A Computational Model of Coping for Simulating Human Behavior in High-Stress Situations

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ABSTRACT

People often encounter high-stress situations. Modeling and being able to predict 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' theory of coping into a Partial Observable Markov Decision Process (POMDP) framework. This includes an appraisal process that models the factors that lead to stress by assessing a person's relation to the environment and a coping process that models people's behavior in the face of such stress. This coping process includes problem-focused coping, whereby people seek to alter the external environment, and emotion-focused coping, whereby people alter their internal beliefs, goals, and intentions in the face of stress. We evaluate the model's assumptions and predictions in the context of a high-stress situation that is increasingly common, the extreme conditions of a hurricane. We collected human survey data from the last several years of major U.S. hurricanes to evaluate the features in the models used for appraisal calculation. Additionally, we conducted a controlled human-subject experiment simulating a hurricane experience to investigate the prediction of the model on how people change their beliefs and goals to cope with the situation. The results show that, as predicted by the model, the proposed model features are significantly associated with the evacuation decisions and post-decision people also change their beliefs and goals in the directions that align with their prior decisions. Lastly, we conduct a simulation study showing that the proposed model is qualitatively closer to the experiment data than the baseline models that do not incorporate coping effects.

KEYWORDS

Modelling; Stress; Hurricane

ACM Reference Format:
Nutchanon Yongsatianchot and Stacy Marsella. 2021. A Computational Model of Coping for Simulating Human Behavior in High-Stress Situations. In *Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), Online, May 3–7, 2021*, IFAAMAS, 9 pages.

1 INTRODUCTION

People regularly face stressful and emotional situations. Occasionally, people also may encounter very high-stress situations such as natural disasters. In this work, we focus on high-stress situations of critical individual and societal importance, hurricanes. The number of hurricane events has shown a significant increase in recent years. In the past four years, there have been at least five major hurricanes affecting the United States [28]. In 2017, Hurricane Harvey, the costliest tropical storm on record, made landfall in Texas, caused unprecedented flooding resulting in hundreds of thousands of inundated houses, at least 107 deaths, and a total damage of $125 Billion. In 2018, two major hurricanes hit the United States: Hurricane Florence, one of the deadliest and costliest hurricanes to ever 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. 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 can repeatedly face the evacuation decision as they receive or seek out new information. Affected individuals must reason under uncertainty because the hurricane's path and impact cannot be forecast with high certainty [32]. Additionally, people can cope with the situation by changing how they perceive the situation. For example, one can choose to believe that the hurricane will miss their area or change how one values the cost of evacuation. Understanding and simulating how people cope with hurricane situations is crucial for forming emergency management plans for hurricane evacuation that could effectively help mitigate the damage and casualties.

Toward that end, we built an agent model of how people cope with such high-stress situations. We started with Lazarus' appraisal theory of emotion and realized a computational model of the theory by modifying a sequential decision framework under uncertainty, namely Partial Observable Markov Decision Process (POMDP). There are two important aspects of Lazarus's theory: the appraisal process, how people subjectively evaluate situations based on a range of factors often called dimensions, and two broad classes of coping: problem-focused coping that seeks to directly take actions in the world to alter the situation, and emotion-focused coping that seeks to change one's goals and beliefs to adapt internally to the situation. We map the appraisal process and appraisal dimensions to reward function, appropriate beliefs' features, and value calculation. Most significantly, emotion-focused coping is expressed as a set of actions that can change the internal model, specifically changing one's beliefs and goals.

In this work, we evaluate two specific predictions from the model in the context of hurricane situations: 1) there is a relationship between the proposed appraisal features and evacuation decisions, and 2) how people who evacuate may cope by changing their beliefs and goals or concerns about hurricane situations differently from people who stay. To evaluate the first prediction, we conducted survey studies from areas affected by two major hurricanes in 2018: Hurricane Florence and Hurricane Michael. The results show that the coefficients of the proposed features are sizeable

Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), U. Endriss, A. Nowé, F. Dignum, A. Lomuscio (eds.), May 3–7, 2021, Online.

and in the predicted direction. To evaluate the second prediction, we conducted a controlled human-subject experiment simulating hurricane experience and controlling information that participants received. Participants are presented with a sequence of hurricane information 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. The results show that, given the same information, people alter their beliefs and goals post their decision to evacuate or stay to be consistent with that prior decision, as predicted by the model.

Last, we conduct a simulation study to qualitatively compare the proposed model with the baseline models without coping. We simulate hurricanes similar to those in the controlled hurricane experiment. Critically, the configuration of the simulation is based on the value obtained from the hurricane surveys. The results show that qualitatively the proposed model is closer to the data than the baseline models without coping.

2 BACKGROUND

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

2.1 Lazarus 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 [1], [20], [26]. Appraisal theories argue that this evaluation occurs along specific dimensions, called appraisal dimensions or variables depending on the specific theory. In fact, there are quite a few numbers of appraisal theories [33], [11], [30], [35]. For this work, we choose a theory proposed by Lazarus [20] as it involves not only the appraisal process itself but also how people cope with emotions and stress and has influenced psychological theories about how people deal with disasters [23].

Lazarus's appraisal theory emphasizes the concept of the person-environment relationship which is always changing, leading to different emotions. The person is not simply reacting to the environment but also selecting and changing the environment as well as altering their internal beliefs and goals in an effort to move toward more positive, less stressful emotional states and away from negative states. In other words, a person copes with emotions by altering externally and internally their relationship with environment.

There are six appraisal dimensions in Lazarus's theory: 1) goal relevance (the extent to which an encounter is related to personal goals), 2) goal congruence or incongruence (the extent to which a situation is consistent or inconsistent with what the person wants or desires), 3) type of ego-involvement (various aspects of personal commitments or agency.), 4) blame or credit (who is deemed accountable for the situation), 5) coping potential (how a person can manage the demands and consequences of the situation), and 6) future expectancy (the degree to which things are likely to change). Coping potential or controllability is a subjective evaluation of the outcomes of taking some actions or altering one's internal beliefs or goals that will change the person-environment relationship.

A critical concept in Lazarus' theory is coping. 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 (drop an intention to achieve a goal), or denial (reject 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 is very human, in effect wishing some desired outcome is more likely. However, it conflates probability and utility.

Of course, there are many existing computational models of appraisal theory of emotion. For recent reviews, please refer to [24] and [3]. The work here is closely related to some of the existing models that include coping or emotion regulation such as [15], [25], [36], [4], [2], [9]. A key difference is that our model is at the level of appraisal dimensions while many existing ones are at the level of either emotion category or valence dimensions. More importantly, we apply and evaluate the model in a high-stress natural disaster scenario, using real human data.

2.2 Hurricane Evacuation Decision

The time between the first notice and the landfall of a hurricane can span days. For example, Hurricane Florence formed on August 31 and made landfall on September 14. Hurricane Michael formed on October 7 and made landfall on October 10. People who stay have a chance to observe new information as the hurricane moves closer and they can decide to evacuate or remain at their home. Those that evacuate are unlikely to return until the hurricane passes. Those that stay far too long may face increasing evacuation costs, may face greater risks due to deteriorating weather and road conditions, and may not be able to evacuate due to crowded hotels or evacuation centers. Altogether, this suggests that hurricane evacuation decision is a form of sequential decision making. Moreover, the hurricane's track, intensity, and impacts can be extremely uncertain and still cannot be predicted accurately [32].

In terms of impact, a hurricane can cause large waves, heavy rain, floods, and strong winds which can damage or destroy objects and buildings, potentially leading to power outages. People who stay during the hurricane may be trapped in a flooded neighborhood, without power and limited supplies of water and food. Worse, their home can potentially be leveled by a very strong hurricane. On the other hand, people who evacuate may get stuck by bad traffic jams or flooded roads as the hurricane approaches and spend a large amount of money to stay in a hotel or have to stay in a public shelter crowded with people and with minimal comfort.

A recent meta-analysis by Huang et al. [17] 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 to 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.

In addition, Dow et al. [10] found that a population that has a lot of experience with hurricanes relies more heavily on their own assessments of risks than on official orders. Similarly, Lindell et al. [22] found people's prior perceptions of risk to strongly correlate with evacuation decisions. Lindell et al. [23] proposed the Protective Action Decision Model (PADM) which is a model on the processing of information derived from social and environmental cues as well as risk assessment and it is influenced by Lazarus's theory. However, PADM is a theoretical model, not a computational model.

With respect to hurricane decision models, Gladwin et al. [14] proposed a decision tree that consists of a series of yes-no questions. Hasan et al. [16] 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.

On the other hand, existing work on Agent-Based Modeling of hurricane mainly focuses on the traveling demand model which concerns estimating the overall trend of evacuation across time. [27], [31], [38]. The main method used to predict the evacuation decision is repeated logistic regression in which separate logistic regressions are fitted to the data at each time interval. A recent work by Sankar et al. [34] proposed a POMDP model for the hurricane decision-making building from their own hurricane data. 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 lay out the assumptions of the model, the description of the model in the POMDP framework, and the selected predictions from the model that we evaluate in this work.

3.1 Model Assumptions

First, we assume that how people cope is a decision problem where people have to determine the best way that they know to cope with the situation. This assumption implies that we view coping as a set of actions. To determine the best action, we follow Lazarus' theory and assume that people subjectively appraise a situation, which could be a result of one's actions or the environment, based on their beliefs and goals. Consequently, the model must include features representing beliefs that are relevant to one's goals in a given situation. In addition, we assume that people evaluate situations in comparison to their expectations or reference point as well as their goal commitment or intention. This has been shown to be crucial for appraisal calculation and utility calculation [18], [29].

For coping potential or controllability, we assume that it is based on the future consequence of actions that people consider. To consider possible consequences of actions, we specifically assume that people maintain a model of the world. One important aspect of this assumption is that people do not have precise knowledge of how the world will be, that people's knowledge of the world is uncertain. Observation or information can help reduce this uncertainty. Consequently, in the context of hurricanes, we do not assume that people have a model of how a hurricane behaves. Instead, we assume that people have a model of how accurate information from a given source will be, *at a particular time in the course of the evolving situation.* Critically, this includes the accuracy of future information, since, in a hurricane, the accuracy of weather forecasts on the strength and path of the hurricane is known to get more accurate as the hurricane gets closer to a particular area where a decision-maker lives.

Lastly, the set of coping actions can be divided into two categories: 1) actions that interact with the world directly (problem-focused coping), and 2) actions that interact with one's model of the world (emotion-focused coping). For emotion-focused coping, the current model focuses on changing beliefs and changing goals. One important characteristic of emotion-focused coping is the cost of the action. Essentially, people do not change their beliefs and goals freely. There must be some constraints to it [4]. Here, we assume that there is a cost of changing one's beliefs and goals which is proportional to the difference between prior beliefs or goals and the new ones.

3.2 Model Description

To capture the above assumptions, we express them in the POMDP framework [6]. POMDP is suitable because it is a framework for sequential decision-making under uncertainty which allows one to express the assumption that people have an uncertain model of the world including one's beliefs and goals [37]. Additionally, casting appraisal and coping into a POMDP framework transforms the traditional definitions of some of these functions, in particular by allowing actions, specifically emotion-focused actions, to directly act on beliefs and goal weights.

POMDP consists of State (S), Observation (Ω), Observation function (O), Action (A), Transition function (T), and Reward (R). Below we provide the details of these transformations.

State (S): State is a sufficient statistic of what occurred in the past, such that what will occur in the future only depends on the current state, satisfying the Markov assumption. In the model, a state is represented by a set of features. For the hurricane situation, the features that we currently include in the model are those that, based on prior psychological research, we assume relate to goals and concerns that people have during a hurricane event. These include perceived safety, flood depth (inch/feet), power outage duration (days), and expected evacuation cost (traveling and lodging). Note that these features are based on one's subjective perception and are uncertain.

Observation (Ω) and the Observation function (O): The observation that people receive at each time step is the information about hurricane impacts. The observation function ($O(o|s, a)$) is the probability that the agent will receive the observation $o \in \Omega$ given the state s and the action a. In the model, the observation function is defined from the perspective of the accuracy of the news at time t ($P(o|s)$) which is a probability that the information will say that the outcome is o given that the actual state is s. For instance, the news at time t will tell people what category of a hurricane is going to be when it hits their area, with certain accuracy conditioned on the actual category of the hurricane. We assume that the accuracy of the news increases over time.

Reward (R): Reward function maps a state to a real number summarizing how good or bad the given state is. ($R(s'|s, a)$) We assume that the reward function is a linear additive of the weighted state's features ($\sum_i f_i w_i$). Weight w_i reflects how desirable or undesirable the feature f_i is. Importantly, these reward weights capture the notion of goal congruence or incongruence in the Lazarus theory.

Action (A) and Transition Function (T): In the current model, we focus on only two problem-focused actions: stay and evacuate, and two broad classes of emotion-focused actions: changing beliefs and goals.

Stay: The agent moves to the next time step and receives new observations or news about the hurricane. This implies that stay action also includes information-seeking behavior. If the next state is the last time step (when the hurricane hits), the agent stops (terminal state).

Evacuate: Evacuate actions result in paying the cost of evacuation, moving to the new location, and stop (terminal state). The cost of evacuation comprises the money spent on traveling and lodging. We assume that the cost of evacuation is based on the best evacuation destination.

Changing Beliefs and Goals: These two actions are emotion-focused coping. Their effect is to change a belief or goal by moving its distribution in a specific direction. For instance, the agent can change their beliefs about the hurricane impacts from moderate to high or can change their goals on monetary from high to low (lower its reward weight). The cost of changing is based on Kullback–Leibler (KL) divergence between the initial beliefs/goals and the new beliefs/goals ($D_{KL}(initial||new)$). This cost is part of the reward calculation. Note that these changes in beliefs and goals could affect later decisions, especially in the case of stay actions where there remains the option of evacuating later on.

Putting it together, the model optimizes the following equation:

$$Q^{\pi}(s, a) = \sum_{s'} P(s'|s, a, o)P(o|s, a)(R - C_{em}(s, a) + V^{\pi}(s')) - ref,$$

$$ref = \frac{1}{m} \sum_{i}^{m} Q(s, a_i)$$

, where C_{em} is the cost of coping, m is the number of actions at state s, π is a policy, and ref is a reference point or expectation. $V(s')$ which is the value of the future consequences can be thought of as the coping potential in the Lazarus theory.

To solve this equation, we use forward search [13] and adapt a method from Bracha and Brown [4] to handle emotion-focused coping. Essentially, we divide the optimization into two steps. First, using the above equation, the agent decides its intention (policy) based on the initial beliefs and goals without considering emotion-focused coping. Then, given the intention, the agent chooses the new beliefs or goals that maximize the objective function.

3.3 Model's Predictions

In this work, as a first step, we consider two predictions or hypotheses (H) that follow directly from the model and casting it in the context of hurricane evacuation decisions.

H1: The subjective beliefs about the hurricane's impacts on goals and concerns (appraisal dimensions) are significantly associated with evacuation decision.

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

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

H1.3: These subjective beliefs predict the evacuation decision better than the static demographic variables.

H2: People alter beliefs and goals in the direction that is positive based on appraisal evaluation given their intentions or decisions.

H2.1: Given the same hurricane information, people who stay rate their beliefs on the impact of a hurricane (category, flooding, outage) to be less severe than people who evacuate. Specifically, people who stay believe the hurricane to be a lower category, to bring less flooding, and to cause a shorter outage than people who evacuate.

H2.2: Given the same hurricane information, people who evacuate increase the importance of safety, flooding, and outage more than people who stay. On the other hand, people who evacuate decrease the importance of avoiding evacuation costs more than people who stay. Let d_i^a be the difference between the importance of goal i prior to the hurricane pre_i^a and the importance of goal i after the hurricane $post_i^a$ for people who choose action a. Hence, $d_i^a = post_i^a - pre_i^a$. Therefore, H2.2 can be restated as follow: given the same hurricane information, d_i^{stay} is less than the d_i^{evac} for i = safety, flooding, and outage, but greater than for i = avoiding evacuation cost.

To elaborate, for the first set of hypotheses, these are derived directly from the nature of these features based on the domain knowledge. Specifically, the higher the perceived safety, the less likely for people to evacuate. Similarly the higher the evacuation cost, the less likely for people to evacuate. On the other hand, the higher the flood depth or the outage duration, the more likely for people to evacuate. For H1.3, from the perspective of appraisal theory, there is no *direct* relationship between most standard demographic features (age, gender, education, etc.) and evacuation decisions because these features do not correspond to any relevant goals and appraisal dimensions. Therefore, we expect the proposed features in the model to predict evacuation decisions better. Beyond these hypotheses, we are also interested in estimating the coefficients (effect size) of these features because they can be used for initializing variables in the simulation.

For the second set of hypotheses, the model predicts that people will choose the coping action that yields the highest utility given their intentions or decisions. In other words, coping will make the current intention or decision feel better relative to the other intention or decision as long as the cost of coping does not exceed its benefit. Therefore, people who stay would shift their beliefs about hurricane impacts in a direction that is 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 thought prior to the decision. In the case of people who evacuate, these would be the opposite. As a result, we would expect people who stay to report their beliefs about hurricane impacts to be less severe than people who evacuate. Similarly, in the case of goals, people who stay would reduce the importance of their goals (reward weight) on hurricane impacts. For instance, they may think that experiencing flooding is not as bad as originally 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, we should observe the difference in the changes of goals between people who stay and people who evacuate as stated in H2.2.

4 HURRICANE SURVEYS

To test the first set of hypotheses, we designed a new survey specifically to measure people's subjective beliefs about the impacts of hurricane (safety, flood depth, and outage) and their estimation of evacuation expenses (traveling and lodging). 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? How likely is it that the hurricane would pose a serious threat to your safety if you stay in your home during the hurricane?

To collect the data, we used the Amazon Mechanical Turk (MTurk) service to send out surveys 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) [7]. We sent out questionnaires on September 21 and stopped collecting on September 29 obtaining 747 responses from SC and NC. 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) [8]. We sent out questionnaires on October 18 and stopped collecting on October 22 obtaining 700 responses from FL and GA.

We excluded any participants that were not from SC and NC for Florence and FL and GA for Michael, based on their self-reported zip code. In addition, we excluded any participants 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 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 use Bayesian Logistic Regression, adjusting for potential confounding factors that could influence both beliefs and decisions including previous experience, official evacuation notices, income, and distance to a coastline. For traveling cost and lodging cost, we log transform them because the utility of money is roughly logarithmic establishing diminishing marginal utility [12]. The data analysis is done using the BRMS library [5].

4.1 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 that we collected. 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 decision while flooding and outage are significantly negatively associated with evacuation decision. 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: The accuracy (Acc) and F1-score (F1) for each different sets of features for both datasets based on leave one out cross validation.

Feature sets	Florence		Michael	
	Acc	F1	Acc	F1
Intercept only	84.80%	.00	80.81%	.00
Demographic	86.11%	.43	80.66%	.26
Demo + Other	90.79%	.67	88.69%	.68
Model-based	**91.52%**	**.68**	**91.06%**	**.75**

Table 2 shows the accuracy and F1 score of different sets of features for each data calculated from Leave One Out Cross-Validation

(LOOCV). The intercept only model is equivalent to predicting the majority which is stay for both datasets. Demographic includes the following features: age, gender, income, education, house structure, pet, vehicle, family size, and distance to coast. Other includes previous experience and official notice. Model-based are the five features in Table 1. The results show that features in the model achieve 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 other sets of features for both datasets. This result support H1.3. Together, these results support H1.

5 HYPOTHETICAL HURRICANE EXPERIMENT

To test the second set of hypotheses, 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. [17] found that the results from hypothetical hurricane studies are similar to the results from actual hurricanes.

5.1 Method

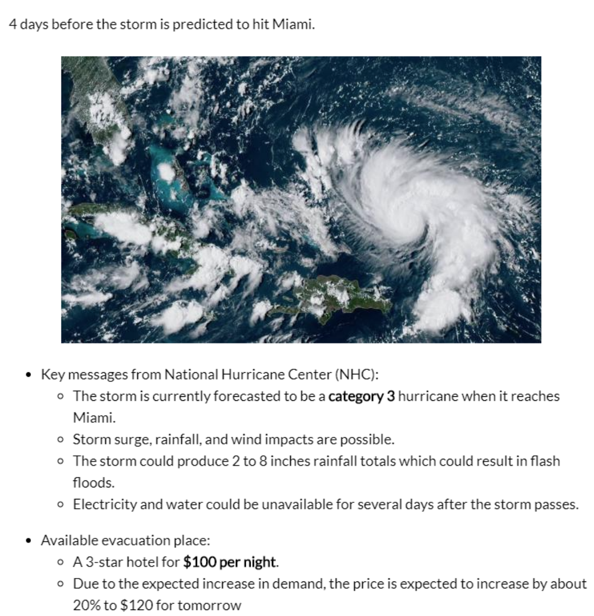

Figure 1: An example of the message in the experiment.

Figure 1 shows the interface of the experiment. In this experiment, for each decision point or time step (day), participants received hurricane information before the hurricane is predicted to hit their area. The first information announcement (five days before the storm) mainly states that there is a new storm. The remaining four information announcements provide more details with predictions as shown in Figure 1. The messages and images are adapted from National Hurricane Center (NHC). Each message contains three predictions: predicted category of the hurricane, predicted flood and rain condition, and predicted outage duration. To increase engagement as well as the realness, we also include audio reading the messages to participants as well as images of the hurricane's evolution.

Below the message, participants are presented with two choices: stay or evacuate. If participants choose to evacuate, they cannot change to stay in the next time steps. After making the decision, they are then presented with questions regarding to their beliefs about the hurricanes (category, flood depth (inch), and outage duration (day)) and the importance of four goals (safety, flooding, outage, and evacuation cost) on the scale from 0 to 100. Note that the importance of goal questions are only asked at the five days before the storm (pre) and at the end after the hurricane hit (post).

There are two conditions for the experiment: 1) a hurricane going from a category 3 to category 4 in the last two time steps (2 days before the hurricane hit), and 2) a hurricane going from a category 3 to a category 2 in the last two time steps.

We recruit participants from FL via MTurk obtaining 119 responses for the first condition and 126 responses for the second condition. The reason we only recruited from FL is that the images in the experiment show the hypothetical hurricane hits FL. After eliminating subjects that are not from FL and do not answer attention checks correctly, 84 responses remain for the first condition and 97 responses for the second condition. Figure 2 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 2 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.

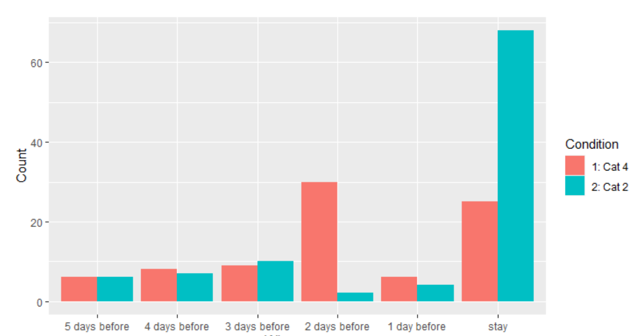

Figure 2: The distribution of evacuation across time.

To analyze the data and test the hypotheses, we use the Bayesian Robust T-Test which assumes a student distribution instead of a normal distribution resulting in more robustness to extreme values [19], [13]. We also do not assume equal variance between the two groups (stay and evac). Importantly, we adjust for the following potential confounders that could influence both beliefs/goals and decisions: previous experience, income, education, distance to coast, and Florida area (east, west, center). For goals (H2.2), we also adjust for the pre rating value. The data analysis is done using BRMS [5].

5.2 Results

Table 3: The estimated difference between stay and evac group for each belief at different times. (stay - evac)

Belief	Est.	SE	90% CI	Prob
4 days before the storm				
Category	-0.40	0.17	[-0.68, -0.11]	0.99
Flood	-4.06	0.81	[-5.37, -2.72]	1.00
Outage	-4.20	1.66	[-7.13, 1.70]	1.00
3 days before the storm				
Category	-0.24	0.14	[-0.47, -0.01]	0.96
Flood	-2.04	0.66	[-3.13, -0.96]	1.00
Outage	-3.06	1.19	[-5.12, -1.23]	1.00
2 days before the storm				
Category	-0.34	0.13	[-0.54, -0.13]	0.99
Flood	-2.13	0.69	[-3.27, -1.01]	1.00
Outage	-2.04	0.90	[-3.57, -0.60]	0.99
1 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]	1.00

Table 3 shows the estimated difference of each belief for each time between people who stay and people who evacuate. 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 at 4 days before the storm. The mean of the stay group is around 4 inches of flood less than the mean of the evacuation group. Table 3 also shows the 90% interval for a one-tailed t-test as well as the probability 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 believe 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 at 1 day before has the probability below 0.95 (not significant at 0.05 level). In summary, the results support H2.1.

Table 4: The estimated difference between stay and evac group of the $pre - post$ **rating for each goal . The importance rating is on a scale of 0 to 100.**

Goal	Est.	SE	90% CI	Prob
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

Table 4 shows the estimated difference in the difference between pre and post importance rating d_i of the four goals between people who stay and people who evacuate. Similar to Table 2, 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 evacuate increase the importance of the goal more than people who stay. We see that, for safety, flood, and outage, the estimated differences are negative while the evacuation cost is positive. However, the probability of the safety case is far below 0.95. One explanation is that most participants always rate the importance of safety to be the maximum value (100) or near it, resulting in not much difference (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 SIMULATION STUDY

In this section, we demonstrate the model and compare it with two baseline models: 1) the proposed model without coping, and 2) the model without coping and lookahead to consider future states and information, which is equivalent to logistic regression using the current information only.

Specifically, we conducted a simulation study with these three models and compared their predictions to the results from the above hypothetical experiments. Simulation was used here and we only make qualitative comparisons because the size of the hurricane experiment data is inadequate to fit the model well.

To handle the complexity, we discretize the hurricane outcomes into eleven sets of outcomes ranging from 0 to 0.95 probability of being unsafe incremented by 0.1 each, from 0 to 5 feet of flooding incremented by 0.5 feet, and from 0 to 40 days outage incremented by 4 days. The distributions of beliefs and accuracy are defined based on truncated normal distribution over these sets of outcomes. The accuracy increases each time step (variance goes down). To ground and constrain the simulation, we use the coefficients from the hurricane survey for the reward weights. We merge traveling and lodging cost into evacuation cost. We also introduce the bias term (intercept term in regression) which reflects the general tendency for people to stay. Figure 3 shows the probability of evacuation for the reward weights across different evacuation costs and hurricane impacts.[1]

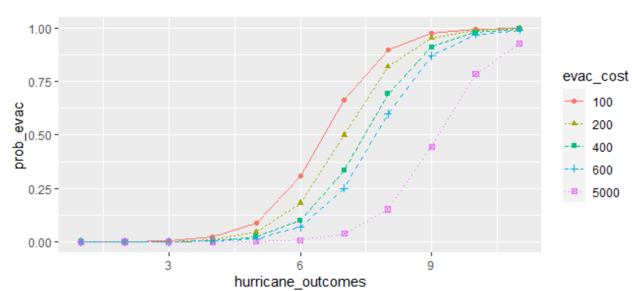

Figure 3: The probability of evacuation across different evacuation cost and hurricane outcomes.

[1] For the implementation of the simulation and the code for the evaluation section, please see https://github.com/yongsa-nut/HurricaneAAMAS2021.

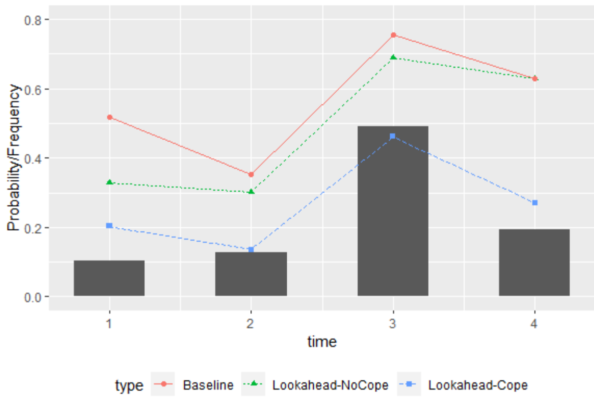

Figure 4: Simulation Results. The bars represent the proportion of evacuation for the remaining people from the experiment data. The red solid line is the baseline model without coping and lookahead, the green dotted line is the model without coping, and the blue dashed line is the full model.

Figure 4 shows the simulation results. The full model tracks the data better than the two baseline models, predicting lower probabilities to evacuate in general.

7 DISCUSSION

The results from two hurricane datasets we collected, Hurricane Florence and Hurricane Michael, supported the hypotheses H1, H1.1, H1.2, and H1.3, as the data shows that the subjective beliefs, about the hurricane's impacts on goals and concerns, are significantly associated with evacuation decision and in the expected direction. Moreover, they can be used to predict evacuation decisions better than standard demographic information. Compared to existing literature [17], we found a stronger association for traveling cost, lodging, flooding, and outage. For traveling cost and lodging, 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 would like to measure the severity of the situation unlike many existing works that only ask how likely your area will be flooded [21], [22].

The results from the controlled hypothetical hurricane experiments supported hypotheses H2, H2.1, and H2.2. Specifically, given the same hurricane information, people who evacuated reported beliefs about hurricane impacts that were significantly worse than people who stayed. This result held across different impacts, safety, flooding, and outages, as well as across different time periods. Similarly, given the same hurricane information, people who evacuate increase the importance of safety, flooding, and outage more than people who stay. On the other hand, people who evacuate decrease the importance of avoiding evacuation cost more than people who stay. Lastly, we conducted a simulation study and compared the results to the hypothetical experiments. The results showed that the model predicts the evacuation probability across time in this experimental data closer than the baseline models.

Altogether, the results support the idea of emotion-focused coping, specifically how such coping, such as wishful thinking, leads utilities and the resulting decisions to in turn alter beliefs to be consistent with those prior decisions. If the aim is to predict and model people well, 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 and standard reinforcement learning agents in which the design process fixes the reward function and the agent cannot change it [37].

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.

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. This suggests that if we do not want people to cope in unhelpful ways by changing their beliefs or goals by emotion-focused mechanisms, such as wishfully thinking the hurricane will not be so bad, the messaging needs to be worded with high certainty or be from a trusted source. In addition, the message may also attempt to convince people about how severe the outcomes and experiences really are. This could change the distribution of people's goals or reward weights, making them more certain. Similarly, 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. This may in turn, of course, 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 key 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 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 specific predictions of the model regarding emotion-focused coping in the hurricane evacuation domain, overall demonstrating the validity of the model.

ACKNOWLEDGMENTS

The authors would like to thank Professor Hugh Gladwin and Michael Lindell for providing historical Hurricane data that helped inform our approach. We also would like to thank Hanna Gratch for help with the experiment. The work is supported by the National Science Foundation under grant no. CMMI-1638234.

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