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A Computational Model of Coping and Decision Making in High-stress, Uncertain Situations: an Application to Hurricane Evacuation Decisions

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Abstract—People often encounter highly stressful, emotion-evoking situations. Modeling and predicting people's behavior in such situations, how they cope, is a critical research topic. To that end, we propose a computational model of coping that casts Lazarus's theory of coping into a Partially Observable Markov Decision Process (POMDP) framework. This includes an appraisal process that models the factors leading to stress by assessing a person's relation to the environment and a coping process that models how people seek to reduce stress by directly altering the environment or changing one's beliefs and goals. We evaluated the model's assumptions in the context of a high-stress situation, hurricanes. We collected questionnaire data from major U.S. hurricanes in 2018 to evaluate the model's features for appraisal calculation. We also conducted a series of controlled experiments simulating a hurricane experience to investigate how people change their beliefs and goals to cope with the situation. The results support the model's assumptions showing that the proposed features are significantly associated with the evacuation decisions and people change their beliefs and goals to cope with the situation.

Index Terms—Computational Model, Stress, Hurricane, Coping, Appraisal.

1 Introduction

People regularly face stressful, emotion-evoking situations. Occasionally people encounter very high-stress situations such as natural disasters. How people decide to cope with such a stressful situation and how they adjust their beliefs, goals, and decisions can have significant consequences, especially in life-threatening situations such as a disaster. Therefore, an important research goal is to predict and understand how people reason and respond to high-stress, emotion-evoking situations. In this work, we specifically explore this in the context of hurricanes, high-stress situations of critical individual and societal importance.

The number of hurricane events in the United States has shown a significant increase in recent years [1]. In 2017, Hurricane Harvey, the costliest tropical storm on record, made landfall in Texas, causing unprecedented flooding resulting in hundreds of thousands of inundated houses, at least 107 deaths, and total damage of $125 Billion. In 2018, two major hurricanes hit the United States: Hurricane Florence, one of the deadliest and costliest hurricanes ever to impact North Carolina and South Carolina, and Hurricane Michael affecting Florida and Georgia.

Upon facing stressful situations such as a hurricane, people have to decide how to cope with them. For a hurricane event, one important decision is whether to evacuate or stay in place. The unfolding of a hurricane event, from formation to landfall, can span days. People who stay repeatedly face the evacuation decision as they observe new information while the hurricane approaches and potentially strengthens. The decision is made under considerable uncertainty because the hurricane's path and impact cannot be forecast with high certainty [2].

Moreover, people can cope with the situation by changing how they perceive it. For example, one can choose to believe that the hurricane will miss their area or change how one values the cost of evacuation. Some may discount or ignore the seriousness of the threat, which could lead to a decision to stay, while others may perceive the threat to be severe, which could result in a decision to evacuate. These behaviors have been documented in many actual hurricanes. For instance, during Hurricane Katrina, many people did not pay attention to hurricane forecasts and warnings even though those warnings were accurate and timely [3]. Similarly, a study has found that, during Hurricane Isaac and Sandy, surveyed residents underestimated the threats posed by flooding and showed little concern over the potential impact of the hurricane from winds and floods despite receiving an abundance of hurricane information [4].

To help mitigate damage and casualties from hurricanes, effective and efficient evacuation and emergency management plans are needed. The crucial part of such plans is the ability to predict and influence people's decision-making, specifically whether they will evacuate or stay in their homes. Designing effective messages to influence their decisions requires understanding how people will reason and cope with stressful situations.

Toward that end, we propose a model of how people cope with such high-stress situations. Informed by Lazarus's appraisal theory of emotion [5], we realize a computational model of the theory by modifying a sequential decision framework under uncertainty, namely the Partially Observable Markov Decision Process (POMDP). There are two overarching aspects of Lazarus's theory. The first aspect is the appraisal process, how people subjectively evaluate

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situations based on a range of factors often called appraisal dimensions or features. The second aspect is two broad classes of coping: problem-focused coping which seeks to take actions in the world to alter the situation directly, and emotion-focused coping which seeks to change one's goals and beliefs to adapt internally to the situation. We map the appraisal process and appraisal dimensions to POMDP's components and optimization. The more significant modification of the POMDP framework is the realization of emotion-focused coping as a set of actions that can change the internal model, specifically changing one's beliefs and goals in the face of emotional stress. The inclusion of emotion-focused coping separates this model from most existing computational models of emotion. The proposed model emphasizes actions that shape emotional experience instead of focusing on inferring mental states or emotion categories.[1]

In this work, we evaluated predictions that derive from the two key assumptions of the model in the context of hurricane situations: 1) a relationship between the proposed appraisal features and evacuation decisions, and 2) how people who stay may cope by changing their beliefs and goals about hurricane situations differently from people who evacuate.

To evaluate the first assumption, in Study 1, we created a new questionnaire tailored to investigate the model's features. We then used it to collect data from areas affected by two major hurricanes in 2018: Hurricane Florence and Hurricane Michael. The data shows that the proposed appraisal features are related to evacuation decisions in the predicted direction.

To evaluate the second assumption, in Study 2 and 3, we conducted two controlled human-subject experiments that simulated hurricane experiences while controlling the information that participants received. In Study 2, participants are presented with a sequence of hurricane messages closely modeled after real messages from the National Hurricane Center (NHC). After each message, participants have to decide whether to evacuate or stay. Afterward, they are asked about their beliefs and concerns about the hurricane. Then we conducted a follow-up experiment to rule out an alternative explanation that the differences could be due to the influence of beliefs on decisions only. In Study 3, we measure pre-and post-decision beliefs by presenting two near-identical messages from Study 2 in sequence. Half of the participants are asked about their evacuation decision, and the other half are not. The results from both experiments suggest that people altered their beliefs and goals to cope with the situation, as predicted by the model.

The paper is structured as follows. The following section, background, reviews important works related to the proposed model and hurricane decisions. The next section lays out the model, its assumptions, description, and predictions. Then, we present three human-participant evaluation studies starting with the survey of people's behavior during actual hurricanes and then the two experiments. We end with a discussion of the model, the results, and the potential future applications of the model.

1. A preliminary version of this article appeared in the Proceedings of the 20th International Conference on Autonomous Agents and MultiAgent Systems (AAMAS'21) [6]. In this full version, we expanded upon related works to cover related psychological theories and hurricane studies. Furthermore, we included additional details and justification for the model's assumptions, descriptions, and predictions. In addition, we provided a complete description of the controlled experiment as well as additional analysis and results. Lastly, we conducted an additional experiment to rule out alternative explanation.

2 Background

In this section, we cover two important background works: Lazarus's appraisal theory of emotion and its related works and the hurricane evacuation decision literature.

2.1 Lazarus's Appraisal Theory of Emotion

Appraisal theories of emotion define appraisal as an evaluation of the significance of the situation for well-being based on individual's goals or concerns, and beliefs [7], [5], [8]. Appraisal theories argue that this evaluation occurs along specific dimensions, called appraisal dimensions or variables depending on a specific theory. In fact, there are quite a few numbers of appraisal theories [5], [9], [10], [11], [12].

For this work, the main appraisal theory is a theory proposed by Lazarus [13], [5]. The main reason is that it involves not only the appraisal process itself but also how people cope with emotions and stress. Moreover, it has influenced psychological theories about how people deal with disasters [14], [15].

Lazarus's appraisal theory emphasizes the concepts of the person-environment relationship [5]. The core idea is that, to understand the emotion and its relational meaning, we need to look from the standpoint of the person's relation to the environment (the person-environment relationship) as a unifying concept. This relationship is always changing, leading to different emotional experiences. The person is not simply reacting to an environment but also selecting and changing it or their relation to it to move toward positive situations and away from negative situations. In other words, the person copes with emotion by regulating or altering their relationship to the environment.

There are two main classes of appraisals in Lazarus's theory. Primary appraisals concern whether what is happening is personally relevant, and secondary appraisals concern coping options and prospects of situations. There are three primary appraisal dimensions: goal relevance, goal congruence or incongruence, and type of ego-involvement. Goal relevance refers to the extent to which an encounter is related to personal goals, whether or not there are aspects of the situation that the person cares about. The second primary appraisal is goal congruence or incongruence, which refers to the extent to which a situation is consistent (facilitates) or inconsistent (obstructs) with the person's desires or goals. The third primary appraisal is type of ego-involvement which refers to various aspects of personal commitments or ego-identity such as self- and social-esteem, moral values, and life goals.

There are three secondary appraisal dimensions: blame or credit, coping potential, and future expectancy. First, blame and credit are based on who is deemed accountable for the situation. Second, coping potential refers to whether and how a person can manage the demands and consequences of the situation by taking actions in the world or altering one's internal beliefs or goals in some way that will change the person-environment relationship. The third secondary appraisal is future expectancy which is the degree to which things are likely to change for the better or worse (becoming more or less goal congruent.)

A critical concept in Lazarus's theory is coping. Lazarus defines coping as "constantly changing cognitive and behavioral efforts to manage specific external and/or internal demands that are appraised as taxing or exceeding the resources of the person." [13, pp. 141] There are two main types of coping: problem-focused coping and emotion-focused coping. Problem-focused coping is the coping processes that directly change the situation or the environment. Emotion-focused coping is the coping processes that change one's goals and/or beliefs to adjust to the situation, such as wishful thinking (forming beliefs based on what one perceives to be positive), resignation (dropping an intention to achieve a goal), or denial (rejecting beliefs). These emotion-focused copings change how one looks at the situation by altering one's internal beliefs (as in wishful thinking and denial), goals, or intentions (as in resignation), which result in reinterpreting the situation. Incorporating emotion-focused coping into a decision-making model suggests a significant change to standard approaches to a decision-theoretic sequential decision-making process. As one example, belief-altering actions such as wishful thinking are very human, in effect wishing some desired outcome to be more likely. However, it conflates probability and utility.

Emotion-focused coping is the core idea of the proposed model. This idea is not unique to Lazarus's theory. There are other influential psychological theories that propose a similar idea in which people alter their beliefs and goals to make them feel better. For example, Gross's emotion regulation theory posits that emotion regulation is an attempt to influence which emotions one has, when one has them, and how one experiences them [16]. There are five regulation strategies in Gross's theory, and one of them is cognitive change or reappraisal, changing one's appraisal of a situation to alter its emotional experience. The theory of cognitive dissonance postulates that the state of dissonance, when a person holds two or more related but inconsistent cognitions (beliefs), is psychologically unpleasant, so people are motivated to reduce it by adding or removing cognitions and changing the importance of cognitions. [17], [18], [19]. Motivated Reasoning theory states that motivation affects reasoning by determining the cognitive processes and representations such as accessing, constructing, and evaluating beliefs to arrive at a particular directional or desired beliefs [20]. Optimism bias proposes that people overestimate the likelihood of positive events and underestimate the likelihood of negative events that will happen in both near and far futures [21], [22]. Crucially, these theories come with a wide range of empirical support. In short, the idea that people alter their beliefs and goals to deal with conflicting, stressful, and emotional situations is well documented and supported by many theories as well as abundant empirical data.

In terms of a computational model, there exist many computational models of appraisal theory of emotion. For reviews, please refer to [23] and [24]. However, there are only a few existing models that include coping or emotion regulation such as [25], [26], [27], [28], and [29]. These models build upon the psychological theories mentioned above. For instance, Gratch and Marsella (2004, 2009) propose EMA (EMotion and Adaptive), a computational model of emotion based on Lazarus's theory. PLEIAD (ProLog Emotional Intelligent Agent Designer) engine proposed by Adam and Lorini (2014) is also based on Lazarus's theory. The models by Bosse et al. (2010) and Martínez-Miranda et al. (2014) are built upon Gross's emotion regulation theory. Bracha and Brown (2012) propose Affective Decision-Making (ADM) model based on optimism bias theory.

There are several key differences between this work and existing models. First, unlike the models by Bosse et al. (2010) and Martinez-Miranda (2014), which simply implement the description of emotion regulation strategies, the proposed model provides a mechanism behind strategy selection. On the other hand, EMA, PLEIAD, and ADM are closely related to this work but have their own limitations. For instance, coping in EMA and PLEIAD does not specify sufficient constraints (i.e., when beliefs change can occur or the limitation of the coping), and ADM does not include the change of goals and the uncertainty of information. More importantly, the majority of existing models have not been evaluated using real data. In contrast, we apply and evaluate the model in a high-stress natural disaster scenario using real human data.

2.2 Hurricane Evacuation Decisions

Hurricanes can cause large waves, heavy rain, floods and strong winds, which can damage or destroy objects and buildings, potentially leading to power outages. Moreover, the hurricane's track, intensity, and impacts can be highly uncertain and still cannot be predicted accurately [2]. People may seek different information and may interpret the same information differently. People who stay during the hurricane may be trapped in a flooded neighborhood, without power and limited water and food supplies. Worse, their home can potentially be leveled by a powerful hurricane. On the other hand, people who evacuate may get stuck in bad traffic jams and spend a lot of money staying in a hotel or having to stay in a public shelter crowded with people and with minimal comfort.

Further, the time between the first notice and the landfall of a hurricane can span days. For example, Hurricane Florence formed on August 31, 2018, and made landfall on September 14. Over this span of time, people can repeatedly face the decision of whether to stay in their homes. People who stay have a chance to observe new, increasingly more accurate information as the hurricane moves closer. However, if they stay too long, they may face increasing evacuation costs, face greater risks due to deteriorating conditions, and not be able to evacuate due to crowded hotels or evacuation centers. Those who evacuate are unlikely to return until the hurricane passes and may have unnecessarily evacuated if the hurricane weakened prior to reaching their home or took a path away from their home.

Moreover, people may have diverse goals and concerns. Some people may value money more than others, while others may heavily dislike being stranded in a flooded house. Similarly, people may have different prior beliefs about the

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hurricane and the trustworthiness of various sources of information which could lead to different people thinking differently about the current and future information.

A recent meta-analysis by Huang et al. [30] summarized 49 studies on hurricane evacuation decision-making, including surveys of people's actual responses to real-world hurricanes and studies of people's expected responses to hypothetical hurricane scenarios. Their results identify that official notice, mobile home, household location, expectations of impacts on personal concerns, and observations of social/environmental cues are consistently significant predictors of evacuation decisions. Additionally, they found that expected flood damage, expected wind damage, and evacuation expense have mixed results with relatively small effect sizes. On the other hand, other demographic characteristics such as gender, age, and race have either minor or inconsistent effects. Moreover, they found that the results from hypothetical hurricanes are comparable to the real hurricanes and suggested such laboratory and internet-based experiments are useful tools for understanding the decision-making process during hurricanes.

The notion of risk perception is closely related to goals and concerns, and a few studies have looked at risk perception in hurricane contexts. Peacock et al. (2005) found spatial factors (wind hazard zones), years as a Florida residence, gender, race, and age to be significant predictors of these risk perceptions [31]. Trumbo et al. (2016) found that greater levels of perceived risk are associated with a greater likelihood of evacuation [32]. Lastly, Lazo et al. (2015) found that risk perceptions are not associated with evacuation intentions but having an evacuation plan, wanting to keep one's family safe, and viewing one's home as vulnerable to wind damage are [33]. In short, the results on risk perception are mixed, and different studies measure risk perception quite differently.

In terms of existing psychology theories or theoretical models on human evacuation behaviors, there are two leading models. First, Protection Motivation Theory (PMT) [34], [15] proposes that protection motivation, which drives how people cope with a disaster, is influenced by two main cognitive processes: threat appraisal and coping appraisal. The combination of threat and coping appraisal influences protection motivation, resulting in either protective or non-protective responses.

Second, Lindell et al. (2012) proposed the Protective Action Decision Model (PADM), a multistage, sequential model consisting of three main stages describing how people typically make decisions about adopting protective actions against environmental hazards [14]. The stages are processing of information (environmental and social cues), psychological decision processes, and behavioral response (information search, protective response, and emotion-focused coping). Both of these models are influenced by Lazarus's theory and similar in terms of how they conceptualize hazard-related attributes, but they emphasize on different aspects of the situation.

With respect to hurricane decision models, Gladwin et al. (2001) proposed a decision tree that consists of a series of yes-no questions [35]. Hasan et al. (2013) proposed a mixed logit model, a variant of logistic regression that accounts for the possibility that the coefficients in the model may vary across observations [36]. On the other hand, existing work on Agent-Based Modeling of hurricanes mainly focuses on the traveling demand model, which concerns estimating the overall trend of evacuation across time [37], [38], [39]. The main methods used to predict the evacuation decision are either exogenous response curves based on a probabilistic distribution or repeated logistic regression in which separate logistic regressions are fitted to the data at each time interval. Recent work by Sankar et al. (2019) proposed a POMDP model for the hurricane decision-making building from their own hurricane data [40]. They represent the POMDP as a dynamic influence diagram (DID) where conditional probabilities are manually defined. The main difference between this model and the proposed model is that our model builds upon established psychological theories.

In sum, existing psychological work highlights the importance of subjective perception of hurricane impacts, albeit with some mixed findings, while existing hurricane behavior models have not considered how people subjectively appraise the hurricane situation as well as how people cope with the situation beyond problem-focused coping (evacuate and stay) and therefore do not consider how emotion-focused coping can alter such evacuation decisions.

3 The Proposed Model

In this section, we introduce the model. First, we lay out the model's assumptions. Then, we detail the description of the model in the POMDP framework and apply it to the hurricane situation. Finally, we list and explain the model's predictions that we evaluate in this work.

3.1 Model Assumptions

The four main conceptual assumptions of the proposed model are the following:

1) How a person chooses to cope with an emotion-evoking situation is a decision problem.
2) The decision is informed by a subjective evaluation of the situation, an appraisal calculation.
3) Appraisals rely on a model of the world.
4) Copings include actions that change the external world (problem-focused coping) and actions that alter the person's own beliefs, goals, or intentions (emotion-focused coping).

1. How people cope with emotion is a decision problem

The first assumption concerns the framing of the overall emotional episode. Faced with an emotion-evoking situation, people must decide how to cope with it. Therefore, the model assumes that how people cope is a decision problem where people choose a way to cope with the situation. This assumption implies that coping is an action which is detailed in the fourth assumption. As a decision problem, the crucial element is the process to determine the "best" action. In other words, people evaluate the consequences of actions. The following three assumptions have to do with evaluation, consequences, and actions in that order.

2. Evaluation: Appraisal Theory

The second assumption is that how people evaluate the situation follows what the appraisal theory of emotion postulates. Specifically, people subjectively evaluate situations

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or outcomes with respect to their beliefs and goals. The following appraisal dimensions are assumed to be important to calculate appraisal and are included in the current model: goal relevance, goal congruence, uncertainty, and control or coping potential.

First, as a consequence of this assumption, goal relevance and goal congruence imply that the model must incorporate the beliefs related to the person's goals to calculate appraisal. For instance, in order to take into account how goal-incongruent living in a flooded house is, the model must include the beliefs about flood conditions along with how important the goal is.

To calculate control, people need to be able to consider the consequences of their available actions, whether they could improve the situation. Similarly, to determine uncertainty, people need to be able to estimate the likelihood of possible consequences of actions or outcomes of situations. This brings us to the next assumption, which concerns what is necessary to calculate control and represent uncertainty.

3. Consequence: The Model of the World

In order to consider possible consequences of actions, the third assumption is that people have a model of the world. This assumption is similar to the idea of the cognitive map [41], and model-based reinforcement learning [42]. The model of the world corresponds to one's beliefs about the world and oneself.

Critically, people have incomplete knowledge of the world. Therefore, they cannot predict the outcomes of the world with certainty. For example, in a hurricane event, people do not know the impact of a hurricane or what information about the hurricane will become available. In other words, there is uncertainty about the current state of the world as well as the dynamics of the world or how the world will be. Furthermore, we also assume that there could be uncertainty associated with how important or congruent goals are. This is because people generally do not know how important goals are with certainty [43], [44], [45]. Nonetheless, people could be more certain about how important *some* goals are. For example, most people are very certain about how important being healthy is, but many of them may not be certain about how important avoiding living in a flooded house is or how bad living in a flooded house could be.

Another related concept that is crucial for hurricane evacuation decision-making is information. Because the knowledge of the world is incomplete and inaccurate, the information plays an important role in acquiring additional knowledge to reduce uncertainty. Information is critical in hurricane events as people, especially the public, will not be able to predict the weather well enough to know whether or when a hurricane is coming to their area and what consequences it will bring.

Moreover, this assumption acknowledges the fact that the decision problem is sequential. People have to consider many decisions in an emotional episode, and the earlier decisions can influence the later decisions. For instance, if one decides to stay until the hurricane gets closer, they can observe more accurate information about the hurricane. However, they may come to learn that the hurricane is indeed severe and too dangerous to evacuate even if they want to.

4. Action: Coping

The fourth assumption, following from Lazarus's theory, is that the set of actions includes actions that interact with the world directly (problem-focused coping) and actions that interact with one's model of the world, changing one's beliefs and goals (emotion-focused coping)[2]. In the current model, we focus only on two broad emotion-focused coping strategies, altering one's beliefs and altering one's goals. These strategies result in changing how one appraises the situation, which could change the emotional experience and subsequent decision-making.

An important concept, especially for emotion-focused coping actions, is the cost of action. In particular, we assume that there is a cost associated with emotion-focused coping that constrains how much one can change their beliefs or goals. A specific function is proposed in the description section. The reason for incorporating cost is that people should not be able to change their beliefs or (importance of) goals freely without limit. It is not easy for people to go from believing and desiring something very much to not believing or desiring it. For problem-focused coping actions, on the other hand, the cost depends on how a decision-maker defines actions in a given domain. For example, the cost of evacuation to a hotel can include transportation costs and lodging costs.

In summary, the proposed model, Coping and Appraisal Decision Model (CADM), frames coping as a decision problem viewing both problem-focused coping and emotion-focused coping as actions, and operationalizes concepts from appraisal theories of emotion, mainly Lazarus's theory, to model the decision process. Putting them all together, Figure 1 shows the diagram of the model, which follows Lazarus's conceptual model closely. From the figure, we can see that there are two main parts of the model. The first part is the mapping from the situation and personal beliefs and goals to appraisal dimensions. The second part is the mapping from appraisal dimensions to coping and, in turn, the influence of coping feeding back to either changing the situation or changing one's beliefs and goals.

3.2 Model Description

The next step is to describe and implement the model within a formal framework. In this section, we begin by explaining how the model maps to the partially observable Markov decision process (POMDP) framework. This includes how each POMDP component connects to the model and how the optimization problem for deciding actions can be viewed as an appraisal calculation. Then, we instantiate the model in the context of hurricane evacuation decisions, thus illustrating how the model is applied to a specific domain.

3.2.1 POMDP Model Components

CADM requires a sequential decision-making framework that includes a representation of beliefs and goals and can

2. We note that Lazarus defines coping as an effortful process and the appraisal process implies nothing about consciousness, meaning it could be either conscious or unconscious [5]. Similarly, emotion regulation strategies including reappraisal could be either conscious or unconscious [46], [16]. We make no distinction regarding conscious and unconscious emotion-focused copings here.

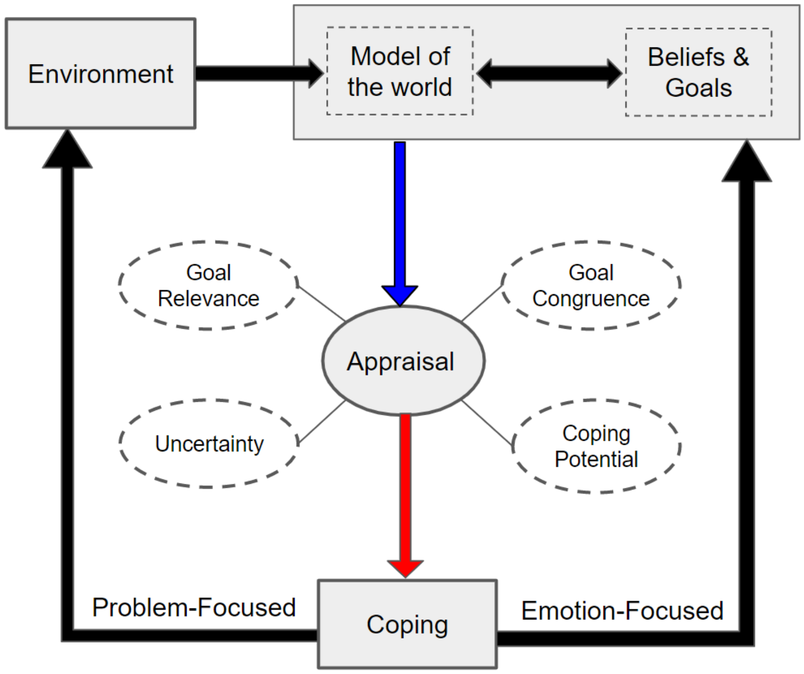

Fig. 1. Coping and Appraisal Decision Model (CADM). The diagram of CADM follows the structure of Lazarus's Theory. CADM can be divided into two main steps. The first step (blue) is the mapping from the situation to appraisal dimensions (those with a dotted line) and appraisal calculation. The second step (red) is the process of using these appraisal dimensions to decide coping, which can be either problem-focused coping that interacts directly with the world or emotion-focused coping that interacts with the internal self–the individual's model of the world, their goals, and beliefs.

capture the uncertainty of knowledge and observations of the world. Toward that end, we choose the partially observable Markov decision process (POMDP) framework [47], which has been shown to be suitable for modeling human decision-making in the hurricane and other domains [48], [40], [49]. POMDP represents a sequential decision-making problem where an agent operates under uncertainty based on partial observations of the situation and sequential actions. At each time step, the agent receives some observation about the current situation, then chooses an action to yield a reward, and moves to the next step where the situation could evolve unpredictably.

POMDP $< S, R, \Omega, O, A, T >$ consists of State (S), Reward (R), Observation (Ω), Observation function (O), Action (A), and Transition function (T). Below we provide the details of these components.

State (S): A state $s \in S$ represents a possible situation in the problem and is represented by a set of k features $F = \{f_1, \ldots, f_k\}$. These features include necessary elements in a given situation that allow the agent to consider the consequences of their actions. Crucially, based on the appraisal theory, state features must also include elements that are concerns and goals presented in the situation. Therefore, identifying these features is the key step in applying the model to a specific domain.

In terms of the hurricane evacuation domain, existing studies have identified the main sources of concern. The concerns that we focus on in this work are perceived safety, flood depth, outage duration, and evacuation expenses or costs, including traveling costs and safe place or lodging costs. These features reflect the severity of a hurricane and are based on one's subjective, uncertain perceptions.

Accordingly, the state features are $F = \{$`safety`, `flood depth`, `outage`, `evacuation cost`$\}$, where `safety` denotes the probability of being safe if the agent stays in its home when the hurricane hits, `flood depth` denotes the flood depth in inch caused by the hurricane, `outage` denotes the outage duration in days caused by the hurricane, and `evacuation cost` denotes the total money spending on evacuation in dollars.

The first three are related to the impact of a hurricane. Safety is obviously the major concern during a hurricane event as a hurricane can destroy buildings and structures. Similarly, hurricanes bring forth heavy rains and floods which are another major concern. Most deaths, in fact, are associated with flooding. The intensity of flooding is measured here in terms of depth. Additionally, a hurricane can destroy power lines resulting in an outage. This can be another concern that people have as many important aspects of modern life depend on electricity such as refrigeration, phones, internet, and medical equipment. The intensity of an outage is in terms of duration.

For evacuation costs, it comprises two main costs: traveling cost and lodging cost. These costs are the concerns that arise when considering evacuation, as you need to pay the cost to travel to somewhere far enough and the cost of the place itself. These costs are represented in log dollars scale (applying a logarithmic function to monetary value in dollars), reflecting diminishing sensitivity of monetary utility [50]. Note there are other costs to evacuation, such as its impact on comfort. These are not directly considered here but can be assumed to be absorbed in the weighting of monetary cost.

Importantly, there is uncertainty associated with the

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agent's knowledge. Therefore, the agent does not know which state it is in precisely. Instead, it maintains a probabilistic distribution over states or a belief state, b, which connects to the notion of belief in the model. Related to this is an initial belief state denoted b_0, which represents the agent's initial or prior beliefs.

Reward (R): Reward function $R(s) \in \mathbb{R}$ maps a state to a real number summarizing how good or bad a given state is. In appraisal terms, it represents a calculation of goal congruence or incongruence of the state according to one's goals or concerns in the model. The reward function is assumed to be a weighted linear addictive function, $R(s) = \sum_i w_i f_i$ where w_i denotes a reward weight of states' features f_i reflecting the degree of congruence or incongruence or how important f_i is to the agent. In addition, an agent can be uncertain about its reward weights. In other words, people may not know how much they value something precisely. Therefore, reward weights can be represented as a probability distribution such as a normal distribution, $w_i \sim N(\mu, \sigma)$, with mean μ and variance σ. As a result, the reward function now calculates the expected reward instead as follows: $R(S) = \sum_i f_i \bar{w}_i$, where $\bar{w}_i$ is the expected or mean of the reward weight w_i.

The key question for the reward function is the values of these reward weights. The modeler has to set them in the simulation manually or learn them from existing data. Still, their characteristics should guide their magnitude and sign of them. For instance, the reward weight for flood depth reflects how important it is to avoid living in a flooded house or how undesirable it is. It scales with the intensity of flooding, which, in this case, is the depth of flooding. As the flood depth increases, the situation becomes worse, less goal congruent, and more undesirable, and the agent should become more likely to evacuate. Therefore, the model expects the reward weight of flood depth to be negative. The same logic applies to the remaining features, resulting in a set of predictions and hypotheses. We detail them more in the next section.

Observation (Ω) and the **Observation function** (O): Observations represent the aspects of the state which an agent can perceive. Formally, the observation function $O(\Omega|s,a) = P(\Omega|s,a)$ is the probability that the agent will receive or see an observation $o \in \Omega$ given the state s and the action a. This observation function reflects how the agent perceives the relationship between observations and states.

In the hurricane event, the observation that people receive at each time step is the hurricane information typically from the National Hurricane Center (NHC), governments, news, family, and friends. The messages usually state a category of a hurricane and predicted impacts [51]. For instance, the message may include "a hurricane will bring heavy rain, flash floods, and strong winds" or "life-threatening storm surge and devastating hurricane-force winds are likely along your area." Hence, the set of observations consists of the hurricane messages ranging from no hurricane to category 5 hurricane, which is the highest category on the Saffir-Simpson hurricane scale, along with their expected impacts including flood depth and outage duration [51].

In addition, as the hurricane gets closer, the accuracy of information increases. Therefore, we define the observation and observation function as follows. Let $t \in [0, T]$ denote the time step up to time T, which is when the hurricane hits. The set of observations Ω_t consists of predictions of hurricane's impacts at time t, and the observation function O_t is the probability distribution that reflects the accuracy of the information at time t.

Action (A) and **Transition Function** (T): There are two broad types of actions in the model: problem-focused coping and emotion-focused coping. The transition function describes the dynamics of these actions – how states' features could change after executing the action. In general, the set of available problem-focused coping actions and their dynamics are domain-specific. For example, in hurricane events, the problem-focused coping actions include evacuation and staying in one's home. On the other hand, the model assumes that the dynamics of the two emotion-focused coping actions in this work, changing beliefs and goals, only depend on the distribution of beliefs or goals.

`Changing beliefs` and `Changing goals`: The effect of the actions is to change the distribution of a belief state or reward weight to a new distribution. For instance, the agent can change their beliefs about the hurricane's impact from moderate to high (increasing the mean of the distribution) or change the importance of a momentary goal from high to low (lower the mean of the reward weight distribution). Therefore, both actions share the same dynamic.

Formally, let A_{em} denote a set of emotion-focused actions. For the case of changing belief, the dynamic of $a_{em}^{b'} \in A_{em}$ results in replacing the current belief state b with b'. Similarly, for the case of changing a goal, the outcome of $a_{em}^{w_i'} \in A_{em}$ is to replace the current reward weight w_i with a new distribution w_i'.

As explained in the assumption section, emotion-focused coping actions must incur some costs to prevent an agent from freely changing their beliefs and goals. The model assumes that the cost of these changes is the difference between the two distributions as measured by the Kullback–Leibler (KL) divergence between the initial belief or goal distribution and the new belief or goal distribution, $C(P,Q) = D_{KL}(P||Q) = \sum_{x \in X} P(X) log(\frac{P(x)}{Q(x)})$, where P is the initial distribution (b or w_i) and Q is the new distribution (b' or w_i'). The KL divergence is chosen because it is a standard measurement of the distance between two distributions. Other forms of the cost function are possible such as a constant cost or a difference between two means [27]. However, these alternative cost functions ignore the shape of the distribution, meaning that they do not take into account the uncertainty of the beliefs or goals. These costs are part of the reward calculation and could have their own reward weight.

In the context of hurricane evacuation decisions, we focus on only two problem-focused actions: `stay` and `evacuate`. The dynamics of the two problem-focused actions, their transition function (T), are described as follows.

`Stay`: If the time is before the hurricane hits $t = \{0, \ldots, T-1\}$, the agent moves to the next time step and receives a new observation o_{t+1}. This means that stay action also includes information-seeking behavior. If the time is the last time step when the hurricane hits $t = T$, the agent receives a reward (cost) based on the hurricane outcome and its reward function and then stops.

`Evacuate`: The agent receives a reward equal to the evacuation cost times its reward weight and stops. In other words, evacuation results in paying the cost of evacuation, moving to a new location, and staying there until the hurricane is gone, as people who evacuate are unlikely to return before that point.

The cost of evacuation comprises the money spent on traveling and lodging. Additionally, the cost of evacuation is assumed to either stay the same or increase over time so that there is an explicit cost of evacuating late. The cost is set to be prohibitively high when it is no longer possible to evacuate.

3.2.2 Optimization Equation

The utility or Q-value of an action for action selection can be expressed as a Bellman equation for POMDP as follows:

$$Q^*(s,a) = \sum_{s',o} P(s'|s,a)P(o|s',a)(R(s,a) + V^*(s')), \quad (1)$$

where $Q^*(s,a)$ is the optimal expected cumulative rewards from state s and action a and $V^*(s') = \max_a Q^*(s',a)$ is the optimal expected cumulative rewards from a state s'. Equation 1 captures the appraisal calculation. Reward function, $R(s,a)$, is the goal congruence calculation. The transition and the observation function express the uncertainty of one's beliefs about the world. The value of the future consequences, $V(s')$, represents the coping potential or control, including the value of future information. Altogether, this equation describes the appraisal calculation and pulls all the main assumptions of the model together.

To solve Equation 1, we use the Forward Search algorithm, an online POMDP algorithm, to calculate the Q-value of the current belief state [52, pp. 593], [53, pp. 150]. The idea of the algorithm is to expand the current belief to all possible belief states up to some maximum depth D and the rewards are passed back to the beginning. At each step, given the current belief b, consider all possible actions $a \in A$. For each action, consider all possible observations $o \in O$. The probability of observing o given b and a is

$$P(o|b,a) = \sum_{s'} P(o|s',a) \sum_{s} P(s'|s,a)b(s). \quad (2)$$

For a given o and a, the new belief b' is

$$b'(s') = \alpha P(o|s',a) \sum_{s} P(s'|s,a)b(s), \quad (3)$$

where α is a normalization constant that makes the belief state sum to 1. The process repeats until reaching a terminal state or the maximum depth and the reward value of that state is passed back (Algorithm 1). The runtime of this algorithm is $O(|A|^D|O|^D)$. This algorithm work for this problem because the hurricane domain is relatively small with about five to seven time steps (days before the hurricane hits). For a larger domain, an approximate algorithm could be considered [54].

Algorithm 1 Forward Search

```
function QVALUE(b,a)
    if b is a terminal state or reach max depth then
        return R(b,a)
    Q ← 0
    for o ∈ O do
        Calculate P(o|b,a) using Equation 2
        Calculate b′ using Equation 3
        Q ← Q+P(o|b,a)(R(b,a)+max_a′ QVALUE(b′,a′))
    return Q
end function
```

3.3 Predictions of Key Assumptions of the Model

In this work, as a first step, we consider two sets of predictions or hypotheses that derive from the key model's assumptions, appraisal calculation and emotion-focused coping, in the context of hurricane evacuation decisions.

Hypothesis 1: State's Features and Reward Function (H1): The subjective beliefs about the hurricane's impacts on goals and concerns (appraisal dimensions) are significantly associated with the evacuation decision. Specifically:

Hypothesis 1.1 (H1.1): Perceived safety and estimated evacuation cost (traveling and lodging cost) are significantly negatively associated with the evacuation decision.

Hypothesis 1.2 (H1.2): Perceived flood depth and outage duration are significantly positively associated with the evacuation decision.

Hypothesis 1.3 (H1.3): These subjective beliefs predict the evacuation decision better than the standard demographic variables.

The first set of hypotheses comes from the model assumption regarding appraisal as a subjective evaluation, particularly of the set state features relevant to one's goals in the hurricane situation: perceived safety, flooding condition, outage, and evacuation cost. From the model, the core appraisal calculation for goal relevance and goal congruence is captured in the reward function. So, these features influence rewards and, consequently, decisions. Therefore, the reward weight w of these features is expected to be nonzero and influences the evacuation decision differently. This yields the first two hypotheses.

H1.1 and H1.2 describe the expected nature of these features, separating them based on the direction. Specifically, for H1.1, the higher the perceived safety, the less likely for people to evacuate. Similarly, the higher the evacuation cost (traveling and lodging costs), the less likely people will evacuate. On the other hand, for H1.2, the higher the flood depth or the outage duration, the more likely people will evacuate.

For H1.3, from the perspective of the model, there is no direct relationship between most standard demographic features (age, gender, education, etc.) and evacuation decisions because these features do not directly correspond to any relevant goals or concerns. Note that demographic features could still be indirectly related to people's goals during hurricane events, but existing evidence has shown that the relationships between many demographic features and evacuation decisions are weak. Therefore, we expect the proposed features in the model to predict evacuation decisions better.

Hypothesis 2: Coping (H2): People use emotion-focused coping to cope with the hurricane by altering their beliefs and goals to align with their decisions.

Hypothesis 2.1 (H2.1): Given the same hurricane information, people who decide to stay (stay group) come to

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believe after the decision that the impact of a hurricane (category of hurricane, flooding, power outage) to be less severe than those that decide to evacuate (evac group). In other words, people who stayed come to believe that the hurricane would be of a lower category; it would cause less flooding and shorter outages than people who evacuated.

Hypothesis 2.2 (H2.2): Given the same hurricane information, the stay group decreases the importance of safety, flooding, and outage more than the evac group. On the other hand, the stay group increases the importance of avoiding evacuation costs more than the evac group. Let $D(g_{t_i}, g_{t_j})^a = g^a_{t_j} - g^a_{t_i}$ be the difference of a group of people who choose action a between the importance of goal g at time t_i and the importance of goal g at time t_j, where $i < j$. H2.2 can be restated as follow: given the same hurricane information, $D(g_{t_i}, g_{t_j})^{stay}$ is less than the $D(gt_i g_{t_j})^{evac}$ for $g =$ safety, flooding, and outage, but greater than for $g =$ avoiding evacuation costs.

For the second set of hypotheses, we investigate the predictions on emotion-focused coping, specifically in relation to problem-focused coping. In the hurricane context, people can choose to use problem-focused coping (evacuate) and/or emotion-focused coping (changing their beliefs and goals). If they decide to stay, they are left with emotion-focusing coping. If they decide to evacuate, they have dealt with the situation and may not use emotion-focused coping anymore. The model predicts that people will choose the coping action that yields the highest positive utility given their evacuation decision after taking into account the cost of coping. In other words, the stay group will use emotion-focused coping, changing beliefs or goals, if it makes the current decision (stay) seem better relative to other decisions (evacuate).

Formally, let b be the initial belief state of the hurricane's impacts, b' be the belief state that the hurricane's impacts are more severe (worse), and b'' be the belief state that hurricane's impacts are less severe (better). In other words, $Q(b', \texttt{stay}) < Q(b, \texttt{stay}) < Q(b'', \texttt{stay})$ because staying when the hurricane is less severe is better than when it is more severe. Consider the last time step before the hurricane hit and the decision to stay, Q-value for emotion-focused coping actions a_{em} and a belief state b can be expressed as:

$$Q(b, a_{em}) = Q(b_{new}, \texttt{stay}) + \mathit{cost}(b, b_{new}).$$

We have a Q-value of no change,

$$\begin{aligned} Q(b, a_{em} = \texttt{no change}) &= Q(b, \texttt{stay}) - \mathit{cost}(b, b) \\ &= Q(b, \texttt{stay}), \end{aligned}$$

and a Q-value of changing to a more severe belief,

$$Q(b, a_{em} = \texttt{more severe}) = Q(b', \mathit{stay}) - \mathit{cost}(b, b').$$

Therefore, $Q(b, \texttt{more severe}) > Q(b, \texttt{no change})$ if and only if $Q(b', \texttt{stay}) - Q(b, \texttt{stay}) > \mathit{cost}(b, b')$. In other words, people would cope by changing their belief if the new belief is better than the old one by more than the cost of changing it. The same logic can be applied to the case of changing goals (reward weights) and the case of the evacuate action. In general, we assume that the cost is low enough because the hurricane predictions are uncertain.

As a result, the model predicts that people who stay would cope by shifting their beliefs about the hurricane's impact to be less severe because this would make the stay action feel better. As a specific example, people who stay may choose to believe that the flood depth would be shallower or the outage duration would be shorter than originally perceived. Therefore, we would expect people who stay to report their post-decision beliefs about hurricane's impacts to be less severe than people who evacuate, as stated in H2.1.

Similarly, in the case of goals, people who stay would cope by reducing the importance of their goals (reward weight) on the hurricane's impact. For example, people who stay may think that experiencing flooding is not as bad as initially thought. On the other hand, people who stay would increase the importance of the goal to avoid evacuation costs as this would make the evacuation action worse and, in turn, make the stay action feel better. As a result, when looking at the goals between two time points, the model predicts that there are differences in the difference of goals before and after the decisions between people who stay and who evacuate, as stated in H2.2.

4 Study 1: Hurricane Questionnaire

In Study 1, we evaluate the first hypotheses about the state's features and reward function, using questionnaires collected from real hurricanes.

4.1 Method

To test the first set of hypotheses, we designed a new questionnaire to measure people's subjective beliefs about the impacts of hurricanes (safety, flood depth, and outage) and their estimation of evacuation expenses (traveling and lodging costs). Examples of these questions are: "How high (in feet) did you expect your house to be flooded?", "How long did you expect for your area to lose electricity after the hurricane hit?", "What do you expect it would cost, in dollars, to travel to a safer place?", and "How likely is it that the hurricane would pose a serious threat to your safety if you stay in your home during the hurricane?"

These questions are derived from the model. First, they aim to measure people's subjective beliefs prior to their decision to evacuate or stay. The questions target the beliefs used to make the decision and ask both people who decided to stay and those who evacuated. Second, these questions attempt to measure their beliefs on the severity of a hurricane's impacts, such as the depth of flooding and the duration of outages, and not just the likelihood that flooding or outages would occur. These two aspects separate this questionnaire from existing ones, where they mainly ask about the likelihood of hurricane's impacts, and some of them only ask either people who evacuated or people who stayed [31], [32], [33].

The questionnaire also includes standard questions used for data analysis and comparison, including demographic information, previous experience, official notice, social influence, and evacuation decisions.

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4.2 Data Collection

To collect the data, we used the Amazon Mechanical Turk (MTurk) service to send out questionnaires to participants in the states affected by the hurricane. We collected data from two recent hurricanes in 2018: Florence and Michael. Hurricane Florence made landfall on September 14, affecting South Carolina (SC) and North Carolina (NC) [55]. We sent out questionnaires on September 21 and stopped collecting on September 29, obtaining 747 responses from SC and NC. The average completion time is 11.15 minutes, and we paid participants $1.00. Hurricane Michael started forming on October 7, became a hurricane on October 8, and made landfall on October 10, affecting Florida (FL) and Georgia (GA) [56]. We sent out questionnaires on October 18 and stopped collecting on October 22, obtaining 700 responses from FL and GA. The average completion time is 10.8 minutes, and we paid participants $1.25.

4.3 Data Analysis

Based on their self-reported zip code, we excluded participants not from SC and NC for Florence and FL and GA for Michael. In addition, we excluded those who answered any money-related question above three standard derivations from the mean. These criteria excluded unreasonable answers, such as answering the traveling cost question with fifty thousand dollars. Lastly, we excluded participants who finished the questionnaire in under three minutes or over one hour. The mean completion time of all questionnaires is around 11.5 minutes. After all the exclusions, we were left with 684 responses for Hurricane Florence and 542 responses for Hurricane Michael.

To estimate the coefficient of proposed features, we used Bayesian Logistic Regression. As mentioned before, log transform was applied to traveling and lodging costs. We also adjusted for potential confounding factors that could influence both beliefs and decisions, including previous experience, official evacuation notices, income, and distance to a coastline. For example, previous experiences can change people's beliefs about hurricane information and its impact. In the case of the official notice, people who receive it may perceive the hurricane's impact to be much more severe. The data analysis for this and subsequent studies was done using the brms library [57].

For H1.3, to compare the predictive performance of proposed features and standard demographic features, we contrasted logistic regressions fitted with different sets of features to predict evacuation decisions. Beyond testing these hypotheses, the estimated parameters from logistic regression can be used to initialize and constraint the model's parameters, the reward weights, in the simulation [6] The data analysis is done using the brms library [57].[3] Below is the list of the models in this section.

- **Coefficient Models** consist of a specific belief adjusting for the confounders for H1.1 and H2.2.
- **Demographic Model** (Demo) consists of only demographic variables including age, education, income, house structure, distance to coast, number of vehicle, has pet, and family size.
- **Demographic and Others** (Demo+) consists of demographic variables plus previous experience, and evacuation notices.
- **Belief Model** (Belief) consists of all five belief variables: safety, flood depth, and outage, traveling cost, and lodging cost.
- **Belief and Other Model** (Belief+) is a hierarchical version of the Belief Model where the main effects are the belief features and the group features are the other features including previous experience, evacuation notices, and selected demographic features: age, income, number of vehicle, and distance to coast.

3. The data analysis and studies' materials for this and subsequent studies can be found https://github.com/yongsa-nut/HurricaneStudies.

4.4 Results

TABLE 1
Coefficients of the proposed features from Hurricane Florence and Hurricane Michael data. Est. = estimate. SE = standard error.

Features	Florence			Michael		
	Est.	SE	95% CI	Est.	SE	95% CI
Safaty	-5.25	.91	[-7.0,-3.7]	-4.72	.81	[-6.4, -3.2]
Flood	0.43	.14	[0.2,0.7]	0.47	.13	[0.2, 0.7]
Outage	0.10	.04	[0.0, 0.2]	0.13	.03	[0.1, 0.2]
Lodging	-0.97	.12	[-1.2, -0.8]	-0.96	.12	[-1.2, -0.7]
Travel	-0.80	.16	[-1.1,-0.5]	-0.54	.14	[-0.8, -0.3]

Table 1 shows the coefficients of the proposed features for the two hurricane data sets. For both hurricanes, the coefficients of safety probability, lodging, and traveling cost are negative, and their 95% credible intervals do not include zero (significant at 0.05 level). On the other hand, the coefficients of flood depth and outage are positive, and their 95% credible intervals do not include zero. Therefore, safety, lodging cost, and traveling cost are significantly positively associated with evacuation decisions, while flooding and outage are significantly negatively associated with evacuation decisions. Additionally, the coefficients are quite similar between the two hurricanes, further demonstrating the robustness of these features. These results support both H1.1 and H1.2.

TABLE 2
Cross-Validation Predictive Performance. The accuracy (Acc) and F1-score (F1) for each different set of features for both datasets based on leave one out cross validation (LOOCV).

Feature sets	Florence		Michael	
	Acc (%)	F1	Acc (%)	F1
Intercept	84.80	.00	80.84	.00
Demo	86.26	.44	80.66	.26
Demo+	90.79	.67	88.69	.68
Belief	*91.67*	*.68*	*91.06*	*.75*
Belief+	**95.03**	**.83**	**93.61**	**.83**

Table 2 shows the accuracy and F1 score of different sets of features within each dataset calculated from Leave One Out Cross-Validation (LOOCV). The intercept model is equivalent to predicting the majority, which is "stay"

TABLE 3
Across-data predictive performance. The predictive performance of the different models when trained on one hurricane dataset to predict the other hurricane.

Model	post-Florence		post-Michael	
	Acc (%)	F-score	Acc (%)	F-score
Train on post-Florence Data				
Demo			74.45	.34
Demo+			85.77	.61
Belief			*89.78*	*.66*
Belief+			**93.43**	**.82**
Train on post-Michael Data				
Demo	86.26	.24		
Demo+	89.47	.64		
Belief	*89.62*	*.69*		
Belief+	**94.88**	**.84**		

for both datasets. The results show that the Belief feature set achieves up to 91.52% accuracy and 0.68 F1-score for Hurricane Florence and 91.06% accuracy and 0.75 F-score for Hurricane Michael outperforming the Demo and Demo+ feature sets for both datasets. Finally, the Belief+ achieves the best results, up to 95.18% and 93.25% accuracy for Hurricane Florence and Hurricane Michael, respectively.

Further, Table 3 shows the predictive results when training on one hurricane to predict another hurricane. The results show that the Belief feature set performs better than the Demo and Demo+ feature sets in all cases. As in the cross-validation case, the Belief+ feature set achieves the best performance. In summary, The results support H1.3.

5 Study 2: Hurricane Experiment

To test the second set of hypotheses on coping, we conducted a controlled human subject experiment that placed subjects in simulated hurricane experiences. Participants experienced a sequence of evolving hurricane announcements modeled after real-world hurricane announcements, followed by a set of questions asking about their decision and beliefs. The controlled experiment ensured that participants received the same information, which could also be experimentally manipulated across conditions. With regard to the validity of the results from hypothetical hurricane experiences, as we noted above, the recent meta-analysis on hurricane behavior by Huang et al. [30] found that the results from hypothetical hurricane studies are similar to the results from actual hurricanes. Importantly, the messages are adapted from the actual messages by National Hurricane Center (NHC), and we recruited participants from FL who are familiar with hurricanes as well as hurricane messages from NHC.

5.1 Method

The objective of this study is to observe, measure, and compare how different people change their beliefs and goals during the hurricane situation. The flow of the experiment is as follows:

1) Subjects answer a pre-survey.
2) Subjects read the experiment instruction and check the audio.
3) The experiment begins:
   - There are a total of 5 hurricane messages starting from 5 days before the hurricane hits to 1 days before the hurricane hits.
   - At each time step (day), subjects read and listen to the hurricane messages
   - Then, subjects have to decide whether to evacuate or stay.
   - If subjects decide to evacuate, they cannot change their decisions in the future time steps but they still see and listen to the messages and have to answer all the questions.
   - Afterward, subjects answer questions about beliefs on the hurricane. Subjects also answer questions about their goals on 5 days before, 3 days before, and after the hurricane hit.
   - Once they finish answering all the questions, they move on to the next time step (day).
   - After the five messages, subjects are presented with the hurricane's outcomes and answer the post questions.

Figure 2 shows the interface of the experiment and Figure 3 shows the overall flow of this experiment.

In short, the experiment is designed to simulate a realistic hurricane experience through a sequence of hurricane messages. For each decision point, the subjects receive hurricane information and then decide what to do. Afterward, they answer questions about their beliefs and their goals. There are five time steps or five days before the hurricane hits. Therefore, there are five decision points in total. We choose five time steps to keep the experiment reasonably short while providing enough time for the hurricane to develop and approach a region.

There are two hurricane conditions: a) a hurricane going from a category 3 to category 4 at two days before it finally hits (tropical storm $\rightarrow 3 \rightarrow 3 \rightarrow 4 \rightarrow 4$), and b) a hurricane going from a category 3 to a category 2 instead (tropical storm $\rightarrow 3 \rightarrow 3 \rightarrow 2 \rightarrow 2$). We call the first condition category 4 and the second condition category 2. These two hurricanes are interesting cases that are in contrast to each other, where the category 4 condition goes from moderate to extreme while the category 2 condition goes from moderate to mild. The experiment is a between-subjects design where participants only experience one of the two hurricanes.

Importantly, a hypothetical hurricane situation has to be impactful and realistic so that there is a reason to cope. In other words, from the model perspective, the cost of coping has to be lower than its benefit. In addition, a realistic hypothetical hurricane would ideally allow the results to generalize to the real hurricanes. Nonetheless, this is still a hypothetical experiment and participants never receive any harm. In the following subsections, we describe the key elements in the experiment to achieve this objective.

5.1.1 *Message Design*

The hurricane messages in the experiment are adapted from the key messages and hurricane information from NHC [51], [58]. The experiment's messages also state that the information comes from NHC. The main reason is that NHC information is perceived to be highly accurate and

Fig. 2. The flow of the hurricane experiment. Each day (time step), subjects see new information about the hurricane. Then, they are asked whether they want to evacuate or stay. Afterward, they move to the next page, showing questions about their beliefs on the hurricane, including category, flood depth, and outage duration. They are also asked about the importance of four different goals (physical safety, avoiding flooding, avoiding outage, and avoiding spending money on evacuation) on the five days before the hurricane, three days before the hurricane, and after the hurricane hit.

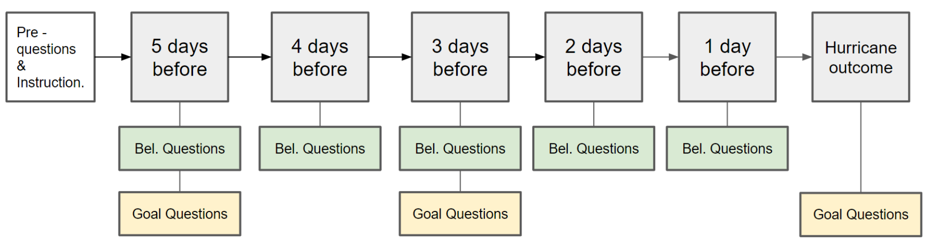

Fig. 3. A timeline of the hurricane experiment. There are five days before the hurricane. Therefore, there are five decision points. Subjects first see the hurricane information and make their decisions. Then, subjects answer questions about their beliefs on the hurricane's impact. Subjects are asked about their goals five days before, three days before, and after the hurricane hit.

people are familiar with it. The experiment's messages start with the predicted category of the hurricane when it hits the target area. They also include the following additional information: expected flooding, wind conditions, and outages. This information corresponds to the beliefs about the hurricane's impact that are measured in this experiment. Finally, evacuation cost, specifically hotel price per night, is also presented with the hurricane information. These evacuation costs ensure that all subjects share the same evacuation cost while also providing the additional cost of late evacuation.

5.1.2 Additional Elements to Increase Realness

Aside from the messages, three additional elements are implemented to improve the realness of the experiment and increase subjects' attention toward the task. First, the city that the hurricane is predicted to hit is chosen based on the subject's zip code. For instance, if the zip code is 33101 (Miami), the message would say, "the storm is forecasted to strengthen and could be hurricane strength when it reaches Miami in 5 days." Second, each hurricane message also includes audio that reads the message out loud. Google text-to-speech is used to generate the audio from the messages [4]. Subjects must listen to the entire message, excluding the evacuation cost, before they make their decision. The audio is also to ensure that the subjects do not skip any information.

Lastly, each message also includes a satellite image of the hurricane moving from the Atlantic Ocean toward the east side of Florida. These images are Hurricane Dorian's satellite images from NHC [5]. The satellite images are used to improve the realness of the information. While it provides a visualization of the hurricane, it conveys little about the

4. https://cloud.google.com/text-to-speech
5. https://www.facebook.com/NWSNHC/photos/

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potential impact of the hurricane, so it would not interfere with the messages. This is in contrast to hurricane cone images commonly seen with hurricane messages because they show a possible track of the hurricane and could interfere with the messages.

5.1.3 Measurement: How and When

There are two main things to measure: beliefs and goals. Importantly, we measure them multiple times throughout the experiment to assess how they change. Here we discuss the rationale behind them.

Measuring belief: As described earlier, we only measure the beliefs after the decision, in other words, the post-decision beliefs. Ideally, to estimate the change of beliefs, we need to compare the subject's beliefs from the moment before and after they make the decision. However, subjects are unlikely to answer both questions differently due to the proximity between the placement of the two questions. To work around that, all subjects in the same condition observe the same information and we assume in this experiment that, *on average*, they would have similar beliefs prior to their decisions and any difference in post-decision beliefs could be attributed to the decision (We address this assumption more directly in Study 3). This is the main reason that a controlled experiment is used rather than a real hurricane. After they observe the information, they are asked to make a decision and then asked about their beliefs. These post-decision beliefs are used for comparison. There are three beliefs in the hurricane's messages being measured: the expected category of the hurricane (tropical storm to category 5), flood depth (inch), and outage duration (days).

Measuring goals: Because the hurricane messages do not include any statement about the importance of goals, we assume that, under the model, the goals should remain the same over time and would only change due to emotion-focused coping. As a result, we compare the importance of a goal between two time points. In particular, subjects are asked at three different times: five days before the hurricane (pre), three days before the hurricane (mid), and after the hurricane has hit (post). We measure four goals—safety, flood, outage, and evacuation cost—from 0 to 100, where 100 is the highest importance.

Other measurements: Finally, there is a brief questionnaire at the beginning of the experiment asking standard demographic questions, previous hurricane experience, and expected hurricane impact. In addition, the experiment also includes two attention check questions.

5.2 Data Collection

We recruited participants from FL via MTurk, obtaining 119 responses for the first condition and 126 responses for the second condition. The average completion time is 15.65 minutes and we paid participants $2.25. We only recruited from FL because FL residents are familiar with hurricanes and images in the experiment show the hypothetical hurricane that hits FL. After eliminating subjects who are not from FL or do not answer attention checks correctly, 84 responses remain for the first condition and 97 for the second condition. Figure 4 shows the distribution of evacuation at different times for the first and second conditions. Notice that the evacuation portions between the two conditions are quite different at two days before the hurricane which is when the hurricane turns from a category 3 to 4 for the first condition and from 3 to 2 for the second condition. This establishes that the manipulation (hurricane information) works. This experiment and the next one were approved by Northeastern University Institutional Review Boards.

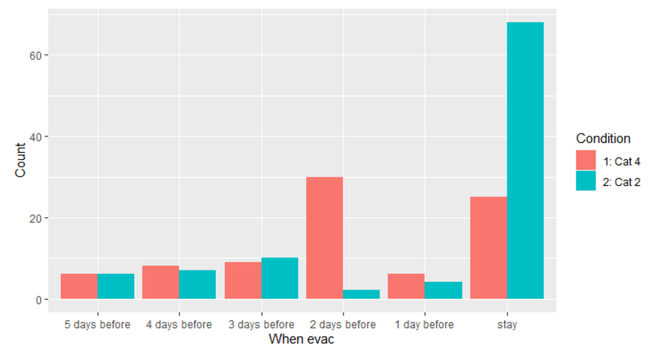

Fig. 4. The distribution of evacuation in the experiment across time.

5.3 Data Analysis

For the data analysis, we used Bayesian Robust ANOVA, where the Gaussian distribution is replaced with the student distribution [59], [60]. Additionally, we did not assume equal variance between the two groups. The prior for coefficients were set to a weakly informative prior of Normal(0,5) for beliefs and Normal(0,10) for goals. These two priors imply relatively little about the magnitude of the coefficients while still constraining them into a reasonable range.

Importantly, for the difference of goals, we also adjusted for the initial (pre) value of the importance of the goal. This allows us to determine the effect of decision on post importance. (We do not have the pre-decision beliefs as discussed above and we address this in the next experiment.) Additionally, we adjusted for the following confounders that could influence both beliefs or goals and decisions: distance to coast, income, FL area, previous experience, and hurricane condition. To elaborate, distance to coast could influence what people believe about flooding and safety. Income could influence how people perceive the importance of money. Previous experiences could influence what people believe about the hurricane's impacts and how important those impacts are. Similarly, the hurricane condition could influence people's beliefs on the hurricane's impacts as well as their evacuation decisions.

5.4 Results

Table 4 shows the estimated mean difference of each belief for each time step, from four days to one day before the storm, between stay and evac groups. The evac group at each time step consists of subjects that decided to evacuate by that time and the stay group consists of those who did not. The negative value indicates that the stay group perceives the beliefs about the hurricane impact to be less than the evacuation group. For example, consider the belief about flooding four days before the storm. The mean of the

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TABLE 4
The estimated mean difference between stay and evac group for each belief at different times (stay - evac).

Belief	Est.	SE	90% CI	Prob
Four days before the storm				
Category	-0.40	0.17	[-0.68, -0.11]	0.99
Flood	-4.06	0.81	[-5.37, -2.72]	0.99
Outage	-4.20	1.66	[-7.13, 1.70]	0.99
Three days before the storm				
Category	-0.24	0.14	[-0.47, -0.01]	0.96
Flood	-2.04	0.66	[-3.13, -0.96]	0.99
Outage	-3.06	1.19	[-5.12, -1.23]	0.99
Two days before the storm				
Category	-0.34	0.13	[-0.54, -0.13]	0.99
Flood	-2.13	0.69	[-3.27, -1.01]	0.99
Outage	-2.04	0.90	[-3.57, -0.60]	0.99
One day before the storm				
Category	-0.14	0.13	[-0.35, 0.08]	0.85
Flood	-1.15	0.54	[-2.05, -0.26]	0.98
Outage	-2.89	0.95	[-4.52, -1.43]	0.99

stay group's belief on flooding is around 4 inches less than the mean of the evacuation group's belief. For the belief on outage duration two days before the storm, on average, the stay group believed that it would be two days shorter than the evac group.

Table 4 also shows 90% intervals for a one-tailed t-test as well as probabilities that people who stay rate their beliefs about hurricane impacts less than people who evacuate (H2.1) would be true given the data. Overall, given the same information, people who stay believed the hurricane impacts (category, flood depth, and outage duration) to be less than people who evacuate as all the differences are negative. Only the expected category one day before the storm has a probability below 0.95 (not significant at 0.05 level). However, even with the same information, people could perceive the information differently which could result in different decision and these observed differences could be due to only the influence of prior-decision beliefs. We expand on this issue and address it in Study 3. In summary, the results only partially support H2.1.

TABLE 5
The estimated mean differences between stay and evac group in the importance rating of four goals for three time periods: pre vs post, pre vs mid, and mid vs post.

Goal	Est.	SE	90% CI	Prob
Pre vs Post				
Safety	-0.64	1.28	[-2.83, 1.38]	0.69
Flood	-3.51	2.19	[-7.11, 0.08]	0.95
Outage	-5.61	2.72	[-10.08, -1.10]	0.98
Evac Cost	5.42	3.53	[-0.14, 11.42]	0.95
Pre vs Mid				
Safety	-0.19	0.58	[-1.16, 0.75]	0.63
Flood	-2.87	1.76	[-5.87, -0.11]	0.96
Outage	-1.42	2.52	[-5.64, 2.56]	0.71
Evac cost	7.10	3.86	[0.96, 13.55]	0.97
Mid vs Post				
Safety	-0.23	0.55	[-1.19, 0.60]	0.66
Flood	-2.36	1.56	[-4.94, 0.16]	0.94
Outage	-4.03	2.40	[-7.96, -0.11]	0.95
Evac cost	6.35	2.68	[2.15, 10.91]	0.99

Table 5 shows the estimated mean difference in the differences of four importance ratings adjusted for the pre value between evac and stay groups. Similar to the belief results, the evac group consists of subjects who decided to evacuate by that time point (3 days before the storm for the mid point and 1 day before the storm for the post point) and those who did not evacuate are counted as the stay group. The table shows three time periods: pre vs. post, pre vs. mid, and mid vs. post. Similar to Table 4, the negative value indicates that the stay group's difference is less than the evac group's difference. In other words, the negative value indicates that people who stay decrease the importance of the goal more than people who evacuate. We see that the estimated mean differences are negative for safety, flood, and outage, while the evacuation cost is positive. However, the probabilities of the outage case at the pre vs. mid and the safety case for all three time periods are far below 0.95. One explanation for the safety case is that most participants always rate the importance of safety to be the maximum value (100) or near it, resulting in not much difference (the ceiling effect). Another explanation is that people are very certain of how important safety is, resulting in a high cost of changing it. Overall, the results support H2.2.

6 Study 3: Hurricane One-shot Experiment

Study 2's results show support for H2, suggesting that there are differences in beliefs and preferences between the stay and the evac groups. However, there is an important alternative explanation that the previous study did not rule out. The pre-decision beliefs could have influenced the decisions, as shown from Study 1's results, and there could be no change between pre-and post-decision beliefs. In an attempt to address this issue in Study 2, we show participants with the same information so, on average, people should have the same pre-decision beliefs. However, because the information is uncertain and the process of belief formulation could be noisy, this could lead to some participants believing hurricanes' severity to be higher than others, and they are more likely to evacuate. As a result, we could observe the difference in post-decision beliefs purely from the influence of pre-decision beliefs on the decisions. In the case of goals, we assume that the messages do not change them since they never mention the goals, so we have both pre-and post-decision importance of goals to test the hypothesis. Therefore, we only focus on the change of beliefs in this study.

6.1 Experiment Design

The main objective of this study is to estimate the influence of decisions on beliefs by comparing pre-and post-decision beliefs. The key issue is that we cannot just present the information once and then ask about their beliefs, decisions, and beliefs again immediately after. The reason is that in a hypothetical setup where decisions are never carried out, people are unlikely to consider the same question at a close time point differently.

To work around this issue, we instead present a sequence of two near-identical information (pre and post) based on the hurricane message three days before the hurricane in Study 2. The only differences between the two messages are the time of the messages (6 AM and 3 PM) and a sentence

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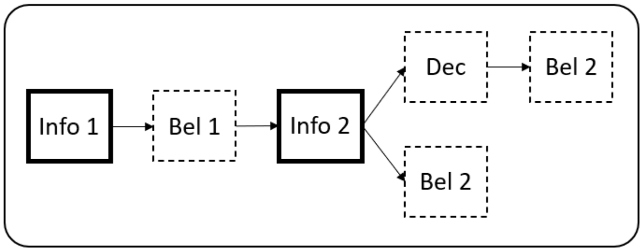

Fig. 5. The flow of Study 3. There are two conditions: decision (top) or no-decision condition (bottom). The bold squares are the information and the dashed squares are the questions (Bel = belief questions and Dec = decision question).

reminding that the strength of the hurricane still remains largely uncertain. Thus, the two messages are practically the same. After each message, participants are asked about their beliefs on the hurricane impacts along four dimensions: the probability of life-threatening events (probability in percentage), flood depth (inch), outage duration (day), and wind speed (mile per hour).

This study has two conditions: the decision and the no-decision condition. Specifically, participants in the decision condition are asked about their evacuation decision after the second message and before the belief questions, while participants in the no-decision condition are not asked about it. Figure 5 shows the flow of Study 3 and the two conditions. To ensure that participants in the no-decision condition do not form any intention whether to evacuate or not, the study is framed as a study on hurricane information and never mentions making any evacuation decisions. For the decision condition, to make the decision more salient, we frame the decision question and the choices to be clearly situated as follows: the question is "Now imagine that, on September 28 that year, you happen to be in Palm Bay, a city on the east coast of Florida. What would you do?" and the choices are "Evacuate to a hotel up north paying at least $150 per night." and "Stay in your place, a single-detached house, and ride out the storm."

With this new study, we can then directly compare the post-decision beliefs adjusted for the pre-decision beliefs among the three groups: the stay, evac, and no-decision groups. The prediction for Study 3 is as follows. First, we expect a little to no change in beliefs for the no-decision group as the two messages are practically the same. Second, same as study 2, we expect the post beliefs of the stay group to be lower than the evac group. Third, we expect the stay group's beliefs to be lower than the no-decision group. The reason is the same as the previous prediction. The stay group copes by changing their beliefs about the hurricane to be less severe. In contrast, the no-decision group's beliefs remain largely the same between the two time points as they merely evaluate the same information. In the case of evac vs. no-decision, according to the model, the evac group copes with this situation by using problem-focused coping, which is to evacuate. Therefore, if they decide to evacuate, they have already dealt with the situation. They may still feel the need to use some degree of emotion-focused coping to further reduce the perception of the threat or alternatively by evacuating the perception of the risk is reduced. This may

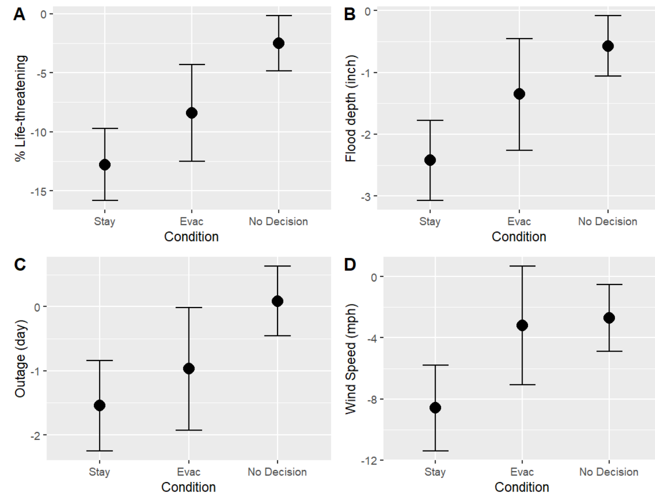

Fig. 6. The estimated mean difference between pre-and post-decision beliefs of each group conditioned on their average pre-decision belief. The dot indicates the mean and the error bar is 95% CI. From left to right, probability of a life-threatening event in percentage (A), flood depth in inch (B), outage duration in day (C), and wind speed in mph (D).

result in no change or a small change that differs from the no-decision group. Accordingly, the relationship between evac and no-decision group is an exploratory question.

6.2 Data Collection and Data Analysis

We recruited 200 participants, 100 in each condition, who currently live in FL via Prolific. The average completion time is about 4 minutes, and we paid participants $0.7. We exclude participants based on two conditions. First, we exclude participants that finish too fast. Specifically, we exclude those that finished reading the first message and answering the four belief questions in under 30 seconds and finished reading the second message and answering questions in under 15 seconds, where the average time is 78.5 and 50.6 seconds, and the first quartile is 47.1 and 22.3 seconds, respectively. Second, we exclude participants that answer the post-decision beliefs much differently from the pre-decision beliefs. Specifically, the difference between the two beliefs is greater or less than three standard derivations away from the mean. After the exclusion, this left us with 166 participants (52 stay, 27 evac, 87 no-decision).

To analyze the data, we fit Bayesian linear regression, where the post-decision belief is the outcome, and the decision group is a predictor while adjusting for the pre-decision belief. We use weakly informative prior of Normal(0,10) for life-threatening and wind speed and Normal(0,5) for flood depth and outage duration as we do not expect to be very large for all four beliefs.

6.3 Results

Figure 6 shows the estimated mean differences between pre- and post-decision beliefs adjusted for pre-decision beliefs for all groups and beliefs. We see that, for the no-decision group, there is no change for the outage, and there are small negative changes for the other three beliefs, especially when compared to the other two groups. Table 6 shows the difference between all pairs for all post-decision beliefs

TABLE 6
The estimated mean differences between stay and no-decision group, stay and evac group, and evac and no-decision group across all four beliefs.

Belief	Est.	SE.	90% CI	Prob.
Stay - No-decsion				
Life-threatening	-10.30	1.96	[-13.53,-7.07]	0.99
Flood	-1.84	0.41	[-2.51,-1.16]	0.99
Outage	-1.63	0.46	[-2.40,-0.87]	0.99
Wind	-5.86	1.86	[-8.92, - 2.88]	0.99
Stay - Evac				
Life-threatening	-4.37	2.66	[-8.76,-0.01]	0.95
Flood	-1.05	0.56	[-1.95,-0.13]	0.97
Outage	-0.57	0.61	[-1.58,0.42]	0.82
Wind	-5.36	2.46	[-9.41, -1.33]	0.99
Evac - No-decision				
Life-threatening	-5.93	2.42	[-9.91,-1.95]	0.99
Flood	-0.79	0.52	[-1.67, 0.04]	0.94
Outage	-1.05	0.57	[-1.99, -0.12]	0.97
Wind	-0.49	2.29	[-4.25, 3.26]	0.59

adjusted for pre-decision beliefs. Note that this is the same as the difference in the difference between pre-and post-decision beliefs as shown in Figure 6. First, the results show that all four stay group's beliefs are less than the no-decision group's beliefs with a probability greater than 0.95. Similarly, all stay group's beliefs are less than the evac group's beliefs with a probability greater than 0.95 except wind speed with a probability of 0.8. Lastly, the evac group's beliefs are less than the no-decision group's beliefs except for wind speed, where both groups' belief is about the same. In summary, the results support the predictions for the stay vs. evac and stay vs. no-decision cases for all four beliefs.

7 Discussion

In this work, we propose a computational model of coping building upon Lazarus's appraisal theory. We cast coping as a decision problem where appraisal calculation is used to evaluate the outcomes of different coping strategies. We evaluate the predictions from two key model's assumptions, appraisal calculation and emotion-focused coping, through a series of studies using questionnaires and controlled experiments.

The results from two hurricane surveys, Hurricane Florence and Hurricane Michael, supported hypotheses H1, H1.1, H1.2, and H1.3. The data shows that the subjective beliefs about the hurricane's impacts on goals and concerns are significantly associated with evacuation decisions and in the expected direction. Moreover, they can be used to predict evacuation decisions better than standard demographic information. Compared to existing literature [30], we found a stronger association for traveling cost, lodging, flooding, and outage. For traveling and lodging costs, this may be due to the log transform. For flooding and outage, this may be due to how we measure these features. In particular, because the model is driven by appraisal theory, we measured the severity of the situation, unlike many existing works that only ask the likelihood of events [33], [61].

The results from studies 2 and 3, the controlled hypothetical hurricane experiments, supported hypotheses H2, H2.1, and H2.2. Specifically, study 2 shows that, given the same hurricane information, people who decided to stay reported beliefs about hurricane impacts that were significantly better than people who evacuated. This result holds across different impacts, safety, flooding, and outages and across different time periods. Similarly, given the same hurricane information, people who stayed decreased the importance of flooding and outage more than those who evacuated. On the other hand, people who stayed decreased the importance of avoiding evacuation cost more than those who evacuated.

The results from study 3 further clarify the impact of decisions on beliefs by ruling out that the observed differences are due to the influence of pre-decision beliefs on decisions. Unlike study 2, study 3 measures both pre-and post-decisions beliefs of practically identical information, and we compare the post-decision beliefs between each group adjusted by their pre-decision belief. The results show that the post-decision beliefs of people who decided to stay are less than those who decided to evacuate and those who only evaluated information without making a decision. This suggests that the people who decided to stay cope by altering their beliefs that the hurricane would become less severe. The results for the evac group show that three out of four post-decision beliefs are less than people who did not make any decision, while one belief, wind speed, roughly is the same between those groups. The possible explanation is that while evacuation is a problem-focused coping to the situation, people may still feel the need to use some degree of emotion-focused coping to further reduce the perception of the threat. Critically, the evac group's beliefs are still greater than the stay group's, demonstrating the influence of emotion-focused coping on beliefs.

Altogether, the results support the assumption on emotion-focused coping, specifically how such coping, such as wishful thinking, alters beliefs and goals to increase the utilities of the prior decision. If the aim is to predict and model people accurately, it is necessary to take into account how people cope with the situation beyond interacting with the situation directly through external actions (problem-focused coping). These emotion-focused coping effects are in contrast to a standard decision-theoretic framework where probability and utility are assumed to be independent. It is also different from standard reinforcement learning agents, where the designers fix the reward function and the agent cannot change it [62].

An important application of this model is to serve as a decision function for an agent. Specifically, the model is designed to simulate an individual human decision-maker, taking into account how people cope with stressful situations. This work is part of a larger project to model and improve a community's response pre and post a natural disaster. The model presented here will simulate multiple agents (people) within a simulation that also models the disaster's impact on a community's infrastructure, its buildings, communication lines, utilities, and emergency services.

The results of this work could also be applied to other similar disasters such as wildfire and flooding, where the time between onset and impact is long enough for people to observe multiple information and make their decisions, but not short-notice disasters such as earthquakes or tsunamis, where people do not have time to think and have to act immediately [15], [63]. Wildfire, for example, has become more common around the world. Similar to the hurricane, people in the affected area received multiple warnings and advice on whether or not to evacuate from the area. However, the research on human behaviors during a wildfire is still limited [63]. The results here could shed some light on future work. In particular, it is important to identify beliefs and goals related to concerns that people may have during wildfires. Additionally, we need to consider how people cope with the situation could influence their beliefs about the wildfire.

More speculatively, there is a long-term research potential that the model could be used counterfactually to explore how to communicate hurricane information. In particular, the model predicts that the ease with which emotion-directed coping alters beliefs and goals depends on a cost calculation tied to the shape of the distribution of beliefs or goals, reflecting their uncertainty. This suggests that if we do not want people to cope by changing their beliefs or goals in unhelpful ways, such as wishfully thinking that the hurricane will not be so bad, the messaging needs to be worded with high certainty or be from a trusted source. However, we also need to be careful how we communicate the uncertainty because errors can result in a loss of trust in sources or authorities [64].

Additionally, the message may also attempt to convince people about how severe or undesirable the outcomes and experiences truly are. This could change the distribution of people's goals or reward weights, making them more certain. Alternatively, early messages with high certainty could result in people making a clear decision and committing to it. The model suggests people would, in turn, adjust their beliefs and goals to suit those decisions. They may start preparation to stay or evacuate early. However, this may, in turn, make it harder to convince them to do the opposite later on, which makes the effect of such manipulations of message content risky even if the model's predictions held. A crucial part of future work is not only to explore how messages could be designed based on the model predictions but also to assess whether such messaging strategies are effective in practice while also taking into account the potential errors and the clear ethical implications.

In conclusion, we proposed a computational model of coping for stressful situations based on Lazarus's theory. Human subject studies using both real-world data and hypothetical scenarios supported the model's assumptions regarding emotion-focused coping in the hurricane evacuation domain, overall demonstrating the validity of the model.

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