the 2020 hurricane season?" with response options 1 (not well at all) to 5 (extremely well). *COVID-19 self-efficacy* was assessed by asking: "How well do you think you could perform the above actions to reduce the harmful effects of the COVID-19 outbreak?" with response options 1 (not well at all) to 5 (extremely well). *Hurricane response efficacy* was assessed by asking: "Of the actions listed above, how much will they help to prepare for the 2020 hurricane season?" with response options 1 (not at all) to 5 (completely). *COVID-19 response efficacy* was assessed by asking: "How much do you think the above actions will help reduce the harmful effects of the COVID-19 outbreak?" with response options 1 (not at all) to 5 (completely).

Perceived threat

Hurricane susceptibility was assessed by asking: "How likely is it that your well-being (health, financial, emotional, social, etc.) will be impacted by a major hurricane (Category 3 or stronger) this year?" with response options 1 (not at all likely) to 5 (extremely likely). *COVID-19 susceptibility* was assessed by asking: "How likely is it that the COVID-19 outbreak will harm your well-being (health, financial, emotional, social, etc.) in the future?" with response options 1 (not at all likely) to 5 (extremely likely). *Hurricane severity* was assessed by asking: "If your community were to be impacted by a major hurricane (Category 3 or stronger) this year, how much do you think your well-being (health, financial, emotional, social, etc.) would be harmed?" with response options 1 (not at all) to 5 (a great deal). *COVID-19 severity* was assessed by asking: "If your well-being (health, financial, emotional, social, etc.) were to be harmed by the COVID-19 outbreak, how much would it be harmed?" with response options 1 (not at all) to 5 (a great deal).[2]

2.2.4 | Covariates

Ipsos (formerly GfK) collects demographics on all panelists upon entry to the KnowledgePanel and updates regularly. Demographic covariates for the present study included age, gender, ethnicity, education, income, and state of residence.

2.3 | Analytic strategy

Unless otherwise indicated, all descriptive and inferential statistics were weighted using study-specific post-stratification weights. These weights were calculated to adjust the final study sample to the demographic compositions of the states of Florida and Texas for adults 18 and older. Weighting benchmarks were based on the American Community Survey (2020) and were calculated using the following demographic cells: gender (male, female), by age (18–29, 30–44, 45–59, 60+), race/ethnicity (White/non-Hispanic, Black/non-Hispanic, other/non-Hispanic, Hispanic, 2+Races/non-Hispanic) household income (Under \$25,000, \$25,000–\$49,999, \$50,000–\$74,999, \$75,000–\$99,999, \$100,000–\$149,999, \$150,000 and over), metro/nonmetro areas, and education (less than high school/high school, some college, bachelor's or higher).

Aspects of the EPPM model were tested using Stata 16.1's generalized structural equation modeling (GSEM) program to account for the negative binomial distribution of hurricane preparatory behaviors. Continuous variables were standardized and can be interpreted in standard deviation units. Two path models were constructed (one for each set of dependent variables: COVID-19 mitigation behaviors and hurricane mitigation behaviors). In each threat-specific model, traditional and social media were hypothesized inputs, with threat processing variables (self-efficacy, response efficacy, threat susceptibility, and threat severity) as mediators predicting self-reported mitigation behaviors. Models were tested controlling for demographics.[3] Error covariances were added between efficacy (self- and response), perceived threat (sus-

[2] It is plausible that severity and susceptibility were correlated because one might report low susceptibility because they did not believe they would experience a major hurricane. To explore this possibility, we examined the relationship between susceptibility and severity with likelihood of hurricane occurrence ("during the next five years, it is very likely a major hurricane [Category 3 or stronger] will happen near me," with endpoints 1 = strongly disagree and 5 = strongly agree). Susceptibility and likelihood regarding hurricane occurrence were correlated: $r = 0.40$, $p < 0.001$, as were severity and likelihood: $r = 0.30$, $p < 0.001$.

[3] At each of the prior waves, participants completed assessments of their prior exposures to Hurricanes Harvey, Irma, and Michael, as well as other exposures to previous hurricanes. Participants reported whether they had lost property, had their home destroyed, been injured, lost a pet, or knew someone who was injured or killed in a previous hurricane. Participants who reported any prior exposure to a hurricane were coded as 1, all others were coded as 0. At wave 3, participants reported whether they themselves or someone close to them had experienced symptoms, been diagnosed, or had a known exposure to COVID-19 and whether they knew someone who had died from COVID-19. Participants who reported any of these exposures to COVID-19 were coded

TABLE 1 Descriptive statistics for key study variables ($N = 1846$)

Variables	COVID-19 (M [SD])	Hurricanes (M [SD])
Traditional media exposure	1.62 [1.91]	3.05 [2.65]
Social media exposure	1.16 [2.08]	2.14 [3.03]
Self-efficacy	3.86 [0.96]	3.40 [1.11]
Response efficacy	3.32 [0.96]	3.10 [1.12]
Perceived susceptibility	2.50 [1.10]	2.28 [1.10]
Perceived severity	2.82 [1.07]	2.73 [1.15]
Mitigation behaviors	–	2.64 [2.58]
Hand hygiene	4.15 [0.80]	–
Social distancing	4.08 [0.95]	–
Mask wearing	3.87 [1.33]	–

ceptibility and severity), and COVID-19 protective behavior (social distancing, mask wearing, hand hygiene) variables in the models to account for high correlations among these sets of variables. For individual scales, due to very low missing data (less than 5% on any one item), row mean substitution (by subscale, if applicable) was implemented to preserve sample size if respondents answered the majority of questions per measure (>50%). Such an approach may produce the least amount of bias compared to other approaches (Bell et al., 2016) and is consistent with prior analyses of this data. Robust standard errors are presented throughout, as appropriate for complex survey data.

3 | RESULTS

3.1 | Descriptive statistics

The final weighted sample ($N = 1846$) closely approximated U.S. Census benchmarks for the states of Florida and Texas. Mean age for the sample was 51.00 years (SD = 16.75), and 53.2% of the sample ($n = 982$) was female. The sample was ethnically diverse; 54.8% of the sample identified as non-Hispanic White, 11.9% as non-Hispanic Black, 28.1% as Hispanic, and the remaining 5.2% as other/multiracial, non-Hispanic. 4.4% had not finished high school, 34.1% had a high school diploma, 31.9% had attended some college, and 29.5% had earned a Bachelor's degree or higher. Median income for the sample was between \$50,000 and \$74,999 annually. Of the sample, 28.7% had previous direct exposure to a hurricane; 17.8% had been personally exposed to COVID-19 (self or close other had been/were currently sick with COVID-19). Descriptive statistics for COVID-19 and hurricane-related media, self-efficacy and response efficacy, susceptibility, and severity, and self-reported mitigation behaviors are presented in Table 1. Correlations among the variables in both the COVID-19 and hurricane models are presented in Table 2. Key variables covaried across threats: COVID-19-related media exposure was associated with hurricane-related media exposure, as were threat processing variables (self-efficacy and response efficacy, susceptibility, severity), and threat-specific mitigation actions.

3.2 | COVID-19 mitigation behavior

Generalized SEM estimates for COVID-19 mitigation behaviors are presented in Table 3. Traditional media exposure directly predicted each of self-efficacy and response efficacy, perceived susceptibility, and perceived severity, whereas social media directly predicted only decreased self-efficacy. Both self-efficacy and response efficacy were significantly and positively associated with all three COVID-19 mitigation behaviors; perceived susceptibility and severity directly predicted increased social distancing but were not associated with mask wearing or hand hygiene. Response efficacy partially mediated the relationships between traditional media exposure and the three COVID-19 mitigation behaviors; self-efficacy also partially mediated the relationship between traditional media and hand hygiene. There were no significant indirect relationships between social media and any COVID-19 mitigation behaviors. See Figure 1 for a graphical representation of these relationships.

3.3 | Hurricane mitigation behavior

Generalized SEM estimates for hurricane mitigation behaviors, collected in advance of the 2020 hurricane season, are presented in Table 4. Traditional media exposure (collected in 2017) was a significant predictor of self-efficacy and response efficacy, perceived susceptibility, and perceived severity; social media (collected in 2017) did not directly predict any of these mediators. Hurricane preparation behaviors were directly predicted by self-efficacy, response efficacy, and perceived susceptibility, but not perceived severity. The relationship between traditional media exposure and hurricane preparation behaviors was partially mediated by self-efficacy, response efficacy, and perceived susceptibility, but not perceived severity. There were no indirect relationships between social media exposure and hurricane mitigation behaviors. See Figure 2 for a graphical representation of these relationships.

Table S3 presents estimates for GSEM models for hurricane mitigation behavior using wave 2 (2018) media exposure collected in the immediate aftermath of Hurricane Michael [to which our sample was exposed primarily indirectly and via the media] rather than 2017 media exposure to hurricanes Harvey and Irma. Results were similar, with the caveat that traditional media exposure was no longer a predictor of self-efficacy.

as 1, all others were coded as 0. An additional set of GSEMs was tested controlling for direct COVID-19 and hurricane exposure; results were unchanged, so the more parsimonious models were kept.

TABLE 2 Correlations among study variables ($N = 1846$)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
1.	1.00															
2.	0.26***	1.00														
3.	0.41***	0.22***	1.00													
4.	0.13***	0.57***	0.39***	1.00												
5.	0.04	0.03	−0.02	−0.005	1.00											
6.	0.05*	0.05	−0.02	−0.004	0.25***	1.00										
7.	0.12***	0.09***	0.04	0.05*	0.49***	0.12***	1.00									
8.	0.12***	0.12***	0.06*	0.10***	0.21***	0.52***	0.23***	1.00								
9.	0.11***	0.10***	0.13***	0.10***	0.05*	0.01	0.06*	0.04	1.00							
10.	0.15***	0.24***	0.14***	0.13***	0.06*	0.12***	0.08***	0.27***	0.24***	1.00						
11.	0.12***	0.13***	0.12***	0.11***	0.05*	0.00	0.08***	0.11***	0.57***	0.25***	1.00					
12.	0.16***	0.14***	0.09***	0.07**	0.08***	0.07**	0.10***	0.21***	0.30***	0.60***	0.36***	1.00				
13.	0.08***	0.11***	0.08***	0.13***	0.37***	0.14***	0.32***	0.17***	0.11***	0.12***	0.11***	0.11***	1.00			
14.	0.09***	0.09***	0.05*	0.05*	0.35***	0.05*	0.41***	0.11***	0.24***	0.13***	0.25***	0.14***	0.47***	1.00		
15.	0.14***	0.13***	0.01	0.03	0.31***	0.06*	0.35***	0.14***	0.13***	0.11***	0.16***	0.14***	0.42***	0.52***	1.00	
16.	0.13***	0.20***	0.04	0.05*	0.13***	0.36***	0.11***	0.46***	0.05*	0.32***	0.10***	0.22***	0.18***	0.14***	0.19***	1.00

Note: 1. COVID-19 traditional media; 2. Hurricane traditional media; 3. COVID-19 social media; 4. Hurricane social media; 5. COVID-19 self-efficacy; 6. Hurricane self-efficacy; 7. COVID-19 response efficacy; 8. Hurricane response efficacy; 9. COVID-19 susceptibility; 10. Hurricane susceptibility; 11. COVID-19 severity; 12. Hurricane severity; 13. Hand hygiene; 14. Social distancing; 15. Mask wearing; 16. Hurricane preparatory behavior. Corresponding variables across disaster contexts are highlighted in gray. *$p < .05$; **$p < .01$; ***$p < .001$

4 | DISCUSSION

Using a representative sample of Gulf Coast residents dealing with the co-occurring threats of COVID-19 and the 2020 hurricane season, we found that constructs derived from the EPPM helped explain mitigation behavior for both threats. We advance prior research by considering the specific type of threat-related media exposure (traditional or social media), finding critical differences between type of media exposure and performance of mitigation behavior for both COVID-19 and hurricanes. Our longitudinal design allowed us to assess media exposure tangent to several different collective traumas: COVID-19-related media exposure was assessed in May 2020, during an early surge in COVID-19 infections, while hurricane-related media exposure was assessed during and in the immediate aftermath of a Category 5 (Irma and Michael in Florida) and a Category 4 (Harvey in Texas) hurricanes, respectively. This allows for a comparison of media exposure to two threats while lowering the bias of retrospective reporting. Accordingly, we present responses to two types of threats: a novel, chronic threat (COVID-19) and an episodic, familiar threat (hurricanes on the Gulf Coast). Of note, we also compare threats to which participants were directly exposed (COVID-19 and hurricanes Irma and Harvey) and exposed primarily via the media and indirectly (Hurricane Michael and other 2018 hurricanes). Although nuances were present, on balance, for all events evaluated, threat processing variables (efficacy and threat perception) were associated with mitigation behaviors; specifically, traditional media exposure was positively associated with mitigation behaviors, while social media was not associated with mitigation behaviors. Key variables tended to covary across threats, perhaps indicating individual differences in media exposure that drive subsequent threat processing and mitigation, or a spillover effect between threats more generally.

4.1 | Media exposure

A key contribution of the present study is the integration and comparison of both type (social media vs. traditional media) and amount (hours) of media exposure as a critical input predicting both threat processing variables and subsequent mitigation behavior. In models predicting COVID-19 mitigation behaviors, greater exposure to COVID-19-related social media was negatively associated with self-efficacy, suggesting that those who obtained more COVID-19 relevant information from social media sources were *less* likely to think COVID-19 mitigation was something they could perform well. In the models exploring hurricane mitigation, social media had no statistically significant effect on response efficacy or threat perception.

An early COVID-19-related commentary from the *Lancet* stressed the importance of leveraging social media to promote effective public health policies, yet criticized the lack of funding used to ensure adequate communication from reputable sources (Garrett, 2020). Unfortunately, our research showed that in the early months of the pandemic, social media was either inversely related to performance of health protective behaviors, or not associated at all; the impact for

TABLE 3 Generalized structural equation model coefficients for predictors of COVID-19 health behaviors ($N = 1846$)

Path	Coefficient	*p*	95% Confidence Interval (Lower Bould)	95% Confidence Interval (Upper Bound)
Direct effects				
Traditional media →				
Self-efficacy	0.10	0.023	0.01	0.19
Response efficacy	0.12	0.022	0.02	0.22
Perceived susceptibility	0.11	0.021	0.02	0.20
Perceived severity	0.10	0.044	0.003	0.20
Social media →				
Self-efficacy	−0.09	0.049	−0.18	−0.0003
Response efficacy	−0.06	0.142	−0.13	0.02
Perceived susceptibility	0.08	0.065	−0.005	0.16
Perceived severity	0.06	0.087	−0.01	0.13
Self-efficacy →				
Social distancing	0.17	0.002	0.06	0.28
Mask wearing	0.16	<0.001	0.07	0.24
Hand hygiene	0.27	<0.001	0.18	0.37
Response efficacy →				
Social distancing	0.32	<0.001	0.22	0.42
Mask wearing	0.29	<0.001	0.20	0.38
Hand hygiene	0.19	<0.001	0.11	0.28
Perceived susceptibility →				
Social distancing	0.10	0.017	0.02	0.19
Mask wearing	0.08	0.094	−0.01	0.17
Hand hygiene	0.01	0.817	−0.08	0.11
Perceived severity →				
Social distancing	0.15	<0.001	0.07	0.24
Mask wearing	0.06	0.177	−0.03	0.15
Hand hygiene	0.02	0.640	−0.07	0.11
Indirect effects				
Traditional media → social distancing				
Via self-efficacy	0.02	0.068	−0.001	0.04
Via response efficacy	0.04	0.035	0.002	0.07
Via perceived susceptibility	0.01	0.069	−0.001	0.02
Via perceived severity	0.02	0.070	−0.001	0.03
Traditional media → mask wearing				
Via self-efficacy	0.02	0.071	−0.001	0.03
Via response efficacy	0.03	0.023	0.005	0.06
Via perceived susceptibility	0.01	0.167	−0.003	0.02
Via perceived severity	0.01	0.211	−0.004	0.02
Traditional media → hand hygiene				
Via self-efficacy	0.03	0.035	0.002	0.05
Via response efficacy	0.02	0.021	0.003	0.04
Via perceived susceptibility	0.001	0.816	−0.01	0.01
Via perceived severity	0.002	0.639	−0.01	0.01

(Continues)

TABLE 3 (Continued)

Path	Coefficient	*p*	95% Confidence Interval (Lower Bould)	95% Confidence Interval (Upper Bound)
Social media → social distancing				
Via self-efficacy	−0.01	0.112	−0.03	0.003
Via response efficacy	−0.02	0.152	−0.04	0.01
Via perceived susceptibility	0.01	0.168	−0.003	0.02
Via perceived severity	0.01	0.120	−0.002	0.02
Social media → mask wearing				
Via self-efficacy	−0.01	0.095	−0.03	0.002
Via response efficacy	−0.02	0.149	−0.04	0.01
Via perceived susceptibility	0.01	0.234	−0.004	0.02
Via perceived severity	0.004	0.288	−0.003	0.01
Social media → hand hygiene				
Via self-efficacy	−0.02	0.071	−0.05	0.002
Via response efficacy	−0.01	0.159	−0.03	0.004
Via perceived susceptibility	0.001	0.821	−0.01	0.01
Via perceived severity	0.001	0.650	−0.005	0.01

Note: Covariates included gender, age, ethnicity, income, education, and state of residence. Estimates of covariate paths, error variances, and covariances are presented in Table S1.
$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

hurricane-related preparation behaviors was null. While this may be disquieting given the proliferation of social media as a conduit for information dissemination (Allington et al., 2020), it also provides an opportunity for communicators to enhance their strategies for communicating on social media. Indeed, several review articles indicated that during COVID-19, social media presented a mix of information, with varying levels of engagement across platforms (Tsao et al., 2021; Venegas-vera et al., 2020). Our findings suggest that in addition to limiting misinformation (Zarocostas, 2020), communicators should seek to promote accurate information with messaging relevant to the populace who needs it. Future research could implement a more fine-grained approach using machine learning or other data-driven techniques to assess what people saw (e.g., factual information compared to misinformation) and how that impacted their perspectives and behaviors (Tsao et al., 2021). Moreover, these relationships may have changed as the pandemic evolved over time (Tsao et al., 2021); future research should continue to explore this as COVID-19 becomes endemic and future threats emerge.

Our study aligns with research from the United Kingdom that suggested exposure to "legacy media" (i.e., television and radio) was associated with more health protective behaviors during COVID-19, while reliance on social media was associated with more misinformation (i.e., conspiracy theories) and less COVID-19 protective behavior (Allington et al., 2021). We bolster this work by incorporating threat processing variables as mediators of these relationships and assessing media exposure and relevant mitigation behaviors to a conceptually distinct threat (hurricanes). Indeed, while some prior literature has assessed traditional and social media exposure to hurricanes, it has largely not been linked to actual mitigation behavior (Ulvi et al., 2019). Our research contrasts prior research finding that media exposure was not significantly associated with household mitigation (except purchase of flood insurance) (Brody et al., 2017). Differences could be due to our timing of data collection, use of a representative sample, or our delineation of type of media (i.e., traditional or social). With respect to timing, our assessment of hurricane-related media exposure was conducted in "real time" during the immediate threat of a Category 5 hurricane (Irma) and recently following a Category 4 hurricane (Harvey); our assessment of mitigation was based on actual self-reported behavior, rather than planned behavior. Moreover, the time lag between initial media exposure and assessment of mitigation allowed time for participants to feasibly complete some of the high effort actions (e.g., make home more hurricane proof). Thus, our methodology may have been subject to less bias than much of the extant research on hurricane mitigation, which has often relied on retrospective reporting and hypothetical behaviors (Thompson et al., 2017).

Optimistically, our research suggests that exposure to traditional event-related media was positively associated with threat processing variables, particularly self-efficacy and response efficacy, and resulting mitigation behaviors. However, it is plausible that those more likely to act were also

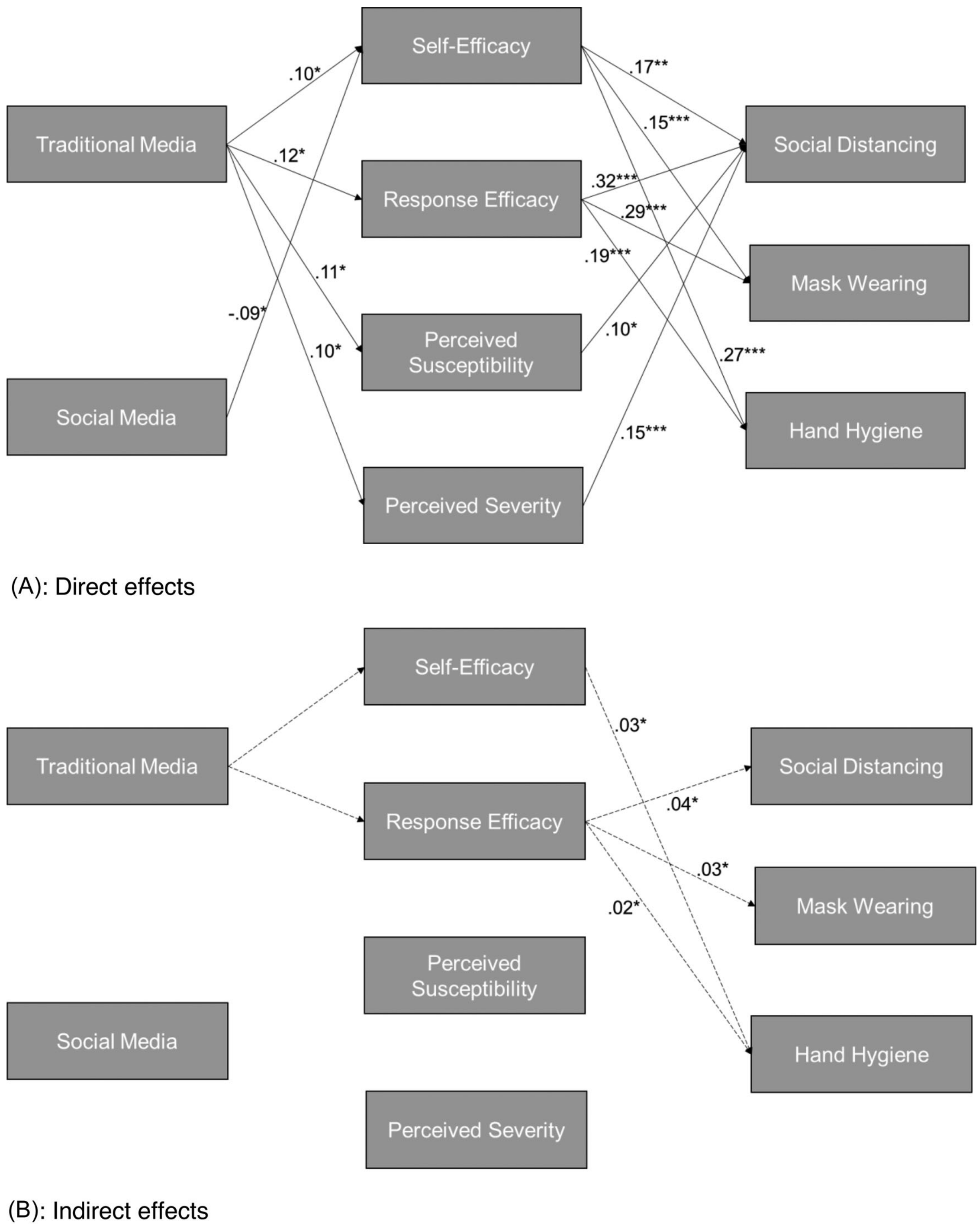

FIGURE 1 Generalized structural equation model predicting COVID-19 health protective behaviors ($N = 1846$): (a) direct effects; (b) indirect effects. *Note*: Non-significant paths not presented in figure for parsimony; all data collected in 2020. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

more likely to turn to traditional media outlets for their information during times of crises, or that relationships were reciprocal (Thompson et al., 2019). Social media use was associated with mitigation behavior for neither COVID-19 nor hurricanes, highlighting a key outlet to target in future communications. Despite the proliferation of misinformation documented on social media outlets during COVID-19 (Allington et al., 2020), early in the COVID-19 pandemic, social media did not appear to have a more deleterious impact on mitigation behaviors compared to the more familiar and less controversial threat of episodic hurricanes. While a literature review of social media for emergency management shows the promise of social media for communicating real-time updates to the populace during the immediate threat of a hurricane (Luna & Pennock, 2018), our results suggest that social media was not effective at inspiring mitigation

TABLE 4 Generalized structural equation model coefficients for predictors of hurricane preparatory behaviors ($N = 1846$)

Path	Coefficient	p	95% (Lower Bould)	95% (Upper Bound)
Direct effects				
Traditional media →				
Self-efficacy	0.11	0.017	0.02	0.19
Response efficacy	0.13	0.003	0.04	0.21
Perceived susceptibility	0.18	<0.001	0.09	0.26
Perceived severity	0.10	0.039	0.01	0.19
Social media →				
Self-efficacy	−0.05	0.291	−0.15	0.05
Response efficacy	−0.03	0.546	−0.13	0.07
Perceived susceptibility	−0.03	0.491	−0.12	0.06
Perceived severity	−0.003	0.948	−0.10	0.10
Self-efficacy → hurricane preparation	0.23	<0.001	0.15	0.31
Response efficacy → hurricane preparation	0.33	<0.001	0.25	0.41
Perceived susceptibility → hurricane preparation	0.18	<0.001	0.09	0.27
Perceived severity → hurricane preparation	0.03	0.549	−0.06	0.11
Indirect effects				
Traditional media → hurricane preparation				
Via self-efficacy	0.02	0.035	0.002	0.05
Via response efficacy	0.04	0.005	0.01	0.07
Via perceived susceptibility	0.03	0.002	0.01	0.05
Via perceived severity	0.003	0.579	−0.01	0.01
Social media → hurricane preparation				
Via self-efficacy	−0.01	0.305	−0.04	0.01
Via response efficacy	−0.01	0.546	−0.04	0.02
Via perceived susceptibility	−0.01	0.497	−0.02	0.01
Via perceived severity	−0.0001	0.949	−0.003	0.003

Note: Covariates included gender, age, ethnicity, income, education, and state of residence. Estimates of covariate paths, error variances, and covariances are presented in Table S2.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***} p < 0.001$

behavior relevant to the episodic threat of the annual hurricane season or the chronic threat of COVID-19. Our research suggests that for both threats, social media was underutilized or sub-optimally effective at encouraging protective mitigation behavior. Future research, perhaps using qualitative methods or experimental designs, should explore how to leverage social media to galvanize protective actions across a range of possible threats.

4.2 | Threat processing variables

Another key contribution of our study is exploring the relationship between media exposure, threat processing, and mitigation behavior with respect to two distinct, concurrently occurring threats: a novel, chronic threat and an episodic, familiar threat. Similar to prior studies on COVID-19 (Chong et al., 2020; Guidry et al., 2021; Roberto et al., 2021) and natural disasters (Becker et al., 2013), we found self-efficacy and response efficacy positively associated with increased mitigation behaviors. Efficacy most consistently functioned as a mediator between traditional media exposure and mitigation behavior, suggesting the potential of traditional media for communicating what actions are effective for mitigating threat. In contrast to prior work on flood risks, which found response but not self-efficacy associated with mitigation (Zaalberg et al., 2009), we found both self-efficacy and response efficacy associated with all COVID-19 mitigation behaviors (hand hygiene, social distancing, mask wearing) and with hurricane mitigation (preparation). These similarities suggest that targeting self-efficacy and response efficacy to promote mitigation during both familiar and novel threats may be fruitful. This is critical as data suggest climate change and other environmental degradation will result in increased

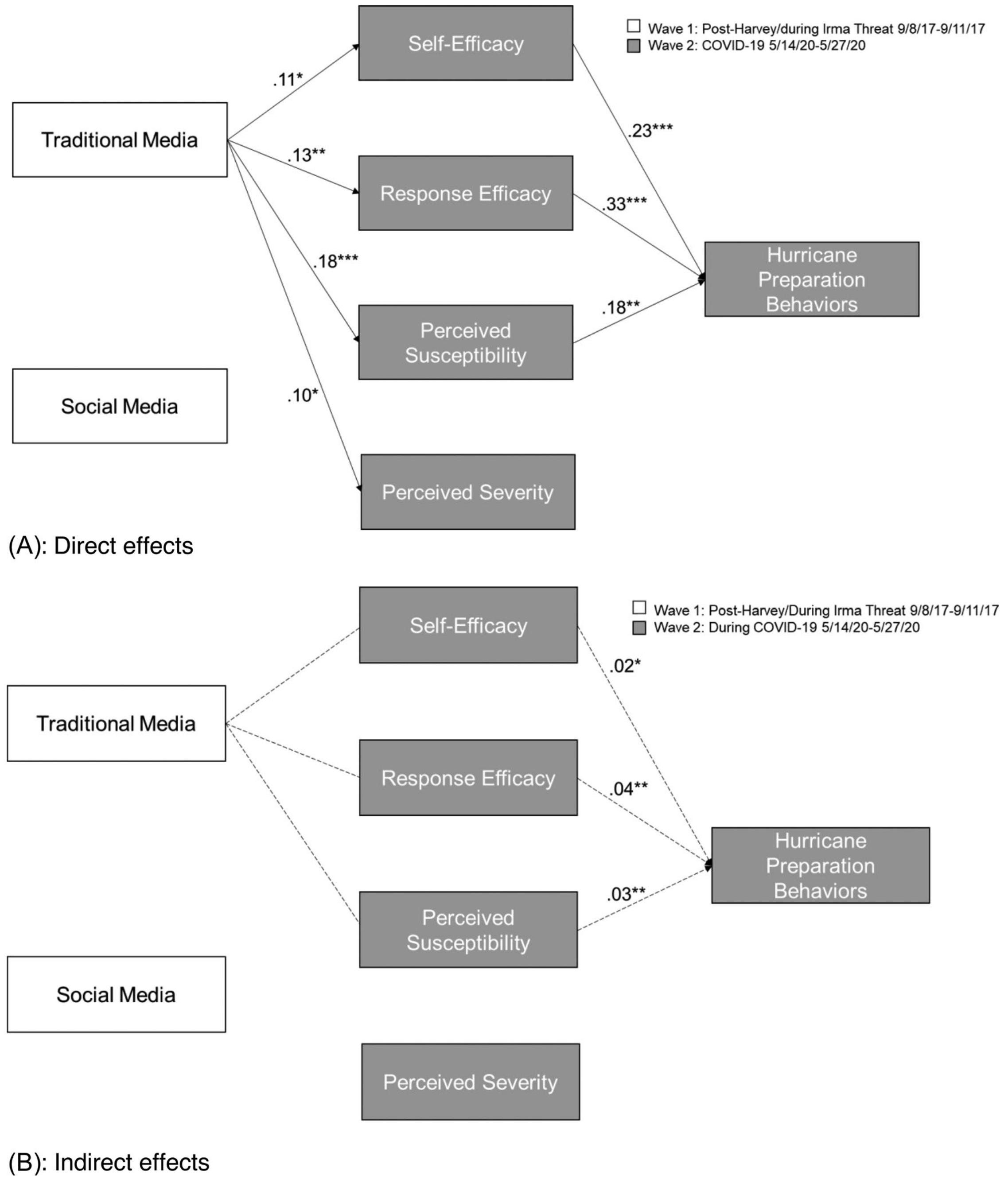

FIGURE 2 Model predicting hurricane preparatory behaviors ($N = 1846$): (a) direct effects; (b) indirect effects. *Note*: Non-significant paths not presented in figure for parsimony. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

severity of weather-related disasters (Trenberth et al., 2018) and increases in novel, zoonotic infectious disease outbreaks (Ebi & Hess, 2020; K. F. Smith et al., 2014). Yet, self-efficacy was a mediator between traditional media exposure for hurricane preparation behaviors but not for mask wearing or hand hygiene behaviors relevant to COVID-19. These differences may have resulted from the ceiling effects of hand hygiene behaviors (Garfin et al., 2021); early missteps with communicating the value of mask wearing, difficulty obtaining masks, and the politization of efforts encouraging this mitigation strategy (H. K. Kim & Tandoc, 2022); or the relative ease of hand-washing and mask wearing compared to more high effort actions involved in hurricane preparation and social distancing. Future research should explore such relationships.

In alignment with inquiry incorporating risk perceptions during COVID-19 (Guidry et al., 2021), a natural disaster (Becker et al., 2013), and coastal residents at risk for hurricanes (Brody et al., 2017), we found susceptibility associated with increased mitigation for hurricane mitigation and some COVID-19 mitigation (social distancing). This adds to prior research on hurricane evacuation behavior:

meta-analytic findings suggest that both general threat perceptions (both severity and susceptibility) are associated with evacuation behavior and intentions (Huang et al., 2016). Yet, prior research using representative samples of Texans and Floridians suggests that while susceptibility is associated with greater evacuation intention, severity exhibits a more complex relationship, which may depend on fine-grained assessments of threat exposure such as storm surge versus high wind (Lazo et al., 2015). Importantly, prior findings demonstrate preparation behavior predicts evacuation intentions (Lazo et al., 2015), suggesting getting people to take preparations in advance of a storm may also prime them to take later emergency action (e.g., evacuation behavior), particularly if they view the threat as likely to occur. This may be particularly relevant in our sample: despite both coastal and inland residents of Florida and Texas being at risk for deleterious consequences of hurricanes, prior research indicates geographic differences in preparation behaviors between coastal and inland residents (Mongold et al., 2021). However, it may also be that given the high intercorrelation between susceptibility and severity some degree of multicollinearity was present. Nevertheless, encouraging preparation in advance of a threat may help encourage other subsequent mitigation behavior (including evacuation). Taken together, these findings suggest that targeted communications focusing on people's risk of susceptibility to a threat may be a more potent strategy to encourage mitigation, perhaps because people's biases tend to estimate that threats will impact them less severely than they will impact others (Sjöberg, 2003). Our findings suggest that this is true for threats that are both episodic (hurricanes) and chronic (COVID-19).

In contrast to prior work exploring climate change mitigation using a representative sample of Taiwanese residents (Sarrina Li & Huang, 2020), we found that for both COVID-19 and hurricanes, perceived efficacy and perceived threat exhibited independent—rather than solely interactive—effects on mitigation behaviors. While prior research on college students found support for a perceived threat and social distancing behavior during COVID-19 (Roberto et al., 2021), research using an online sample of adults found that only severity was associated with behaviors (Magnan et al., 2021), and experimental work ($N = 326$) found perceived efficacy—but not perceived threat—was associated with behavioral intentions (Yang et al., 2021). Relatedly, a sample of 2500 coastal North Carolina home owners found only limited support for the association between risk perceptions and intention to engage in hurricane mitigation (Slotter et al., 2020). Likewise, risk perceptions were not necessarily associated with mitigation intentions in Caribbean communities at high risk for climate-related threats (R. A. Smith, 2018). We extend and clarify this study by using a large, representative sample of residents from Florida and Texas and using actual self-reported behavior (rather than intentions) in our measures of mitigation. This addresses some key methodological limitations common in prior disaster research (Garfin & Silver, 2016; Thompson et al., 2017), which often relies on convenience and community-based samples and hypothetical rather than actual behavior.

4.3 | Limitations

While we were able to incorporate key components of the EPPM to guide analyses, we did not test the entire theoretical model (e.g., fear response). Although we assessed threat-related media exposure, we did not evaluate message content, which may further explain outcomes. The relationship between hurricane-related media exposure and hurricane mitigation was assessed using a longitudinal design, while the relationship between COVID-19-related media exposure was assessed cross-sectionally. However, this also allowed us to examine how media exposure was associated with self-reported mitigation using data collected in real time during and in the immediate aftermath of an actual threat. Since social media during COVID-19 was a source of both essential facts and misinformation, the null effect between social media exposure and COVID-19 severity could have been a statistical artifact as we do not know the specific information our participants were exposed to: it is plausible that social media may have both encouraged and discouraged mitigation depending on the content. Threats from COVID-19 and hurricanes were not equally distributed in our sample: throughout the COVID-19 pandemic there was wide geographic variability in objective threat of COVID-19 and not everyone lived near the coast. This may have been a particular issue in a large state like Texas, given that prior research suggests those closer to the coast are more likely to adopt protective actions to mitigate flood and wind damage from hurricanes (Jasour et al., 2018), despite those further away from the coast also being at risk (Mongold et al., 2021).

4.4 | Implications

Our findings have several implications for constructing messaging during the ongoing COVID-19 pandemic, infectious disease outbreaks more generally, and as we deal with the increasing threat of climate change and related weather-related hazards such as hurricanes. Perhaps most importantly, key constructs derived from the EPPM were relevant across threat types: on balance, results were strikingly similar for hurricanes (an episodic, familiar threat) and COVID-19 (a novel, chronic threat). This suggests that communication strategies designed to promote mitigation behavior for familiar threats may be readily implemented as new threats emerge. Results also suggest messages communicated on traditional media may be particularly effective at encouraging mitigation behavior: those targeting the efficacy of those behaviors or the susceptibility of one to the threat may be particularly salient. Although social media is underutilized for promoting mitigation, this void provides an opportunity to guide future communications using that medium. Although some variability was found (i.e., severity was not associated with mitigation in the hurricane model), overall key EPPM constructs may provide a useful framework for guiding messaging campaigns to promote mitigation behaviors during co-occurring threats that are both chronic and novel, and familiar and episodic.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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