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A Cognitive-Affective Scale for Hurricane Risk Perception

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The aim of this study was to develop a reliable and valid measure of hurricane risk perception. The utility of such a measure lies in the need to understand how people make decisions when facing an evacuation order. This study included participants located within a 15-mile buffer of the Gulf and southeast Atlantic U.S. coasts. The study was executed as a three-wave panel with mail surveys in 2010–2012 (T_0 baseline $N = 629$, 56%; T_1 retention $N = 427$, 75%; T_2 retention $N = 350$, 89%). An inventory based on the psychometric model was developed to discriminate cognitive and affective perceptions of hurricane risk, and included open-ended responses to solicit additional concepts in the T_0 survey. Analysis of the T_0 data modified the inventory and this revised item set was fielded at T_1 and then replicated at T_2. The resulting scales were assessed for validity against existing measures for perception of hurricane risk, dispositional optimism, and locus of control. A measure of evacuation expectation was also examined as a dependent variable, which was significantly predicted by the new measures. The resulting scale was found to be reliable, stable, and largely valid against the comparison measures. Despite limitations involving sample size, bias, and the strength of some reliabilities, it was concluded that the measure has potential to inform approaches to hurricane preparedness efforts and advance planning for evacuation messages, and that the measure has good promise to generalize to other contexts in natural hazards as well as other domains of risk.

KEY WORDS: Cognitive-affective processes; hurricanes; natural disasters; risk perception

1. INTRODUCTION

The focus of this study is hurricane risk perception, with the specific aim to develop a new, reliable, and valid quantitative measure of this concept based in current theory. Despite the considerable research that has been conducted involving risk and natural hazards,[1,2] the formal development of measures for risk perception has been relatively limited.[3] Researchers working in this area, moreover, have pointed out that prior inconsistent findings involving hurricane risk perception may be related to measurement deficiency.[4,5] Researchers discussing the social science agenda on hurricanes have also highlighted the need for improved conceptualization and measurement of hurricane risk perception and the need to examine its temporal stability.[6] There

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have been calls from funding authorities for social and physical scientists to join in their efforts to address this gap in understanding specifically for hurricanes.[7,8] Therefore, the work presented herein is needed to address this important gap in knowledge and the deficiency in methods that exists for this oftentimes central concept.

The usefulness of such a measure lies in several areas. Risk perception is held to be one of a number of factors influencing hurricane evacuation behavior, as well as preparedness. Both of these areas receive considerable research attention, so an improved or alternate measurement could find wide application. Also there are more comprehensive models for these phenomenon based in extant theory such as precaution adoption as well as models designed specifically for disasters, such as the protective action decision model.[9,10] In many of these approaches risk perception in one form or another plays a key role but its measurement is not based in more current risk theory. An improved measurement approach will be of use for various one-off studies as well as for potential integration into one of these broader models seeking to illuminate disaster-related human and social dynamics. Other utilities exist as well, such as improving assessment of risk perception for the development of emergency warning communications. There is also good potential for generalization to other natural disaster contexts.

In the study presented here we use a three-wave panel survey of southeast and Gulf coastal residents to develop a measure of hurricane risk perception based in the cognitive-affective psychometric model. The resulting measures are examined as they associate with participant demographics, two personality trait measures (dispositional optimism and locus of control), an existing measure for perception of hurricane risk, and a measure of hurricane evacuation intent.

2. BACKGROUND

In support of this study we will organize the background review into three topics. First, hurricane risk perception has been examined in a number of studies, with a variety of quantitative approaches applied. We will look at what has likely been the best approach to date. We will then examine this concept in light of current risk perception theory, with its emphasis on both cognitive and affective processes. Our alternate measurement scheme—grounded in this theoretical approach—will be described there. And we will present a set of concepts that we will use for consideration of the external validity of the measure we propose.

2.1. Perception of Hurricane Risk: Current Approach

As stated above, the natural hazards literature has maintained a strong focus on risk perception and the role it plays in preparedness and response, with this work having been applied to various natural hazard contexts.[2,11] The same is true of hurricanes specifically.[3,12–16] Whether for investigating the constituents of risk perception or studying it as an independent variable, various approaches for its measurement have been used—not uncommonly with ad-hoc single-item measures.

Work by Peacock, Brody, and Highfield stands as a good example of research that has been done on hurricane risk perception with a more developed measure.[3] Drawing on previous conceptualizations of hazards risk perception they developed their measure relative to personalized risks for hurricanes (as opposed to probability of occurrence), as previously stated by Lindell and Perry: "certainty, severity, and immediacy of disaster impacts to the individual, such as death, property destruction and disruption of work and normal routines."[5, p. 27]

Toward that end they employed a three-item scale: "How likely do you think it is that a hurricane will prevent you or members of your household from being able to go to work or go to your jobs during the next hurricane season?" "How likely do you think it is that a hurricane will disrupt your daily activities during the next hurricane season?" and "How likely do you think it is that a major hurricane will potentially damage your home during the next hurricane season?" Each item had a three-point response of *very unlikely*, *somewhat likely,* and *very likely*. Using this three-item scale ($\alpha = 0.73$) for the dependent variable labeled perception of hurricane risk (PHR) in a study of Florida homeowners, they examined the influence of experiential (years as a Florida resident, hurricane experiences), sociodemographic (gender, age, income, race, education, children in household), and spatial factors (home location in wind hazard zones). In a multiple regression they found all variables to be significant predictors of PHR with the exception of the presence of children in the home, hurricane experience, and hurricane knowledge. In a later study Ge, Peacock, and Lindell replicated the PHR measure in a study focusing on factors influencing Florida homeowners' participation in hurricane hazard mitigation incentive programs.[17] In this study their three-item PHR measure (α = 0.73) was used in concert with other psychological variables: worry, intrusive thinking, and knowledge. Their analysis showed that PHR was a significant predictor of various aspects of their hazard mitigation model, and presented a number of significant associations with other variables. A citation search in Web of Science showed that the researchers' 2005 paper introducing PHR has been cited about 70 times. The bulk of the citations involve work across a range of natural hazards, evoking other aspects of the paper, especially its treatment of experience. In addition to the follow-up by Ge *et al.* two studies have replicated the PHR measure for hurricanes.[18,19] These studies were part of this research team's preliminary investigations leading to this current project. In one of these investigations PHR served to illuminate the way in which Gulf Coast residents viewed the upcoming hurricane season in the wake of Hurricanes Katrina and Rita. In another it demonstrated that PHR diminished over a two-year period in which there were no major storms, also in a sample of Gulf Coast residents. Reliabilities for the three-item measure were good in both studies ($\alpha = 0.81$ and 0.82). In those studies the PHR measure was casually referred to as hurricane outlook; herein the term PHR will be used as per the original studies.

2.2. Dual-Process Risk Perception: Proposed Approach

While the PHR measure has demonstrated utility, the underlying conceptual foundation is more relevant to concern over disruption and damage, not to death or injury specifically. As an alternate approach the measure developed in the present study employs the psychometric model of risk perception, within which risk perception is defined as a function of the individual's cognitive and affective estimations of the probability of harm from a given hazard. The original work led by Slovic and colleagues demonstrated that three important dimensions could be used to describe risk perception: number of people affected, dread, and knowledge.[20–22] Others have expanded the concept to include a variety of elements such as interference with nature or new age beliefs.[23–26] This approach has provided a solid foundation for describing how individuals orient toward a range of technological and behavioral hazards.[27,28] This body of work has provided a robust set of concepts to capture the manner in which people think about risk, such as controllability, voluntariness, predictability, catastrophic potential, and a host of other largely cognitive aspects.

Over the last decade or so, Slovic and colleagues have been exploring the role of affect.[29–32] In this work, individuals are described as possessing an "affect pool" in which images of the world held by the individual, including its hazards, are tagged with emotional markers. As people make judgments they call from this pool just as they rely on other heuristics such as imaginability or similarity. Attention to this aspect of risk perception has been significant and has grown to balance the previous focus on more cognitive processes, with a good variety of contextual foci employed such as causes of death, driving safety, new products, and environmental issues, for example.[33–36] A more balanced perspective has emerged that considers risk as thoughts and as feelings, or as logical versus intuitive processes, or cognitive versus experiential, or more generally as a dual-process phenomenon.[37]

An interesting example of the examination of affect in the context of natural disasters is demonstrated in a study of how reaction to the 2004 Indian Ocean tsunami influenced risk-benefit perception and future optimism.[38,39] Individuals in Sweden who were not affected by the disaster but were given reminder cues about it demonstrated more negative affective states that influenced risk perception within several unrelated domains. While not directly applied to measuring disaster risk perception, this work is relevant because it helps to succinctly define the meaning and operationalization of affect as it relates to risk perception. In the article, the authors define affect as "the specific quality of goodness or badness experienced as a feeling state (with or without awareness) and demarcating a positive or negative quality of a stimulus,"[38, p. 64] and demonstrate a set of affective terms that were useful for measurement in this context. Slovic and colleagues have of course also expanded on a definition of affective risk perception, evoking earlier perspectives by Epstein describing an experiential system for knowing.[29,37]

While consideration of affect-based risk perception is relatively new, the research focus on cognitively-based risk perception extends back some time, at least to its evocation by Starr.[29,40] Here it is held that there is a parallel system that Slovic labeled the analytic system in which judgments are arrived at through the application of logical connections, systematic comparison of evidence and information, and a conscious justification for action.[31] Measurement approaches for this extend back to the early work on the psychometric paradigm (much of which was cognitively based), to emphasize individuals' identification and assessment of objective, observable properties of a hazard (e.g., as per one of our measures presented below, potential financial losses from hurricanes).

The development of an alternate measure for hurricane risk perception described here was based on this theoretical foundation. To accomplish this, the study included a set of items designed to apply recent findings on cognitive-affective modeling of risk perception to create and evaluate a two-dimensional scale of hurricane risk perception tapping either cognitive or affective factors. These include, for example, cognitive elements such as the degree to which the individual perceives personal control over hurricane risk, thinks the risk of hurricanes is increasing, or believes scientists understand hurricane risk; and affective elements such as the degree to which individuals dread the possibility of a hurricane and how anxious or angry the idea of a hurricane makes the individual. Affective items were based on those employed by Västfjäll and colleagues.[38] The overall approach in this effort was confirmatory; defined by the model proposed in the original funding application for this study. For the purposes of this article and to distinguish from PHR, these scales will be referred to simply as cognitive and affective.

2.3. Associated Concepts

In addition to the PHR scale for comparison, three measures were included to serve as external checks. Two established scales were selected based on their previous use in disaster studies, in hurricane studies along with PHR, or in other contexts of risk perception. The third measure was created to serve one of the goals of this study's broader effort to model evacuation expectation.

In previous work on hurricanes, dispositional optimism was found to be associated with PHR and a measure of optimistic bias.[19] Otherwise, dispositional optimism has been most extensively applied in the context of health behavior.[41] Dispositional optimism is considered to describe an individual's future expectations concerning whether things are likely to go well or not. In the health domain, this trait has generally been found to be predictive of better outcomes, largely because optimists are more perseverant toward goals.[42] Inclusion of dispositional optimism in this area of work has been extensive. There are also a few studies that have specifically found a relationship between dispositional optimism and various measures of risk perception in genetic testing, cancer treatment, and AIDS prevention.[42–46] Optimists tend to perceive lower levels of risk. In a review of this work Klein and Zajac relate dispositional optimism to the psychometric model and dual-process risk perception, arguing specifically that dispositional optimism should be more related to affective rather than cognitive risk perception.[47] This construct is most often measured using the Life Orientation Test-Revised (LOT-R), the properties of which are described below.[48]

Locus of control has also been held to be associated with risk perception, often through a common association with self-efficacy. The concept is polar from those who are considered "internals" as they ascribe a strong degree of perceived personal control over risks to the "externals," who see risks as less under their control and more a consequence of outside forces. Internals tend to perceive greater self-efficacy, and also perceive lower levels of risk.[49] The concept has also been used widely in health behavior studies, where a health-specific variation on the scale is often used (the multidimensional health locus of control scales) to examine subjects such as pregnancy risks or treatment decisions for cancer.[50–52] The concept has also been applied to safety studies involving, for example, driving, aircraft piloting, or agriculture.[53–55] And locus of control has been used in studies of natural disasters, including hurricanes, flooding, and earthquakes.[4,56–58] Again, results show that externals typically perceive greater risk while internals exhibit greater self-efficacy—thus often demonstrating greater levels of preparedness. This construct was first developed by Rotter, and subsequently revised by Duttweiler as the internal control index, which remains its most common conceptual base although a wide variety of population, language, and other contextual versions have been developed.[59–62] Its properties are described below.

Dispositional optimism and locus of control are both held to be stable personality constructs. There have been studies examining them together, showing that optimists tend to also be internals.[63–65]

Lastly, a measure of evacuation expectations was developed for the broader project in which both preparedness and evacuation expectations will be examined using a wide range of predictive factors. The concept is obviously applicable to the current study and has been examined in one form or another in an extensive range of previous studies.[66–69] The general expectation is that perception of greater risk acts positively on expectation to evacuate.[18,19] Our approach for measurement is detailed below.

2.4. Hypotheses

Expected outcomes from this study are based in the theoretical perspectives outlined above as well as on the basis of previous results. The emphasis is on the psychometric properties of the proposed scale.

- H1: The perception of risk for hurricanes can be represented as a two-dimensional model clearly separating the factors of cognitively- and affectively-based risk.
- $H2_{a,b}$: The cognitive and affective dimensions of risk perception will each exhibit acceptable internal reliability as additive scales ($\alpha \geq 0.70$).
- $H3_{a,b}$: The cognitive and affective risk perception scales will each be significantly positively correlated with Peacock's PHR measure.
- $H4_{a,b}$: The cognitive and affective risk perception scales will each be significantly negatively correlated with dispositional optimism (i.e., optimists perceive less risk).
- $H5_{a,b}$: The cognitive and affective risk perception scales will each be significantly negatively correlated with locus of control (i.e., internals perceive less risk).
- $H6_{a,b}$: The cognitive and affective risk perception scales will each be significantly positively correlated with evacuation expectation.

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3. METHODS

3.1. Participants and Procedures

Development of the measure of hurricane risk perception was part of a larger investigation of orientation toward hurricane evacuation. The study was executed as a three-wave panel design from 2010 to 2012. For purposes here the three data collections are referred to as T_0 (baseline), T_1, and T_2.

The design of the larger project included contacting participants at the time of a major hurricane landfall. Our sampling approach was therefore to maximize this likelihood, which called for a spatially uniform random sample of the Gulf and Atlantic coasts. This required a participant located approximately every 4.5 miles for a total sample of approximately 600 at T_0 to satisfy *a priori* power analysis and expected attrition. An important limitation should be noted here. Because the sample was spatially uniform along the coast it created an underrepresentation of urban areas. If the sample size had been increased in urban areas for better proportional representation then the size and cost of the study would have been amplified considerably with no gain for events that would miss urban areas. This was a necessary tradeoff. Perhaps ironically, there were no major land falling hurricanes in the study area over the three years of data collection, an unusual condition that has extended to historical proportions at this time.[70]

Participants were located within an approximately 10- to 15-mile buffer of the U.S. coast from Wilmington, North Carolina, to Brownsville, Texas. This area has historically seen 88% of landfalling major hurricanes (64 of 73 category 3-4-5 storms between 1900 and 1999).[71] The seven states involved in the study have a combined coastline of approximately 2,800 miles. We subtracted 300 miles from this figure to remove the northern part of North Carolina, the southern tip of Florida from Homestead to Naples, and the Florida Keys because of the unique conditions faced in each of these locations in terms of hazard exposure and evacuation (a marked dropoff in hurricane probability further north, very sparse population around the southern tip of Florida, and the island rather than coastal nature of the Keys). Along the remaining approximately 2,500 miles of coast all census tracts falling within the buffer were identified and mapped.

Sample points were selected by first scaling the coastline into approximately equal segments (about 100 miles) to be populated with census tracts. Census tracts are based on population (ranging approximately 1,200 to 8,000), often follow natural or built boundaries, and vary in size.[72] Since the size of tracts is not uniform, random selection could not be used within these segments to achieve spatial consistency. Rather, each segment was further subdivided (about 25 divisions) to determine the general location of the specific tracts to be used (effectively creating about 600 locations along the coast in two steps). Final selection of specific tracts was in many cases easily determined. When multiple points fell within a single tract their selection was simple random. When multiple candidate tracts were presented at the sampling interval judgment was used to eliminate potentially problematic tracts (broken, or in some cases, barrier island) and the final selection

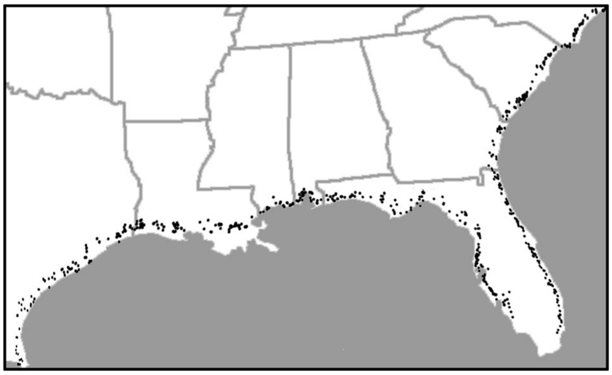


Fig. 1. Location of respondents in T_0 survey (each point represents a household).

was simple random. The list of census tracts with their attendant number of sample points was sent to Survey Sampling Inc. (a major provider of survey lists in the United States),[73] which provided a head of household mailing list. Based on previous experience with the sample provider, data-collection service, and the techniques employed we anticipated a 50% or better response rate so we selected a total of 1,262 addresses for the baseline mailing.

Data were collected by self-administered mail questionnaires with the survey administration conducted by the University of Wisconsin Survey Center (UWSC). Best practice methods were used, including advance notification, \$2 cash incentives (in the first mailing of each wave), multiple prompts, and up to three questionnaire mailings.[74] Questionnaires were professionally designed as eight-page booklets and included a good variety of measurement concepts, including those used herein.

The T_0 survey was done in July 2010 and achieved an adjusted response rate of 56% ($N = 629$ after removal of 138 nondeliverables). The location of respondents is mapped in Fig. 1. The baseline questionnaire emphasized individual and household demographics, stable personality measures, and the initial item pool for risk perception. The T_1 survey was executed in July 2011 and achieved a 75% adjusted retention rate ($N = 427$). The T_2 survey was executed at a 16-month interval in November 2012 at the end of the hurricane season and achieved an 89% adjusted retention rate ($N = 351$).

Recipients were required to be year-round residents, were instructed that any adult member of the household could participate, and were told at baseline that this was a three-year study in which the same person should complete each questionnaire. T_1 and T_2 questionnaires included a previous participation confirmation item and repeat demographic questions were also used to assure panel fidelity. Some cases did not match on these items; thus the sample size for the present analysis uses the 325 cases positively confirmed to have completed each of the three questionnaires. Examination of the demographic characteristics of the baseline and retention samples is presented below in Section 4.

3.2. Measurement

Initial items for the study were presented in the T_0 survey. Items for the cognitive dimension were based on the general principles of the psychometric model and item wording approaches previously employed by the investigators.[18,19] These eight initial items spanned the concept, including knowledge and experience, control, increasing threat, etc. A total of 15 items were included in the T_0 pool for affect and featured both positive and negative statements. As this dimension represented a newer avenue of work in this context we included the larger item pool. Prior to finalizing the initial inventories they were pretested (with the balance of the questionnaire) within a small group of student volunteers attending a university located on the Gulf Coast.

In the T_0 questionnaire both of the inventories were followed by an open-ended item asking that participants list any other concepts or words that might be added to the set just completed. Approximately 150 participants at baseline T_0 provided one or more additional terms to consider. An exploratory analysis of the dimensionality and reliability of the T_0 responses, consideration of new ideas offered by respondents, and the judgment of the research team yielded the item inventory fielded in the T_1 and T_2 data collections. The affective set was reduced to eight statements and the cognitive set was expanded to 12 statements. Specific item wordings are provided in Table I, in which the final items are parsed from those not continued from T_0 and those not retained in the final analysis (detailed below).

As described above, four measures for external assessment were included. Their properties are presented in Section 4. Demographic measures included household gross annual income (in dollars), state of residence, respondent's sex, age (in years at last birthday), race/ethnicity (U.S. Census categories), educational achievement (in years), number of persons in the household, and presence of

Table I. Risk Perception Item Wordings ($N = 325$)

Label	Item	T_1 M(*SD*)	T_2 M(*SD*)	*r*	$t_{(324)}$	*d*
Affective	People have different kinds of *emotional responses* to the threat of a hurricane. In thinking about the possibility of your location being hit by a major hurricane with the potential for widespread damage, how strongly would you disagree or agree with the following statements? *Thinking about the possibility of a major hurricane*					
Fear	Makes me feel fearful.	3.11 (1.08)	3.31(1.03)	0.50^{**}	3.5^{**}	0.19
Worry	Makes me feel worried.	3.46 (1.04)	3.70 (0.92)	0.46^{**}	4.2^{**}	0.24
Dread	Makes me feel dread.	3.30 (1.16)	3.58 (1.06)	0.46^{**}	4.3^{**}	0.24
Depressed	Makes me feel depressed.	2.65 (1.09)	2.79 (1.13)	0.47^{**}	2.3^{*}	0.12
Affective risk	Additive scale ($\alpha = 0.85$ and 0.84)	12.54 (3.63)	13.37 (3.38)	0.61^{**}	5.0^{**}	0.27
Not used	Makes me feel: active, brave, focused, repulsed, sad, anxious, angry, capable, exhilarated.					
Cognitive	People *understand* hurricanes in different ways. In thinking about the nature of hurricanes generally, how strongly would you disagree or agree with the following? *Thinking about the nature of hurricanes*					
Catastrophe	I think that hurricanes may cause catastrophic destruction.	4.37 (0.62)	4.50 (0.62)	0.33^{**}	3.7^{**}	0.18
Widespread	I think that hurricanes may cause widespread death.	3.70 (1.00)	3.81 (0.97)	0.43^{**}	2.5^{*}	0.10
Financial	I think hurricanes pose great financial threat.	4.18 (0.62)	4.26 (0.61)	0.36^{**}	2.2^{*}	0.12
Generations	I think hurricanes pose a threat to future generations.	3.68 (0.84)	3.71 (0.89)	0.45^{**}	0.5	0.03
Cognitive risk	Additive scale ($\alpha = 0.68$ and 0.67)	15.84 (2.34)	16.24 (2.26)	0.51^{**}	3.2^{**}	0.17
Not used	I think that: I am experienced with hurricanes, I can control being physically harmed by a hurricane, the threat from hurricanes is increasing, hurricanes are very unpredictable, I can control the amount of property damage from a hurricane, hurricanes are hard to prepare for, it is difficult to understand hurricane forecast information, I am knowledgeable about hurricanes.					

$^{*}p < 0.05$; $^{**}p < 0.01$.
Response: 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree (some items reverse coded).

children in the household. Number of previous hurricane landfalls experienced (any category) and length of time (in years) residing within 20 miles of the coast were also recorded (among other measures).

3.3. Analysis

The goal of this study was to develop and test an item pool to capture perception of risk for hurricanes such that cognitive and affective components were clearly differentiated and reduced to a manageable item set. The approach was confirmatory to yield a two-dimensional solution. The approach included assessment of the psychometric properties of the resulting measures for internal reliability, distributional characteristics, and external validity checks against three relevant and previously established measures.

Basic descriptive statistics were calculated for demographics and item measures. Cross-tabulation χ^2 tests, independent and paired *t*-tests, and one-way ANOVA tests were used to assess differences among measures and across samples. Confirmatory maximum likelihood factor analysis with oblique rotation was used to test dimensionality, with Cronbach's alpha used to assess internal reliability of resulting additive scales. Pearson correlations were used to evaluate test-retest reliability and external validity. OLS multiple regression was used to test the predictive capacity of the scales over evacuation expectation, as well as to compare the new scale with PHR. The confidence level was set at $p \leq 0.05$. All analyses were done in SPSS v. 22.

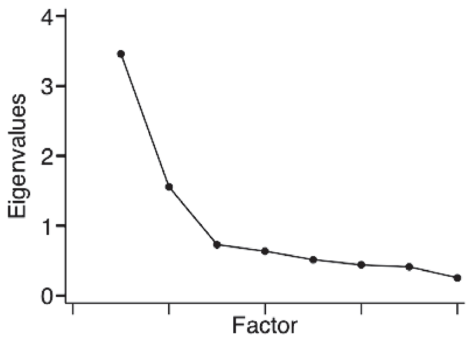
4. RESULTS

4.1. Participants

Demographic variables were reported for the participants completing the T_2 survey ($N = 325$) as well as those in the T_0 survey who were lost to follow-up (LTF) ($N = 304$). Comparisons between these

T_1 Rotated Solution (oblique, blanked < .20)
$\chi^2_{df=13} = 10.9$ $p = .62$ (N = 325)

	Factor 1	Factor 2
Affect: Fear	.89	
Affect: Worry	.81	
Affect: Dread	.72	
Affect: Depressed	.66	
Cognitive: Catastrophe		.76
Cognitive: Widespread		.70
Cognitive: Financial		.56
Cognitive: Generations		.39
Variance (61.6%)	42.6	18.9
Cronbach's α	.85	.68



T_2 Rotated Solution (oblique, blanked < .15)
$\chi^2_{df=13} = 22.6$ $p = .05$ (N = 325)

	Factor 1	Factor 2
Affect: Fear	.89	
Affect: Worry	.79	
Affect: Dread	.68	
Affect: Depressed	.66	
Cognitive: Catastrophe		.68
Cognitive: Widespread		.63
Cognitive: Financial		.54
Cognitive: Generations		.52
Variance (60.2%)	38.7	21.4
Cronbach's α	.84	.67

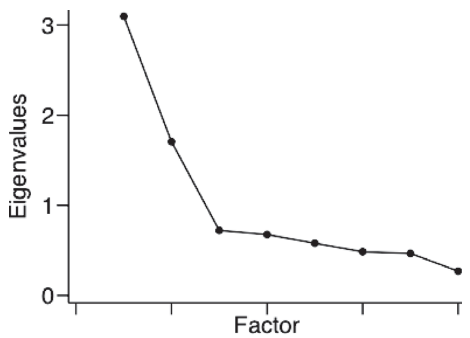


Fig. 2. Rotated solutions and scree plots.

groups were conducted. Study participants were 62% male (LTF 48% male, $t_{(627)} = 3.5$, $p < 0.01$, $d = 0.28$) with an average age of 61 years (LTF 58 years, $t_{(627)} = 2.4$, $p < 0.05$, $d = 0.21$). Participants were 90% white, 4% African American, and 6% all others (LTF 86%, 6%, 8%, n.s.), and were 5% Hispanic (LTF 8%, n.s.). The average number of years of education was 14.5 (LTF 14.4, n.s.), with those at T_2 showing 24% holding a graduate degree, 19% a bachelor's degree, 6% having competed technical college, 27% having completed some college, 19% having completed high school or a GED, and 5% having less than a high school diploma. The average number of persons in the household was 2.2 ($SD = 1.1$), ranging from 1 to 8 (LTF 2.3, $SD = 1.3$, n.s.), with 17% of households including children (LTF 23%, $\chi^2_{(1)} = 4.1$, $p = 0.04$). The average household annual gross income was $55,200 (LTF $49,500, $t_{(627)} = 2.8$, $p < 0.01$, $d = 0.23$). Participants reported having lived within 20 miles of the coast for an average of 33 years (LTF 31 years, n.s.), and on average had experienced 4.5 ($SD = 4.4$) hurricanes (LTF 4.4, $SD = 4.3$, n.s.). There were no significant differences between T_0 and T_2 in the proportions of participants living within the eight coastal states included in the study area.

Finally, we note that this sample was not intended to be representative of the entire coastal population, as the spatial distribution was of greatest importance. We can offer some comparisons to 2010 Census figures (county level): 37% of our sample was over age 65 compared to 17% in the population, 45% were female compared to 51%, 95% had completed high school compared to 86%, 43% had completed college as compared to 26%, and the median household income was approximately $55,000 compared to approximately $48,000. Therefore, our sample is somewhat older, more male, better educated, and wealthier than the average for this coastal area.

4.2. Dimensionality

Item wordings for the risk perception scales are presented in Table I, as described above. Factor analysis was initially used to reduce the number of variables within each of the two proposed dimensions. The goal was to reduce the needed items in each dimension to four or five. The eight affective items presented two factors. The first factor included the four negative affect items and accounted for over half (63%) of variance explained (32% of 51%, eigenvalues 3.0 and 2.0). These were provisionally retained for inclusion in the confirmatory model. The 12 cognitive items presented six factors. The first factor included five variables and accounted for about half (44%) of the total variance explained (18% of 41%, eigenvalues 2.8 and 2.2). One of the variables (increasing threat) presented cross-loadings. This variable was dropped and the remaining four were provisionally retained for inclusion in the confirmatory model.

The eight candidate variables from T_1 were then used in two-factor confirmatory analysis. The model presented good sampling characteristics for factor analysis (KMO = 0.83, Bartlett's sphericity $\chi^2_{(28)} = 855, p < 0.001$). Results are presented in Fig. 2 (top). The scree plot confirmed the two-factor solution, as did the model fit assessment and loading structure. Additive scales were then computed for the variables falling into each of the two factors. The same variable set was then analyzed in the same manner for the T_2 data. The model also presented good sampling characteristics for factor analysis (KMO = 0.79, Bartlett's sphericity $\chi^2_{(28)} = 763$, $p < 0.001$). Nearly identical results were produced and additive scales were computed for the variables falling into the two factors of that analysis. Descriptive statistics are presented in Table I for all scales. The resulting scales and all but one of the of the eight indicator variables (generations) showed a significant increase in perceived risk from T_1 to T_2 with generally small to medium effect sizes.[75]

4.3. Reliability, Stability, and Association

Cronbach's alpha was used to assess internal reliability, as reported in Fig. 2 (and Table II). Results were nearly identical for the two years, with the affective risk scales exceeding conventional standards for alpha reliability (0.85 and 0.84), and the cognitive scales very closely approaching the typical convention of 0.70 (0.68 and 0.67). The alpha values for the combined scales were very good to acceptable in both years (0.80 and 0.76). To further explore scale reliability the analysis was rerun on T_1 data using the full 427 cases available (not constrained to the 325 panelists), in which case alpha increased to the 0.70 convention. As noted above, the cognitive variable "increasing threat" was not included due to its marginal performance in the factor analyses (poor model fit and cross-loading). If included in the additive scales alpha improves slightly for both years (0.71 and 0.70). Our approach was to maintain the best factor model so analyses presented below do not include "increasing threat."

As discussed above, one new and three previously used measures were also included in the project to serve as validity checks. The new measure, developed for use in this study, is an indicator of hurricane evacuation expectation. In this three-item set respondents are asked to report the percentage likelihood that they would leave if faced with an evacuation order for a category 1, category 2, and category 3 storm. Responses were in 10% bins. The three responses were then summed for a scale in each year (T_1 M = 22.1, SD = 8.4, $\alpha = 0.89$; T_2 M = 23.2, SD = 8.0, $\alpha = 0.90$). Test-retest stability of the resulting item was strong ($r = 0.68$, $p < 0.01$) and indicated a significant increase ($t_{(324)} = 3.1$, $p < 0.01$, $d = 0.17$).

The first replicated measure was the previously described three-item PHR measure by Peacock *et al.* (measured at T_0, M = 11.4, SD = 7.27, $\alpha = 0.91$).[3] Second, the standard six-item LOT-R was used to assess dispositional optimism.[75,76] Items scored 1–5 agree/disagree include, for example, "In uncertain times, I usually expect the best," and "If something can go wrong for me, it will." The measure presented acceptable characteristics (measured at T_0, M = 22.3, SD = 3.80, $\alpha = 0.83$). And a short form of the internal control index (ICI)[60,76] to assess locus of control was created prior to this investigation based on an ad-hoc study of undergraduate students at the lead investigators' university (N = 180). The 28-item ICI was reduced to a 10-item set through exploratory factor analysis, yielding a scale with good reliability and strong association with the full measure ($\alpha = 0.76$, $r = 0.93$, $p < 0.001$, ICI items 3, 13, 14, 15, 16, 20, 22, 23, 26, 2). The measure used herein presented acceptable characteristics (measured at T_1, M = 39.6, SD = 5.28, $\alpha = 0.73$). High levels indicate internal.

Table II reports correlations among the scales. Coefficients presenting no substantive interest are gray. Test-retest associations were strong (affective $r = 0.61$, cognitive $r = 0.51$, $p < 0.01$), as were associations between dimensions at both time points (T_1 $r = 0.38$, T_2 $r = 0.26$, $p < 0.01$). Both dimensions at each time were significantly associated with PHR (r ranging 0.15 to 0.31, $p < 0.01$). The cognitive measures presented no association with dispositional optimism or locus of control. The affective measures were both associated with dispositional optimism and locus of control (r ranging –0.18 to –0.26, $p < 0.01$). Cognitive and affective scales were both associated with evacuation expectation within their respective time periods (r ranging 0.13 to 0.25, $p < 0.01$). Also of interest, PHR was significantly associated with both

Table II. Correlations Among Scales, M(*SD*) on Diagonal

	α	PHR	Optimism	Control	Evac T_1	Affect T_1	Cog. T_1	Evac T_2	Affect T_2	Cog. T_2
PHR[a]	0.91	11.42 (7.27)	-0.17^{**}	-0.14^{*}	0.10	0.23^{**}	0.23^{**}	0.10	0.31^{**}	0.15^{**}
optimism	0.83		22.31 (3.79)	0.37^{**}	0.04	-0.26^{**}	-0.06	0.12^{*}	-0.25^{**}	-0.02
Locus of control	0.73			39.56 (5.27)	0.13^{**}	-0.18	-0.05	0.13^{*}	-0.21^{**}	-0.02
Evacuation T_1	0.89				22.07 (8.35)	0.21^{**}	0.13^{*}	0.68^{**}	0.18^{**}	0.25^{**}
Affective T_1	0.85					12.55 (3.59)	0.38^{**}	0.18^{**}	0.61^{**}	0.18
Cognitive T_1	0.68						15.93 (2.24)	0.11	0.22^{**}	0.51^{**}
Evacuation T_2	0.90							23.18 (7.98)	0.20^{**}	0.25^{**}
Affective T_2	0.84								13.39 (3.38)	0.26^{**}
Cognitive T_2	0.67									16.28 (2.22)

$N = 325$. * $p < 0.05$; ** $p < 0.01$.
[a]PHR correlation with evacuation expectation at T_0 $r = 0.16$** ($N = 629$).

dispositional optimism and locus of control, but not with evacuation expectation.

Finally, correlations were also assessed among the risk perception measures and the demographic items, using the T_2 measures. The only significant associations found were among cognitive ($r = -0.15$, $p < 0.01$) and affective risk ($r = -0.23$, $p < 0.01$) with educational attainment, and household income (cognitive $r = -0.19$, affective $r = -0.15$, $p < 0.01$).

4.4. Exploratory Follow-Up

As a final exploratory analysis the blending of the PHR and dual-process measures was examined, as were their unique predictive characteristics. The three PHR items were included with the eight cognitive-affective items (measured at T_2) in an exploratory factor analysis (maximum likelihood, eigenvalue > 1 and oblique rotation). The resulting model presented three factors: the PHR items (eigenvalue 3.9 with 35.4% variance, loadings 0.75 to 0.96), the affective items (eigenvalue 2.1 with 19.0% variance, loadings 0.66 to 0.90), and the cognitive items (eigenvalue 1.5 with 13.7% variance, loadings 0.38 to 0.78) (no cross-loadings greater than 0.20). Model fit was good ($\chi^2_{(25)} = 23.1$, $p = 0.57$). A multiple regression was then run to predict evacuation expectation (T_2). The resulting model ($R^2 = 0.12$ $F_{(5, 319)} = 8.9$, $p < 0.01$) included T_2 cognitive ($\beta = 0.20$, $t = 3.6$, $p < 0.01$), T_2 affective ($\beta = 0.19$, $t = 3.3$, $p < 0.01$), dispositional optimism ($\beta = 0.13$, $t = 2.2$, $p < 0.05$), locus of control ($\beta = 0.13$, $t = 2.3$, $p < 0.05$), and PHR ($\beta = 0.05$, $t = 0.8$, $p = 0.41$). Finally, we report that PHR, which was measured at T_1, is significantly associated with the evacuation expectation measure taken also at T_0 (but not associated in the following two years).

5. DISCUSSION

5.1. Findings

The measure developed in this study presents a number of positive attributes. The approach taken here is grounded in a substantive body of risk perception theory that is demonstrated to be generalizable from technological contexts. In this way the approach used here is consistent with a good number of other studies making use of the more current perspectives on risk. Also, the specific measurement items were based on previous work by the investigators and demonstrate a degree of consistency with these earlier applications.[18,19] The initial development of the item inventories included collection of open-ended responses, with participants providing a robust pool of suggestions. The proposed factor structure was readily identified and found to be dimensionally stable over an 18-month test-retest.

This study tested six hypotheses (five as pairs) to examine this proposition for a new approach for measuring hurricane risk perception using a dual-process cognitive-affective theoretical base. The first hypotheses inform the dimensionality of the proposed measure, that perception of risk for hurricanes can be represented as a two-dimensional model clearly separating the factors of cognitively- and affectively-based risk. This was clearly supported by the confirmatory factor analysis in terms of factor structure and model fit.

In $H2_{a,b}$ the reliabilities of the resulting additive scales were the next hypothesized characteristic, that the cognitive and affective dimensions of risk perception will each exhibit acceptable internal reliability as additive scales ($\alpha \geq 0.70$). Here the affective scale at both time points was clearly supported. However, the cognitive scale at both time points did not meet our stated criteria for acceptance, but fell very marginally short of the accepted standard. Also, by adding an additional variable to the scale (increasing threat) the reliability for the cognitive scale at both time points meets the conventional requirement, as does it at T_1 if a large sample size is permitted. Given these mitigating findings we hold that the cognitive scale for the measure is just acceptable and would generally recommend at least the provisional inclusion of the additional variable.

One key point of interest was tested in $H3_{a,b}$: that the cognitive and affective risk perception scales will each be significantly positively correlated with Peacock's PHR measure. Here we see clearly that the hypotheses are supported, with significant correlations presented for both dimensions at both times. While an assessment of the face validity of the measures argues fairly strongly for there being at least somewhat different constructs involved, the resulting measures retain a logical association.

The remaining hypotheses assess external validity for dispositional optimism ($H4_{a,b}$), locus of control ($H5_{a,b}$), and evacuation expectation ($H6_{a,b}$). Findings here are mixed across the two dimensions. The affective scales at both time points present consistent supportive results. Significant negative correlations were found with dispositional optimism and locus of control, indicating optimists and internals perceive less affect-related risk. The cognitive scales, on the other hand, were not supported at either time period. In consideration of these differential results we propose that our particular external measures, as personality constructs, are simply more affectively related. We must also imagine that there are other measurement items that were not devised that may better represent the concepts of cognitively- related risk perception.

However, both scales at both time points were supported in their relation with evacuation expectation, showing that greater levels of perceived risk are associated with a greater likelihood for evacuation. For reference, PHR was also associated with dispositional optimism and locus of control, but not with evacuation expectation. This is the first point in the findings at which it becomes apparent that while PHR is a reliable measure and certainly valid within the general domain of hurricane studies, it may not be as effective for sole use in examination of expectations. It should be noted that when personal impact measures such as those in the PHR are combined with other measures of potential death or injury the association with actual evacuation decisions (as opposed to hypothetical) can be stronger (see Huang *et al.*'s meta analysis).[77]

The analysis was concluded with three exploratory tests. First, we were curious about the unique dimensionality of the PHR scale as compared with the cognitive-affective scales. Including all variables in an exploratory factor analysis provided fair evidence that the three scales are associated yet quite distinct. Next, when we tested the relative utility of the measures in a regression, PHR was not a significant predictor of evacuation expectation for T_2 when included with the cognitive-affective scales. Also, the cognitive and affective scales remained significant predictors of evacuation expectation while controlling for locus of control and dispositional optimism. While PHR was not significant in the regression using the T_1 and T_2 measures, it was significantly correlated with evacuation expectation at T_0. Here we conclude that the cognitive-affective approach is unique and potentially more effective for behavioral expectation studies, and also suggest that the unique dimensionality of the PHR scale and its demonstrated associations argue for its inclusion as a separate measure in hurricane evacuation studies.

From a broader perspective the overall findings of this study fall very much in line with previous work using the concepts evoked here. As discussed in Section 2 and elsewhere herein, risk perception has been shown to correlate with evacuation expectation (or intention) and behavior, and has been shown in this and other contexts (e.g., health behavior) to be associated with dispositional optimism and locus of control. This measure thus fits logically into the overall portfolio of approaches to understand hurricane evacuation. It should also be again acknowledged that this measure is essentially a reorganization and application of ideas and approaches that are not ours to take credit for. Finally, we do believe that this approach is generalizable to other contexts within natural hazards, and elsewhere.

5.2. Limitations

This study features several limitations. The final sample was biased toward those living in rural areas who were more likely to be older, male, white, and of a higher socioeconomic status than the coastal population of interest as a whole. Components of this bias are relevant to risk perception, as individuals presenting these demographics have been shown to be less risk averse. The results did show such associations among risk perception, educational attainment, and household income. As these analyses were based on correlations the results may be biased conservatively. The overrepresentation of these particular population groups is an issue with mail survey research generally,[74] although this approach offers particular advantages, including the ability to reach populations without regular phone or Internet access. Use of mail surveys did allow relatively precise spatial sampling as well, and also provided an avenue for mid-cycle maintenance contact (thank-you notes were sent, with a reminder of the next upcoming survey). Future work should examine these measures in more diverse samples. We also offer a note that the use of cash incentives can open concern over biasing of responses, even to the degree of influencing the manner of affect-based responses we elicited.[78]

In addition, our final sample size was relatively small, with a total of 629 participants included at baseline, 427 at T_1, 325 at T_2. While we did not meet our initial goal of sampling 1,000 participants in the eight coastal states of interest, our 75% retention rate at T_1 and 89% rate at T_2 were impressive and well above the norm.[74] We believe our retention rate was so high for a number of reasons, including the retention methods employed by the University of Wisconsin Survey Center and the fact that our research team called a number of participants on the telephone to engage them regarding another aspect of the study that entailed real-time telephone interviews.

A third limitation of this work is that some of the reliabilities are not as strong as desired. Specifically, the reliabilities for the cognitive measures did not strictly meet the acceptable threshold. This has been seen in previous use of this approach and may be an indicator of the relative complexity of assessing cognitively- based risk perception. Further use of these measures in other populations and contexts will contribute to improvements.

5.3. Implications for Research and Practice

In terms of research application, the items included herein represent an efficient and highly usable set of survey items that are not only appropriate for mail surveys, but also may be readily adapted to phone or web platforms. This work also may be adaptable to other natural hazard contexts and thus, in addition to strengthening hurricane risk perception theory, may also lead to theory development for a variety of other natural hazards contexts. Because the study presented in this article is part of a much larger program of research, the items specified here will be applied in our future and ongoing work assessing the relationship between risk perception, hurricane preparedness levels, and evacuation behaviors.

In addition to the contributions to the research literature, this study also has potential for practical application. In particular, the hazards and disaster research field has a long history of translating empirical research findings into hazard risk communications.[79] The items developed herein may be particularly useful in terms of developing effective preparedness messages through a more nuanced understanding of risk perception and how this influences advanced protective actions and possibly actual evacuation dynamics. Moreover, this work can help such practitioners better understand how various population groups orient toward hurricane risk. This study was limited in the examination of population subgroups, although associations with the cognitive-affective measures were seen with respect to educational attainment and household income. Calls for this variety of insight that might inform more tailored preparedness efforts were widespread after recent hurricanes (including Katrina, Rita, Gustav, and Sandy, among others), and thus we believe this work could serve as a basis for responding to this need.

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