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Modeling Evacuees' Intended Responses to a Phased Hurricane Evacuation Order

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Abstract: Phased evacuation is an under-studied strategy, and relatively little is known about compliance with the phased process. This study modelled households' responses to a phased evacuation order based on a household behavioral intention survey. About 66% of the evacuees reported that they would comply with a phased evacuation order. A latent class logit model sorted evacuees into two classes ("evacuation reluctant" and "evacuation keen") by their stakeholder perceptions (i.e., whether government agencies have responsibility for the safety of individuals) and evacuation perceptions (i.e., whether evacuation is an effective protective action), while risk perception becomes non-significant in interpreting their compliance behavior to a phased evacuation order. Those that evacuate to the home of friends/relatives and/or bring more vehicles during evacuation are less likely to follow phased evacuation orders. "Evacuation reluctant" individuals with a longer housing tenure are more likely to follow phased evacuation orders. "Evacuation keen" individuals with a longer travel delay expectation are more likely to comply with phased evacuation orders. This study not only unveiled the impacts of incorporating three psychological perceptions (i.e., risk, stakeholder, and evacuation perceptions) in modeling compliance behavior (e.g., parameter sign/significance shift) but also provides insights of evacuees' compliance behavior to phased evacuation orders.

Keywords: hurricane evacuation; phased evacuation; warning responses; behavioral intention; compliance

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1. Introduction

Severe traffic jams occurred in Florida during Hurricane Irma (2017) because over six million people were ordered to evacuate using a road system that could not manage the associated traffic [1]. Westbound travel times from Jacksonville Beach to Tallahassee were doubled during the evacuation, and northbound travel from Florida to Georgia was even worse [2]. Theoretically, phased (staged or sequenced) evacuation orders could have been issued to increase evacuation efficiency and reduce travel times by spreading the demand over time [3]. This demand-management strategy identifies and sequences different "evacuation phases" (generally) by risk level and assigns different suggested evacuation times to each. Typically this is done either geographically, with higher-risk zones starting first [4,5] or by evacuating people with distinct characteristics first, such as tourists and special-needs residents prior to other residents [6,7]. Phased evacuation strategies exist in the emergency management plans of several coastal states (e.g., Florida, Louisiana, and Texas) that are affected by hurricanes relatively frequently [4,8,9]. Even so, the effectiveness of this strategy is not well understood given that household decision-making has a significant effect on the strategy's effectiveness. Furthermore, few studies have examined how households react to this approach directly.

Prior studies of human decision-making for evacuations have well documented that household behavioral responses to evacuation orders vary. From the household point of view, responding to such orders is complicated, and decisions are ultimately determined by a multi-dimensional set of factors that influence their decisions, including messaging, past experiences, risk perception, resources, personalization, and many other factors. These factors interact with each other to drive whether to evacuate and when to evacuate, among other choices [10,11]. Authorities often view these households' responses in simple terms of compliance or non-compliance to the order. In looking at such behavior, it is clear that not everyone from high-risk areas complies with evacuation notices [12] and that from event to event there are variations in the levels of compliance. One recent study suggested that this ranges from 12% to 97% in different cases of hurricane evacuations [13]. Furthermore, not everyone in relatively low-risk areas without evacuation notices stays [12]. Among those who evacuate, some do so before the evacuation orders officially begin, while others depart later—after the hurricane path becomes more certain [14]. Considering these behavioral patterns, it is challenging to predict what proportion of the population is likely to comply with phased evacuation.

This study begins to address this gap by examining the rate of intended phased evacuation compliance and identifying factors associated with this compliance based on responses from a household evacuation behavioral intent survey of 415 households from the Hampton Roads, VA area. While an imperfect approximation of behavior during a real hurricane, such behavioral intention data provide an improved insight into this issue over the common convention of assuming 100% compliance with orders or arbitrarily setting compliance factors with little empirical evidence. This study presents statistical models to understand household compliance behavior. The compliance rates and the estimated latent class logit model can help researchers and evacuation planners develop more realistic transportation models to analyze the impact of phased evacuations. The model's parameters and related interpretations also lead to suggestions for emergency management agencies about what they can do to motivate greater compliance in practice.

The remainder of this paper is organized as follows. Section 2 describes how phased evacuations are implemented in current practices and provides insights from related research. This section also presents a review of studies focused on responses to evacuation orders, which guides variable selection and hypothesis formation for responses to a phased evacuation order. Section 3 describes the household survey conducted in the Hampton Roads area and presents the associated descriptive analysis. In Section 4, the binary logit model and the latent class logit model are introduced and their use in estimating the likelihood of compliance is described. Then, Section 5 presents the estimated logit models. Parameters are then interpreted and discussed to understand the intended compliance behavior of evacuees living in the Hampton Roads area. The final section provides conclusions and future directions.

2. Literature Review and Hypotheses

2.1. Current Practices and Studies of Phased Evacuation

Phased evacuation is a hurricane evacuation demand-management strategy that is intended to spread peak travel demand over time. The approach typically identifies people who are exposed to greater risk (such as lower-lying areas) and orders these groups to leave the endangered area at an earlier time. The following examples illustrate this approach. Louisiana implements phased evacuation by identifying regions and specifying when they should evacuate: areas south of the Intracoastal Waterway (50 h before the onset of tropical storm winds), areas south of I-10 (40 h before the onset of tropical storm winds), and areas on the east bank of the Mississippi River in the New Orleans metropolitan area (30 h before the onset of tropical storm winds) [4]. How these regions are determined varies. In the example above, natural bodies of water (the Intracoastal Waterway and the Mississippi River) and major highways (I-10) are used, while Texas uses zip codes [9] and Florida uses mile marks [8]. In addition to these descriptions, zones are also often mapped and color-coded for visual presentation, and individuals can check where they are located by entering addresses on interactive webpages or in apps [15].

Studies that predict the benefits of this strategy using optimization or simulation approaches generally assume that evacuees will follow the guidance as ordered and without shifting the departure time, destination, or route [16–24]. Even with the assumption of full compliance (100%), Zhang et al. [25] found that phased evacuation does not significantly improve evacuation performance (in terms of the percentage of completed evacuations and average travel speed) when the level of demand or the congestion in the road network is low. Alternatively, several simulation studies (e.g., Chiu et al. [26]) used a fixed partial compliance rate to evaluate whether phased evacuation is an effective demand-management strategy given different assumptions. Chiu et al. [26] found that the phased evacuation strategy further improves the traffic situation when it is implemented with the contra-flow strategy, especially for zones of higher risk. Pel et al. [27], who tested multiple assumed compliance rates in their study of optimizing evacuation instructions, even found that lower levels of compliance sometimes lead to higher evacuation efficiency. This body of knowledge, with its mixed results, highlights the importance of additional study to understand compliance rates and their effects on evacuation.

Some studies modeled hurricane-evacuation order-compliance behavior without considering phasing. Yin et al. [28] studied evacuation order compliance behavior with a random parameter binary logit model based on data collected from Hurricane Ivan (2004). The statistical significance of the random coefficients for order issuance reveals household heterogeneity in responding to evacuation orders (i.e., order compliance and the presence of shadow evacuation). Ling et al. [29] further distinguished those who received an evacuation order from those who did not with data from Hurricane Matthew (2016). Two separate random parameter logit models were estimated to understand order-compliance behavior and shadow evacuation, respectively. These researchers found that consistent/sufficient warning information and large/diverse social networks both encourage evacuation-order compliance, which reminds public agencies to be consistent in their warning dissemination and pay attention to isolated households.

There is a wide range of factors that could influence warning-response behavior. Lindell and Perry's protective action decision model (PADM) is one of the theoretical frameworks that organize factors and was designed for disaster scenarios, specifically [3,10,30]. The framework starts with the environmental/social cues, information sources/channels, and warning messages, which flow into a pre-decision process, influence perceptions, and eventually affect the decision-making of people with different characteristics. The next subsection discusses these factors by group in detail.

2.2. Factors Affecting Warning Responses

This subsection examines the literature focused on warning responses and interprets that work in terms of the match or mismatch with guidance in agency notices. By reinterpreting warning responses in terms of agency perspectives, we are able to formulate hypotheses for potential explanatory variables that predict "compliance" with phased evacuation expectations. While focusing on a narrower goal than the broader understanding of human behavior, understanding compliance is nonetheless important for predicting the degree to which such interventions are likely to achieve their desired results—a goal that is important for those planning emergency evacuations.

Based on prior research, households choose whether they will comply based on a number of factors. Among others, these factors include receiving warning messages, message content, warning confirmation, warning-source credibility [31–33], perceived risk, and the possession of a plan [34,35]. When warned, households interpret the warning message, try to understand it, attempt to confirm its accuracy with other sources, assess the degree to which that message is relevant to them, and consider if actions are feasible prior to making a decision [11]. Each of these phases can be influenced by a myriad of factors. For example, the degree of perceived risk affects whether the individual thinks they need to take action to protect themselves. The possession of a plan affects whether, and how, the individual implements the protective action [34,35]. More details on these factors are presented below to guide the hypothesis development and selection.

2.2.1. Perceptions

An individual's perception of the credibility of the warning source affects their confidence in the warning message and thus their likelihood of taking the suggested protective action [35,36]. This is supported by later studies that found that the credibility of the information source affects the effectiveness of evacuation warnings [37,38], and individuals' trust (i.e., a response based on perceived credibility) in a warning source increases their probability of evacuation [36,39]. Different information sources were also noted to have different perceived characteristics, such as expertise, trustworthiness, and protection responsibility [40]. The associated hypothesis is:

Hypothesis 1 (H1): *individuals who think a government agency is more or equally responsible for their safety than themselves are more likely to comply with a phased evacuation order.*

Government agencies are generally seen as the most credible information source [41]. However, whether an individual can perceive such credibility (from the perspective of protection responsibility belief) affects their trust in the released information and subsequent decision-making.

Previous studies have indicated that individuals who perceive greater personal risk are more likely to comply with the warning and take actions to protect themselves [12,35,42–44]. Risk perception is the most consistent indicator in explaining evacuate/stay decisions [12], and is often expressed by multiple factors, such as an individual's perception of property damage or injury/death. One exception is the study by Stein et al. [45], in which the authors developed a composite score expressing risk perception and found that it was significant in determining evacuation compliance. Risk perception itself is a subjective judgement, but it is related to hazard-exposure factors, such as proximity to the coastline/water areas and house structures. The following hypothesis is based on this discussion:

Hypothesis 2 (H2): *individuals with greater risk perceptions are more likely to comply with a phased evacuation order.*

An additional type of perception is protective action perception, which is one's attitude toward evacuation in this case. The theory of reasoned action (TRA) distinguishes two types of attitudes: general attitudes toward an object (e.g., hurricane) and attitudes toward a behavior with respect to the object (e.g., hurricane evacuation) [46]. Past studies have found that attitudes toward a behavior are an important predictor of action [46]. Therefore, the TRA considers attitude toward a behavior along with subjective norm (related to normative beliefs) and perceived behavior control (related to behavior facilitators/impediments) as the three factors leading to the formation of a behavioral intention; people are expected to carry out their intentions when behavior facilitators are sufficient [47]. In the context of evacuation, evacuation perception, together with the two perceptions mentioned above (i.e., stakeholder perception and risk perception), are the three core perceptions in Lindell and Perry's protective action decision model (PADM) framework [3,10,30]. The following hypothesis is related to evacuation perception:

Hypothesis 3 (H3): *individuals who think evacuation is an effective protective action are more likely to comply with a phased evacuation order.*

2.2.2. Initial Evacuation Decisions

Initial evacuation decisions refer to decisions evacuees make before knowing about the phased evacuation order. A phased evacuation order designates departure times by area. It is likely that not everyone living in the same area finds the designated departure time suits them or their initial evacuation decisions, which could lead to noncompliance behavior. For example, studies about modeling departure-time choice found that: (1) greater risk motivates early departure [48–53]; and (2) resource affluence, such as higher income [51,54] and vehicle ownership [51,55], also leads to early departure.

Hypothesis 4 (H4): *individuals who evacuate to the home of a friend/relative are more likely to comply with a phased evacuation order.*

The home of a friend/relative provides more convenience in terms of flexibility to evacuees compared to hotels/motels or shelters. Specifically, (1) the home of a friend/relative does not have a strict capacity limitation and (2) the home of a friend/relative does not have check-in or opening hours. This flexibility allows individuals who choose the home of a friend/relative to evacuate at different times.

Hypothesis 5 (H5): *individuals who plan to bring more personal vehicles during evacuation are less likely to comply with a phased evacuation order.*

Individuals bringing more vehicles are more likely to evacuate with more household members. Evacuating at an officially designated time seems less convenient than departing at a time when most or all household members are ready.

2.2.3. Other Factors

Dow and Cutter [56] found that those who did not evacuate in past storms are more likely to state they will stay in a future storm. The main reason for staying in a future storm as stated by these respondents is that they believe their home is safe. They also found that the "hurricane savvy" are more likely to depend on personal judgement rather than official orders [57]. These discussions lead to the following hypotheses:

Hypothesis 6 (H6): *individuals who did not evacuate when an order was issued to the area previously are less likely to comply with a phased evacuation order.*

The hypothesis is based on the logic that previous noncompliance behavior affects individuals' intended compliance to evacuation orders issued in the future.

Hypothesis 7 (H7): *individuals who experienced a hurricane more recently are less likely to comply with a phased evacuation order.*

These individuals may rely on their recent experience more than guidance from officials.

Warning-source credibility and preference may vary with housing tenure. First, similar to the finding about the "hurricane savvy," individuals who have longer housing tenure should be more familiar with the surrounding environment and thus are more likely to be able to make independent decisions. Second, an individual's temporary/permanent residence influences their information-search behavior, perceptions towards how credible an information source is, and their evacuation decisions [58,59]. Pennington-Gray et al. [58] found that international tourists are more likely to use social media than domestic tourists. Cahyanto and Pennington-Gray [59] found that out-of-state and international tourists have higher credibility perceptions of the local authority than in-state tourists; international tourists are more likely to evacuate. These studies lead to the hypothesis:

Hypothesis 8 (H8): *individuals who have longer housing tenure are less likely to comply with a phased evacuation order.*

Travel delay as an impediment factor influences evacuation convenience and thus affects evacuation-choice behavior [3,60–62]. Travel delay information is available to individuals in real time from various sources, such as smartphone apps and news media. This study treats the length of travel delay as an observed factor since the information is available once individuals' destination choices are predicted.

Hypothesis 9 (H9): *individuals who expect longer travel delays are less likely to comply with a phased evacuation order.*

Individuals who evacuate longer distances are more likely to expect longer travel delays. They generally prefer to depart early [63] so that they can reach destinations before the storm's landfall, which makes them potentially less likely to comply with a phased evacuation order.

Lastly, the possession of a plan increases the likelihood of warning compliance [35]. Dash [64] found that having an evacuation plan increases the likelihood of evacuation because a plan helps individuals know what to do (such as where to go and when to leave). The associated hypothesis is:

Hypothesis 10 (H10): *individuals with an evacuation plan are more likely to comply with a phased evacuation order.*

First, individuals with an evacuation plan are more likely to have better knowledge of the evacuation zone they live in. Such knowledge may equip them with a better understanding towards a phased evacuation order regarding which zone should begin to evacuate and at what time. Second, an evacuation plan prepares people to act, which may include closely following information from authorities. Following this information at least allows those individuals to be aware of the released evacuation order.

3. Survey and Data Descriptions

The analysis was based on data from a survey distributed to 2500 randomly selected households in coastal areas near Hampton Roads, Virginia. More details describing the survey distribution procedure can be found in [60]. The total sample size (n) for the survey is 415, which corresponds to a 19% response rate, a cooperation rate of 96%, a refusal rate of 1%, and a contact rate of 20%. Survey data were weighted to improve the representativeness of survey respondents in the population. Details on the weighting process can be found in [60].

In the survey questionnaire, respondents who stated they would evacuate in the described hypothetical hurricane scenario ("a Category 4 hurricane (130–156 mph wind speed) arriving on the next Thursday morning" and "a mandatory evacuation order had been given") proceeded to the question regarding their compliance behavior to a phased evacuation order. The question asked, "If officials asked that different areas/zones start evacuating at different times, but your area/zone is asked to wait for a later slot, which of the following are you most likely to do?" Available options included evacuate with the first group (8%), evacuate without considering the recommended start times (22%), evacuate at the recommended time for my zone (58%), evacuate later than recommended for my zone (1%), decide not to evacuate (0%; only one record), and "I don't know" (11%). Those who chose "I don't know" were removed from further analysis. Respondents who selected evacuating at, or later than the recommended time for their zone, were considered to be compliant with the phased evacuation order, while the others were considered to be noncompliant.

Table 1 presents descriptive statistics of both the dependent variable and potential independent variables for evacuees. About 75% of the evacuees think that they are likely or very likely to be impacted by a hurricane in the future. If a hurricane were to impact them, 90% of the evacuees think that they will experience property damage. Only 3% of the evacuees think that the government is more responsible for their safety than themselves, while 57% of the evacuees think the opposite. About 79% of the evacuees think that evacuation is an effective protection action.

Table 1. Data descriptions (unweighted).

Description	All Evacuees				In Final Model	
	No. of Observation	Range	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variable: Whether an evacuee chose to comply with the phased evacuation order (1 = Yes)	301	[0, 1]	0.66	0.47	0.66	0.47
Perceptions						
How likely an evacuee thinks they will be impacted by a hurricane (in Likert scale)	300	[0, 4]	2.78	1.11	(na)	(na)
How likely an evacuee thinks it is that they will experience property damage (in Likert scale)	291	[0, 3]	2.24	0.67	2.26	0.66
An evacuee's perception of safety responsibility (0 = more an individual/household responsibility, 1 = equal responsibility, 2 = more a government responsibility)	296	[0, 2]	0.46	0.56	0.42	0.54
Whether an evacuee thinks evacuation is an effective protection action (1 = Yes)	301	[0, 1]	0.79	0.41	0.83	0.38
Initial decisions of evacuees						
The number of cars an evacuee specified they will bring during an evacuation	299	[0, 3]	1.34	0.56	1.36	0.57
Departure day in relative to storm landfall (0 stands for more than three days before the storm landfall, 1 stands for three days before, 2 stands for 2 days before, 3 stands for 1 day before, 4 stands for the day of storm landfall, and 5 stands for the day(s) after storm landfall)	301	[0, 5]	2.20	1.08	(na)	(na)
The distance to the chosen destination in miles	237	[39.66, 205.38]	107.74	48.29	(na)	(na)
Whether an evacuee chose the home of a friend/relative as the destination (1 = Yes)	270	[0, 1]	0.53	0.50	0.53	0.50
Prior experiences and plans						
Whether an evacuee experienced property damage before (1 = Yes)	285	[0, 1]	0.58	0.49	(na)	(na)
Whether an evacuee experienced injury to self and/or injury or death of a friend or relative (1 = Yes)	277	[0, 1]	0.03	0.17	(na)	(na)
The number of times an evacuee chose to stay	284	[0, 20]	0.84	2.29	(na)	(na)
The number of years passed since the last hurricane experience	248	[0, 64]	7.81	8.04	(na)	(na)
The length of expected travel delay in hours	264	[−4, 37]	3.73	3.67	3.79	3.75
Whether an evacuee has an evacuation plan (1 = Yes)	299	[0, 1]	0.91	0.29	(na)	(na)
Socio-demographics						
An evacuee's age in years	285	[25, 95]	58.09	14.61	(na)	(na)
Housing tenure in years	290	[1, 79]	32.39	19.81	31.19	19.36
Whether an evacuee is a female (1 = Yes)	297	[0, 1]	0.53	0.50	(na)	(na)
Whether an evacuee is single (1 = Yes)	294	[0, 1]	0.10	0.29	(na)	(na)

Table 1. *Cont.*

Description	All Evacuees				In Final Model	
	No. of Observation	Range	Mean	Std. Dev.	Mean	Std. Dev.
Whether an evacuee has a household member who are over age 65 (1 = Yes)	301	[0, 1]	0.40	0.49	(na)	(na)
Whether an evacuee has a disabled household member (1 = Yes)	255	[0, 1]	0.32	0.47	(na)	(na)
Whether an evacuee has a pet (1 = Yes)	288	[0, 1]	0.52	0.50	(na)	(na)
Whether an evacuee owns their residence (1 = Yes)	301	[0, 1]	0.89	0.32	(na)	(na)
The number of cars in an evacuee's household	301	[0, 4]	2.11	0.85	(na)	(na)
The number of drivers in an evacuee's household	301	[1, 4]	1.99	0.76	(na)	(na)

(Note: 'na' means not applicable. The number of observations varies for "All Evacuees" because the authors kept as many records as possible for each variable in describing the data. However, in the model estimation, only response records without any missing values for selected variables were used. See the last two columns for the statistics of variables included in the final model.)

Regarding their prior experience, more evacuees faced property damage (58%) while few of them suffered injury to self and/or injury or death of a friend or relative (3%). The other interesting findings include: (1) 91% of the evacuees claim they have an evacuation plan; and (2) the average expected length of the travel delay is about 4 h.

Some highlights in the socio-demographic profiles of evacuees showed that (1) the average age of all evacuees is around 58 years old; (2) the average housing tenure is 33 years; (3) the gender discrepancy of evacuees is not large (53% of them are female); (4) only 10% of them are single; and (5) the average household vehicle ownership is over two but the number of drivers is less than two, which means that some households may have to leave some of their vehicles behind during evacuation. The last finding is also supported by the average number of cars evacuees specified that they would bring during an evacuation (which is 1.34).

4. Methodology

Whether an individual will comply with the phased evacuation order is a binary choice. The probability of individual i choosing one alternative ($Y = 1$, i.e., COMPLY) instead of the other ($Y = 0$, i.e., NOT COMPLY) in a typical binary logit model is shown in Equation (1) [65]. While the typical binary logit model served as a starting point, compliance to the phased evacuation order was statistically estimated by other variants of binary choice models with theoretical needs (i.e., incorporating household perceptions into modeling) in mind.

$$P_i(Y = 1) = \frac{\exp(\boldsymbol{\beta}'\boldsymbol{x_i})}{1 + \exp(\boldsymbol{\beta}'\boldsymbol{x_i})} \tag{1}$$

where, $\boldsymbol{\beta}$ is the parameter vector to be estimated; $\boldsymbol{x_i}$ is the vector of selected variables with values for individual i.

Latent class logit models use a discrete approximation to sort individuals (by their heterogeneity) into a certain number of classes [65]. The modeling approach is unlike random parameter logit models, which use continuous distributions to express individual heterogeneity. The discrete distribution is considered as making the latent class logit model less flexible than the random parameter logit model [66]. However, a benefit of using latent class models is saving the effort of specifying a distribution [66]. Both modeling approaches were tested during the model estimation process for statistical exploration purposes. However, in this study, the random parameter logit model was not found to be statistically superior to the latent class model in fitting the survey data by comparing their goodness-of-fit statistics, such as the pseudo R^2 values.

Another reason for using the latent class logit model in this study was to address the concern of incorporating unobserved indicator variables as independent variables in explaining choice behavior. The latent class model's underlying theory states that individual choice behavior "depends on observable attributes and on latent heterogeneity that varies with factors that are unobserved by the analyst" [66]. Unobserved psychological characteristics of individuals (e.g., attitudes and perceptions) are one example. Incorporating psychological variables in latent class models is considered as the application of an intuitive market segmentation in modeling choice behavior [67–69]. The modeling approach has been applied not only in classic topics (e.g., estimating mode choice behavior) but also in emerging topics such as human-infrastructure interactions (e.g., incorporating cyclists' behavior in infrastructure design [70,71]) and energy supply (e.g., considering consumers' security and sustainability perceptions in energy transition [72]). The following equations show the latent class logit model for binary choices.

$$P_i(Class = j) = \frac{\exp(\boldsymbol{\theta}' \boldsymbol{z_i})}{1 + \exp(\boldsymbol{\theta}' \boldsymbol{z_i})} \tag{2}$$

$$P_i(Y = 1 | x_i, j) = \frac{\exp\left(\boldsymbol{\beta}_j' \boldsymbol{x_i}\right)}{1 + \exp\left(\boldsymbol{\beta}_j' \boldsymbol{x_i}\right)} \tag{3}$$

where, $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are the parameter vectors to be estimated; $\boldsymbol{x_i}$ and $\boldsymbol{z_i}$ are the vectors of selected variables with values for individual i.

Some common statistics in the choice model evaluation are calculated using the log likelihood function. First, pseudo R^2 equals $1 - LL(\hat{\beta})/LL(0)$, where $LL(\hat{\beta})$ is the log likelihood function at the maximum and $LL(0)$ is the log likelihood function assuming β is zero. Second, the chi-squared statistic for testing $H_0 : \beta = 0$ is calculated by $2(LL(\hat{\beta}) - LL(0))$ [65].

5. Model Estimation Results

Table 2 shows the model estimation results for both the typical binary logit model and latent class model. The pseudo R^2 value for both models are considered as providing a satisfactory fit [73], but the latent class model performs better than the typical binary logit model when comparing their pseudo R^2 values. The following parameter interpretations and hypothesis discussions (in the next section) therefore focus on results from the latent class model. The estimated typical binary logit model serves as a baseline and provides additional discussions when some variables have their estimated parameter significance/sign shifted.

Table 2. Model estimation results.

Variable	Binary Logit Model				Latent Class Binary Logit Model				Hypothesis
	Coefficient	Std. Error	z-Value	*p*-Value	Coefficient	Std. Error	z-Value	*p*-Value	
(na)	(na)				Class-membership model				(na)
Constant	0.38	0.76	0.5	0.61	−2.06 *	1.08	−1.90	0.05	(na)
How likely an evacuee thinks it is that they will experience property damage (in Likert scale)	0.23	0.24	0.98	0.32	0.09	0.32	0.29	0.77	H2 (rejected)
Whether an evacuee thinks evacuation is an effective protection action (1 = Yes)	1.39 ***	0.38	3.59	0.00	2.21 ***	0.74	2.99	0.00	H3 (not fully rejected)

Table 2. *Cont.*

Variable	Binary Logit Model				Latent Class Binary Logit Model				Hypothesis
	Coefficient	Std. Error	z-Value	*p*-Value	Coefficient	Std. Error	z-Value	*p*-Value	
An evacuee's perception of safety responsibility (0 = more an individual/household responsibility, 1 = equal responsibility, 2 = more a government responsibility)	0.85 ***	0.31	2.74	0.00	0.92 **	0.40	2.29	0.02	H1 (not fully rejected)
(na)	(na)				Class 1 choice model: evacuation keen				(na)
Whether an evacuee chose the home of a friend/relative as the destination (1 = Yes)	−1.04 ***	0.34	−3.03	0.00	−2.16 **	1.02	−2.1	0.03	H4 (rejected)
The number of cars an evacuee specified they will bring during an evacuation	−1.14 ***	0.28	−4.02	0.00	−0.97 **	0.42	−2.28	0.02	H5 (not rejected)
Housing tenure in years	0.02 **	0.01	2.30	0.02	0.52	0.32	1.61	0.10	H8 (rejected)
The length of expected travel delay in hours	−0.04	0.03	−1.27	0.20	0.46 **	0.22	2.07	0.03	H9 (rejected)
(na)	(na)				Class 2 choice model: evacuation reluctant				(na)
Whether an evacuee chose the home of a friend/relative as the destination (1 = Yes)	(na)	(na)	(na)	(na)	−2.16 **	1.02	−2.1	0.03	H4 (rejected)
The number of cars an evacuee specified they will bring during an evacuation	(na)	(na)	(na)	(na)	−0.97 **	0.42	−2.28	0.02	H5 (not rejected)
Housing tenure in years	(na)	(na)	(na)	(na)	0.03 **	0.01	1.97	0.04	H8 (rejected)
The length of expected travel delay in hours	(na)	(na)	(na)	(na)	−0.02	0.06	−0.37	0.71	H9 (rejected)
Model's goodness-of-fit statistics	N = 235; $LL(0)= -153.1$; $LL(\hat{\beta})= -122.8$; pseudo $R^2= 0.20$				N = 235; $LL(0)= -162.9$; $LL(\hat{\beta})= -120.8$; pseudo $R^2= 0.26$				(na)

(Note: 'na' means not applicable; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

5.1. Class-Membership Model

The number of classes was derived after testing different values (ranging from two to three; specifying four or greater classes led to model breakdown immediately in this case). Two classes provided the best statistical fit in this study and are consistent with some past studies in modeling hurricane evacuate/stay choice behavior [74,75].

Surprisingly, risk perception is not significant (in either model) in estimating phased evacuation order compliance behavior. Risk perception is a strong factor in estimating hurricane evacuate/stay choice behavior [48,63,76]. The insignificance is, perhaps, due to the reason that these individuals have already decided to evacuate. Other factors outweigh risk perceptions when individuals consider whether to comply with the phased evacuation order.

Two of the factors that are significant when determining class membership are stakeholder perceptions (i.e., whether government agencies have responsibility for the safety of individuals) and evacuation perceptions (i.e., whether evacuation is an effective protective action). The two factors were much less frequently considered or incorporated in past evacuate/stay choice behavior modeling studies, and constitute a new topic of modeling phased evacuation order compliance behavior. Those individuals who hold a more positive perception towards evacuation and/or think that government is (either equally or more) responsible for individuals' safety are more likely to belong to Class 1, and are more in favor of evacuation ("evacuation keen"). Those who do not are more likely to belong to Class 2, and are less in favor of evacuation ("evacuation reluctant").

5.2. The Choice Model

In each class, a positive parameter suggests that an evacuee is more likely to comply with a phased evacuation order when the value increases (in the case of continuous variables) or when the indicator equals one (in the case of binary indicators). A negative parameter means the opposite. As shown in Table 2, individuals in the two classes share similarities in their phased evacuation order compliance behavior (i.e., parameters of the same value or of the same sign). However, individuals in the two classes can be quite the opposite sometimes (i.e., parameters of the opposite sign).

Parameters for individuals' initial accommodation decisions in the two classes are not significantly different from each other and were thus forced to be equal during model estimation. The negative sign indicates that individuals who choose to evacuate to the home of a friend/relative are less likely to comply with the phased evacuation order no matter the class to which class they belong. The same phenomenon applies to the variable expressing individuals' initial decisions regarding the quantity of vehicles to bring. That is, individuals who choose to bring more vehicles with them during evacuation are less likely to comply with the phased evacuation order no matter the class to which they belong.

The parameters for housing tenure are of the same sign in the two classes. However, the estimated parameter is not significant in Class 1 but is significant in Class 2. This means that "evacuation reluctant" individuals tend to comply with the phased evacuation order if they live in the local area for a longer period. Meanwhile, housing tenure does not play a significant role among "evacuation keen" individuals.

The parameters for the expected travel delay are of the opposite sign in the two classes. In addition, the parameter is significant in Class 1 but not significant in Class 2. This means that "evacuation keen" individuals tend to comply with the phased evacuation order if longer travel delays are expected. Meanwhile, longer travel delays do not play a significant role among "evacuation reluctant" individuals. Even if travel delays do play a role, "evacuation reluctant" individuals are less likely to comply with the phased evacuation order when longer travel delays are expected. The authors tested the latent class mixed logit model to see whether the potential opposite sign was due to heterogeneity in interpreting travel delays among individuals of the two classes. However, the latent class mixed logit model did not provide any significant results or improvements in this case.

6. Hypothesis Discussion

Hypothesis H1 and Hypothesis H3 are not rejected by the latent class model to an extent. First, the two hypotheses are not fully supported by the estimated model because the two perception factors were used as latent variables in the class-membership model rather than the choice model. That is, whether individuals of the two identified classes will comply with a phased evacuation order are found to be probabilistic instead of deterministic, which is similar to past studies on evacuation order compliance (without phasing) [28]. Second, the two hypotheses are considered as supported to an extent because "evacuation keen" individuals tend to be more likely to comply with a phased evacuation order. Figure 1 plots the estimated class membership probability for being "evacuation keen" (on the x-axis) against their estimated compliance probability (on the y-axis). Each dot in Figure 1 represents an evacuee. As shown, most of the dots aggregated at either the upper right corner (i.e., more likely to be "evacuation keen" and more likely to comply with the phased evacuation order) or the bottom left corner (i.e., less likely to be "evacuation keen" and less likely to comply with the phased evacuation order).

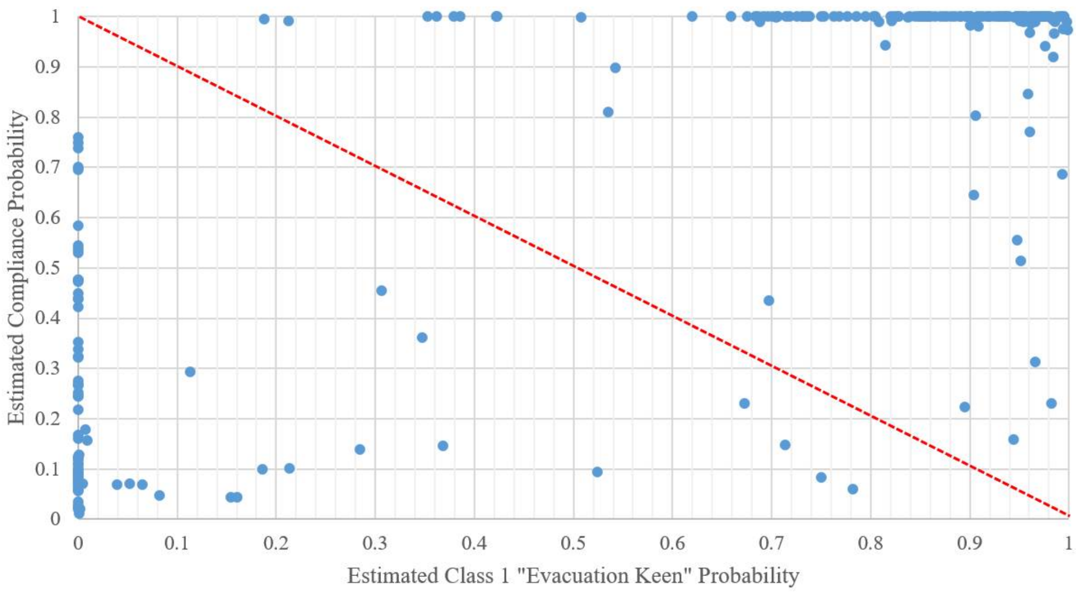

Figure 1. Estimated class-membership probability and compliance probability.

Hypothesis H2 is rejected since the variable is not significant in either model. Risk perception might have already played its role when evacuees were making the decision of whether to evacuate or stay in the described hypothetical scenario. That is, risk perceptions significantly distinguish evacuees from non-evacuees [12]. However, risk perceptions do not significantly distinguish among evacuees when evacuees were given the new information of a phased evacuation order (which asks evacuees to wait for a later time slot and then evacuate).

Hypothesis H4 is rejected; these individuals are less likely to indicate phased evacuation compliance. The unexpected result can be explained by the relatively longer evacuation distance (average = 122 miles) made by those who choose the home of a friend/relative as the accommodation. The average evacuation distance is about 89 miles for hotel/motel users and shelter users. Individuals who evacuate longer distances are more likely to depart early [63] to ensure safe arrival before the storm landfall.

Hypothesis H5 is not rejected. One type of noncompliance induced by the car choice could be departing early (perhaps with the first group receiving the evacuation order) to purchase more resources (such as gas). Another type of noncompliance induced by the car choice could be evacuating on their own timeframe without considering the order because bringing more vehicles indicates that a respondent may have more household members and need to bring more personal belongings [51,55]. The mobilization time could vary because of the larger number of participants and time spent on packing/loading.

Hypothesis H6 is rejected since the factor reflecting previous noncompliance is not significant in the final model. DeYoung et al. [77] state that individuals who did not comply with an order in a previous evacuation are more likely to evacuate only when an order is issued for a storm of a higher category in the future. Their explanation is that individuals gain more confidence from their past decisions when ignoring the order and adjust their risk perceptions. That is, individuals who did not experience significant losses from choosing to stay in the storm they experienced will change their evacuate/stay decision only when they are exposed to a greater risk [77]. In our study, there is no comparison regarding the storm category between the described scenario and the respondent's past experience, which may have led to this nonsignificant result.

Hypothesis H7 is not supported since the factor was not significant in the final model. The nonsignificant result might be explained by a similar reason as above—how the past experienced scenarios compare with the current scenario. A longitudinal survey tracking behavior of the same group of populations could possibly explain how individuals' evacuation choices and compliance behavior change from storm to storm. Dow and Cutter [57] indeed found, from their longitudinal survey data, that "hurricane savvy" populations rely more on individuals' own risk assessments than on official orders. However, their longitudinal survey collected responses from different groups of populations.

Hypothesis H8 is rejected because of the significant positive sign. The estimated model showed that the longer the housing tenure, the more likely he/she is to comply with a phased evacuation order (especially among "evacuation reluctant" individuals). First, longer housing tenure allows individuals to interact with local officials more often, which increases individuals' trust in officials [78–80]. The increased trust leads to higher compliance likelihood when an official phased evacuation order is issued. Second, the majority of shadow evacuations were due to incorrect understanding of evacuation zones [81]. Shadow evacuation is defined as people living outside the evacuation zone choosing to evacuate [55,82], which is also a type of noncompliance behavior in the context of this paper (i.e., evacuating without an order or before receiving an evacuation order). Individuals who have longer housing tenure are more likely to be aware of the evacuation zone they live in, which leads to better understanding of a phased evacuation order and thus greater compliance.

Hypothesis H9 is rejected. "Evacuation keen" individuals (i.e., Class 1) who expect longer travel delays are more likely to comply with a phased evacuation order. This is different from a previous finding, which indicated households are more likely to evacuate earlier when they expected longer travel delays [60]. It is likely that "evacuation keen" individuals have more positive perceptions towards stakeholders (as a trusted information source) and evacuation (as a protective action). These individuals might extend their trust to believe that the phased evacuation order announced by the authority can help alleviate congestion and increase evacuation efficiency.

Hypothesis H10 is rejected since it was not significant in the final model. During the model testing process, individuals with an evacuation plan were found to be less likely to ignore the phased evacuation order but they were also more likely to evacuate with the first group who received the phased evacuation order (i.e., a type of noncompliance behavior). Past studies found that having an evacuation plan enabled individuals to know what to do [64]. The pre-set evacuation plan may allow these individuals to respond to the phased evacuation order more quickly and even start their evacuation trips earlier.

7. Conclusions

Based on a household behavioral intention survey, about 66% of the residents who decided to evacuate (and knew what their response to the phased evacuation order would be) stated that they would comply with a phased evacuation order. This study found that individuals' intended responses to a phased evacuation order are affected by multiple factors that characterize individuals or households. Therefore, the compliance rate could be different across zones within the study area.

The findings from this research provide a reference for studies requiring an overall compliance rate but that cannot conduct a separate household survey. The estimated model provides insights into factors affecting individuals' intended phased evacuation order compliance behavior, which has not been investigated extensively in the past. The identified factors can help to better understand what motivates individuals' compliance so that related actions can be taken by authorities to improve the rate. The implementation of phased evacuations will be more successful with a better understanding of individuals' compliance schemes to a phased evacuation order.

7.1. Theoretical Contributions

The three core perceptions (e.g., risk, stakeholder, and evacuation) illustrated in the PADM theoretical framework were all included in the modeling [3,10,30]. First, risk perception was found to be nonsignificant in modeling evacuees' phased evacuation order compliance behavior in this study. Past modeling studies considered risk perceptions much more frequently than the other two perception factors in the decision to evacuate/stay. This study re-emphasized the importance of considering and incorporating other perception factors in modeling evacuation behavior. Second, future studies need to be careful in using perception factors in modeling. The three perceptions were included as latent variables, which provided intuitive market segmentation among evacuees. The "segmentation" process sees a parameter sign and significance shift phenomenon (e.g., the length of travel delays). Future studies may conduct additional tests when they have a greater number of observations and/or observe a greater level of variance in travel delays. Then, testing latent class mixed logit models could potentially help to find out whether heterogeneity in interpreting travel delays among individuals exists.

7.2. Implications for Practitioners

These significant factors remind authorities to take action if they wish to improve the phased evacuation order compliance rate. The first factor for practitioners to consider is that local authorities should focus on increasing their credibility as a warning information source. The estimated model suggests that when individuals believe that government agencies have more or equal protection responsibility as individuals, this significantly affects the likelihood of their compliance. One approach is to interact with local residents more often through multiple channels, such as by creating online/onsite evacuation education programs. More interactions can help increase individuals' perceptions of the authority's credibility regarding disasters so that individuals' trust of, and responses to, a released order can be improved. An associated point is that authorities should consider delineating zones in a more understandable manner to help households with shorter housing tenure better interpret a phased evacuation order, which potentially can help motivate greater compliance. Knowing the evacuation zones helps individuals to clearly understand an issued order. People who lived outside of evacuation zones sometimes evacuated only because of their unfamiliarity with the delineation of evacuation zones [83]. Another approach to increase the credibility of authorities is to clearly convey the protection responsibility of authorities to individuals, which can be emphasized during interactions with local residents and reinforced by releasing official announcements about authorities' disaster preparedness (e.g., levee protection) on normal days. In addition to these pre-storm preparations, local authorities can also motivate greater compliance during the disaster event by delivering travel-delay information in a more precise or specific manner, such as estimating travel time by destination or direction, to help individuals maintain realistic expectations about their evacuation trips and thus make more informed decisions regarding evacuation, such as the choice of evacuate/stay or departure time. In addition, some evacuation-related decisions (i.e., accommodation and car choice) have an impact on individuals' compliance behavior. For example, local authorities can consider providing more accessible accommodations, because the correlation between evacuating to the home of a friend/relative and evacuation distance is 0.39 in this study. That is, closer accommodations can increase individuals' compliance to a phased evacuation order. Local authorities can also consider improving the vehicle occupancy rate by encouraging carpool/ridesharing and providing protection tips for vehicles left behind. Less traffic on the road can decrease potential travel delays and improve the overall evacuation.

7.3. Study Limitations and Future Research Directions

Regarding future research, it is worthwhile to find out whether individuals make the same decision in a real evacuation as they expressed in a behavioral intention survey, which factors affect their revealed preferences, which effects remain the same, which effects change, and which new effects occur. An additional question is whether, and how, the results of optimization or simulation studies change after considering the variations in compliance behavior. Future research may also consider whether, and how, individuals' preventive activity experiences (e.g., participating in evacuation drills) could affect their evacuation-related choices. In addition, this study collapsed early evacuation and ignoring an order as non-compliance due to the number of observations. Future research might explore the distinction between the two decisions, particularly if respondents who do one or the other are geographically concentrated for some socially relevant reasons.

This study was made in a hurricane-evacuation scenario. It is expected that there are commonalities in household behavioral responses to hurricanes, so the findings and implications are generally applicable to other hurricane-prone areas. Regarding model application, most of the factors included in the final model can be collected from the U.S. Census directly, while some factors (i.e., risk perception and evacuation perception) can be derived from objective measures (e.g., proximity to water areas and previously evacuated). Surrogates for stakeholder perception might need additional research to reduce repeated survey efforts, which has been identified as a gap in the societal dimensions of resilience [84]. Future studies investigating phased evacuation order compliance behavior in other disaster scenarios might arrive at different findings, which will be interesting for comparisons.

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