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DOI: 10.1111/risa.14202

ORIGINAL ARTICLE

Evacuate or social distance? Modeling the influence of threat perceptions on hurricane evacuation in a dual-threat environment

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Funding information
National Science Foundation, Grant/Award Number: CMMI: 2051578; Natural Hazard Center at University of Colorado Boulder, USA

Abstract
This study investigates how different risk predictors influenced households' evacuation decisions during a dual-threat event (Hurricane Laura and COVID-19 pandemic). The Protective Action Decision Model (PADM) literature indicates that perceived threat variables are the most influential variables that drive evacuation decisions. This study applies the PADM to investigate a dual-threat disaster that has conflicting protective action recommendations. Given the novelty, scale, span, impact, and messaging around COVID-19, it is crucial to see how hurricanes along the Gulf Coast—a hazard addressed seasonally by residents with mostly consistent protective action messaging—produce different reactions in residents in this pandemic context. Household survey data were collected during early 2021 using a disproportionate stratified sampling procedure to include households located in mandatory and voluntary evacuation areas across the coastal counties in Texas and parishes in Louisiana that were affected by Hurricane Laura. Structural equation modeling was used to identify the relationships between perceived threats and evacuation decisions. The findings suggest affective risk perceptions strongly affected cognitive risk perceptions (CRPs). Notably, hurricane and COVID-19 CRPs are significant predictors of hurricane evacuation decisions in different ways. Hurricane CRPs encourage evacuation, but COVID-19 CRPs hinder evacuation decisions.

KEYWORDS
COVID-19, hurricane evacuation, hurricane hazard intrusiveness, optimistic bias, risk perception

1 | INTRODUCTION

Through decades of research, we have learned much about what leads individuals and households to evacuate in response to the threat of a hurricane (Baker, 1991; Dow & Cutter, 1998; Huang et al., 2016; Lindell et al., 2005; Tinsley et al., 2012; Wu et al., 2014, 2020). Louisiana and Texas are two states that have extensive experience with hurricanes and evacuation decision making. Hurricane season in 2020 was complicated, however, by the ongoing COVID-19 pandemic. Warning messages and protective actions for hurricanes are different and, at times contradictory, from what experts advise for protecting individuals from the risk of COVID-19 infection. Evacuations and sheltering, often in a congregate setting, are counter to recommended practices for reducing COVID-19 risk, which asks residents to avoid unnecessary travel and socially distance where possible. This novel confluence of hazards and protective action recommendations left emergency managers and households to make decisions based on opposing hazard adjustment information.

Some prior research on disasters and hazard adjustments has examined how perceived threat influences protective action decision making, proposing models such as the Protective Action Decision Model (PADM) to explain these relationships (Lindell, 2018). However, most of these PADM evacuation studies have not explored the multivariate relationships among threat perception variables (affective risk perception [ARP], cognitive risk perception [CRP], optimistic bias, and hazard intrusiveness) and how it influences evacuation decisions (Huang, Wu, et al., 2017; Lin et al., 2014; Lindell et al., 2005, 2011; Wei et al., 2014). In addition, to date, only a few studies have examined COVID-19 impacts on hurricane evacuation decisions (Botzen et al., 2022; Collins et al., 2021; Collins, Polen, Dunn, Maas, et al., 2022; Whytlaw et al., 2021). Given the novelty, scale, span, impact, and messaging around COVID-19, we expect to see hurricanes along the Gulf Coast—a hazard addressed seasonally by residents with mostly consistent protective action messaging—produce different reactions in residents in this pandemic context. Thus, the research objective of this study

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is to understand *the ways in which risk perceptions, hurricane hazard intrusiveness, and optimistic bias affect people's protective action decisions*.

This study examines the relationships among perceived threat variables related to both Hurricane Laura, which affected the Louisiana and Texas coasts in August 2020, and the COVID-19 pandemic and hurricane evacuation decisions, using household-level survey data collected in the months following the hurricane. The following sections provide a review of relevant literature, research objectives, methodology, analytical findings, and conclusions.

2 | LITERATURE REVIEW

The PADM shows how several factors influence people's behavioral responses when facing disasters (Lindell, 2018; Lindell & Perry, 2012). PADM explains how external factors affect internal factors and then lead to people's behavioral responses. The external factors include environmental/social cues, warnings, and receiver characteristics. Internal factors include a per-decisional process, threat perceptions (ARP, CRP, optimistic bias, and hazard intrusiveness), protective action perceptions, and stakeholder perceptions. Studies have long been focused on how both external and internal factors affect behavioral response during different types of disaster events (Huang et al., 2012; Jon et al., 2016; Kang et al., 2007; Lindell et al., 2016, 2017; Strahan & Watson, 2019; Wang et al., 2018; Wei et al., 2017; Wu et al., 2012, 2015a, 2015b). Baker (1991) reviewed 15 post-event hurricane evacuation studies published between 1963 and 1990, and Huang et al. (2016) conducted a statistical meta-analysis examining 49 hurricane response studies published between 1991 and 2014. Both studies concluded that perceived threat variables, such as negative emotional reactions, CRPs, and hazard intrusiveness, are better predictors of protective action decisions during hurricanes compared to other variables (Baker, 1991; Huang et al., 2016). Variables measuring receiver characteristics and protective action perceptions had very low correlations with hurricane evacuation decisions. Environmental and health-related studies also found optimistic bias affects people's protective action behaviors (Cho et al., 2013; Radcliffe & Klein, 2002; Wu, Arlikatti, et al., 2017). In a state-of-the-art assessment of warning communication, Mileti and Sorensen (1990) also noted that CRPs are the key influence on the public's response to disaster warnings. According to the PADM, risk assessment involves the evaluation of the threat, which shapes protective action decisions during disasters (Lindell, 2018; Lindell & Perry, 2004, 2012). Risk studies generally measure perceived threat variables by collecting data on people's negative emotions toward a threat (Fischhoff et al., 1980; Slovic et al., 1980), perceived personal consequences from a threat (Huang et al., 2012; Lindell & Hwang, 2008; Wu, Arlikatti, et al., 2017), and hazard intrusiveness (Ge et al., 2011; Lindell & Prater, 2000). Trumbo et al. (2016) extended this line of research by further defining and investigating how well affective and CRPs predict hurricane evacuation decisions. The following sections review the disaster science literature that addresses the relationships among these factors.

2.1 | Affective risk perceptions

Early risk literature exploring ARP focused on negative emotions such as fear and anger in response to a wide range of hazards using correlation or regression analyses (Fischhoff et al., 1978; Floyd et al., 2000; Lerner & Keltner, 2001; Maddux & Rogers, 1983; Oh et al., 2021; Rogers, 1983; Slovic, 1992). In recent studies, COVID-19 ARP is measured by the feeling of fear and worry about transmission of the virus (Clay & Rogus, 2021; Johns Hopkins University, 2020; Raker et al., 2020).

While more limited than CRP, a handful of researchers have explored emotional reactions to environmental hazards. For example, Prati et al., 2012 found that study participants experienced fear, helplessness, worry, and terror during the 1997 Umbria–Marche Earthquake in Italy using descriptive statistics and crosstabulation analyses. More recently, researchers in multiple studies have used nine items from the Mood Adjective Checklist developed by the University of Wales Institute of Science and Technology (MAC UWIST) to study emotional reactions during disasters (Jon et al., 2016; Lindell et al., 2016; Matthews et al., 1990; Wei et al., 2017; Wu, Arlikatti, et al., 2017). The nine emotional response measures include the typical ARP emotions of depressed, annoyed, fear, and nervous alongside other emotions, such as passive, alert, optimistic, relaxed, and energetic. Some studies condense these emotions into three indexes: Shock (depressed, annoyed, and passive), fear (alert, nervous, and fearful), and vigilance (optimistic, relaxed, and energetic) when studying people's earthquake emotional reactions (Jon et al., 2016; Lindell et al., 2016). This categorization approach might not be ideal, however, since some indexes have relatively low reliability ($\alpha < 0.60$).

Studies have compared ARP differences when experiencing similar disaster events. Two studies, using correlation and regression analyses, found that Japanese survey respondents are more likely to feel shock and fear than respondents from New Zealand when facing earthquakes with similar shaking intensity (Jon et al., 2016; Lindell et al., 2016). They also found fear is correlated with CRPs but not the earthquake response behavior measures in either study area. Wu, Arlikatti, et al. (2017) found that survey respondents after a flood in India had higher levels of depressed, nervous, and fearful emotions when compared to flood survivors in Colorado using *t*-tests. Similar to the earthquake studies, depressed, annoyed, nervous, and fearful emotions are correlated with CRPs strongly but not protective action decisions. On the other hand, Trumbo et al. (2016) found people's ARP (fear, worry, dread, and depression) and CRP affect their evacuation decisions in a hypothetical hurricane scenario using linear regression analysis.

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2.2 | Cognitive risk perception

CRP measures found in the literature are related to the idea of personal consequences during environmental hazards and pandemics. In general, it measures people's expectations of home damage, family injury, and the disruption of daily routines during disasters (Mileti & Peek, 2000; Mileti & Sorensen, 1987). For pandemic or epidemic studies, researchers usually measure people's perceived likelihood of being infected and subsequent health consequences (Brug et al., 2004; Iorfa et al., 2020). Early studies concluded people have difficulties conceptualizing probabilities and treat risk perception intuitively (Fischhoff et al., 1978; Kunreuther & Slovic, 1996; Slovic, 1992). Recent studies also found that people treat probabilities as integer values rather than decimal values (Wu et al., 2014, 2015b); thus, researchers mainly measure the perceived likelihood of disaster consequences when conducting survey studies (Huang et al., 2012; Maghelal et al., 2017; Trumbo et al., 2016).

The importance of CRP has long been recognized in PADM and disaster response studies (Baker, 1991; Huang et al., 2016; Huang, Lindell, et al., 2017; Iorfa et al., 2020; Lindell et al., 2005; Martin et al., 2007; Wu et al., 2012). In general, these studies found that CRP is a good predictor of evacuation decisions using regression analyses. Among the different types of CRP measures, studies using correlation and regression analyses found perceived personal casualties or injuries to be strongly associated with evacuation decisions (Fu et al., 2007; Huang, Lindell, et al., 2017; Sharma & Patt, 2012). Hurricane wind, storm surge, and flood impact variables are also highly associated with evacuation decisions (Dow & Cutter, 2000; Huang et al., 2012; Morrow & Gladwin, 2005; Van et al., 2002; Whitehead et al., 2000). Perceived job and service disruption are also reported as significant predictors in several hurricane evacuations studies using regression analysis, but depending on the studies, they can have either negative or positive impacts (Dow & Cutter, 2000; Morrow & Gladwin, 2005; Smith & Mccarty, 2009).

Recent studies that examined the COVID-19 impacts during the 2020 hurricane season found that COVID-19 CRP negatively predicts evacuation intentions; on the other hand, hurricane CRP positively predicts evacuation intentions (Botzen et al., 2022). Similarly, Borowski et al. (2021) found COVID-19 CRP has a negative impact on the intention of sharing rides during a flood evacuation.

2.3 | Relationships among perceived threat variables

Hazard intrusiveness (also referred to as hazard salience) and optimism are two additional threat-related variables mentioned in the PADM literature and health studies. Hazard intrusiveness is defined as the thoughts, discussions, and hazard-relevant information received from one's risk information source and channel (Ge et al., 2011; Lindell & Perry, 2004). Although hazard intrusiveness is mentioned in PADM (Lindell, 2018), it is seldom included in disaster response studies. Instead, this idea is mostly included in hazard adjustment studies, with researchers finding that hazard intrusiveness could affect people's CRP (Greer et al., 2020; Lindell, 1994, 2013; Wu, Greer, et al., 2017) and ARP (Weinstein et al., 2000). A recent study also found hazard intrusiveness significantly predicts a latent CRP variable that is constructed by using four CRP1 variables (perceived likelihood of potential damage to their homes or properties, injuries, job disruptions, and daily routine disruptions) (Li et al., 2023).

In previous work on environmental hazards, optimistic bias is found to be negatively associated with ARP (Lindell et al., 2016; Wu, Arlikatti, et al., 2017). This variable, however, is mostly found in risky behavior and health-related studies (Klein & Helweg-Larsen, 2002; Weinstein, 1989). For example, Rutter et al. (1998) found that motorcycle riders with unrealistic optimism have lower CRP of motorcycle riding behavior. Cancer and infectious disease studies also found optimistic bias is negatively associated with perceived health risk (Radcliffe & Klein, 2002), lung cancer risk (Dillard et al., 2006), heart disease (Davidson & Prkachin, 1997), and H1N1 Flu risk (Cho et al., 2013). Overall, both disaster and health studies suggest that hazard intrusiveness and optimism do not affect protective action directly; rather, they interact with ARP and CRP and then affect protective action decisions.

Finally, in terms of the relationship between ARP and CRP, early studies suggest that cognition is driven by emotion (Zajonc, 1980, 1984). Alhakami and Slovic (1994) proposed the model of Affect Heuristic and studied technology-related risk perceptions. The model suggests affective emotions affect CRPs. Some recent experimental and clinical studies find that cognitive risk judgments are affected by an individual's negative affectivity when facing technological risk or taking part in risky behaviors (Dohle et al., 2010; Finucane et al., 2000; Slovic et al., 2007).

2.4 | Research objectives

PADM and risk studies have provided some fundamental insights into how perceived threat affects protective actions. Still, as mentioned above, most studies use univariate analyses to examine the relationship among these variables. Few studies have explored how these variables relate to each other and the ways in which they affect protective action decisions. As mentioned in Lindell (2018), researchers should focus on the intercorrelation of perceived threat factors. More importantly, none of the previous studies examined these relations in a dual-threat event with contradicting protective action recommendations.

Based on the PADM and the health sciences literature, the relationship between perceived threat and hurricane evacuation decisions can be illustrated in Figure 1. The following are the specific research hypotheses based on the literature that address the overarching research question.

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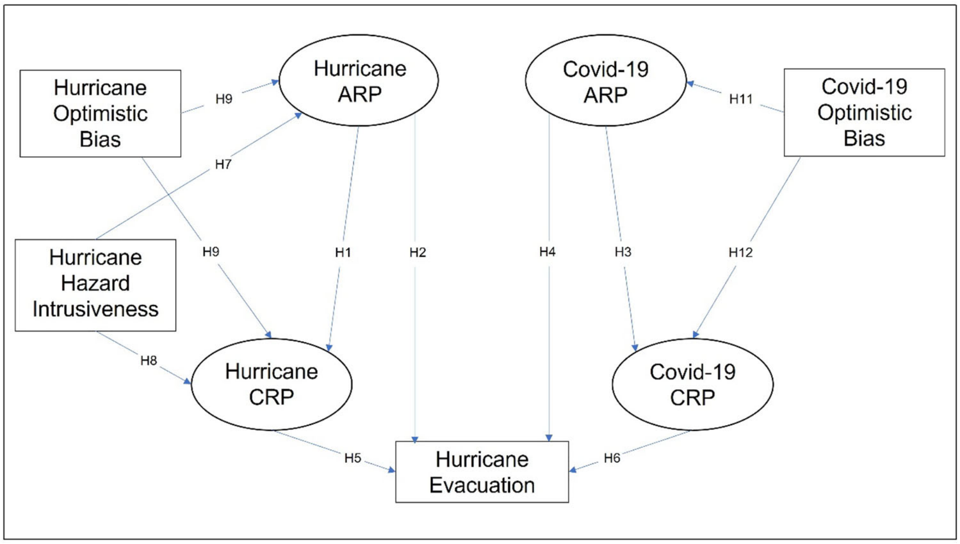

FIGURE 1 The hypothetical structural equation modeling (SEM) model of hurricane evacuation decision.

H1. Hurricane ARP has a significant effect on hurricane CRP.
H2. Hurricane ARP has a significant effect on hurricane evacuation decisions.
H3. COVID-19 ARP has a significant effect on COVID-19 CRP.
H4. COVID-19 ARP has a significant effect on hurricane evacuation decisions.
H5. Hurricane CRP has a significant effect on hurricane evacuation decisions.
H6. COVID-19 CRP has a significant effect on hurricane evacuation decisions.
H7. Hurricane hazard intrusiveness has a significant effect on hurricane ARP.
H8. Hurricane hazard intrusiveness has a significant effect on hurricane CRP.
H9. Hurricane optimism bias has a significant effect on hurricane ARP.
H10. Hurricane optimism bias has a significant effect on hurricane CRP.
H11. COVID-19 optimism bias has a significant effect on COVID-19 ARP.
H12. COVID-19 optimism bias has a significant effect on COVID-19 CRP.

A research question is also included to address the intercorrelations among these variables.

RQ1: What are the direct, indirect, and total effects among perceived threat variables and evacuation decisions?

This study used a household survey to test the above research hypotheses and answer the research question. The survey asked about people's hurricane and COVID-19 risk attitudes and hurricane protective action decisions during Hurricane Laura in August 2020 while facing the COVID-19 threat.

3 | METHODOLOGY

3.1 | Data collection and study participants

This study used a disproportionate stratified sampling procedure to identify households located in mandatory and voluntary evacuation areas during Hurricane Laura. Based on National Hurricane Center archives and news media reports on August, 25th, 2020, four areas in Texas and Louisiana were selected for the study (National Hurricane Center, 2020; Santana & Martin, 2020). Table 1 shows the sampling locations and the numbers of household mailing addresses available in each area. Figure 2 shows relative locations of each study area in the Gulf Coast and Hurricane Laura track. In each study area, 1200 household addresses were randomly selected. The mailing list was obtained from the *Marketing Systems Group* using a random selection process. Following Dillman et al. (2014) survey procedures, each household was sent as many as three survey packages (waves 1, 3, and 4) and one reminder postcard (wave 2). The questionnaires were sent by the University of North Texas Printing & Distribution Solution in January, February, and March 2021. In total, survey packages were sent out to 4800 households, 304 households responded to the survey, 35 households refused, and there were 629 undeliverable survey packages. The overall survey response rate is 7.35% (8.26% in Texas mandatory evacuation area, 5.52% in Texas voluntary evacuation area, 9.55% in Louisiana mandatory evacuation area, and 6.30% in Louisiana voluntary evacuation area). The response rates were calculated using the formula suggested by Fowler (2002).

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TABLE 1 Survey locations.

State	Study area	City/county/parish	Available mailing addresses[a]	Disproportionate stratified sample
Texas	Mandatory evacuation	Jefferson County Galveston County • Bolivar Peninsula • Galveston City	134,906	1200
	Voluntary evacuation	Galveston County (exclude Bolivar Peninsula and Galveston City)	108,932	1200
Louisiana	Mandatory evacuation	Calcasieu Parish Vermilion Parish • Pecan Island • Intracoastal City • Esther • Forked Island • Mouton Cove • South Erath • South Delcambre • South Gueydan	89,998	1200
	Voluntary evacuation	Vermilion Parish • Houses that located outside the Erath and Delcambre city boundaries and south of Hwy 14 • South of Abbeville • South of Hwy 335 • West of Vermilion River (exclude Esther)	6854	1200

[a]The number of mailing addresses that *Marketing Systems Group* provided in January 2021.

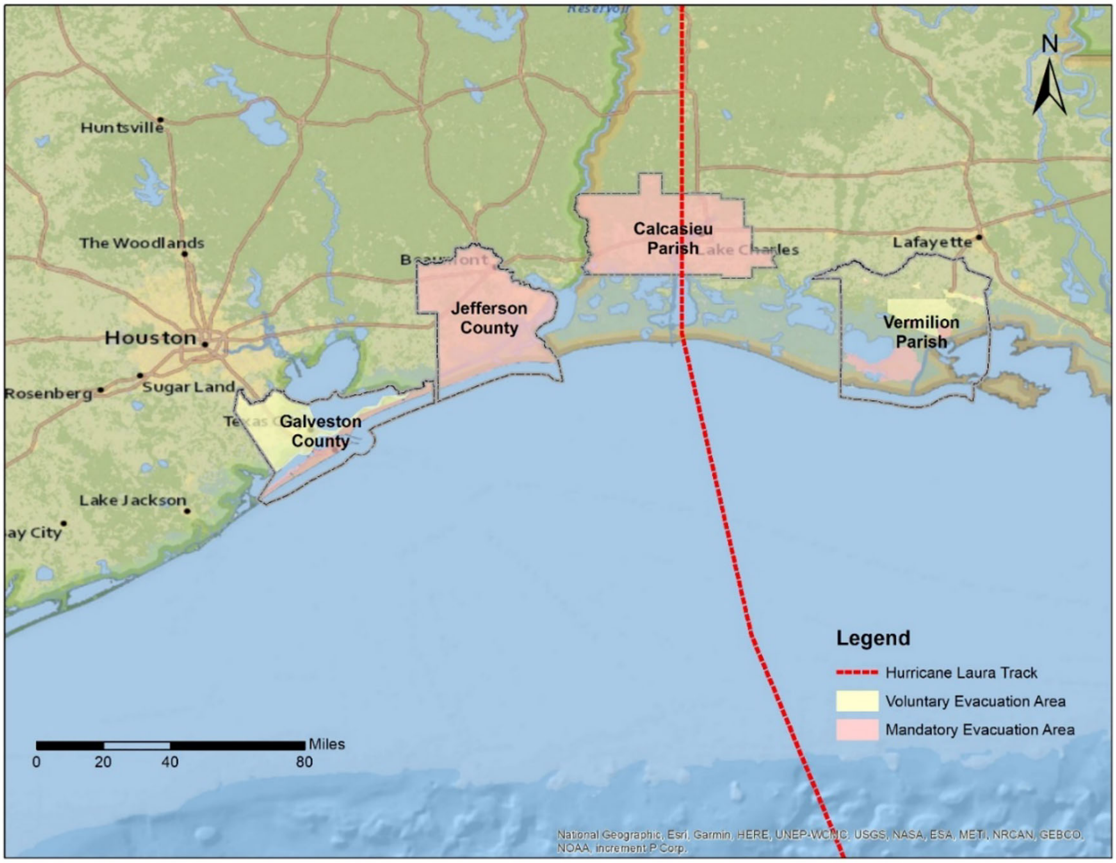

FIGURE 2 Survey location.

TABLE 2 Demographics variable difference (2020 census vs. household survey).

State	Louisiana				Texas			
County/parish	Vermilion		Calcasieu		Jefferson		Galveston	
Data type	Census	Survey	Census	Survey	Census	Survey	Census	Survey
Persons between 18 and 65[a] (%)	76.87	52.90	77.65	54.90	78.41	51.4	78.62	52.90
Persons 65 years and over[a] (%)	23.13	47.10	22.35	45.10	21.59	48.6	21.38	47.10
Female persons (%)	51.70	62.70	51.10	51.90	48.90	65.7	50.90	62.70
White alone (%)	81.50	83.00	70.10	88.0	59.10	79.40	80.30	83.70
Median household income[b]	$52,219	25K–49K	$52,866	50K–79K	$50,840	50K–79K	$74,633	25K–49K
Bachelor's degree or higher (%)	16.20	35.50	21.90	40.40	19.30	50.00	32.10	35.50
Homeownership (%)	74.40	87.40	68.50	94.30	61.50	91.40	67.50	78.20

[a]18-year old and younger were excluded from the Census percentage calculation since the household survey can only collect data from respondents who are 18 years and older.
[b]Household income data were collected using a categorical variable in the survey.

Overall, 53.40% of the survey respondents evacuated. The survey respondents' average age is 60-year old. Among the survey respondents, 40.20% are male and 59.80% are female. These survey respondents are predominantly White (85.90%). More than half of the respondents are married (59.80%). As for their education levels, 19.00% of the respondents have an advanced degree, 31.20% are college graduates, and 26.40% have some college/vocational school diploma, 20.70% are high school graduates, and only 2.70% have an education level that is less than high school. The mode of income level is between $25,000 and $49,999, and 85.70% of the respondents are homeowners. As Table 2 indicates, according to the United States Census Bureau (2022), the survey respondents are considerably older than the age groups in the four survey areas. The distributions of gender, racial, and education groups are similar, but the ratings of income level, education level, and homeownership differ from the U.S. Census Bureau's 2020 data in the study areas.

3.2 | Measure

A survey questionnaire was designed to collect data to understand Texas and Louisiana coastal residents' concerns about the COVID-19 pandemic during a hurricane threat and identify the factors that affect different aspects of survey respondents' Hurricane Laura response. The measures include hurricane CRP, evacuation factors, hurricane ARP, self-identified evacuation area, risk information source/channel, evacuation behaviors, evacuee reentry concerns, Hurricane Laura impacts, COVID-19 diagnosis, family essential worker, COVID-19 family risk, COVID-19 ARP response, COVID-19 CRP during Laura response, COVID-19 considerations during Hurricane Laura evacuation, COVID-19 protective action, demographic variables, stakeholder confidence level, everyday emotional state, hurricane experience, and Hurricane Delta response. In total, there are 49 questions in the questionnaire. These questions generate 146 variables. This dataset has 69 nominal variables, 63 ordinal variables, and 14 scale variables (interval/ratio). The survey is available upon request. For the purpose of this study, only the perceived threats and evacuation decision variables were included and analyzed. The survey was built on previous hurricane surveys (Huang et al., 2012; Wu et al., 2012), and COVID-19 related variables were adopted from the *Disaster Research Response (DR2) COVID-19 Repository* (National Institute of Environmental Health Science, 2018).

Respondents were asked to report their hurricane ARP (depressed, annoyed, nervous, and fearful) using five-point Likert scales (*1 = Not at all* to *5 = Very great extent*). Their COVID-19 ARP (threatened, afraid, and stressed) was measured using seven-point Likert scales (*1 = Not true of me at all* to *7 = Very true of me*). Hurricane CRP variables were measured by asking respondents to report their perceived likelihood of flood/surge damage to their home, wind damage to their home, family members being injured/killed, job disruption, and community service disruption. COVID-19 CRP variables were measured by asking respondents to report their perceived likelihood of getting infected with COVID-19 during the evacuation, staying at evacuation destinations, returning home, and having severe health effects from being infected with COVID-19. The survey used five-point Likert scales (*1 = Not at all likely* to *5 = Almost a certainty*) to measure hurricane CRP and COVID-19 CRP variables.

The hurricane optimistic bias variable was measured by asking respondents to rate their optimistic emotions using a five-point Likert scale (*1 = Not at all* to *5 = Very great extent*). The COVID-19 optimistic bias variable was measured by asking respondents to report the likelihood of being able to cope with the health effects of COVID-19 if infected using a five-point Likert scale (*1 = Not at all likely* to *5 = Almost a certainty*).

Hurricane hazard intrusiveness was measured by asking respondents to report whether they have received hurricane risk information from seven different information channels (*T.V., radio, social media, internet, phone calls, person (face-to-face), and others*). Since these were *Yes/No* questions, hurricane hazard intrusiveness was calculated by summing up yes responses to the above seven variables. Lastly, the hurricane protective action decision is measured by asking if

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TABLE 3 Descriptive statistics and reliability test.

Item	Mean	St. Dev	Variance	Factor loading	Cronbach's α	
Hurricane ARP	**HARP1 (depressed)**	2.288	1.321	0.417	0.817	0.840
	HARP2 (annoyed)	2.819	1.385	0.159	0.705	
	HARP3 (nervous)	3.198	1.361	0.705	0.878	
	HARP4 (fearful)	2.896	1.393	2.719	0.886	
Hurricane CRP	**HCRP1 (home flood damage)**	2.364	1.315	0.491	0.717	0.786
	HCRP2 (home wind damage)	2.783	1.286	2.769	0.858	
	HCRP3 (person injury/Killed)	2.228	1.342	0.874	0.773	
	HCRP4 (job disruption)	2.919	1.623	0.330	0.637	
	HCRP5 (service disruption)	4.136	1.178	0.536	0.717	
COVID-19 ARP	**CARP1 (threatened)**	3.823	2.089	0.193	0.951	0.941
	CARP2 (afraid)	3.915	2.238	2.684	0.954	
	CARP3 (stressed)	3.633	2.170	0.123	0.933	
COVID-19 CRP	**CCRP1 (infected during evacuation)**	2.117	1.246	2.870	0.941	0.852
	CCRP2 (infected at evacuation destination)	2.162	1.352	0.710	0.918	
	CCRP3 (infected during reentry)	1.814	1.101	0.299	0.868	
	CCRP4 (serious health issue if infected)	2.717	1.413	0.121	0.624	
Hurricane optimistic bias		2.828	1.151			
COVID-19 optimistic bias		2.979	1.406			
Hurricane intrusiveness		2.640	1.352			
Evacuation decision		0.534	0.499			

Note: Only the endogenous latent constructs require reliability tests.
Abbreviations: ARP, affective risk perception; CRP, cognitive risk perception.

anyone in their household evacuated from Hurricane Laura. The means and standard deviations of all the variables are included in Table 3.

3.3 | Analytical method

Structural equation modeling (SEM) was used to test the hypotheses. SEM is a multivariate method that examines the relationships among constructs and variables in a hypothetical model (Dattalo, 2013). As indicated in Figure 1, this study has three exogenous variables (hurricane/COVID-19 optimistic bias and hurricane hazard intrusiveness), one endogenous variable (hurricane evacuation), and four endogenous latent constructs (hurricane/COVID-19 ARP and hurricane/COVID-19 CRP). Factor analyses and Cronbach's α were used to check the reliability of the latent constructs. Table 3 shows that the four latent variables have good to excellent Cronbach's α values that are above or close to 0.80 (Cronbach et al., 2004).

The Maximum Likelihood Estimation approach in SPSS AMOS 26 (Arbuckle, 2019) was used to estimate the parameters in the model and the hypotheses. Modification Indices were also used to identify significant covariances to improve the model fit (Lei & Wu, 2007; Peters et al., 2004). In reviewing AMOS' Modification Indices reports, hurricane ARP and COVID ARP's error terms were correlated to improve the overall results. Several indexes were used to determine the SEM model fit. A χ^2/df value between two and five indicates a good model fit, and a less than three χ^2/df value indicates an acceptable model (Bentler & Bonett, 1980). Other commonly used model fit indexes are also used (Kline, 2005). Comparative fit index (CFI), Tucker Lewis index (TLI), and incremental fit index (IFI) have to reach a threshold of 0.90 (Bentler, 1990; Bollen, 1989; Hu & Bentler, 1999; Marsh & Hocevar, 1985). A value better than 0.80 is considered a good model fit for the goodness of fit index (GFI) and adjusted goodness of fit index (AGFI). The root mean-square error of approximation (RMSEA) lower than 0.08 indicates a good model fit (Browne & Cudeck, 1992). Bootstrapping methods were used to mitigate multivariate normality concerns in the SEM model (Hancock & Liu, 2012) and control for Type I errors given the multiple variables incorporated in each SEM model (Keselman et al., 2008; Rasmussen, 1988).

4 | RESULTS

4.1 | Hypotheses testing

The hypotheses test results are shown in the initial SEM (Figure 3). Four hypotheses were nonsignificant at the 0.05 level: Hurricane ARP to hurricane evacuation decision (H2), COVID-19 ARP to hurricane evacuation decisions (H4),

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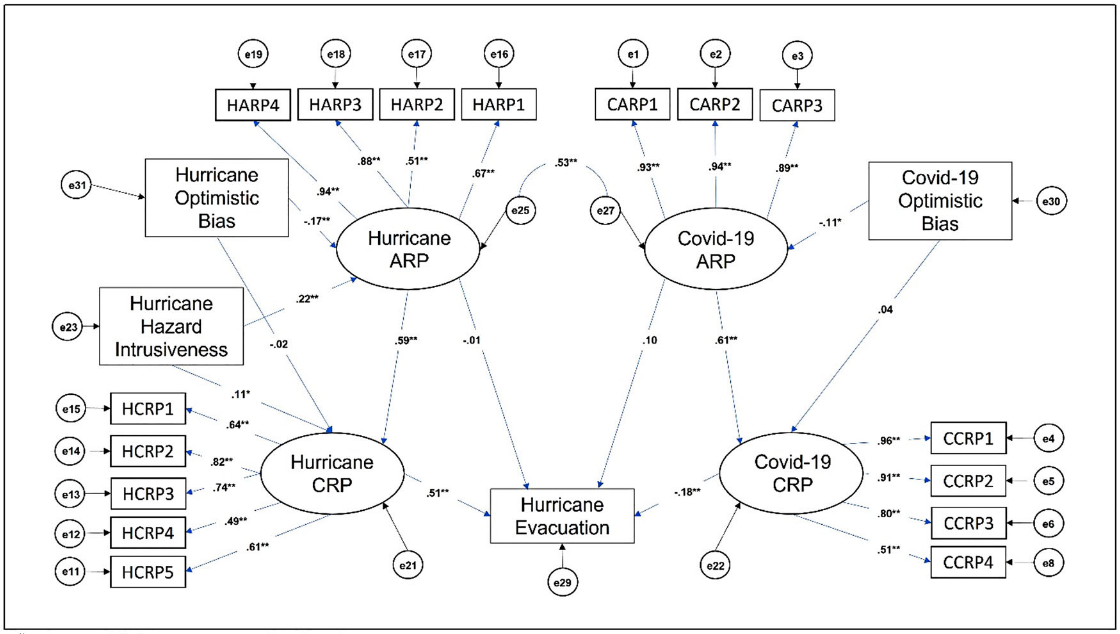
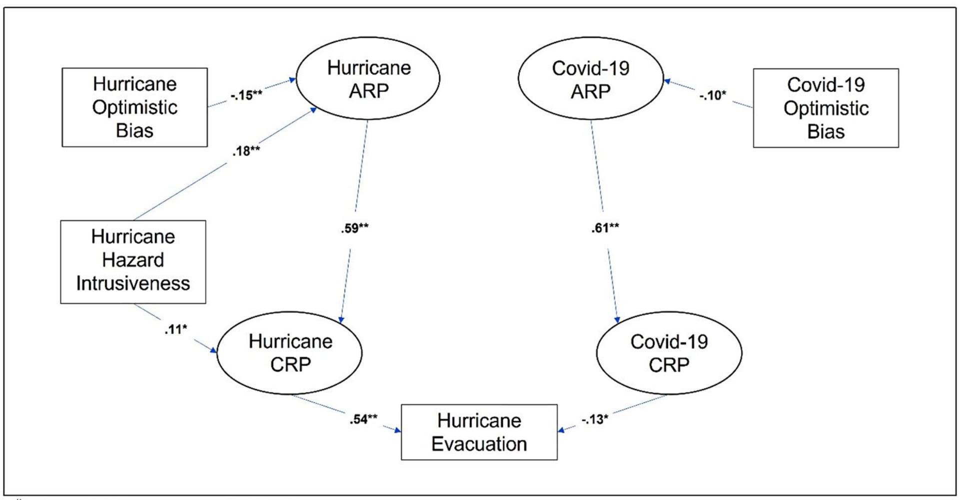


The coefficients are standardized.
* p-value is significant at .05 level
**p -value is significant at .01 level

FIGURE 3 The initial Hurricane Laura evacuation decision structural equation modeling (SEM) with indicators. *Note*: The coefficients are standardized; **p*-value is significant at 0.05 level; ***p*-value is significant at 0.01 level.



The coefficients are standardized.
* p-value is significant at .05 level
**p -value is significant at .01 level

FIGURE 4 Final Hurricane Laura evacuation decision structural equation modeling (SEM). *Note*: The coefficients are standardized; **p*-value is significant at 0.05 level; ***p*-value is significant at 0.01 level.

hurricane optimistic bias to hurricane CRP (H9), and COVID-19 optimistic Bias to COVID-19 CRP (H12). Thus, a revised model was derived by eliminating these nonsignificant hypotheses.

Modification indices were used to improve the model fit. The final SEM model is shown in Figure 4. The χ^2/df is 2.108, which suggests this model has a good model fit (Bentler & Bonett, 1980). Additional model fit indexes also suggest the final SEM model has a good model fit (Gefen et al., 2000; Steiger, 2007). The values of CFI (0.944), TLI (0.935), and IFI (0.944) are better than the minimum cutoff of 0.90. The values of GFI (0.900) and AGFI (0.873) are also better than the minimum cutoff of 0.80. The RMSEA is 0.027, which is lower than the suggested 0.80.

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TABLE 4 Direct, indirect, and total effects.

Variable	Direct effect	Indirect effect	Total effect
HOB → HARP	−0.151*	–	−0.151*
HOB → HCRP	–	−0.090*	−0.090*
HOB → HEvac	–	−0.048*	−0.048*
COB → CARP	−0.102*	–	−0.102*
COB → CCRP	–	−0.062*	−0.062*
COB → HEvac	–	0.008*	0.008*
HHI → HARP	0.182*	–	0.182*
HHI → HCRP	0.113*	0.108*	0.221*
HHI → HEvac	–	0.118*	0.118*
HARP → HCRP	0.593*	–	0.593*
HARP → HEvac	–	0.318*	0.318*
CARP → CCRP	0.608**	–	0.608*
CARP → HEvac	–	−0.081*	−0.081*
HCRP → HEvac	0.536*	–	0.536*
CCRP → HEvac	−0.133*	–	−0.133*

Abbreviations: CARP, COVID-19 affective risk perception; CCRP, COVID-19 cognitive risk perception; COB, COVID-19 optimistic bias; HARP, hurricane affective risk perception; HCRP, hurricane cognitive risk perception; HEvac, hurricane evacuation decision; HHI, hurricane hazard intrusiveness; HOB, hurricane optimistic bias.
*p-Value is significant at 0.05 level.
**p-Value is significant at 0.01 level.

The overall hypothesis test results are illustrated in Figure 4. Four hypotheses that address the relationship among the perceived threat variables are supported. Hurricane optimistic bias has a negative impact on hurricane ARP (H9) ($\beta = -0.15$, $p < 0.01$). Hurricane hazard intrusiveness has a positive impact on hurricane ARP (H7) ($\beta = 0.18$, $p < 0.01$). It also has a positive impact on hurricane CRP (H8) ($\beta = 0.11$, $p < 0.05$). Hurricane ARP has a positive impact on hurricane CRP (H1) ($\beta = 0.59$, $p < 0.01$). This effect is quite strong compared to other coefficients. As for the COVID-19 perceived threat variables, three hypotheses were supported. COVID-19 optimistic bias has a negative impact on COVID-19 ARP (H11) ($\beta = -0.10$, $p < 0.05$). Similar to the relationships between hurricane ARP and CRP, COVID-19 ARP also has a strong positive impact on COVID-19 CRP (H3) ($\beta = 0.61$, $p < 0.01$). Finally, in terms of the hurricane evacuation decision, hurricane CRP has a strong and positive impact on evacuation decision (H4) ($\beta = 0.54$, $p < 0.01$); on the other hand, COVID-19 CRP shows a relatively weak, but significant, negative impact on evacuation decision (H6) ($\beta = -0.14$, $p < 0.05$).

4.2 | Indirect, direct, and total effects

In terms of RQ1, the indirect and total effects of the final model are shown in Table 4. Results show hurricane hazard intrusiveness has direct ($\beta = 0.113$, $p < 0.05$) and indirect ($\beta = 0.108$, $p < 0.05$) effects on hurricane CRP and its total effect ($\beta = 0.221$, $p < 0.05$) on hurricane CRP is positive. This finding suggests hurricane ARP partially mediates the relationship between hurricane hazard intrusiveness and hurricane CRP and there still remains the direct effect of hazard intrusiveness on hurricane CRP.

Table 4 also shows a number of indirect effects. Four factors indirectly and positively contribute to hurricane evacuation decisions. These factors include COVID-19 optimistic bias ($\beta = 0.008$, $p < 0.05$), hurricane hazard intrusiveness ($\beta = 0.118$, $p < 0.05$), and hurricane ARP ($\beta = 0.318$, $p < 0.05$). In contrast, hurricane optimistic bias ($\beta = -0.048$, $p < 0.05$) and COVID-19 ARP ($\beta = -0.081$, $p < 0.05$) negatively contribute to hurricane evacuation decisions. Among the indirect effects, hurricane ARP has the strongest and positive effects on hurricane evacuation. Finally, hurricane optimistic bias ($\beta = -0.090$, $p < 0.05$) has a negative indirect effect on hurricane CRP. COVID-19 optimistic bias ($\beta = -0.062$, $p < 0.05$) also has a negative indirect effect on COVID-19 CRP. Based on Figure 4, both of these indirect effects are through their ARP variable.

5 | DISCUSSION AND CONCLUSIONS

5.1 | Findings

There have been calls from disaster researchers to address the gap in understanding the interrelationships among threat perceptions and how those perceptions affect protective actions in different hazard contexts (Lindell, 2018). The final model of this study sheds light on this issue by analyzing data from a household hurricane response survey collected after Hurricane Laura while people were facing the COVID-19 pandemic. The challenge of this dual hazard context is that the recommended hurricane protective

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action—evacuation—contradicts the suggested COVID-19 protective action—social distancing. Therefore, this event provides disaster researchers an opportunity to address a gap in the PADM literature.

Our findings on hurricane threat perceptions generally align with environmental hazard studies with some new insights. Although Trumbo et al. (2016) found that optimism affects hurricane evacuation, this study further identified that the impact of hurricane optimistic bias on hurricane evacuation decisions is indirect and negative by using SEM analysis. A similar pattern can be found between hurricane hazard intrusiveness and hurricane evacuation. Previous studies have shown that hazard intrusiveness positively affects hazard CRP (Greer et al., 2020; Lindell, 1994; Wu, Greer, et al., 2017). This study indicates that not only does it have a direct effect on CRP, but it also has an indirect effect on CRP through ARP. As for the relationship between ARP and evacuation decisions, findings in previous studies based on regression and correlation analyses are mixed (Trumbo et al., 2016; Wu, Arlikatti, et al., 2017); our findings suggest ARP indeed affects hurricane evacuation, but the effect is indirect.

In terms of the interrelationships among the perceived hurricane threat variables, findings suggest optimists are less likely to have negative emotions toward hurricane threats. People with higher negative emotions toward hurricanes (ARP) and those who receive more hurricane hazard information tend to have higher hurricane risk perceptions regarding personal consequences (CRP). Thus, perceived personal consequence, which is influenced by all these other threat perceptions, positively and strongly affects survey respondents' evacuation decisions.

The findings regarding COVID-19 threat perception and hurricane evacuation decisions are similar to many recent studies (Borowski et al., 2021; Botzen et al., 2022) but with some new results regarding the ways in which COVID-19 threat perception operates. Overall, the perception of personal consequences regarding COVID-19 (CRP) has an adverse effect on hurricane evacuation. Similar to the relationships among hurricane threat perception variables, COVID-19 CRP is also affected by other COVID-19 threat perception variables. A number of findings, however, diverge from the literature.

First, the relationships among COVID-19 optimistic bias, emotional reaction (ARP), and personal consequences (CRP) are similar to the associations we observed with hurricane threat perception. In addition to previous studies' understanding regarding optimistic bias and CRPs (Cho et al., 2013; Weinstein, 1989), our findings suggest COVID-19 optimistic bias indirectly affects COVID-19 CRP. Our study shows it has a negative impact on COVID-19 negative emotions (ARP), and then COVID-19 negative emotions have a strong and positive effect on the perceived personal consequences due to COVID-19 (CRP). This finding implies that when someone is optimistic about COVID-19, they will feel less threatened, afraid, and stressed about COVID-19, which leads to a lower level of CRP toward COVID-19.

Overall, the final model (Figure 4) suggests that optimistic bias and hurricane hazard intrusiveness affect ARP significantly, ARP significantly affects CRP, and CRP has a significant impact on evacuation decisions. The difference is that hurricane CRP encourages hurricane evacuation, while COVID-19 CRP discourages hurricane evacuation, even though the effect is considered small compared to hurricane CRP. Therefore, in a situation when a hurricane and a pandemic threaten people, an evacuation decision is not made without considering the pandemic. The pandemic threat can still affect people's decisions to a certain degree.

5.2 | Limitations

Similar to other household survey studies (Dow & Cutter, 2000; Jon et al., 2016; Wu et al., 2012), the respondents of this study included a higher portion of the elderly population (over 65-year old), people with higher education level, income level, and homeowners comparing to census data (Table 2). Although the overrepresentation of this demographic group has been known to be a shortcoming of general public survey studies (Dillman et al., 2014), it does not necessarily have a substantial impact on disaster research findings. Bohrnstedt (1983) suggested this is an issue only when the demographic characteristics are strongly correlated with psychological and behavioral variables. Several review studies on household evacuation and disaster preparedness have shown that the correlations among these variables tend to be very low (Baker, 1991; Huang et al., 2016; Lindell & Perry, 2000). Therefore, a sample with an overrepresentation of some demographic groups would not bias the findings.

In addition, although other survey approaches, such as phone surveys, in-person surveys, and surveys with incentives, might generate a sample with a better representation of demographic characteristics, it would require a much higher budget to perform such tasks. A mail survey study does have its advantages for disaster studies. During the COVID-19 pandemic, a mail survey rather than an in-person survey also protected researchers and study participants from exposure risk. It provides less disturbance to disaster-affected individuals since the researchers would not have direct contact with potential participants. It also provides participants with a better sense of information security, encouraging them to share their experiences. Future work might consider using survey incentives or an oversampling procedure to achieve a sample with better representation if the budget allows. For example, one direction a researcher could take is to oversample evacuees who evacuated to different evacuation destinations (e.g., public shelter, friends/peers' homes, or hotel/motel) and examine the factors affecting such decisions.

Third, our survey response rate is relatively low compared to other early hurricane evacuation studies in the area (Huang et al., 2012; Wu et al., 2012). Low survey response rates (less than 10%) have been noted as a trend in household survey studies in recent years (Leeper, 2019). Although a high survey response rate reduces the chance of results in a biased sample,

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studies have shown that surveys with a low response rate do not necessarily result in such an issue. This issue only occurs when demographic characteristics are highly correlated with questionnaire responses; however, studies have shown this is not the case (Groves et al., 2008; Tourangeau, 2017). Wright (2015) also suggested studies with low response rates (less than 10%) do not necessarily lead to a biased sample.

Finally, a dual hazard event that has contradicting protective action suggestions (evacuation vs. social distancing) is fairly novel as of the time of this writing. When this study was conducted, there was not enough literature focusing on this issue (Clay et al., 2022; Collins et al., 2021; Collins, Polen, Dunn, Jernigan, et al., 2022; Collins, Polen, Dunn, Maas, et al., 2022). Therefore, this study solely focuses on the interrelationships among threat perception variables and how they affect hurricane evacuation decisions in this novel case. This is also based on other research findings that suggest threat perception variables are the key factors of evacuation decisions (Baker, 1991; Huang et al., 2016). Moreover, COVID-19 hazard intrusiveness was not included in the analysis since no validated survey questions were available at the time when the survey was sent out. Future studies should try to build upon this and incorporate other theoretically and methodologically sound variables to investigate this issue further.

5.3 | Implications for research and practice

This research aimed to address the gap in the hazard risk perception literature by parsing out the associations among different aspects of threat perception and their effects on evacuation decisions using the structural equation model analysis. The findings of this research could lead to theory development for future situations when an environmental hazard is intertwined with respiratory infectious disease risk. This is because evacuation is one of the popular protective action choices before, during, and after a disaster, such as a hurricane, flood, tsunami, or wildfire. In addition, the research objective presented here is part of a larger program of research. The analytical results presented here will be applied to ongoing and future studies that focus on developing programs that facilitate a more efficient evacuation decision process. Moreover, the findings of this research can provide valuable recommendations for emergency management practice. For example, the results indicate COVID-19 might discourage people from making an evacuation decision to a certain degree; however, hurricane risk perception regarding personal consequences still plays a bigger part during the decision-making process.

ACKNOWLEDGMENTS

This work was supported by the U.S. National Science Foundation under Grant CMMI 2051578 and Natural Hazards Center, Natural Hazards Center, University of Colorado Boulder. None of the conclusions expressed here necessarily reflect the views other than those of the authors.

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How to cite this article: Wu, H.-C., Murphy, H., Greer, A., & Clay, L. (2023). Evacuate or social distance? Modeling the influence of threat perceptions on hurricane evacuation in a dual-threat environment. *Risk Analysis*, 1–14. https://doi.org/10.1111/risa.14202

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