PERCEPTIONS ON HURRICANE INFORMATION AND TRACKING MAPS

A Dissertation

by

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ABSTRACT

Tropical storms and hurricanes have caused extensive casualties and damage in past decades. Recent data indicate that the annual losses from hurricanes are increasing, partly because the U.S. coastal population has increased significantly in the past 20 years. Moreover, the housing values in these areas have increased as well. Thus, population and economic growth in the vulnerable coastal areas have made hurricanes a serious problem and created the potential for a catastrophic loss of life. The existing research literature lacks a sufficient scientific understanding of hurricane information searching and dynamic protective action decision making during events in which additional information becomes available over time. The hurricane evacuation decision context is well understood; the National Hurricane Center (NHC) issues hurricane forecast advisories every 6 hours until a hurricane turns into a tropical depression. Emergency managers and residents in the risk area are most likely to make decisions on their protective actions based on these hurricane forecast advisories. Therefore, this study uses the *DynaSearch* program to conduct a computer-based experiment that examines hurricane information search pattern by students playing the roles of county emergency managers, their understanding of hurricane strike probabilities and their choices of protective action recommendations during four different hurricane scenarios. This study simulates the approach of a hurricane by providing experiment participants a sequence of hurricane forecast advisories and examining how they search for information, change their threat perceptions and implement protective actions over time. The results show that (1) People prefer *graphic information* (especially the forecast track and uncertainty cone) over *numeric and text information*

about hurricanes; (2) *hurricane intensity* was the parameter that was most commonly viewed and *hurricane wind radius* was the parameter that was least commonly viewed; (3)*forecast track* had a large number of clicks and long click durations, whereas *uncertainty cone* had fewer clicks but longer click durations; (4) participants' judgments of the extent to which they used each of the parameters were not entirely consistent with their search patterns; (5) participants found a hurricane's *current location* and *day-5 forecast* were the most informative time periods; (6) there was no evidence that participants' personal concern (whether a hurricane will head toward to their county or not) affected their information search pattern in this study; (7) participants failed to evacuate appropriate risk areas in timely manner; and (8) participants had difficulty interpreting strike probabilities. These results suggest the problem of misinterpretation of the uncertainty cone is less severe than some might have concluded from the evidence provided by Broad et al. (2007). Moreover, the results suggest that participants were able to utilize the available information in the tables and tracking maps to make reasonable judgments about each city's relative strike probability. However, their failure to take appropriate actions suggests a need for more comprehensive training on what actions to take in response to the hurricane information displays.

DEDICATION

To my cute wife, Rosie

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NOMENCLATURE

ETE	Evacuation Time Estimation
EOC	Emergency Operation Center
HKT	Hurricane Knowledge Test
NHC	National Hurricane Center
NWS	National Weather Service
PADM	Protective Action Decision Model
PARs	Protective Action Recommendations
P_s	Strike Probability Judgment
RQ	Research Question
RH	Research Hypothesis

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER I

INTRODUCTION

It is important to study the process by which people track hurricanes because these storms can cause extensive casualties and damage. Category 5 hurricanes with wind speeds over 155 mph are extremely dangerous but even a less intense hurricane can inflict major impacts because of its high winds, tornadoes, inland flooding, and storm surge. For example, Hurricane Katrina was only a Category 3 hurricane but caused about 1,500 fatalities and $81.2 billion damage to Louisiana, Mississippi, Florida and Georgia (NHC, 2005). A few weeks later, Hurricane Rita struck the Texas coast as another Category 3 hurricane. Hurricane Rita caused the evacuation of more than two million people from the coastal area but, fortunately, only 55 fatalities and $12 billion damages (NHC, 2006). Hurricane Ike, a less intense hurricane yet the costliest hurricane in Texas history ($29.5 billion damage), was a Category 2 hurricane when it made landfall on Galveston Island in 2008 (NHC, 2008). Recent data indicate that the annual losses from hurricanes are increasing, partly because the U.S. coastal population has increased significantly in the past 20 years. Moreover, the housing values in these areas have increased as well. Thus, population and economic growth in the vulnerable coastal areas have made hurricanes a serious problem and created the potential for a catastrophic loss of life (Pielke & Landsea, 1998; Green et al., 2007). Existing hurricane emergency management research has mainly focused on hurricane risk assessment and protective action assessment. Fewer studies address information seeking behaviors during a hurricane emergency. This study will start by introducing the Protective Action Decision Model (Lindell et al, 2007) as its theoretical framework. The next section in the literature review will discuss the psychological process of evacuation decision making n terms of information processing, which includes the association system and the analytic system. This section explains how people process information during a hurricane emergency. Next, this study will discuss information sources and users and then how people process hurricane information within the context of the PADM. The last part of the literature review will examine existing hurricane information seeking studies. The literature review section as a whole notes the lack of a scientific understanding of dynamic decision making—especially information seeking behavior—during events in which additional information is available over time. Emergency managers and residents in the risk area are most likely to make decisions on their protective actions based on hurricane forecast advisories. This study uses the *DynaSearch* program to conduct a computer-based experiment that examines hurricane information seeking patterns of students playing the roles of county emergency managers, their understanding of hurricane strike probabilities and their choices of protective action recommendations during four different hurricane scenarios. This experiment will address five research hypotheses and eleven research questions that seek to answer how people process hurricane information and how they use this information to assess their risks and choose the proper protective actions. This study simulates the approach of a hurricane by providing experimental participants a sequence of hurricane forecast advisories and examining how they search for information, change their threat perceptions and implement protective actions over time.

CHAPTER II

LITERATURE REVIEW

2.1 Hurricane Risk Communication

The likelihood that individuals or properties could result in an adverse outcome at a particular location within a time period is risk (Lindell et al., 2007). Hurricanes have fairly effective forecast technologies compare to other type of natural hazards. Meteorologists are effective in predicting hurricanes' track and providing information about characteristics such as its intensity, size, and forward movement speed. Based upon this information, meteorologists can formulate hurricane forecast advisories and warning messages. This forecast advisories and warning message serve as one of the information resources to coastal residents and help them make protective action decisions before hurricane winds arrive. Studies have shown that evacuation and sheltering in-place are perhaps the most common protective actions for tropical storm threat (Drabek, 1986; Mileti et al., 1975). Risk areas residents must decide whether the hurricane conditions described in a forecast advisory warrant taking these or any other hurricane protective actions. Lindell et al. (2007) proposed a Protective Action Decision Model (PADM see Figure A1) that explains how people decide whether to respond in an emergency. The information flow in the PADM begins with observing environmental cues, observing the behavior of other people or receiving information through difference channels such as peers, authorities, or news media (Fiske & Taylor, 1991; Lin et al., 2013).Information from social and environmental cues and warming messages trigger three pre-decisional processes: reception, attention, and interpretation. These pre-decisional processes are critical, because they trigger information seeking and protective action decision making. People cannot act upon information if they do not receive it or pay attention to it (Lindell & Perry, 2004). Even if they receive and heed the available risk information, they might misinterpret the environmental or social cues or fail to comprehend warning messages (Turner et al., 1986; Wu et al., 2012). Once the pre-decision processes have been completed, the protective action decision stages and information seeking activities become the next steps. Risk identification, risk assessment, protective action search, protective action assessment, and protective action implementation are the five decision stages. The outcome of risk identification is "warning belief" (Drabek, 1999; Mileti, 1974; Lindell & Perry, 2004) and warning belief is positively correlated with hurricane response (Baker, 1991). The next step, risk assessment, is people's expectation of personal consequences (lives and property) during an emergency. The existing literature shows that the risk assessment variables (people's expectations) are also important variables that explain people's disaster responses (Danzing, Thayer, & Galanter, 1958; Diggory, 1956; Fritz & Marks, 1954; Perry 1983; Tyhurst, 1957; Mileti & Sorensen, 1987; Drabek, 1999; Lindell & Perry, 2004). After the risk is identified and personal consequences are expected, people start to seek protective actions. In this stage, people are likely to seek their available protective action choices based on their past experience or by observing other's behavior (Lindell & Perry, 2004). Next, the protective action assessment stage, people start to make decisions among available protective actions by weighting the choices. In this process, people in a risk area have to consider their knowledge, skill, equipment, social cooperation, evacuation vehicle availability or financial status to decide the best protective action for them (Lindell & Prater, 2002; Lindell & Perry, 2004). Once the best possible protective action has been selected, the only question left is when to implement the protective action. In the case of a hurricane, evacuees sometimes make their evacuation decisions in the last minutes and fail to recognize the possibility of high volumes of traffic and hazardous weather conditions (Lindell & Perry, 2004).

During the above decision making stages, an individual might need to obtain information to complete some of the stages and this behavior refers to information seeking activity. People are particularly likely to rely on information seeking activities to complete their assessment of the risks and protective actions when environmental and social cues and warning messages are ambiguous or inconsistent. These information seeking activities support the decision making stages and help individuals to select their protective actions. The first task of information seeking activity is the information needs assessment. This is the stage where people realize that there is a need to seek some information to help them make protective action decisions against a certain type of disaster. Next, in the communication action assessment stage, people tend to seek information for risk identification from officials or news media, and obtain information for protective action search, protective action assessment, and protective action implementation from their peers (Lindell & Perry, 1992, 2004; Drabek, 1969). The last stage of information seeking activity is communication action implementation. People try to obtain their answers for the questions that were generated in the decision making stages. In this stage, people either find out the answers and return to the decision making stages or find out the information source is unavailable. If the source is unavailable, the best outcome is to turn to another source or channel to seek the information needed to implement their protective actions (Lindell & Perry, 2004).

Consistent with the PADM, Baker (1991) reported a positive correlation between the levels of threat belief—the degree to which individuals believe that the evidence indicates the normal environment has changed (Lindell et al., 2007; Drabek, 1986)—and response to hurricane threat. In such situations, the tasks in the decision stages and the information seeking activities could affect each other reciprocally. As the NHC issues hurricane advisories every six hours for an approaching hurricane, people's risk identification, risk assessment, protective action search, protective action assessment, and protective action implementation can change over time. Previous research guided by the PADM has been focused on post-impact surveys of people in the hurricane risk areas. However, this type of retrospective data collection cannot examine the reciprocal relationship between information search and protective action decisions. Consequently, experiments are needed to address this aspect of the PADM. In addition, by using an experimental approach, researchers are able to identify cause-and-effect relationships. Specifically, an experiment design can assess causality by assigning the causes of variation in the independent variable before the dependent variable is measured.

2.2 Hurricane Information Source and Users

Although hurricane warning technology progresses every year, people still lose their lives and property during hurricane season. One of the problems has been that some people do not know whether or when to evacuate because they misinterpret hurricane uncertainty information and thus make poor evacuation decisions (Weber, 1994; Weber & Hilton, 1994). For example, Wu et al. (2012) found that people assign higher strike probabilities for hurricanes with higher intensities (i.e. judgments of strike probability are higher for a Category 4 hurricane than for a Category 1 hurricane), even though hurricane category does not affect strike probabilities. Moreover users of hurricane information can differ significantly in their knowledge of hurricane information. Generally, the NHC provides hurricane forecast information to the public, as well as to local emergency managers, local elected officials, and news media. Figure A2 shows a hurricane information communication network model. Original hurricane information from NHC is transmitted to some intermediate sources (emergency managers, local officials, and news media) and then to the ultimate receivers—households. However, some households might obtain information directly from the NHC website.

Hurricane information is used by variety of individuals and organizations that play different roles in society. As a hurricane approaches, local emergency managers' and local elected officials' major task is to protect the public from death, injury, damage and disruption. Local emergency managers and other officials provide warnings, evacuation transportation support, evacuation traffic management, and shelter accommodations on the basis of their understanding of the information received from the NHC—usually via HURREVAC and HURRTRAK, as well as the forecast advisories on the NHC website (Demuth et al., 2012). Frequently, emergency managers are responsible for interpreting hurricane information to their local elected officials, because the emergency managers have the expertise that elected officials lack even though the latter have the legal authority to order evacuations. Evacuation is one of the most effective protective actions against hurricanes, but local officials have to balance the disruption of an evacuation against the uncertainty about whether a hurricane will strike. Local officials must decide whether to evacuate based on hurricane strike probabilities and the costs of the four possible outcomes of an evacuation decision (Figure A3). Outcome A is a correct decision; an evacuation preceded a hurricane strike so lives were saved. Outcome B is a “false positive” decision error that could cost millions of dollars (Lindell, Kang & Prater, 2011; Whitehead, 2003; Wu, Lindell & Prater, 2012), whereas an Outcome C is a “false negative” error that could cause hundreds or thousands of avoidable deaths (Jonkman, Maskant, Boyd &Levitan, 2009). Ideally Outcome D is also a correct decision; an evacuation was not ordered and it ultimately proved to be unnecessary. Thus, the challenge is to weight the probability and consequences of the two decision errors. Accordingly, local officials often try to avoid Outcome B (unnecessary evacuation) by delaying evacuations until the strike probability becomes sufficiently high. Unfortunately, evacuation takes time. Indeed, some jurisdictions with large coastal populations need at least 36 hours to evacuate (Lindell, 2008). Thus, local officials need to decide whether or not to issue an evacuation order 36 hours or more before the arrival of the tropical storm force wind (39 mph). But the reality is that NHC has advised that the hurricane strike probability is only 25% or less at that time (Lindell & Prater, 2007).

The news media is another type of hurricane information user, usually the primary intermediate source for hurricane forecast information transmitted from the NHC to the risk area population (Piotrowski & Armstrong, 1998; Lindell, Lu & Prater, 2005; Zhang et al., 2007; Morss & Hayden, 2010). In addition, local emergency managers rely on the news media to deliver their warnings and protective action recommendations to citizens as well (Perry & Lindell, 2007). Risk area residents are most likely to acquire hurricane information from TV, radio, or newspapers even though the NHC's forecast advisories are available on the internet from the NHC website (Lee et al., 2009; Sherman-Morris, 2005, Demuth et al., 2009). Therefore the news media obtain information from the NHC and interpret it in terms of their own meteorological knowledge. Finally, the news media also have to digest the information, summarize it in a few bullet points, and present it to their audiences (Churchill, 1997; Demuth, 2012). News media meteorologists' understanding of hurricane risk information is especially important. They have to interpret the forecast advisories in a way that makes it easy for their audiences to understand. On the other hand, unlike the NHC and local emergency managers, the news media are private sector organizations whose goals are to gain public attention and make profits for their companies. Thus, the news media have an incentive to dramatize the NHC's original message so they can gain market share; however, during an emergency, many news media outlets provide messages with low distortion and high specificity (Perry & Lindell, 2007). In fact, Demuth's (2012) interviews showed that media personnel feel responsible to deliver understandable and precise hurricane information to the general public without creating chaos.

The most important hurricane risk information users are those people in the risk areas. The ultimate goal of making hurricane forecast advisories is to increase awareness of an imminent threat. People receive hurricane information from either local emergency managers or the news media, but most of the time it is from the news media. Therefore, channel access becomes one of the major issues disseminating hurricane information. Indeed, channel access and channel preference differ by location, ethnic groups and technology. Perry and Nelson (1991) conducted a survey on hazard information dissemination among different ethnic groups during a flood in Abilene, Texas and a hazardous material train derailment with in Mt. Vernon, Washington. They found that Whites preferred articles and brochures; African-Americans preferred radio, newspapers, and brochures; and Mexican-Americans were more likely to obtain information through social network contacts. On the other hand, a more recent study found that, although the traditional information channels (TV, radio, newspapers) are still the major information sources, there is a growing desire to obtain hurricane risk information from Internet sources such as Facebook, Twitter, etc. The young and middle age population segments, in particular, use the Internet on a daily basis and try to obtain risk information from the World Wide Web (Liu et al., 2011). In addition, people who live in different areas might have different access to different information channels as well. Thus, technological changes and different study locations are likely to affect information channel preferences among different ethnic groups. Therefore, it is important to examine the hurricane information search processes of households, since they are also able to receive information from the NHC directly through internet.

2.3 NHC Forecast Advisory Information

The NHC provides information to users by means of hurricane forecast advisories. Generally, a forecast advisory includes information such as hurricane location, wind speed, storm size, Saffir-Simpson category, and forward movement speed. Hurricane tracking maps are widely used by the news media, households, and local jurisdictions' emergency operation centers. However, hurricanes are somewhat unpredictable so their track direction, size, intensity, and forward movement speed change over time (Wu et al., 2012). For example, the forecast advisory that the NHC issued on August 12, 2004 predicted that Hurricane Charley (2004) would strike Tampa, Florida (NHC, 2004); however, the hurricane changed its track and instead struck Punta Gorda, Florida, which is 40 miles away from Tampa (NHC, 2006). This incident and others make it clear that hurricane forecast advisories need to include information about uncertainties in hurricane parameters in order for people to avoid being surprised by changes in hurricane behavior (Pielke, 1999). The hurricane uncertainty cone was developed to provide people with information about potential errors in the NHC's forecast track, so they can make timely and responsible decisions (Broad et al., 2007). Unlike the forecast track lines, the uncertainty cones help hurricane tracking map users realize that locations on the hurricane forecast track line are not the only risk areas (National Research Council, 2006). As the NHC explains,

> "…the cone of uncertainty represents the probable track of the center of a tropical cyclone, and is formed by enclosing the area swept out by a set of circles along the forecast track (at 12, 24, 36 hours, etc.). The size of each

circle is set so that two-thirds of historical official forecast errors over a 5-year sample fall within the circle" (NHC, 2012).

2.4 Hurricane Information Communication Studies

There are only few researches that have examined the hurricane information communication. These studies used experimental design to address these issues; however, none of them examined the way in which people search for information about approaching hurricanes. Christensen and Ruch (1980) did a study with 24 participants who lived on Galveston Island. They provided their participants hurricane information such as storm location, forward movement speed, storm track, and wind speed. In this study, the participants had to decide their protective actions (wait for further information (=1) to evacuate immediately (=10)) after receiving the hurricane information. The results of this study suggested that participant's protective action decisions escalated as the storm approached to the coast. In addition, hurricane experience and emergency manager's recommendations are positively correlated to each other.

Baker (1995) conducted a study on hurricane protective action decisions with 400 residents in Pinellas County, Florida. This was an experimental study with a four between-subjects manipulation. The residents were randomly assigned to four different conditions. In each condition, the hurricane strike probability information for Pinellas County is different (50%, 30%, 10% or none). Also, there were 16 different hurricane threat scenarios in each condition. The authors provided four threat cues (storm location, wind speed, hurricane watch/warning, and local officials' evacuation action) to the experiment participants. The author concluded that participants' evacuation expectations are highly effected by local officials' evacuation orders.

The Baker (1995) and Christensen and Ruch (1980) studies provided useful information on people's responses to different type of hurricane information; however, these studies did not address hurricane information searching patterns during a hurricane event. On the other hand, the Broad, Leiserowitz, Weinkle and Steketee (2007) study touched the issue of hurricane information interpretation. The authors believed that the cone of uncertainty display is a very useful piece of information which shows the natural of hurricane threat (strike probabilities); however, unfortunately, it is not well understood by general public. In addition, this study pointed out that people prefer using a hurricane forecast map with both dashed track line and uncertainty cone according to a NWS survey study, but the authors stated that some news media outlets tend to show the uncertainty cone without forecast track line to prevent people attach greater certainty to the forecast track line then it should be. Although the NHC/NHS have putted a lot of efforts explaining the use of hurricane uncertainly cone for many years, this study showed anecdotal evidence that the uncertainty cone is misinterpreted by people.

Wu et al. (2012) conducted an experimental study on hurricane strike probability judgment. There were 162 participants from an Introductory Psychology subject pool. This study had different levels of within and between subject manipulations. All of the participants received eight different hurricane track display maps (4 hurricane directions X 2 intensity) plus one hurricane map showing hurricane locations only. As for the between subject manipulation, each group received different type of hurricane maps, that is one group received hurricane map with forecast track only; one group received hurricane map with uncertainty cone only; and one group receive hurricane map with both forecast track and uncertainty cone. The experiment participants had to assign strike probabilities (p_s) for the eight different directions from the hurricane center (north, northwest, west, southwest, south, southeast, east, and northeast) for each hurricane scenario[1]. This study concluded that (1) people realized that hurricanes could make turns, hurricane does not always follow forecast tracks or uncertainty cone. The results from strike probability assignment suggested that people assign non-zero strike probabilities to the sectors that are not in the hurricane direction. Even in the extreme case, the participants did not assign zero strike probabilities to the direction that is completely opposite to the direction that a hurricane forecast track was heading. Never the less, the judgments of strike probabilities distributions were unimodaled and were centered on the direction that the hurricane forecast track was heading. This research also suggested that people had difficulty utilizing probability. The results indicated that the sum of the judged strike probabilities for the eight sectors were higher than one.

To sum up, these previous studies showed that people are capable of using different forms of hurricane information such as verbal information (Baker, 1995), numeric information (Baker, 1995), and graphic information (Wu et al., 2012). In addition participants' protective actions decision increased as storm approaches to coastal areas (Christensen & Ruch, 1980). Thus, hurricane response is a dynamic decision task because

[1] Originally the authors divided the experiment participants to three groups—the strike probability group, miss probability group and miss odds group. However they converted miss probability and miss odds to the implied strike probability for the statistical analyses.

its threat level changes over time, so local officials' and residents' situational assessments should also change as the threat level changes. That is, as mentioned earlier, hurricanes can be characterized in terms of their current position, proximity to coastal jurisdictions, their past track, forecast track, intensity, size (radius of hurricane or tropical storm wind) and forecast movement speed. The NHC can forecast these hurricane parameters over time horizons from 1-5 days. However, research to date has failed to examine the extent to which people rely on these parameters and time horizons to make decisions about how to respond to an approaching hurricane. Although Christensen and Ruch (1980) showed that people take different protective actions as a hurricane approaches, there is a need to study how people's information search patterns and p_s change as well as their protective action decisions over time.

The limitations of previous hurricane experiments can be addressed by using a hurricane tracking task in which experiment participants can view one or more table of numerical hurricane parameters such as the storm's distance from possible points of landfall, storm intensity, and forward movement speed. These parameters would be the table's rows and different points in time from the current time to five days in the future would be the columns. In addition, the hurricane information displays could include tracking maps that present graphical information such as current location, as well as forecast tracks and uncertainty cones over periods carrying from one to five days. Moreover, this display could include a text containing any NHC watches and warnings. After searching the display page, participants could be asked to report their strike probability judgments for different cities and to report any protective actions they would take in respects to that forecast advisory. This process would be repeated for multiple forecast advisories.

2.5 Processing Uncertainty Information

As noted earlier, survey research based on the PADM can only examine the search for hurricane information retrospectively and, thus, is quite limited in the conclusions that can be drawn about the information search process. Experiments are better suited to addressing this question, but the hurricane decision making experiments conducted to date have focused on other issues. Thus, it is appropriate to consider some of the findings from some basic studies of decision making and the role of information search processes in these decisions. Decision making is one of the main tasks that people face every day. In many situations, people make decisions based on information they have received recently together with the lessons they have learned from their previous experiences in these types of situation. Researchers have concluded that the psychological decision process has two systems (National Research Council, 2006). The first, the associative system, helps an individual to make decisions automatically. This system does not require an individual to go through complex cognitive operations, so people can make decisions very fast (Epstein, 1994; Chaiken & Trope, 1999; Sloman, 1996). Our reflex actions are based on this associative system. For example, when an individual sees a baseball coming toward to her face, she will try to dodge the baseball immediately without explicitly considering the consequence of being hit by a ball in the face. It is also used for repetitive decisions such as which brand of toothpaste to buy. On the other hand, the second system— the analytic system—helps individuals to consider any information they have received and make decisions logically and rationally (Epstein, 1994; Chaiken& Trope, 1999; Sloman, 1996). The analytic system does not function like the associative system. Instead of functioning automatically, it requires effortful conscious awareness to make a decision (National Research Council, 2006). One of the major tasks for the analytic system is searching for information and choosing the best option from multiple alternatives. Information search and decision making are well studied areas for psychologists and consumer researchers. Choice between bets is the most widely studied type of decision making studies (Kahneman&Tversky, 1979; Tversky&Kahneman, 1992; Bradstatter et al., 2006, Payne, Bettman, & Johnson 1993). These studies infer people's decision processes by presenting experiment participants a series of alternative choices that differ in their probabilities and payoffs. However, Willemsenand Johnson (2011) believes that process tracing data can better explain participants' decision behavior than simply observing their choices. That is, requiring experiment participants to search for information that describes the attribute of each alternative before making a choice is more informative than simply presenting them with the information needed to make a choice. Further, process tracing can help researchers to assess the heterogeneity among participants in their information search processes (Willemsen & Johnson, 2011). Researchers have used several different techniques to examine people's information search processes—having participants talk aloud while they are thinking (Ericsson & Simon, 1980); recording the physical retrieval of information board elements (Payne, 1976; Jacoby et al., 1985); recording participants' eye movements (Russo &Rosenm 1974; Duchowski, 2007; Wang, 2011), or simply asking people what information they would use (Willemesen& Johnson, 2011). For most process tracing studies, information boards have been used to display decision alternatives in the rows and the attributes of those alternatives in the columns. When participants first see an information board, the content of a cell is covered so they are not able to view the information until they remove the cover. Requiring participants to obtain information by means of observable behaviors allows experimenter to record the sequence in which each cell is accessed and how long/how many times it was viewed during an experiment (Ford et al., 1989).

Although the associative and analytic decision making systems function in different ways, they generally work with each other. Specifically the analytic system must guide the associative system to process the information and make a decision (Damasio, 1994). It does this by activating a mental model of a situation and directing attention to different aspects of that situation, retrieving relevant information from long-term memory, and transferring that information to working memory to make assumptions about that situation—commonly identified as situational comprehension.

Mental models are important for understanding decision making because experts and non-experts can have different mental models for the same knowledge domain (Bostrom et al, 1994). It is important to recognize that people's interpretation of environmental cues and comprehension of warnings depends upon their schemas or mental models of the situation. Therefore, it is important for emergency managers to understand people's mental models of hurricanes because these mental models determine what information people seek, heed, and use in making protective action decisions. For example, emergency managers and coastal residents might have significantly different mental models of hurricane evacuation. Attention also plays an important role in understanding hurricane information users' cognitive processes because of the limits it imposes on mental load. In general, individuals can pay attention to only four to six independent variables when making decisions or judgments (Strayer & Drews, 2007). Therefore, people tend to pay the greatest attention to the information elements that they think are most relevant to the situation, the elements that are different from other elements, or the elements that most obviously change over time (Sarter, 2006; Durlach, 2004). For example, people are likely to pay more attention to any elements of hurricane tracking maps that are large, bright, colorful, flashing or moving. Moreover, researchers have found that reading habits can also affect people's attention; a top-bottom and left–right reading habit could make observer focus on the top-left quadrant display and miss an important element if it is displayed in the bottom-right quadrant (Sarter, 2006; Strayer & Drews, 2007)[2]. Working memory affects mental models as well. Working memory allows an individual to maintain relevant information for ready access but there is also a limitation on working memory (Boduroglu, et al., 2007; Ericsson & Kintsch, 1995). People cannot remember all the information that is relevant to a task but, if they can develop a schema and "chunk" task relevant information, it is possible to improve their working memory and perform better on the task (Ericsson et al., 1980). Because situational comprehension is influenced by each person's mental model, one can expect significant differences in people's situational comprehension, even when they are given the same information. For

[2] This might not be true across all cultures, since reading patterns differ across cultures.

example, Lowe (2000) conducted a series of weather map related experiments on meteorology experts and non-experts. He found that meteorologists generally have a better understanding of weather maps and pay more attention to the most important weather information because they can link situational information with their mental models of weather system to form a better situational assessment.

2.6 Research Hypotheses and Research Questions

Based on the findings and limitations of previous research, this study will use an experiment to address some unanswered questions such as people's preference for the form of information, and the change of p_s and PARs when facing an escalating hurricane threat. This experiment manipulates several factors: within-subjects (multiple forecast advisories and multiple hurricanes) and between-subjects (multiple hurricane sequences and different decision maker locations) manipulations. The reasons for these manipulations are listed below. (1)Multiple forecast advisories(within): The NHC provides new information about a hurricane in forecast advisories that are released every six hours, so examining participants' reactions to an approaching hurricane will provide a more complete understanding of hurricane information searching and decision making overtime. (2) Multiple hurricanes scenarios (within): This manipulation will allow us to examine the differences in the processing of information about hits, near misses, and "far misses" (i.e. a manipulation of the perceived personal relevance of each scenario). (3) Multiple sequences (between): This manipulation will allow us to assess the input of serial position effects. Research on judgment and decision making has shown that people's judgments are influenced by their context (e.g., Kahneman & Tversky's, 1974 "anchoring and adjustment heuristic”), which suggests that a person’s response to a near miss that was preceded by a hit would differ from their response to a near miss preceded by a “far miss”. (4) Different location (between): Assigning participants to two different locations provides an opportunity to replicate some of the results. Specifically, participants should respond in much the same way, regardless of the county to which they are assigned, (1) to a hurricane traveling directly toward their county, (2) to a hurricane traveling toward a county hundreds of miles away, and (3) toward a county midway between these two counties. The research questions and research hypothesis for this study are as follows.

1. Research questions related to information search.

RQ1: When an experiment participant receives a graphic hurricane map, a numeric hurricane parameter table, and a verbal warning/watch message, which is the type of information that they prefer to use?

RQ2: Will hurricane track direction and county location make a difference in participants’ search for graphic, numeric, and verbal information about an approaching hurricane?

RQ3: What is the overall frequency and duration of search for each graphic display element (current location, past track, forecast track, uncertainty cone)in the hurricane tracking map?

RQ4: What is the overall frequency and duration of search for each time horizon ranging from current status to five days in the hurricane tracking map?

RQ5: What is the frequency and duration of search for each hurricane parameter (distance to Port Isabel, distance to Sabine Pass, forward movement speed, intensity and hurricane wind radius) in the hurricane parameter table?

RQ6: What is the frequency and duration of search for each time horizon ranging from current status to five daysin the hurricane parameter table?

RQ7: Are there scenario order effects (in which a given hurricane scenario gets a different response, depending on whether it is first or last)?

2. Research hypotheses and questions related to judgment of strike probabilities (p_s) and protective action recommendations (PARs)

RH1: The variance among participants in their strike probability (p_s) judgments for each target city will decrease over forecast advisories (from 1-6), as each hurricane approaches the point of landfall (i.e., there will be increasing agreement about landfall location).

RH2: Participants will assign non-zero strike probabilities to cities that are not located in the direction that a hurricane is heading.

RH3: The number of protective action recommendations (PARs) will increase over forecast advisories (from 1-6) as each hurricane approaches the point of landfall, but the slopes of the curve will be higher for scenarios in which the hurricane strikes the participant's location than for scenarios in which the hurricane strikes a distant location.

RH4: The number of PARs will be positively correlated with the respondents' judgments of p_s for their own jurisdictions.

RH5: All participants will activate the emergency operation center (EOC) on the first forecast advisory.

RQ8: Will participants make different protective action decisionsfor different hurricane scenarios?

RQ9: Will $\Sigma p_s \leq 1$, since the target locations are not an exhaustive list of all possible points of landfall even though they are mutually exclusive?

RQ10: Will participants' demographic characteristics (age, gender, permanent residence, hurricane experience, or evacuation experience) account for differences in their judgments of p_s and PARs?

RQ11: What is the percentage of participants that evacuate the appropriate number of risk areas (e.g., Risk Areas 1-4 for a CAT 4 hurricane) before that evacuation time estimate deadline (i.e., at least 32 hours before storm arrival for both counties)?

CHAPTER III

METHODS

3.1 Procedure

This research was performed in a laboratory setting using a non-probability (convenience) sample of 80 experiment participants recruited from the population of Texas A&M University students, each of whom was paid $20 for participating in the experiment[3]. There are two reasons for using a non-probability sampling technique for this study. First, the principal objective of this study is to test people's cognitive processes in a dynamic hurricane tracking task. We believe that university students, like the general public, are able to provide reasonable data on this topic. Second, this is a pilot study that will allow researchers to obtain basic data and identify trends in hurricane tracking without the complications of using a random probability sample. Thus, the experimenter posted recruiting flyers on bulletin boards around the Texas A&M campus and personally distributed these recruiting flyers on campus. The recruiting process continued until 80 participants successfully completed the experiment[4].

Each participant was assigned to one of the eight conditions by using a systematic

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[3] This experiment was complete voluntary. The incentives for this experiment were not only limited to the 20 dollars payment. The experimenter also explained in the debriefing statement and the informed consent declaration to the participants in the very beginning of the experiment that there is a need for hurricane information search studies and indicated that the data would be confidential. These might have increased participants' motivation to contribute to this study.

[4] After each participant finished the experiment, the experimenter exported the data from the *DynaSearch* program into *Excel* spreadsheets and checked if each participant had finished all the tasks properly. If not, the data were marked as invalid data and excluded from the data analyses. The experimenter then reassigns the same experimental condition to the next available participant. In total, there were 98 participants in the experiment, with 80 of them finishing the experiment successfully.

random assignment method. The experimenter assigned random identification (ID) number in the range from 0.00 to 100.00 to each participant. Then, the experimenter assigned the first participants to conditions based on their ID numbers. Since there are eight conditions, participants with ID number from 0.00 to 12.50 were assigned to condition 1, IDs from 12.51 to 25.00 were assigned to condition 2 and so on so forth. The experimenter assigned participants to conditions beginning with the one who signed up for the experiment first. When one of the conditions reached 10 participants, the experimenter reallocated the ranges for the random numbers from eight ranges to seven ranges and assigned participants to the remaining seven conditions. This process continued until each condition had10 participants. This random assignment process allowed the researcher to probabilistically rule out any plausible rival hypotheses that result from participants' personal characteristics such as gender, race, or age. In other words, random assignment makes the participants' attributes in each condition statistically equivalent. Therefore, any differences observed on the dependent variables are most likely due to the treatment effects from the between and with-in subject manipulations.

Before the participants began, the experimenter displayed four documents in each participant's workstation. These were (1) a sign identifying which county EOC the participant represented; (2) a hurricane evacuation time estimate (ETE) table (Table B1 or Table B2) from Lindell et al. (2002), (3) a hurricane risk area map (Figure A4 or Figure A5), and a Gulf of Mexico counties map (Figure A6). Half of the experiment participants saw the display documents for Jefferson County; the other half of the participants saw the display documents for Cameron County. All participants saw the same Gulf of Mexico counties map that shows all the U.S. counties that around the Gulf of Mexico. These documents were posted on the walls of each participant's workstation throughout the experiment. The participants were able to examine the maps and the ETE table during the experiment. The participants also read *The Local Official's Guide to Making Hurricane Evacuation Decisions* and took the *Hurricane Knowledge Test* (HKT) before the experiment (Lindell et al, 2008)[5]. These materials allowed participants to acquire basic knowledge about hurricanes and appropriate protective actions for coastal counties. After participants had read the Official's Guide and taken the HKT, the experimenter gave them a city classification sheet. The participants could use the hurricane risk area map to identify the cities within their jurisdictions. This task was designed to enhance each participant's ability to recognize the location of their county on the maps. After completing these preliminary tasks, the participants began the hurricane tracking experiment using a computer program called *DynaSearch*. This program has been developed by the Texas A&M University Hazard Reduction and Recovery Center in conjunction with Clemson University Savage Visualization Laboratory[6]. For this experiment, *DynaSearch* was set up to present the participants with four different hurricane scenarios. Each of the four hurricane scenarios had six forecast advisories and each advisory represented a single day rather than the six-hour period that the NHC forecast advisories represent. The one-day

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[5] The *Local Official's Guide to Making Hurricane Evacuation Decisions* is a document that developed by Lindell, and Prater (2012). This Official's Guide is based on a document developed for the Texas Governor's Division of Emergency Management. Along with the *Local Official's Guide*, they also developed the *Hurricane Knowledge Test* to evaluate readers' understanding of the material in the official's guide.

[6] Manuscript in preparation.

time interval was used instead of the six-hour time interval to move the hurricanes scenario at a pace that seemed most likely to maintain participants' interest. Thus, the first forecast advisory was seven days before the hurricane made landfall and the sixth forecast advisory was one day before the hurricane made landfall. Each hurricane forecast advisory provided the hurricane's current information and the forecast information for the following five days. *DynaSearch* can display a hurricane parameter table, a Gulf of Mexico hurricane tracking map and an NHC watch/warning message box on a single forecast advisory screen (Figure A7). For each forecast advisory screen, the participants had five minutes to view the information. The hurricane parameter tables displayed each cell's content as numbers or verbal labels. In this application, the participants viewed a grid whose rows represented different hurricane parameters and the columns represented different forecast time horizons. *DynaSearch* provides a function that allows the cells in the grid are blank until the user moves the mouse cursor over the cell and clicks it. The information disappears when the user releases the mouse button. It is important to recognize that the contents of each cell changed over time as the participant progresses through the hurricane forecast advisory pages because Patrick and James (2004) have noted that process tracing has not previously been used in studies of dynamic decision making and a more recent literature search supports this conclusion. Moreover, *DynaSearch*'s hurricane tracking map display provides information in graphic form—a feature that does not appear to have been used in previous process tracing studies (see Schulte-Mecklenbeck et al., 2011). Similar to the process for viewing cells in the information board, the tracking map displays no visible information about a hurricane until the participant moves the mouse cursor over the desired element in the map legend table below the tracking map. Checking an element allows the participant to view a hurricane's current location, its forecast track, and uncertainty cone for each of the next five days and the past track for previous 5 days. *DynaSearch* records the order and the amount of time a participant spends viewing each cell in the hurricane parameter, each feature in the map legend and the watch/warning text box. After each forecast advisory page, *DynaSearch* displayed two sets of questions to obtain the participants' judgments about hurricane strike probability for six locations around the Gulf of Mexico and 11 protective actions for the county to which he/she was assigned.

After the information search task and making decisions about p_s and PARs, participants then proceeded to a final questionnaire page that asked them to report the extent to which they used each feature that was available on the hurricane forecast advisory pages (*Not at all =1* to *Very great extent =5)*. Participants also completed 11 perceived workload questions on this questionnaire page. These questions asked them to rate the amount of information displayed, the way the information was displayed, task difficulty, task time pressure, mental activity required by the task, physical activity required by the task, their overall workload, frustration level, stress level, and their overall performance.

This experiment was concluded by obtaining four demographic variables—years of education, sex, hometown (high school location), citizenship, and three questions on hurricane experiences[7]. After the experiment was complete, the experimenter was able to extract the dependent variables (hurricane parameter table search data, hurricane tracking map search data, watch/warning text box search data, p_s data, and PARs data) from each participant's .txt data file and use SPSS to analyze the data.

3.2 Experiment Design

This study is a four-factor experimental design—2 (location) x 4(hurricane scenario) x 4 (scenario sequence) x 6 (forecast advisories). This experiment is a mixed design; hurricane scenario and forecast advisory are within-subject factors whereas location and hurricane sequence are between-subject factors. For the within-subject design, all participants will receive four different hurricane scenarios during the experiment. Hurricane A tracks directly toward Cameron County; Hurricane B tracks directly toward Jefferson County; Hurricane C tracks to a point roughly 140 miles between these counties. Hurricane D tracks toward New Orleans, Louisiana. The four different hurricane scenarios are counterbalanced to control order effects (Order 1=CADB; Order 2= ABCD; Order 3=DCBA; and Order4=DBAC)[8]. Finally, for the location factor, participants were randomly assigned to play the role of an Emergency Management Coordinator in either the Cameron County TX or Jefferson County TX Emergency

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[7]These included the experiences on personal loss, property loss and evacuation due to hurricane.

[8] These hurricane scenarios will be recoded into hurricane alpha to delta for the purpose of testing some of the research questions and research hypotheses. Hurricane Alpha is a hurricane that tracks directly toward the county to which a participant is assigned; Hurricane Beta is a hurricane that tracks roughly 140 miles away from the county to which a participant is assigned; Hurricane Gamma is a hurricane that tracks toward the other county (i.e., a point that is 280 miles away from the county that a participant is assigned); and Hurricane Delta is Hurricane D.

Operation Center (EOC).All hurricanes originated at points that are approximately 750 miles (144 hours of travel time) from the U.S. Gulf coast and have approximately the same average forward movement speed, radius of hurricane wind and tropical storm wind. There were slight variations from one forecast advisory to the next in order to more closely simulate the changing behavior of actual hurricanes. However, all hurricane scenarios had the same pattern of change in hurricane category over forecast advisories.

The first set of dependent variables comprised five hurricane parameters from the hurricane parameter table: (1) Distance to Port Isabel (Cameron County), (2) Distance to Sabine Pass (Jefferson County), (3) Forward Movement Speed, (4) Hurricane Category, and (5) Hurricane wind Size. The second set of dependent variables came from the hurricane tracking map: (1) Current Location, (2) Past Track, (3) Forecast Track, and (4) Uncertainty Cone. The third set of the dependent variables were the watch/warning text messages. By calculating the click count and click duration for the cells in the hurricane parameter table, the map legend and watch/warning text box, the researcher could assess the importance that each participant attached to each hurricane parameter, map element, and text message. The fourth set of dependent variables comprised the hurricane strike probability judgments for six cities around the Gulf of Mexico: Tampa, Apalachicola, New Orleans, Beaumont/Port Arthur, Brownsville and Tampico (Figure 3.3.3). The fifth set of the dependent variables consisted of the eleven protective action recommendations (PARs). These are (1) activate the EOC, (2) activate the emergency alert system, (3) advise beach motel/hotel businesses of the potential storm, emergency evacuation may be required, (4) recommend schools to close tomorrow, (5) recommend immediate activation of public shelter, (6) recommend immediate evacuation of the following residents: people with special needs, people without transportation, tourists, mobile homes, and recreational vehicles, (7) recommend immediate evacuation of the general population in Risk Area 1, (8) recommend immediate evacuation of the general population in Risk Area 2, (9) recommend immediate evacuation of the general population in Risk Area 3, (10) recommend immediate evacuation of the general population in Risk Area 4, (11) recommend immediate evacuation of the general population in Risk Area 5. Thus, this experiment provided information about the participants' search patterns for numeric and graphic information, strike probability judgments, and protective action decisions during a simulated hurricane scenario. Figure A8 shows the relationship among independent variables and the dependent variables.

3.3 Analytic Method and Sample Size

Student t-test was used for RH2 and RQ9; bivariate correlation was used for RH4; ANOVA (Analysis of Variance) was used for RH1, RH3, RQ1, RQ3, RQ4, RQ5, RQ6, RQ8, and RQ11; and MANOVA (Multivariate Analysis of Variance) was used for RQ2, RQ7 and RQ10. There are several reasons for using MANOVA over multiple ANOVA for these three research questions. First, using multiple ANOVAs can inflate the overall type I error rate (α)[9]. Second, MANOVA can be used to test interaction effects on multiple DVs. Thus for a given sample size, MANOVA has greater statistical power then ANOVA

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[9] Type I error rate (α): the probability of falsely rejecting the null hypothesis when the null hypothesis is actually true.

because MANOVA accounts for the covariance of DVs (Baguley, 2004; Chartier & Allaire, 2007). Researchers should also determine an appropriate sample size before collecting data. This requires setting the type I error (α) rate and type II error (β) rate[10] before the sampling process. The α rate and β rate are usually arbitrarily set as .05 and .20. β is important because it determines the statistical power (π) for the analysis, which is 1-β. The statistical power is the probability that an analysis will reject the null hypothesis when it is false. Generally a larger sample size has a smaller variance and can therefore improve the chance of detecting an effect of a given size (Tabachnick & Fidell, 2001). In practice, however, time and budget constraints limit a study's sample size, so researchers use statistical power analysis to determine the minimum sample size needed for conducting a statistical analysis. In this experiment, MANOVA will be used to detect mean differences, so four multivariate inferential statistics will be used. These statistics are as follows (Srivastava, 1983; Marcoulides& Hershberger, 1997; Young, 2006).

1) Wilks' Lambda : $\Lambda = \frac{|W|}{|B+W|}$,

2) Pillai's Trace: $V = \mathit{trace}\,(B\,(B + W)^{-1})$,

3) Hotelling-Lawley Trace: $T = \mathit{trace}\,(W^{-1}B)$,

4) Roy's largest root: $\theta = W^{-1}B$

W is the within-groups sums of squares and crossproducts (SSCP) matrix and B is the between-groups SSCP matrix (Srivastava, 1983; Marcoulides & Hershberger, 1997;

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[10] Type II error rate (β): the probability of failing to reject the null hypothesis when the null is actually false.

Young, 2006). The Wilks' ʌ test shows the dependent variables' variance by the independent variables; the Pillai's trace shows the dependent variables' variance by the largest separation of the independent variables; the Hotelling-Lawley trace is usually used when an independent variable has two groups; and the Roy's largest root shows the dependent variable's variance by the largest eigenvalue (Anderson, 2003).

When estimating the sample size for a statistical analysis, a researcher must select a statistic that will later be used to assess statistical significance. Among the four statistics listed above, Wilks' ʌ is the most widely used statistic for MANOVA (Olson, 1974; Stevens, 2002). Young (2006) used Monte Carlo simulation to conduct a series of factorial MANOVA statistical power analyses by calculating the ranges of minimum sample size per independent variable based on α level, statistical power (1-β), effect size and number of dependent variables for Wilks' ʌ. Since the design of the present study makes an effect very easy to be visualized and noticed, the effect size will be set to be a very large ES[11]. In addition, this research will follow the conventional levels of the critical values for α (.05) and 1-β (.80). By using the sample size range tables that Hair et al. (2009) provided, the sample size range for this experiment is from 14 to 23 per group. Therefore, the total

[11] The effect size (ES) is *the degree to which H_0 is false is indexed by the discrepancy between H_0 and H_a* (Cohen, 1992). Cohen (1992) provided a table for social science researchers to choose an ES based on the statistical test to be used and the levels of the visibility of an effect. The author identified three levels of the effect size—small, medium and large—stating "*a medium ES represents an effect likely to be visible to the naked eye of a careful observer….the small ES to be noticeably smaller than medium but not so small as to be trivial, and the large ES to be the same distance above medium as small was below it*. " Hair et. al., (2009) includes four levels of the effect size for MANOVA analysis which are very large, large, medium and small.

sample size for this experiment will be 80[12].The Ford et al. (1989) review of a series of 35 process tracing studies revealed that there were only nine studies with a sample size greater than 80. Therefore the sample size is above the average for most of the Ford et al. (1989) process tracing studies. In addition, the within-subject manipulation requires all participants to make their judgments on four different hurricane scenarios. This within-subject manipulation provides increased power to detect a given effect size.

[12] Power analyses were conducted for each student t-test and ANOVA test as well by using an online tool developed by the Institute for Social Research, York University, Canada (http://www.math.yorku.ca/SCS/Online/power/). The statistical power for each analysis is different depending on the analysis for each RH and RQ; however, all of them are above .80.

CHAPTER IV

RESULTS

4.1 Experiment Results on Information Search

In response to RQ 1, the statistical analyses results indicates that there was a significant difference on the information search for the hurricane advisories (click count: $F_{2,158} = 159.50$, $p < .01$; click duration: $F_{2,158} = 35.32$, $p < .01$). Table B3 shows the average click count for each hurricane forecast advisory element. *DynaSearch* recorded more clicks on the hurricane parameter table cells (M= 13.80) than the hurricane map elements (M= 7.81) and hurricane warning/watch message (M= .76). On the other hand, Table B4 indicates the participants spent more time on all the hurricane map elements (M = 9.09s) than the hurricane parameter table cells (M= 8.38s) and hurricane warning/watch message (M= 4.32s). Combining these results, the participants spent more time checking the map elements but clicked more cells in the hurricane parameter table consistent, with these results, the post-experiment self-report questionnaire indicated that the experiment participants believed the map elements were more useful to them than the table cells (Table B5).

The multivariate statistics results are not significant for RQ2. The between subject manipulation (assigning participants as either Cameron County or Jefferson County emergency managers) did not yield statistical significant results on hurricane information searching (click count and click duration) on the four hurricane scenarios. There was only a slight difference on hurricane parameter table searching. The Cameron County participants had more clicks and longer click durations when facing Hurricane A (traveling to Cameron County) than Hurricane B (traveling to Jefferson County) and had fewer clicks and shorter clicking durations when facing Hurricane C (traveling to Corpus Christi, Nueces County between Cameron and Jefferson County) and Hurricane D (traveling to New Orleans, LA). Also, the Jefferson County participants had more clicks and longer click durations when facing Hurricane B than Hurricane A and had fewer clicks and shorter click durations when facing Hurricane C and D. Nevertheless, none of these differences was statistically significant.

Tables 4.1.4 and 4.1.5 show the test results for RQ3-RQ6. In response to RQ3 and RQ4, the results indicate that the participants had a longer total number of clicks on the *hurricane forecast track* (M= 80.23 clicks) compared to other hurricane map elements (*current location, past track, and uncertainty cone*) and the results were statistically significant ($F_{3,237} = 108.66$, $p < .01$). On the other hand, they spent more time processing the *hurricane uncertainty cone* (M=115.93s). The total click duration for *uncertainty cone* is significantly higher than other map elements ($F_{3, 237} = 101.37$, $p < .01$). Unlike click count, click duration for *forecast track* was the second highest among the map display elements. As for the hurricane tracking map time horizon, the experiment participants were more interested in the *day 5* as indicated by both the click counts ($F_{4,316} = 61.65$, $p < .01$) and click duration ($F_{4,316} = 110.83$, $p < .01$). They had the highest total click count on the *day 5* (M= 59.14 clicks) and also the longest total click duration on the *day 5* as well (M= 110.61s). Table B7 shows the answers for RQ5 and RQ6. The F value indicates there was a significant difference on click counts ($F_{4,316} = 20.41$, $p < .01$) for the hurricane parameter table elements. The participant clicked 88.69 times on the hurricane *intensity* items over the four hurricane scenarios. The click durations for the hurricane parameter table are also significantly different from each other ($F_{4,316}$= 25.35, p <.01), with the participants favoring the hurricane *intensity* item the most (M= 59.85s). The second highest click count among hurricane parameter table elements is *distance to Port Isabel* (Cameron County, TX, M= 71.90 clicks) and the second longest click duration among hurricane parameter table elements is also *distance to Port Isabel* (Cameron County, TX, M= 45.07s). In fact, half of the participants were assigned to be emergency managers for Cameron County and the other half were assigned to Jefferson County. The reason why there were more clicks and longer click durations for Port Isabel than Sabine Pass is possibly due to the fact that the Port Isabel label is located on the very top left of the hurricane parameter table (Figure A7). In response to RQ6, the results indicate that there are statistically significant difference in the click count ($F_{5,395}$= 19.82, p< .01) and click durations ($F_{5,395}$= 36.73, p< .01) over the time horizon elements. The participants spent most of their time checking the *current* status of the hurricanes (click count: M= 74.60 clicks; click duration M= 62.09s), compared to other time horizon items (*day 1, day2, day3, day4, day5*). In addition, day *5* is the second highest on both click count (M= 73.94 clicks) and click duration (M= 62.09s).

The results of two-way mixed MANOVA analyses for each display item (*parameter table, tracking map, message box*) showed that the four scenario sequences resulted in significant differences on click counts and click durations for each display item (*parameter table*: $F_{18,454}$= 25.93, p< .01; *tracking map*: $F_{18,454}$= 14.81, p< .01; *message* *box*: $F_{18,454}$= 5.21, p< .01) (Table B8). Table B8 shows that the participants generally clicked more often and spent more time searching data on the first hurricane they faced during the experiment. The participants assigned to Sequence 1 had the highest click counts and longest click durations on hurricane C whereas the participants assigned to Sequence 2 had the highest click count and longest click duration on hurricane A; Moreover, the participants assigned to Sequence 3 had the highest click counts and longest click durations hurricane D whereas the participants who assigned to Sequence 4 condition had the highest click counts and longest click durations on hurricane B. Table B8 also revealed that the last hurricane scenario in each sequence condition also had the lowest click counts and click durations.

Figure A9 combines the results of above RQs. Among the forecast advisory items, the participants generally paid more attention on hurricane intensity (table), forecast track (map), uncertainty cone (map), and text message. As for the time horizon items, they paid more attention to the current forecast and the fifth day forecast on the parameter tables, and paid more attention to the 5 day track forecast in the tracking map.

4.2 Experiment Results on p_s and PARs.

Partially consist with RH1, Figures 4.2.1-4.2.4 show that the variance among participants in their strike probability (p_s) judgments for each target city decreased over forecast advisories for hurricane scenarios A (Figure A10), B (Figure A11), and D (Figure A13). The target city for hurricane scenario C (Figure A12) (Corpus Christi) was not a city that the experiment participants could assign strike probabilities to. Figure A12 shows that the adjacent cities (Brownsville and Beaumont/Port Arthur) variance in p_s for hurricane scenario C stayed almost the same during six forecast advisories. The analyses also indicate that the mean p_s for the target cities increased over forecast advisories and the results are statistical significant (Table B9). In the case of hurricane scenario A, the p_s for Brownsville, TX increased from .60 to .88 over the six forecast advisories ($p < .01$); in the case of hurricane scenario B, the p_s for Beaumont/ Port Arthur, TX increased from .60 to .90 over the six forecast advisories ($p < .01$);in the case of hurricane scenario D, the p_s for New Orleans, LA increased from .51 to .89 over the six forecast advisories ($p < .01$). As for the case of hurricane scenario C, Beaumont/Port Arthur and Brownsville are two cities that are located closest to the landfall location, so the p_s value for these two cities are higher than for the other cities, but the p_s decreased over the six forecast advisories.

Consistent with RH2, the test results show that the participants assigned non-zero strike probabilities to cities that are not located in the direction that a hurricane is heading. The results are statistically significant (Table B10 to 4.2.5). These four tables also indicate that the mean p_s for cities that are closer to the landfall location had higher mean p_s than the cities that are further away from the landfall location. For example, the mean p_s for Beaumont/Port Arthur, TX and Tampico, Mexico are higher than the mean p_s for Tampa, FL, Apalachicola, FL, and New Orleans, LA in Hurricane A scenario for all six of the advisories, because Hurricane A is heading toward Brownsville, TX, and Beaumont/Port Arthur, TX and Tampico, Mexico are the cities that located closer to Brownsville, TX than the other cities in the target list.

Consistent with RH3, the participants significantly increased their mean number of PARs over the six forecast advisories ($p < .01$). In Hurricane A, the mean number of PARs increased from 2.29 to 6.29; Hurricane B, the mean number of PARs increased from 2.13 to 5.83; in Hurricane C, the mean number of PARs increased from 2.08 to 5.25; in Hurricane D, the mean number of PARs increased from 1.29 to 3.29. Note that the Hurricanes A and Hurricane B had higher rate of increase in PARs over the six forecast advisories compared to Hurricanes C and B scenarios (Table B14). This is due to the fact that Hurricane A was heading toward Cameron County and Hurricane B was heading toward Jefferson County and our participants were either assigned to be emergency managers for Cameron County or Jefferson County. Figure A14 shows that the slopes of the curves are higher for scenarios in which the hurricane tracks toward the participant's location than for scenarios in which the hurricane strikes a distant location. For example the slope of Cameron County's PAR curve is steeper than the slope of Jefferson County's PAR curve in Hurricane A and that this result is reviewed for Hurricane B.

The correlation analyses results are partially consistent with RH4. In most of cases, the p_s judgment and the number of PARs are significantly correlated with each other for each forecast advisory (i. e., the diagonal cells in Tables 4.2.7 and 4.2.8). The only two exceptions are the correlations between p_s and PARs in Forecast Advisories 4 and 5 in Cameron County.

Contrary to RH5, the results indicate that not all participants activated the emergency operation center (EOC) on the first forecast advisory. However, the percentage of the participants who activate the the EOC on the first forecast advisory increased with hurricane tracking experience. There were 52.50% of the participants who activated the EOC in FA1 during first hurricane; 65.00% who activated the EOC in the FA1 during second hurricane; 72.50% who activated the EOC in the FA1 during third hurricane; and 76.25% who activated the EOC on the FA1 for the last hurricane.

In response to RQ8, participants who were assigned to different counties made different protective action decisions depending upon the hurricane scenarios but the analyses indicate that this effect was significant only in the last Forecast Advisory 6 ($p< .01$) not the first forecast advisory. Table B17 lists the respondents' mean number of PARs after viewing Forecast Advisory 6 for each hurricane scenario. When the Cameron County group tracked Hurricane A, they tended to recommend more protective actions to (M=8.25) than the Jefferson County group (M=4.33) because Hurricane A was heading toward Cameron County. Conversely, participants who were assigned to Jefferson County tended to recommend more PARs for Jefferson County when tracking Hurricane B (M = 8.33); whereas participants who were assigned to Cameron County tended to recommend fewer PARs to Cameron County for Hurricane B (M = 3.33). As for the remaining hurricanes, Cameron County participants recommended more PARs than those in Jefferson County when tracking Hurricane C (M=6.15)[13], and Jefferson County group recommended more PARs than Cameron County group when tracking Hurricane D(M = 4.70). These results are probably due to the fact that the landfall location for Hurricane C, Corpus Christi, is somewhat closer to Cameron County, and the landfall location for

[13] The t-test indicates that the effect is not significant.

Hurricane D, New Orleans, is much closer to Jefferson County.

The t-test results for RQ9 indicate that most of the sum of p_s for each advisory are significantly larger than 1.0, even though they are not an exhaustive set of alternatives (Table B18). This experiment had four hurricane scenarios and each scenario had six forecast advisories. Among these 24 advisories, 21 of them produced a sum of p_s that was bigger than 1.0 ($p < .05$); and these of them had non-significant results. Interestingly, $\sum p_s$ decreased over forecast advisories for three of the hurricane scenario (A, B and C) but not the forth (D). Moreover, all three of the forecast advisory that was not significantly different from 1.0 was the last three forecast advisories for scenario C.

In response to RQ10, the demographic data of our experiment participants are as following. Age: 3.8 % of the respondents were younger than 20 years old, 85.0% were in their 20s, 7.5% were in their 30s, and 3.8% were more than 40 years old. Sex: 48.8% of the respondents were male, and 51.3% were female. Education level: 2.5% of the respondents were undergraduate freshmen, 5.0% were sophomores, 8.8% were juniors, 22.5 % were seniors, 56.3% were graduate students, and 5.0% were not in any of the education level group (other). Citizenship: 45% of the respondents were international students and 55% were U.S. citizens[14]. Hurricane evacuation experience: 75.0% of the respondents had no hurricane evacuation experience, and 25.0% did have hurricane evacuation experience. Personal loss from hurricane disasters: 90.0% of the respondents did not have personal loss experience, 10.0% of them did. Property damage regarding to

[14] None of the participants were from Cameron County, TX or Jefferson County, TX.

hurricane disasters: 76.3% of them did not have property damage experience, whereas 23.8% did. Among these groups, only the non-US citizen group and hurricane evacuation experience had significant differences in their p_s judgments and PARs.

Table B19 shows that international students (non-US citizens) tended to assign higher p_s to all the cities and recommended more PARs when facing hurricane threat ($p<$. 01). On the other hand, Table B20 shows that participants who have had hurricane evacuation experience tended to assign higher p_s to all cities and recommend more PARs to their counties when facing hurricane threat ($p<$. 05).

In addressing to RQ11, it is important to note that all four hurricane scenarios will designed to reach CAT 4 in the Forecast Advisory 5 so participants who were assigned to be the emergency managers in Cameron County should have recommended evacuation of Risk Areas 1-4 after viewing Forecast Advisory 5 in Hurricane A scenario. Moreover, those who were assigned to be the emergency managers in Jefferson County should have issued the same PARs when facing Hurricane B. The data in Table B21 indicate that, in the first case (Hurricane A, Cameron County), 78% of the respondents recommended evacuation for Risk Area 1; 70% of the respondents recommended evacuation for Risk Area 2; 55% of the respondents recommended evacuation for Risk Area 3; 33% of the respondents recommended evacuation for Risk Area 4; and 28% of the respondents recommended evacuation for Risk Area 5. The percentages of participants who recommended evacuation for the four risk areas are significantly different from each other at $p<$ .01(Table B21). In the other case (Hurricane B, Jefferson County condition), however the data in Table B21 indicate that 65% of the respondents recommended evacuation for Risk Area 1; 65% of the respondents recommended evacuation for Risk Area 2; 60% of the respondents recommended evacuation for Risk Area 3; 50% of the respondents recommended evacuation for Risk Area 4; and 48% of the respondents recommended evacuation for Risk Area 5. The percentage of participants who recommended evacuation for the four risk areas are not significantly different from each other ($p = 1.06$, *ns*) (Table B21).

CHAPTER V

DISCUSSIONS

This study examined the way in which people search for information about approaching hurricanes in terms of graphic information (current location, forecast track, forecast uncertainty cone, past track), numeric information (distance to locations, forward movement speed, intensity, hurricane wind radius), and verbal warning/watch message. In addition, similar to the Christensen and Ruch (1980), Baker (1995), and Wu et al. (2012) studies, this one provided research findings on people's interpretation of environmental cues such as their p_s judgments and PARs.

In addition, this study found that people generally prefer graphic information over other types of information (Table B3 to Table B5). Previous studies also found that people prefer receiving disaster information from brochures, TV, newspapers, and internet (Nelson & Perry, 1991; Perry & Nelson, 1991; Perry & Lindell, 2007; Liu et al., 2011). The results of this study imply that the above types of information sources should provide graphic information such as hurricane maps that help information receivers to process hurricane information easily. In addition, among the hurricane graphic displays, people prefer uncertainty cones (as indicated by longer click duration) and forecast tracks (as indicated by higher click counts). These results confirmed the Broad et al. (2007) conclusion that people prefer hurricane forecast maps. Specifically, receivers prefer receiving a hurricane forecast map with both the forecast track information and uncertainty cone (Broad et al., 2007).On the other hand, not all numeric information is ignored by hurricane information users; one important result from this study is that participants paid very close attention to Saffir-Simpson Hurricane Wind categories. Among the hurricane parameter table elements, *DynaSearch* recorded a very high click count and long click durations for the hurricane intensity cells (Table B7).

This research makes significant contribution to the existing literature by examining the extent to which people search for hurricane forecast information in different periods of a five day time horizon. This study found that the experiment participants generally focused on hurricane's current location and its five day forecasts[15]. These results are confirmed in both the hurricane parameter table search and hurricane map search data. None of the existing hurricane research has addressed the issue of how far in advance people want information about an approaching hurricane. Currently, NHC provides3-Day and 5-Day hurricane forecast graphics on the internet. The data from this study suggest users might prefer using the 5-Day graphics over 3-Day graphics, although the forecast might be less accurate. This study also found that a learning effect occurred during the experiment. Generally, the participants spent a much longer time searching for information on the first hurricane scenario then on the last hurricane scenario. Nevertheless, hurricane intensity, current location, day 5 location, forecast track, and uncertainty cone had the same relative utilization regardless of number of scenarios they had encountered (Figure A9). It is noteworthy that the click counts and click durations of

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[15] Given the fact that respondents were able to obtain a hurricane's current location in the hurricane map display by clicking on forecast track items and the results from Table 4.1.5; although the current location click counts and click duration are low in Table B6, This might have been an artifact of the difficulty some participant had in recognizing the current location button as a source of information. Thus, it is likely that a hurricane's current location is important to hurricane information users even thought there were low click counts and click duration for the current location button.

the *distance to Port Isabel* cells are significantly higher than the *distance to Sabine Pass* cells in the first hurricane scenario (click count: t_{79}= 4.50, p< .01; clicking duration: t_{79} = 2.92, p< .01); buy, this difference was not significant in the last hurricane scenario (click count: t_{79} = .16, *ns*; click duration: t_{79} = -.54, *ns*). These results can be explained by the finding that reading habits can affect people's attention (Sarter, 2006; Strayer & Drews, 2007). That is, top-bottom and left-right reading habit could have produced higher click counts and longer click durations for *distance to Port Isabel* cells in the first hurricane scenario but, after three different hurricane scenarios, the participants developed a deeper understanding of the track and focused more on the information they believed would help them to make their p_s judgments and PARs.

Similar to Christensen and Ruch's (1980) findings, this study found that people's p_s judgments and PARs escalated as hurricanes approached to the counties to which they were assigned during the experiment. The mean p_s for Brownsville, Cameron County, TX and Beaumont/Port Arthur, Jefferson County, TX escalated over the six forecast advisories as the hurricanes—Hurricane A and Hurricane B, respectively—approaching these two counties (Table B9). Similar results were also found on the selection of the number of PARs over the six forecast advisories. Not only did the mean number of PARS over six forecast advisories increased over all four hurricane scenarios, but also the slopes of the curves of increasing PARs are higher for scenarios in which the hurricane strike the participant's location than for scenarios in which the hurricane strikes a different location (Table B14 & Figure A14). The results of the experiment did not confirm RH5 (*All participants will activate the emergency operation center (EOC) on the first forecast* *advisory*), which suggests that the participants failed to recognize the importance of an EOC to effective emergency response operations (Perry, 2003). Moreover, the analyses indicate that county factors did not make significant difference on EOC activation in the first advisory (Hurricane A: $F_{1,78}$= 6.60, *p*= .012; Hurricane B: $F_{1,78}$= .49, *ns*); however, county had a significant effect on EOC activation in the sixth advisory (Hurricane A: $F_{1,78}$= 7.93, *p*< .01; Hurricane B: $F_{1,78}$= 11.54, *p*< .01). The percentage of the participants who activated their EOCs was not only higher after viewing the sixth advisory than the first advisory, but was even higher when a hurricane was heading toward their county.

The results of this experiment confirmed that people realized that hurricane could make turns and might not always follow the forecast track, even though this experiment did not include any curved forecast tracks. The participants assigned non-zero strike probabilities to all six of the cities on the Gulf of Mexico in all four scenarios. On the other hand, however, the participants again failed to realize that $\sum p_s$ should be smaller than one—just as in Wu et al. (2012). These results further confirmed that people do have a difficulty in either understanding the basic principle of probability theory or implying there are more than two outcomes.

Research hypothesis 4 confirmed that the risk assessment variables (p_s) are correlated with people's disaster responses (PARs) as previously reported by Danzing, Thayer, and Galanter (1958), Diggory (1956), Fritz & Marks(1954), Perry (1983), Tyhurst (1957), Mileti and Sorensen (1987), Drabek(1999), Lindell andPerry (2004), and Baker(1991). The results of RH4 shows that the p_s values for the city in their own county are significantly correlated with PARs in 21 of 24 cases. In fact, a further analysis indicates that the results are even clearer if the analysis is limted only to examining Hurricane A data in Cameron County and Hurricane B data in Jefferson County. In Hurricane A/Cameron County, the correlations between p_s and PARs are FA1: .55, FA2: .63, FA3: .44, FA4: .55, FA5: .57 and FA6: .57 (all $p < .01$). In Hurricane B/Jefferson County, the correlations between p_s and PARs are FA1: .47, FA2: .55, FA3: .46, FA4: .56, FA5: .57 and FA6: .41 (all $p < .01$). These correlations are generally higher than the average correlation for all four hurricane scenarios.

The results of RH10 confirmed Christensen and Ruch (1980)'s finding that hurricane experience has a significant effect on local official's PARs. However, among our three hurricane experience variables, only evacuation experience made a difference in p_s and PARs. On the other hand, curiously enough, international students generally assign higher p_s and more PARs comparing to US citizen students. Further research is needed to replicate this result.

Finally, Lindell (2008) reported that coastal jurisdictions with populations need at least 36 hours to evacuate, which means that their local officials need to make decisions about evacuation orders 36 hours or more before the arrival of the Tropical Storm force wind. The results of this experiment indicate that, after viewing Forecast Advisory 5, more than half of the participants recommended evacuating Risk Area 1-3, but less than half of them recommend evacuating Risk Area 4 (Tables 4.2.13 & 4.2.14). Therefore, not all the participants realized that they need to give evacuation orders before it is too late.

CHAPTER VI

CONCLUSION

The results of this study provide mixed evidence for people's ability to comprehend hurricane information for the pre-decisional stage in the PADM model. During the pre-decisional stage people prefer graphic information (especially the forecast track and uncertainty cone) over numerical and text information about approaching hurricanes. Nevertheless, people pay close attention to Saffir-Simpson Hurricane Category more than other numeric parameter. In addition, people find a hurricane's *current location* and *day-5 forecast* are the most informative time periods. Click counts and click durations give generally the same results but there are some significant differences. For example, the *text messages* (*NHC Watch/Warning*) and *uncertainty cone* had relatively fewer click counts but longer click durations. Also, this study is able to identify that a learning effect occurred during the experiment. That is, there was a substantial decrease in both click counts and click durations from Scenario 1 to Scenario 4 as people developed their strategies for performing the tracking task. In Scenario 1, our participants generally focused more on *distance to Port Isabel, hurricane intensity, forecast track, uncertainty cone, current location, day-forecast,* and *text message* in terms of the click counts and click durations. However, in scenario 4, they spent less time on *distance to Port Isabel* and *text messages*. On the other hand, this research also found that participants' information search patterns were not affected by hurricane track direction or the county location to which they were assigned. These results imply that people's information search patterns are determined primarily by the task at hand rather than by their context. There were no evidence suggesting that people's personal concern (whether a hurricane will head toward to their county or not) affected their information search pattern in this study.

This study also found that people's p_s judgments and PARs escalated as hurricanes approached the participants' assigned counties during the six hurricane forecast advisories. Furthermore, the slope of the curve of increasing PARs was higher for the scenario in which the hurricane struck the participant's assigned county than for the other three scenarios. In addition, the participants understood that hurricane tracks/uncertainty cones are changeable in terms of its direction. The analyses confirmed that, similar to other research, the risk assessment variables (p_s)were positively correlated with disaster response (PARs). That is, high hurricane risk assessments were linked with more hurricane response items.

Nonetheless, there are negative findings as well. First, many participants failed to activate the EOC as soon as they received the first forecast advisory, despite the fact that an EOC is the essential local facility supporting response to tropical cyclones. Second, people failed to evacuate risk areas which under the hurricane threat in an appropriate timing. Not all the participants gave evacuation orders 36 hours or more before the arrival of tropical storm force wind even though the *Official's Guide* explained the concept of ETEs and the table of ETEs for each county was posted on the wall of the participant's workstation. Third, this experiment confirmed that people have difficulty understanding some of the basic principles of probability theory because the sums of the p_s judgments for the six coastal cities (a mutually exclusive but nonexhaustive set) exceeded one.

Perhaps some of the participants treated the p_s judgments as ordinal (ranked) variables. Fourth, the results indicate that only evacuation experience and citizenship made a difference in p_s and PAR judgments, even though previous studies suggested that *age, gender, education, hurricane experience on personal loss* and *hurricane experience on property loss* would have an effect on evacuation decision making. In fact, one of the limitations of this research is that only few participants had experienced personal loss (8 out of 80) and property loss (19 out of 80) during hurricanes. To obtain more variation in some of these demographic and experiential variables, researchers will need a web-based version of the *DynaSearch* program to obtain data from a broad sample of the general population or emergency managers through the Internet. Another limitation of this study is that the current version of *DynaSearch* only allows researchers to provide graphic, numeric, and text messages. However, local emergency managers/risk area residents are able to receive information from other sources as well. In the new version of *DynaSearch*, researchers will be able to provide visual (TV News) as well as audio (radio) information to experiment participants to study the process by which people choose information from these other sources.

Overall, the core value of this study has been to test people's reception, attention and comprehension of hurricane risk information, the p_s inferences they make from that information, and the PARs they make based upon it. The undergraduate and graduate level students that participated in this experiment were able to provide interpretable data on this topic. However, it remains to be seen if this pilot study has provided results that are similar to those of emergency managers and the general population. This student sample allowed us to obtain basic data and trends about hurricane tracking without the complications of using a randomized sample. In the future, researchers will not only be able to obtain data form a more diverse sample, the new version of *DynaSearch* will also provide them with the capability to design more complex hurricane scenarios involving recurved and stalled tracks. Ultimately, a systematic program of research on hurricane tracking could lead to the development of better training materials and improved tracking displays that will allow emergency managers, local elected officials, and coastal residents to make more informed decisions about whether and when to evacuate from approaching hurricanes.

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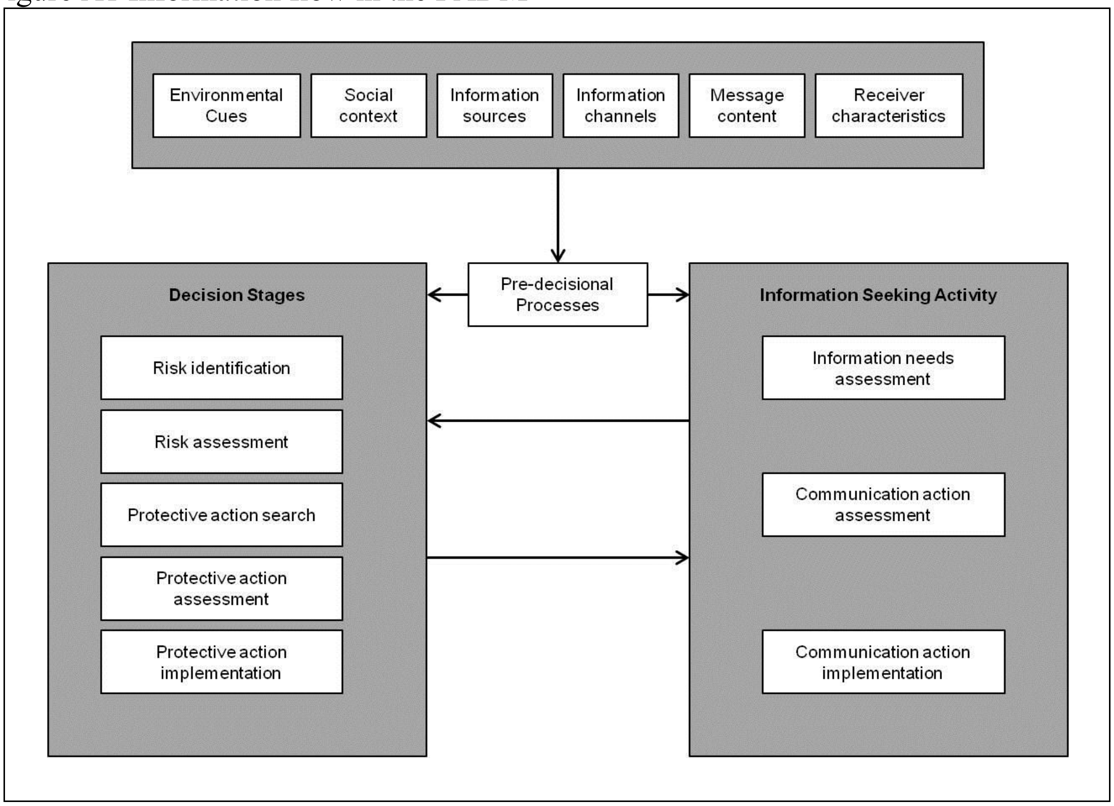
APPENDIX A

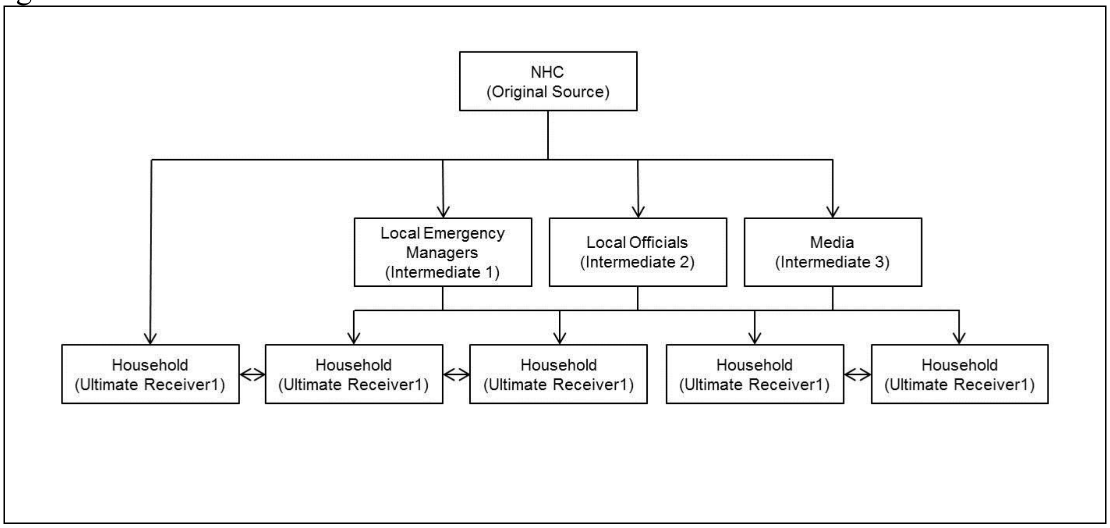
FIGURES

Figure A1 Information flow in the PADM*



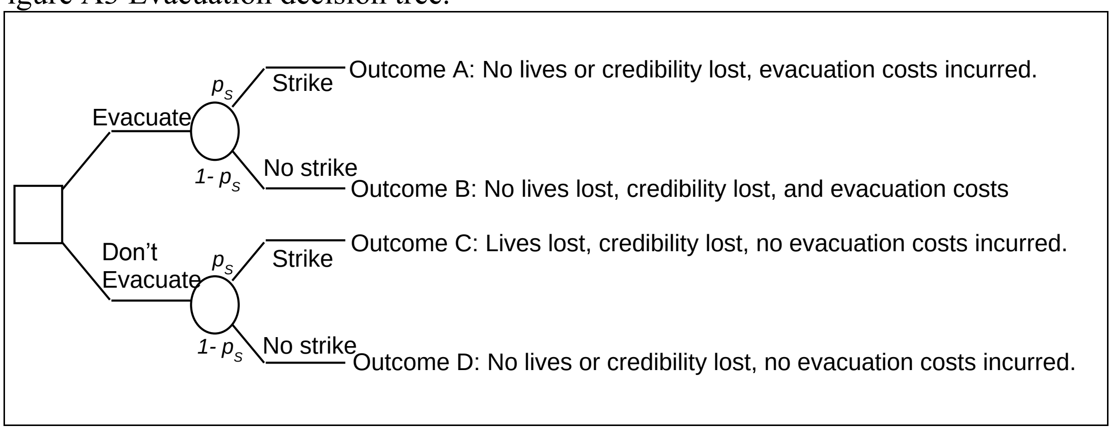
*from Lindell and Perry (2004)

Figure A2 Hurricane information communication network model*



*modified from Lindell and Perry (2004)

Figure A3 Evacuation decision tree.



*modified from Wu et . al. (2013)

Figure A4 Jefferson County risk area map

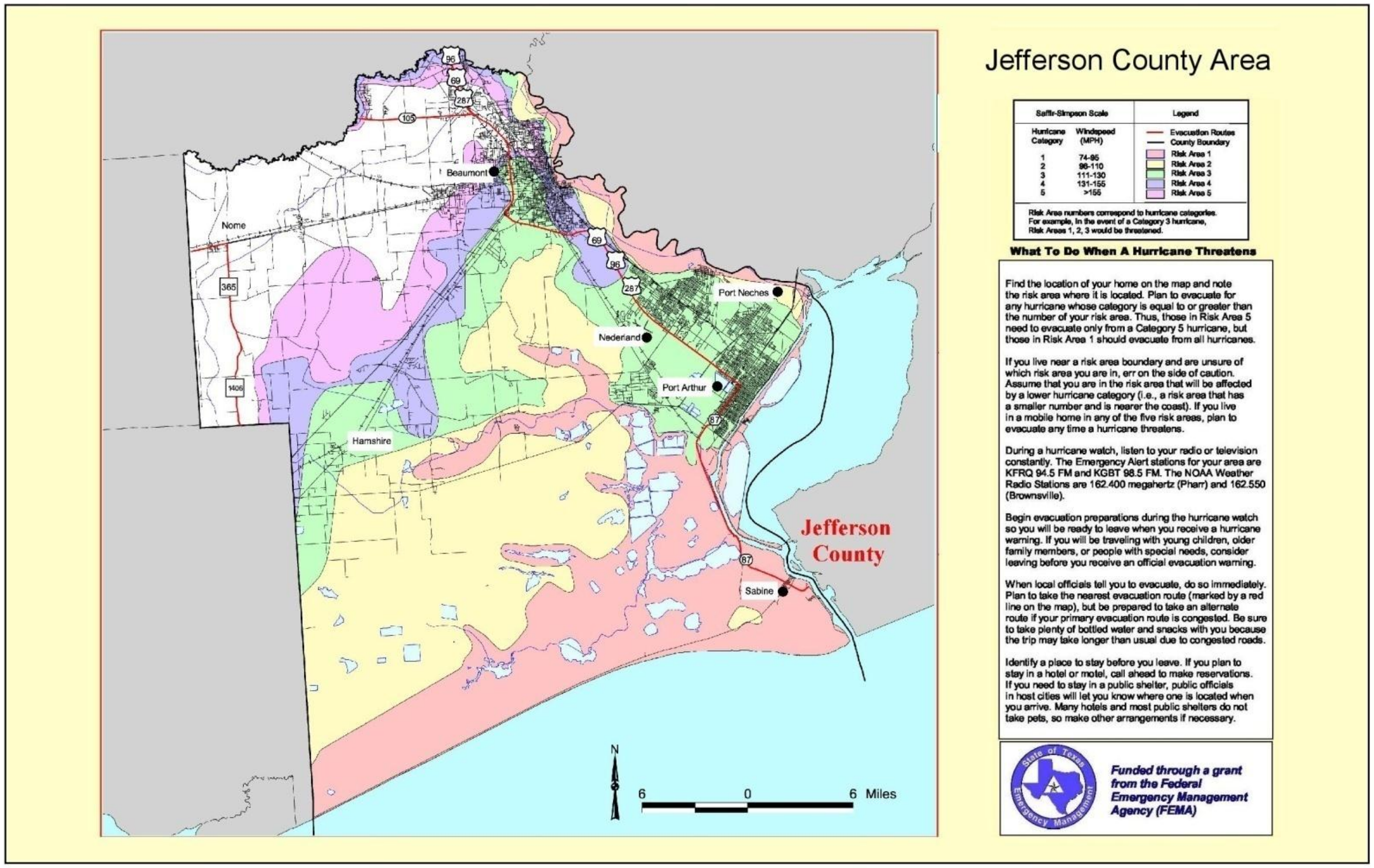


Figure A5 Cameron County risk area map

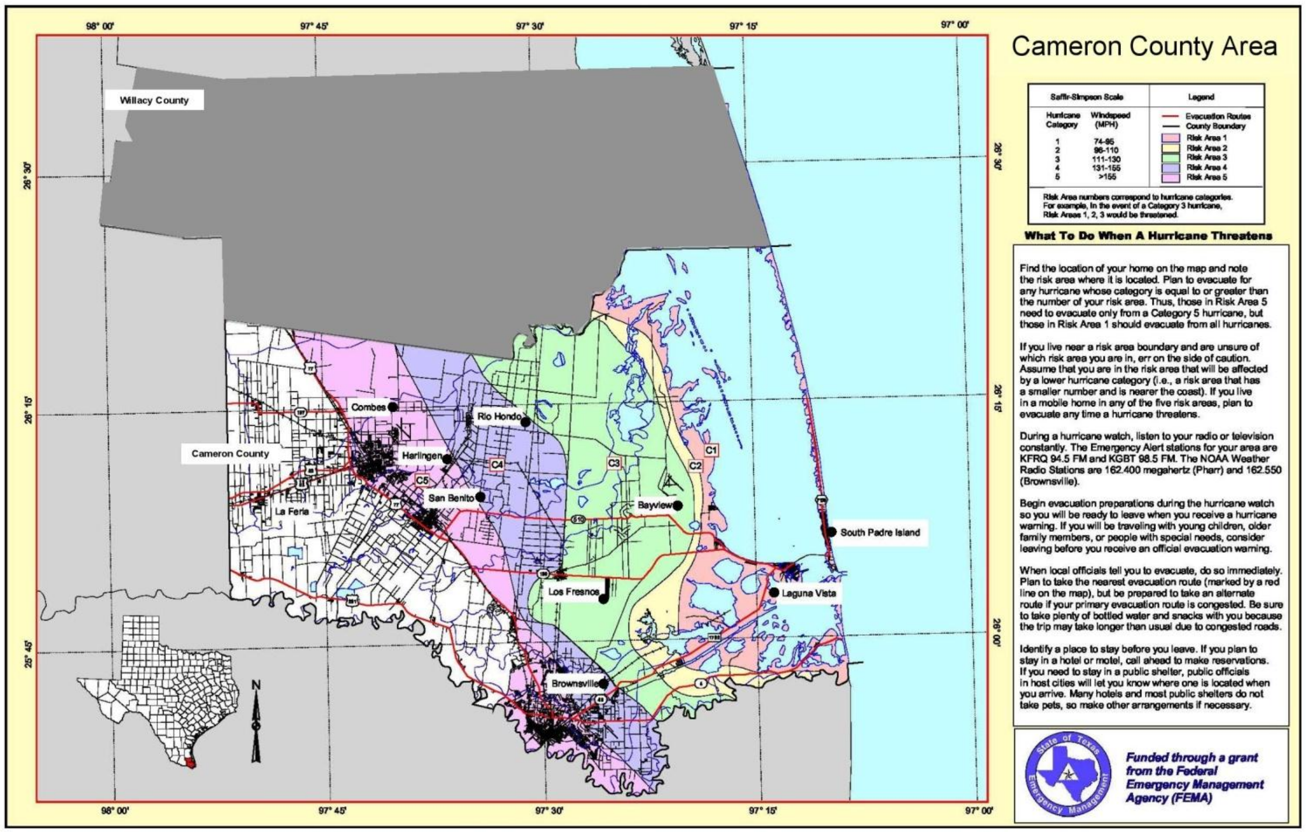


Figure A6 Gulf Coast counties map

Figure A7 *DynaSearch* display—hurricane forecast advisory 1

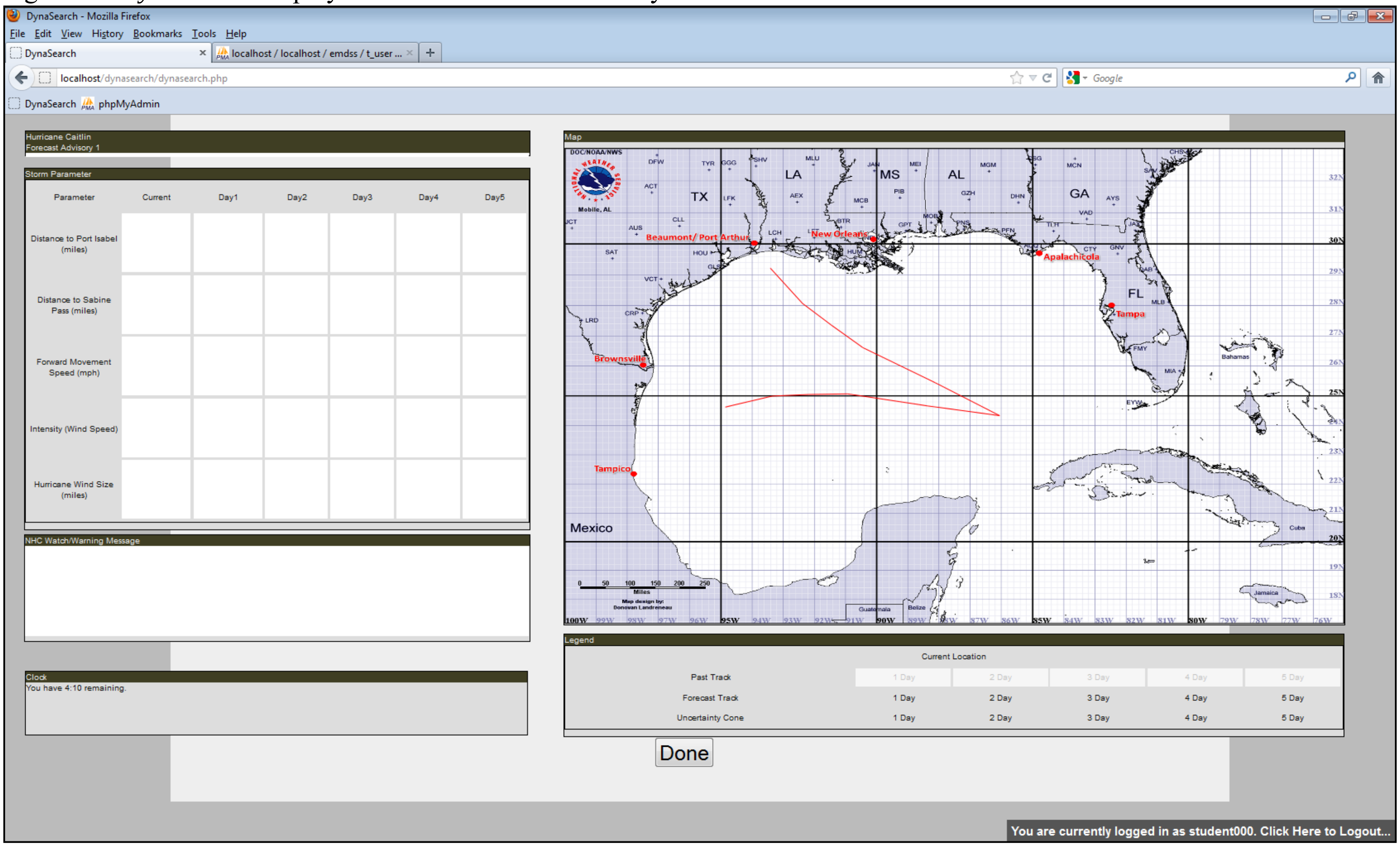


Figure A8 Experiment conceptual model

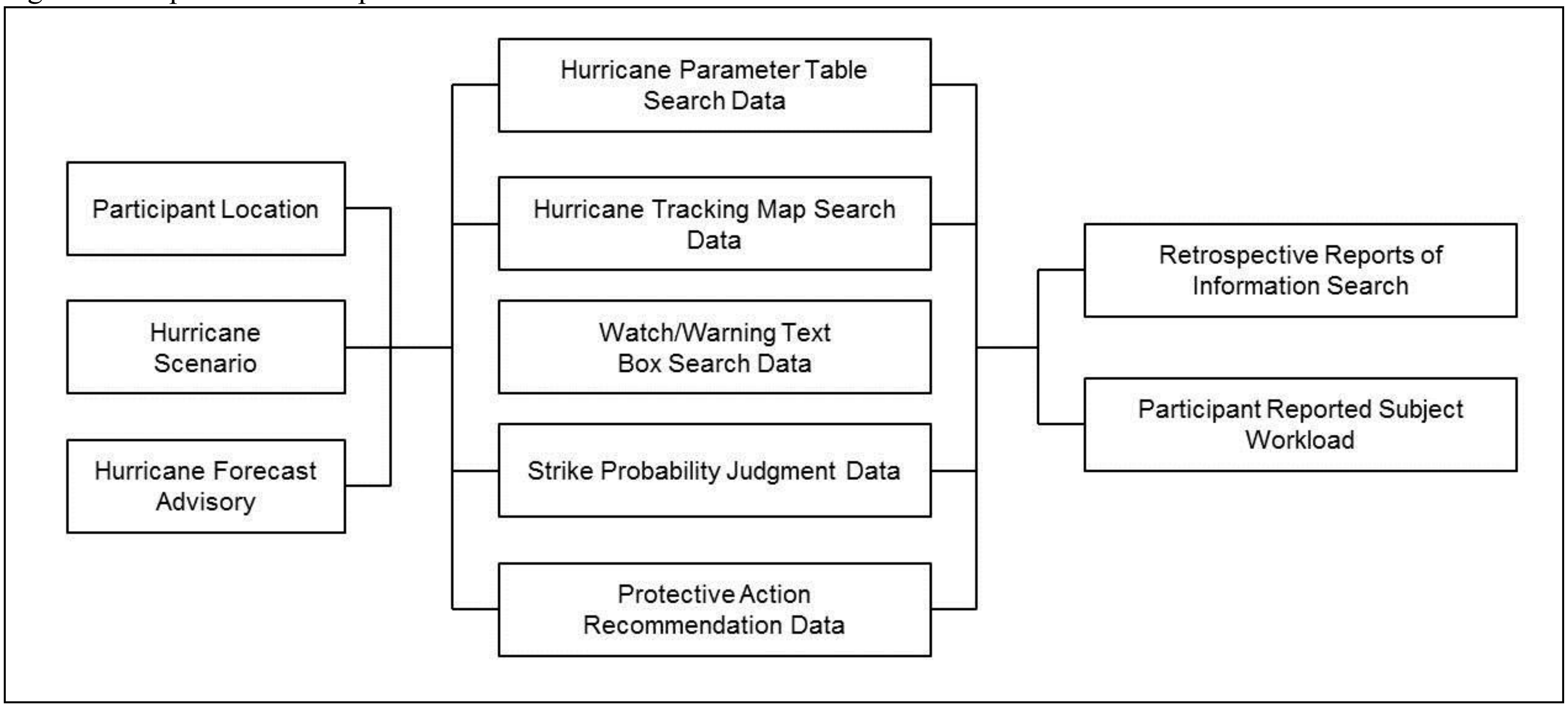


Figure A9: Average click counts and click durations for the first and fourth hurricane scenarios.

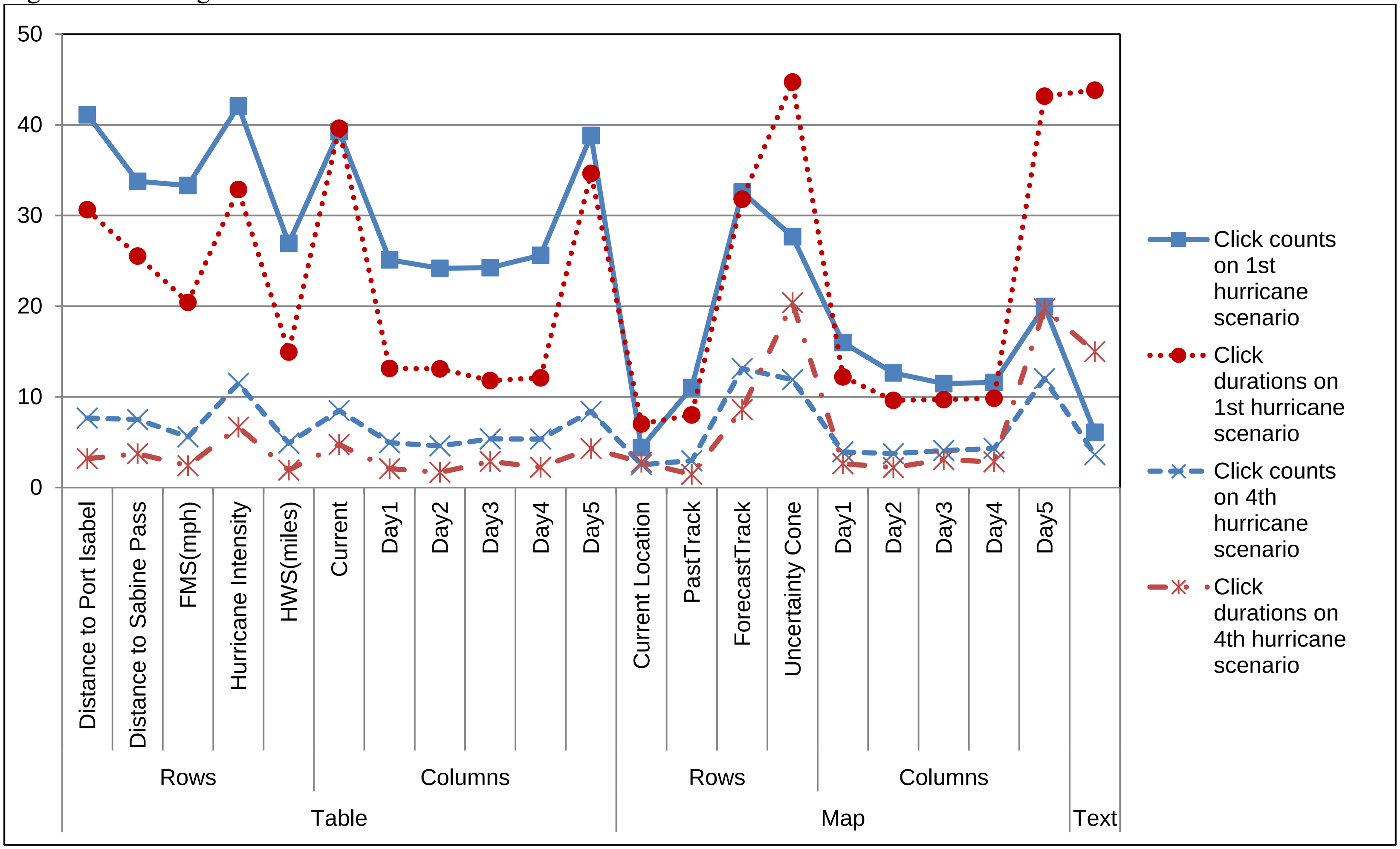
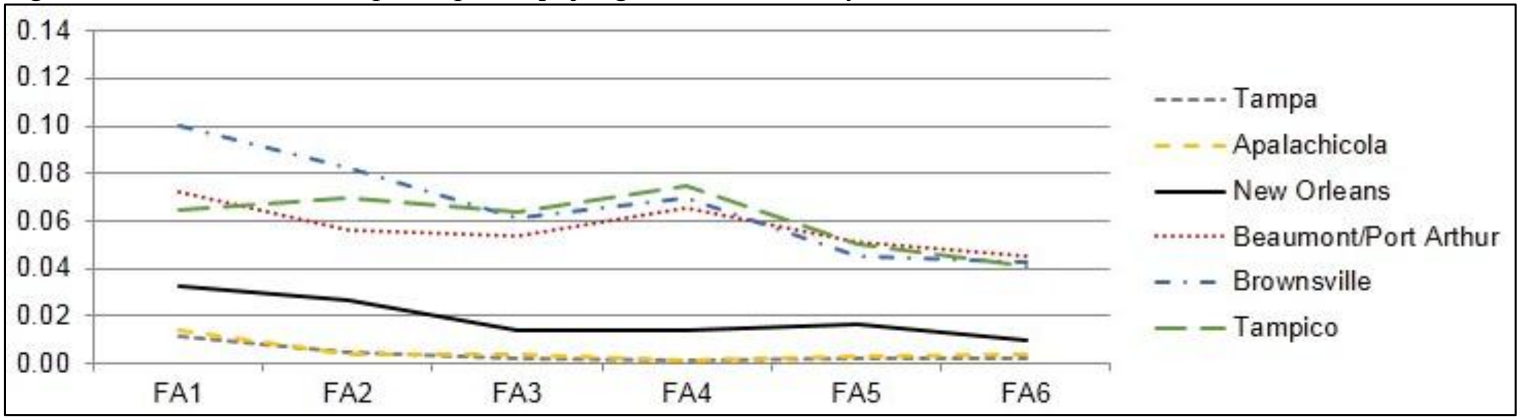
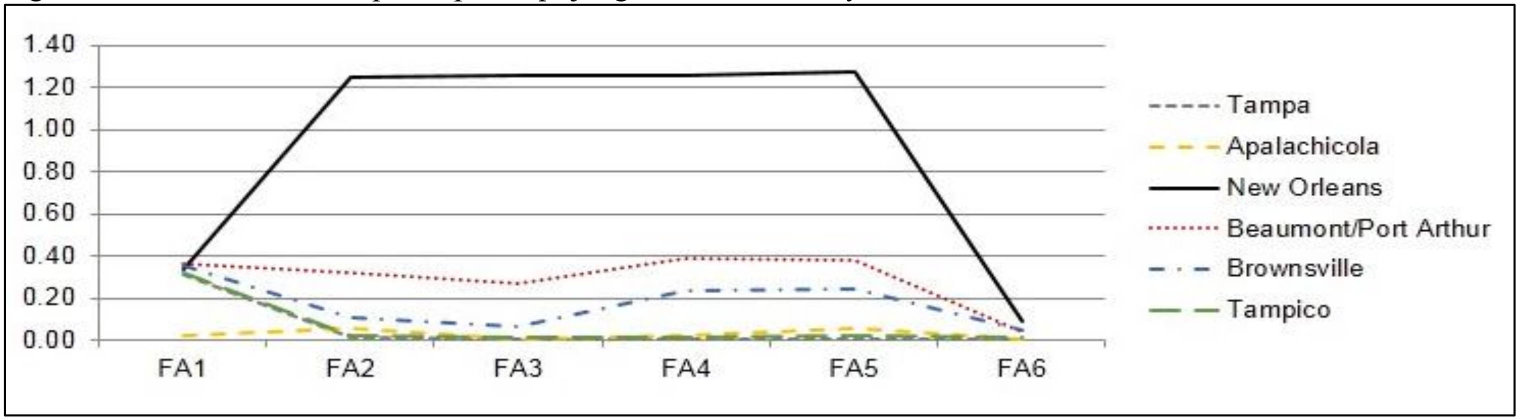


Figure A10: The variance in participants' p_s judgment for each city in Hurricane A condition



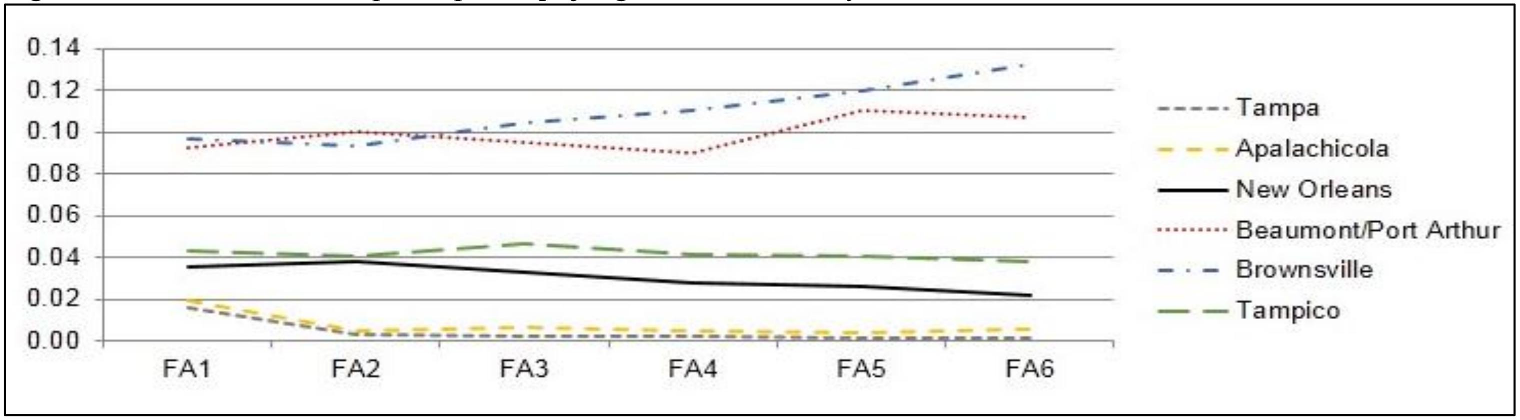
FA = Forecast Advisory

Figure A11: The variance in participants' p_s judgment for each city in Hurricane B condition



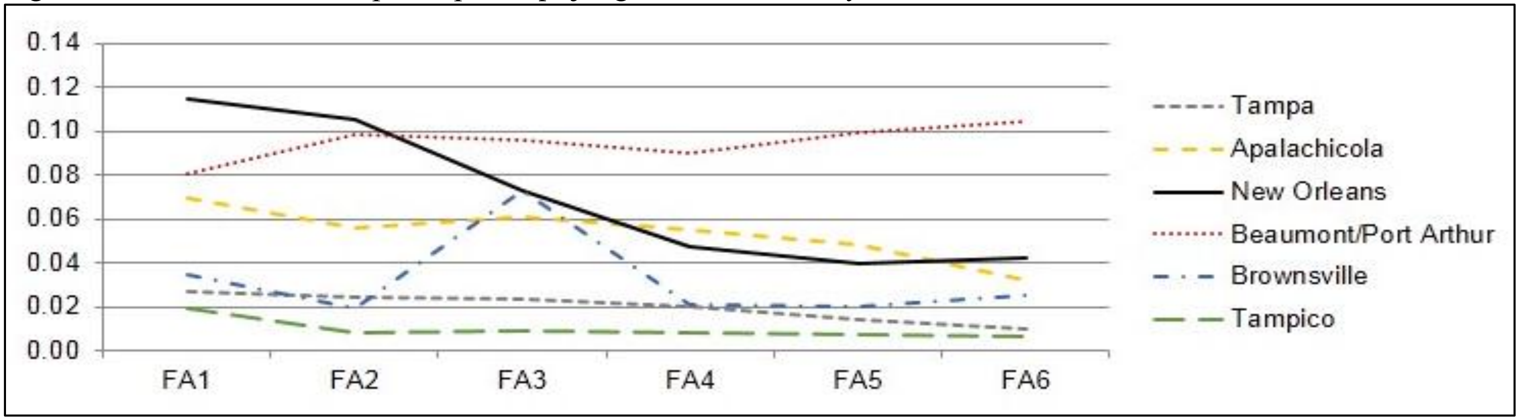
FA = Forecast Advisory

Figure A12: The variance in participants' p_s judgment for each city in Hurricane C condition



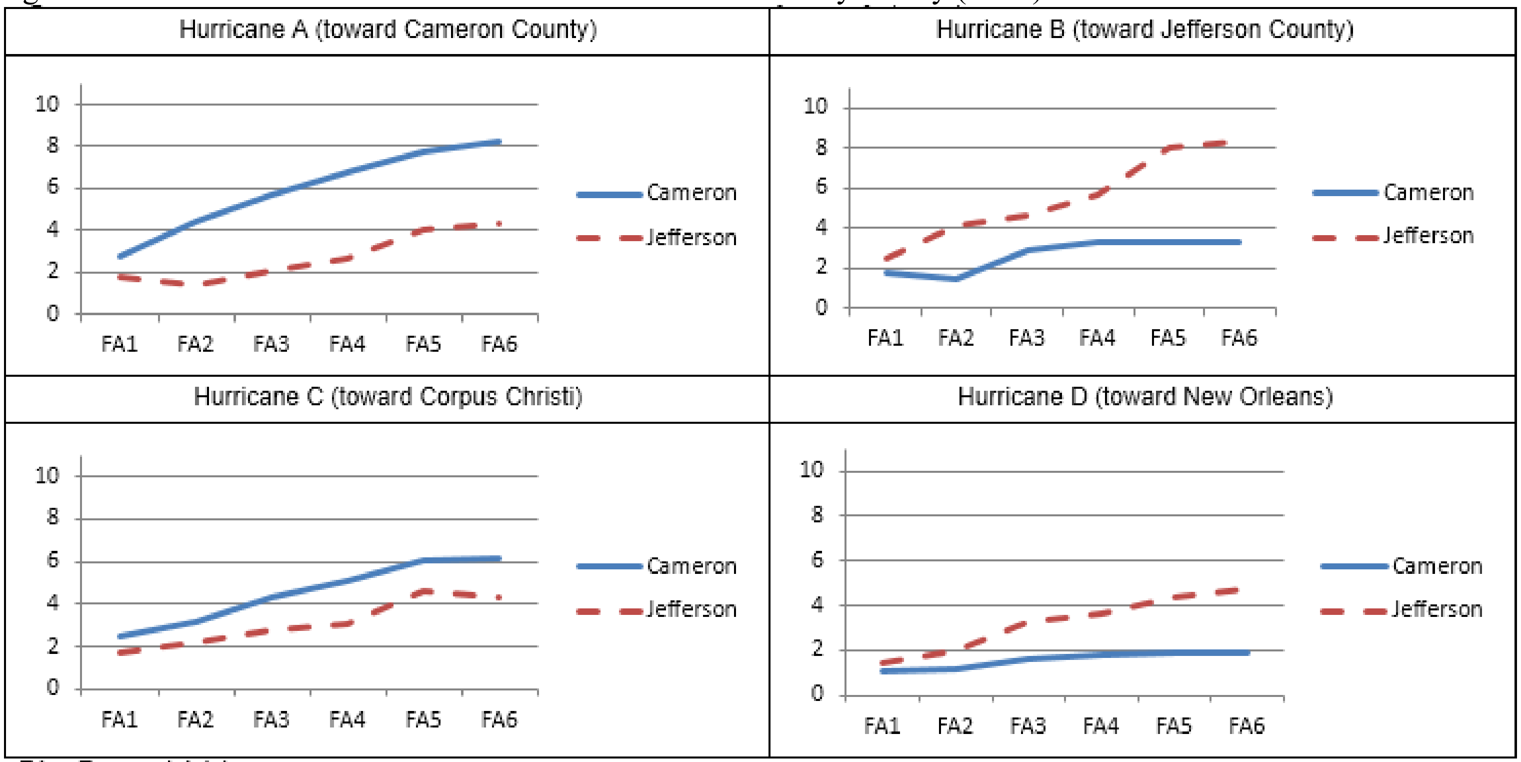
FA = Forecast Advisory

Figure A13: The variance in participants' p_s judgment for each city in Hurricane D condition



FA = Forecast Advisory

Figure A14: Mean number of PARs over six forecast advisories by county (n=80)



FA = Forecast Advisory

APPENDIX B

TABLES

Table B1 Cameron County evacuation time estimates

Saffir-Simpson Category	Category One	Category Two	Category Three	Category Four	Category Five
Risk Area	1	2	3	4	5
ETE(hrs)	15	21	28	32	33

Table B2 Jefferson County evacuation time estimates

Saffir-Simpson Category	Category One	Category Two	Category Three	Category Four	Category Five
Risk Area	1	2	3	4	5
ETE(hrs)	15	21	28	32	33

Table B3: Descriptive statistics for click counts for each type of hurricane forecast advisory element (n=80).

Hurricane Forecast Advisory Element	Mean	S.D.
Hurricane Parameter Table cells	13.80	7.54
Graphic Hurricane Map cells	7.81	3.98
Hurricane Warning/Watch message	.76	.63

F(2,158)=159.495, *p*<.01

Table B4: Descriptive statistics for click duration (second) for each type of hurricane forecast advisory element (n=80).

Hurricane Forecast Advisory Element	Mean	S.D.
Hurricane Parameter Table cells	8.38	4.89
Graphic Hurricane Map cells	9.09	5.12
Hurricane Warning/Watch message	4.32	4.89

F(2,158)=35.315, *p*<.01

Table B5: Descriptive statistics of hurricane forecast advisory elements self-report variables (n=80).

	Categories	Variables	M	S.D
Survey Question: To what extent do you use hurricane forecast advisory elements? (Not at all=1; Small extent=2; Moderate extent=3; Great extent=4; Very great extent=5)	Information Table Items	1. Storm distance from Port Isabel	1.81	1.22
		2. Storm distance from Lake Sabine	1.89	1.26
		3. FMS	2.00	1.06
		4. Intensity	2.53	1.11
		5. Wind Size	2.08	1.17
	Map Item	6. Current Position	3.30	.89
		7.Past Track	2.38	1.17
		8.Forecast Track	3.34	.87
		9.Uncertainty cone	3.44	.91
	Text box item	10. Watch/warning message	2.16	1.46

Table B6: Over all frequency of clicks for hurricane tracking map display element and its time horizon (n=80)

	Mean	S.D.	Test result
Hurricane tracking map display element			
Clicks count			
Current location	13.53	20.67	
Past track	24.05	31.92	$F_{3,237}$=108.657, p<.01
Forecast track	80.23	46.15	
Uncertainty cone	69.66	33.29	
Click duration			
Current location	18.39	27.58	
Past track	14.55	17.77	$F_{3,237}$=101.367, p<.01
Forecast track	69.25	47.30	
Uncertainty cone	115.93	76.80	
Hurricane tracking map time horizon			
Clicks count			
Day 1	32.69	28.46	
Day 2	28.29	22.33	
Day 3	26.83	19.45	$F_{4,316}$=61.649, p<.01
Day 4	28.00	18.18	
Day 5	59.14	25.00	
Click duration			
Day 1	23.86	23.46	
Day 2	20.84	19.08	
Day 3	22.09	19.09	$F_{4,316}$=110.826, p<.01
Day 4	22.34	18.17	
Day 5	110.61	73.13	

Table B7: Over all frequency of clicks for hurricane parameter table and its time horizon (n=80)

	Mean	S.D.	Test result
Hurricane parameter table display element			
Click count			
Distance to Port Isabel	71.90	50.37	
Distance to Sabine Pass	63.78	45.66	
Forward movement speed	58.05	36.80	$F_{4,316}$=20.413, p<.01
Intensity	88.69	55.41	
Hurricane wind radius	48.75	33.05	
Click duration			
Distance to Port Isabel	45.07	29.30	
Distance to Sabine Pass	40.76	31.48	
Forward movement speed	31.51	22.10	$F_{4,316}$=25.346, p<.01
Intensity	59.85	49.76	
Hurricane wind radius	23.97	17.40	
Hurricane parameter table time horizon			
Click count			
Current	74.60	54.64	
Day1	46.34	32.80	
Day2	43.63	31.26	$F_{5,395}$=19.816, p<.01
Day3	45.35	31.72	
Day4	47.31	32.87	
Day5	73.94	52.66	
Click duration			
Current	62.09	55.09	
Day1	22.65	22.17	
Day2	21.15	19.02	$F_{5,395}$=36.729, p<.01
Day3	21.05	17.57	
Day4	20.23	15.97	
Day5	53.99	42.99	

Table B8: Respondents' search pattern on hurricane parameter table for each hurricane scenario by hurricane scenario sequence

	Hurricane parameter table				Hurricane tracking map				Message box				N
	Click count		Click duration		Click count		Click duration		Click count		Click duration		
	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.	
Hurricane A													
Sequence 1*	72.25	42.57	37.94	23.93	37.75	20.90	39.29	20.20	4.35	3.60	20.03	22.10	20
Sequence 2**	189.35	111.40	112.19	60.17	76.30	55.13	75.51	36.17	6.00	4.95	32.75	37.28	20
Sequence 3***	39.85	36.20	19.45	16.52	34.65	21.01	32.53	23.50	3.70	3.66	12.81	19.63	20
Sequence 4****	46.95	45.57	18.86	14.81	31.85	17.23	35.04	21.64	3.65	3.83	14.64	22.71	20
Total	87.10	88.95	47.11	51.15	45.14	36.69	45.59	31.08	4.43	4.08	20.06	27.02	80
Hurricane B													
Sequence 1	41.95	27.93	24.14	26.47	29.60	16.28	30.44	21.74	4.40	3.63	16.64	22.31	20
Sequence 2	66.70	43.31	33.90	29.98	38.40	35.76	40.56	31.20	3.50	3.73	22.30	33.14	20
Sequence 3	46.00	40.26	27.02	29.03	43.85	25.79	47.93	35.54	4.30	4.44	21.44	36.57	20
Sequence 4	171.10	94.34	113.60	66.00	69.70	31.74	76.26	42.92	5.40	4.31	54.78	61.68	20
Total	81.44	77.28	49.67	55.02	45.39	31.61	48.80	37.26	4.40	4.02	28.79	43.05	80
Hurricane C													
Sequence 1	171.70	69.99	120.64	54.08	81.30	25.73	112.24	59.08	7.40	4.59	41.75	35.48	20
Sequence 2	45.65	42.98	21.01	25.72	37.20	34.19	43.18	41.67	3.50	3.32	15.35	21.96	20
Sequence 3	79.80	71.32	48.94	44.77	56.60	32.11	73.89	46.37	6.00	7.07	31.87	49.24	20
Sequence 4	37.35	39.44	15.77	14.30	24.70	16.52	28.65	18.92	3.35	3.90	8.78	11.13	20
Total	83.63	78.07	51.59	56.25	49.95	34.88	64.49	53.86	5.06	5.13	24.44	34.71	80
Hurricane D													
Sequence 1	48.45	32.71	23.98	19.83	36.20	21.61	46.01	29.16	5.05	3.78	27.33	30.27	20
Sequence 2	29.30	28.46	12.18	16.61	32.95	32.14	41.24	37.61	3.00	3.11	21.69	45.17	20
Sequence 3	176.70	94.52	151.17	87.16	75.45	44.41	102.18	64.39	5.55	5.53	46.04	46.98	20
Sequence 4	61.55	64.29	23.86	18.56	43.35	21.40	47.59	24.32	3.85	4.08	26.11	44.34	20
Total	79.00	83.37	52.80	73.21	46.99	35.12	59.25	48.08	4.36	4.26	30.29	42.46	80
Wilks' λ Statistics	$F_{18,454}$=25.934 (p<.01)				$F_{18,454}$=14.807 (p<.01)				$F_{18,454}$=5.207 (p<.01)				

*Sequence 1 is hurricanes C, A, D, and then B
**Sequence 2 is hurricanes A, B, C and then D
***Sequence 3 is hurricanes D, C, B and then A
****Sequence 4 is hurricane B, D, A and then C

Table B9:Cities' mean p_s for each forecast advisory (Hurricane A)

Hurricane Scenario	City	FA1	FA2	FA3	FA4	FA5	FA6	F-statistic
A	Brownsville (Cameron County, TX)	.60	.76	.79	.83	.87	.88	26.96**
B	Beaumont /Port Arthur (Jefferson County, TX)	.60	.80	.88	.89	.93	.90	14.69**
C	Beaumont /Port Arthur (Jefferson County, TX)	.42	.37	.36	.31	.32	.31	3.01*
	Brownsville (Cameron County, TX)	.47	.60	.58	.51	.54	.48	3.39**
D	New Orleans, LA	.51	.69	.78	.84	.87	.89	47.15**

*statistically significant at .05 level
**statistically significant at .01 level

Table B10: Mean p_s for Hurricane A (n=80)

Forecast Advisory	Location	M	S.D.	t-statistic (Test Value=0)
1	Tampa, FL	.05	.11	4.45**
	Apalachicola, FL	.06	.12	4.88**
	New Orleans, LA	.14	.18	6.91**
	Beaumont /Port Arthur, TX	.32	.27	10.60**
	Brownsville, TX	.59	.32	16.89**
	Tampico, Mexico	.31	.25	10.83**
2	Tampa, FL	.03	.07	3.65**
	Apalachicola, FL	.03	.06	4.41**
	New Orleans, LA	.10	.16	5.27**
	Beaumont /Port Arthur, TX	.24	.24	9.04**
	Brownsville, TX	.75	.29	23.52**
	Tampico, Mexico	.29	.26	9.93**
3	Tampa, FL	.02	.04	3.35**
	Apalachicola, FL	.02	.06	3.67**
	New Orleans, LA	.07	.12	5.00**
	Beaumont /Port Arthur, TX	.21	.23	8.24**
	Brownsville, TX	.79	.25	28.73**
	Tampico, Mexico	.25	.25	8.97**
4	Tampa, FL	.01	.03	2.62**
	Apalachicola, FL	.01	.04	3.03**
	New Orleans, LA	.05	.12	3.95**
	Beaumont /Port Arthur, TX	.23	.26	8.03**
	Brownsville, TX	.83	.26	28.31**
	Tampico, Mexico	.24	.27	7.83**
5	Tampa, FL	.01	.05	2.61**
	Apalachicola, FL	.02	.05	3.27**
	New Orleans, LA	.05	.13	3.19**
	Beaumont /Port Arthur, TX	.17	.23	6.85**
	Brownsville, TX	.87	.21	36.95**
	Tampico, Mexico	.18	.22	7.23**
6	Tampa, FL	.02	.05	2.80**
	Apalachicola, FL	.02	.06	2.81**
	New Orleans, LA	.04	.10	3.40**
	Beaumont /Port Arthur, TX	.13	.21	5.67**
	Brownsville, TX	.88	.21	38.23**
	Tampico, Mexico	.13	.20	5.56**

*statistically significant at .05 level

**statistically significant at .01 level

Table B11: Mean p_s for Hurricane B (n=80)

Forecast Advisory	Location	M	S.D.	t-statistic (Test Value=0)
1	Tampa, FL	.10	.56	1.67**
	Apalachicola, FL	.09	.15	5.22**
	New Orleans, LA	.42	.58	6.37**
	Beaumont /Port Arthur, TX	.60	.61	8.84**
	Brownsville, TX	.36	.60	5.37**
	Tampico, Mexico	.15	.57	2.34*
2	Tampa, FL	.04	.14	2.73**
	Apalachicola, FL	.08	.25	2.90**
	New Orleans, LA	.50	1.12	3.96**
	Beaumont /Port Arthur, TX	.80	.57	12.58**
	Brownsville, TX	.25	.32	6.91**
	Tampico, Mexico	.07	.16	3.68**
3	Tampa, FL	.03	.08	3.16**
	Apalachicola, FL	.04	.11	3.71**
	New Orleans, LA	.47	1.12	3.74**
	Beaumont /Port Arthur, TX	.88	.52	15.14**
	Brownsville, TX	.22	.26	7.62**
	Tampico, Mexico	.05	.13	3.72**
4	Tampa, FL	.02	.06	2.81**
	Apalachicola, FL	.05	.14	3.35**
	New Orleans, LA	.43	1.12	3.47**
	Beaumont /Port Arthur, TX	.89	.63	12.76**
	Brownsville, TX	.21	.48	3.88**
	Tampico, Mexico	.05	.13	3.22**
5	Tampa, FL	.02	.06	2.59*
	Apalachicola, FL	.06	.23	2.28*
	New Orleans, LA	.42	1.13	3.36**
	Beaumont /Port Arthur, TX	.93	.62	13.50**
	Brownsville, TX	.22	.50	3.93**
	Tampico, Mexico	.04	.15	2.67**
6	Tampa, FL	.02	.06	2.81**
	Apalachicola, FL	.04	.10	3.36**
	New Orleans, LA	.23	.31	6.84**
	Beaumont /Port Arthur, TX	.90	.20	40.43*
	Brownsville, TX	.13	.23	4.97**
	Tampico, Mexico	.04	.13	2.47*

*statistically significant at .05 level
**statistically significant at .01 level

Table B12: Mean p_s for Hurricane C (n=80)

Forecast Advisory	Location	M	S.D.	t-statistic (Test Value=0)
1	Tampa, FL	.04	.13	2.86**
	Apalachicola, FL	.07	.14	4.38**
	New Orleans, LA	.16	.19	7.35**
	Beaumont /Port Arthur, TX	.42	.30	12.33**
	Brownsville, TX	.47	.31	13.47**
	Tampico, Mexico	.17	.21	7.20**
2	Tampa, FL	.02	.06	3.62**
	Apalachicola, FL	.04	.07	4.53**
	New Orleans, LA	.12	.19	5.52**
	Beaumont /Port Arthur, TX	.37	.32	10.52**
	Brownsville, TX	.60	.30	17.50**
	Tampico, Mexico	.14	.20	6.29**
3	Tampa, FL	.02	.05	3.25**
	Apalachicola, FL	.03	.08	3.70**
	New Orleans, LA	.11	.18	5.41**
	Beaumont /Port Arthur, TX	.36	.31	10.48**
	Brownsville, TX	.58	.32	16.04**
	Tampico, Mexico	.14	.22	5.63**
4	Tampa, FL	.02	.05	3.18**
	Apalachicola, FL	.03	.07	3.43**
	New Orleans, LA	.08	.17	4.43**
	Beaumont /Port Arthur, TX	.31	.30	9.21**
	Brownsville, TX	.51	.33	13.77**
	Tampico, Mexico	.11	.20	4.89**
5	Tampa, FL	.01	.04	2.71**
	Apalachicola, FL	.02	.06	2.89**
	New Orleans, LA	.07	.16	4.08**
	Beaumont /Port Arthur, TX	.32	.33	8.719**
	Brownsville, TX	.54	.35	13.87**
	Tampico, Mexico	.11	.20	4.80**
6	Tampa, FL	.01	.04	2.59*
	Apalachicola, FL	.02	.07	2.70**
	New Orleans, LA	.06	.15	3.76**
	Beaumont /Port Arthur, TX	.31	.33	8.37**
	Brownsville, TX	.48	.36	11.73**
	Tampico, Mexico	.10	.20	4.39**

*statistically significant at .05 level
**statistically significant at .01 level

Table B13: Mean p_s for Hurricane D (n=80)

Forecast Advisory	Location	M	S.D.	t-statistic (Test Value=0)
1	Tampa, FL	.10	.17	5.62**
	Apalachicola, FL	.27	.26	9.29**
	New Orleans, LA	.51	.34	13.37**
	Beaumont /Port Arthur, TX	.31	.28	9.81**
	Brownsville, TX	.13	.19	6.29**
	Tampico, Mexico	.06	.14	3.94**
2	Tampa, FL	.09	.16	5.10**
	Apalachicola, FL	.21	.24	7.75**
	New Orleans, LA	.69	.33	18.99**
	Beaumont /Port Arthur, TX	.41	.31	11.62**
	Brownsville, TX	.09	.14	5.56**
	Tampico, Mexico	.04	.09	3.49**
3	Tampa, FL	.08	.15	4.48**
	Apalachicola, FL	.20	.25	7.34**
	New Orleans, LA	.78	.27	25.70**
	Beaumont /Port Arthur, TX	.39	.31	11.13**
	Brownsville, TX	.12	.27	3.92**
	Tampico, Mexico	.03	.10	3.15**
4	Tampa, FL	.07	.14	4.59**
	Apalachicola, FL	.19	.23	7.43**
	New Orleans, LA	.84	.22	34.51**
	Beaumont /Port Arthur, TX	.32	.30	9.57**
	Brownsville, TX	.08	.15	5.04**
	Tampico, Mexico	.03	.09	2.97**
5	Tampa, FL	.06	.12	4.12**
	Apalachicola, FL	.14	.22	5.88**
	New Orleans, LA	.87	.20	39.02**
	Beaumont /Port Arthur, TX	.31	.32	8.79**
	Brownsville, TX	.06	.14	3.68**
	Tampico, Mexico	.03	.09	2.88**
6	Tampa, FL	.04	.10	3.43**
	Apalachicola, FL	.11	.18	5.32**
	New Orleans, LA	.89	.21	38.79**
	Beaumont /Port Arthur, TX	.31	.32	8.49**
	Brownsville, TX	.06	.16	3.50**
	Tampico, Mexico	.02	.08	2.66**

*statistically significant at .05 level
**statistically significant at .01 level

Table B14: Participants' mean number of PARs over six forecast advisories for each of the four hurricane scenarios (n=80)

Forecast Advisories	Hurricane A (Brownsville, TX)		Hurricane B (Beaumont /Port Arthur, TX)		Hurricane C (Corpus Christi, TX)		Hurricane D (New Orleans, LA)	
	M	S.D.	M	S.D.	M	S.D.	M	S.D.
FA 1	2.29	3.13	2.13	2.73	2.08	2.82	1.29	2.22
FA 2	2.90	3.39	2.75	3.48	2.68	3.28	1.58	2.59
FA 3	3.90	3.61	3.80	3.52	3.54	3.27	2.43	3.19
FA 4	4.74	3.76	4.46	3.86	4.06	3.62	2.73	3.36
FA 5	5.91	4.05	5.68	4.15	5.34	3.73	3.10	3.79
FA 6	6.29	4.23	5.83	4.32	5.25	3.89	3.29	4.08
F-statistic	$F_{5,395}$=29.69, p<.01		$F_{5,395}$=28.731, p<.01		$F_{5,395}$=20.380, p<.01		$F_{5,395}$=10.107, p<.01	
PARs increase rate	174%		175%		152%		155%	

Table B15: Correlations between p_s and the number of PARs for Brownsville (Cameron County) (n=40)

			Number of PARs					
			FA1	FA2	FA3	FA4	FA5	FA6
		Mean	2.03	2.54	3.64	4.24	4.74	4.90
p_s	FA1	.44	.48	.37	.15	.01	-.06	-.14
	FA2	.47	.37	.50	.34	.16	.09	.02
	FA3	.46	.22	.45	.47	.22	.11	.05
	FA4	.45	.17	.34	.37	.29	.24	.10
	FA5	.45	.07	.17	.23	.23	.25	.14
	FA6	.40	.12	.31	.43	.41	.48	.38

Shaded correlations are statistically significant at p<.05

Table B16: Correlations between p_s and the number of PARs for Beaumont /Port Arthur (Jefferson County) (n=40)

			Number of PARs					
			FA1	FA2	FA3	FA4	FA5	FA6
		Mean	1.86	2.41	3.19	3.75	5.27	5.43
	FA1	.38	.54	.50	.42	.38	.15	.14
	FA2	.42	.58	.60	.53	.47	.46	.43
p_s	FA3	.43	.41	.38	.45	.44	.46	.43
	FA4	.42	.36	.42	.46	.49	.45	.45
	FA5	.42	.33	.30	.38	.44	.54	.47
	FA6	.40	.38	.41	.44	.44	.55	.56

Shaded correlations are statistically significant at $p<.05$

Table B17: Respondents' PARs after viewing Forecast Advisory 6 for each hurricane scenario by county

Number of PARs	M	S.D	N	t-statistic
Hurricane A: Brownsville				
Cameron County Group	8.25	3.22	40	4.66 ($p<.01$)
Jefferson County Group	4.33	4.25	40	
Total	6.29	4.23	80	
Hurricane B:Beaumont /Port Arthur				
Cameron County Group	3.33	3.82	40	-6.33 ($p<.01$)
Jefferson County Group	8.33	3.22	40	
Total	5.83	4.32	80	
Hurricane C:Corpus Christi				
Cameron County Group	6.15	3.79	40	2.11 (*ns*)
Jefferson County Group	4.35	3.83	40	
Total	5.25	3.89	80	
Hurricane D:New Orleans				
Cameron County Group	1.88	3.31	40	-3.29 ($p<.01$)
Jefferson County Group	4.70	4.32	40	
Total	3.29	4.08	80	

$F_{3,76}=33.32$ ($p<.01$)

Table B18 The sum of p_s for each advisory (n=80)

Hurricane	Advisory	M	S.D.	t-statistic (Test Value=1)
A (Brownsville)	1	1.48	.94	4.54**
	2	1.44	.76	5.23**
	3	1.37	.69	4.75**
	4	1.38	.68	4.95**
	5	1.31	.63	4.38**
	6	1.21	.59	3.21**
B (Beaumont /Port Arthur)	1	1.72	2.76	2.32*
	2	1.73	2.34	2.80**
	3	1.69	1.69	3.65**
	4	1.66	2.29	2.56*
	5	1.69	2.51	2.46*
	6	1.35	.63	4.98**
C (Corpus Christi)	1	1.32	.89	3.23**
	2	1.29	.88	2.97**
	3	1.24	.87	2.45*
	4	1.06	.87	.62
	5	1.07	.91	.74
	6	.98	.89	-.22
D (New Orleans)	1	1.39	.97	3.57**
	2	1.51	.94	4.89**
	3	1.59	.92	5.77**
	4	1.54	.79	6.12**
	5	1.47	.77	5.44**
	6	1.43	.71	5.39**

*statistically significant at .05 level
**statistically significant at .01 level

Table B19 Differences in p_s judgments and PARs by citizenship

Decision Making		M	S.D	N	t-statistic
Strike Probability Decisions (p_s)	Tampa				
	US Citizen	.04	.06	36	.15 (*ns*)
	International Student	.04	.06	44	
	Total	.04	.06	80	
	Apalachicola				
	US Citizen	.07	.08	36	.72 (*ns*)
	International Student	.08	.08	44	
	Total	.08	.08	80	
	New Orleans				
	US Citizen	.33	.32	36	.15 (*ns*)
	International Student	.34	.14	44	
	Total	.34	.23	80	
	Beaumont/Port Arthur				
	US Citizen	.39	.18	36	1.99($p < .05$)
	International Student	.47	.18	44	
	Total	.43	.19	80	
	Brownsville				
	US Citizen	.37	.15	36	2.07($p < .05$)
	International Student	.44	.16	44	
	Total	.41	.16	80	
	Tampico				
	US Citizen	.09	.09	36	1.81 (*ns*)
	International Student	.14	.14	44	
	Total	.12	.12	80	
Protective Action Recommendation Decisions (PARs)	Total Number of PARs				
	US Citizen	3.06	1.52	36	2.90($p < .01$)
	International Student	4.17	1.84	44	
	Total	3.67	1.78	80	

Wilks' λStatistics $F_{7,7}$=2.09 (p<.01)

Table B20: Difference in p_s judgment and PARs by hurricane evacuation experience

Decision Making		M	S.D	N	t-statistic
	Tampa				
	Group A (without exp)*	.03	.06	60	1.70 (*ns*)
	Group B (with exp)*	.06	.07	20	
	Total	.04	.06	80	
	Apalachicola				
	Group A (without exp)	.06	.07	60	2.84($p<.01$)
	Group B (with exp)	.12	.09	20	
	Total	.08	.08	80	
	New Orleans				
	Group A (without exp)	.32	.25	60	.91 (*ns*)
	Group B (with exp)	.38	.16	20	
Strike Probability Decisions (p_s)	Total	.34	.23	80	
	Beaumont/Port Arthur				
	Group A (without exp)	.41	.17	60	2.04($p<.05$)
	Group B (with exp)	.51	.22	20	
	Total	.43	.19	80	
	Brownsville				
	Group A (without exp)	.39	.14	60	2.42($p<.05$)
	Group B (with exp)	.48	.18	20	
	Total	.41	.16	80	
	Tampico				
	Group A (without exp)	.09	.10	60	2.33($p<.05$)
	Group B (with exp)	.18	.16	20	
	Total	.12	.12	80	
Protective Action Recommendation Decisions (PARs)	Total Number of PARs				
	Group A (without exp)	3.55	1.67	60	1.04(*ns*)
	Group B (with exp)	4.03	2.10	20	
	Total	3.67	1.78	80	

Wilks' λStatistics $F(7.,72)=2.210$ ($P<.05$)

*Group A: participants without any hurricane evacuation experience; Group B: participants with hurricane evacuation experience

Table B21: The percentage of participants who recommend evacuation on each risk area after viewing Forecast Advisory 5 (Hurricane A, Cameron County condition only, n=40)

Risk area	Percentage of participants who recommend evacuation	S.D
1	78%	.42
2	70%	.46
3	55%	.50
4	33%	.47
5	28%	.45

$F_{4,156}$=17.64, p<.01

Table B22: The percentage of participants recommend evacuation on each risk area after viewing Forecast Advisory 5 (Hurricane B, Jefferson County condition only, n=40)

Risk area	Percentage of participants who recommend evacuation	S.D
1	65%	.48
2	65%	.48
3	60%	.50
4	50%	.51
5	48%	.51

$F_{4,156}$=1.94 (*ns*)