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Article

Integrating Regret Psychology to Travel Mode Choice for a Transit-Oriented Evacuation Strategy

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Abstract: Facing the potential dangers from sudden disasters in urban cities, emergency administrators have to make an appropriate evacuation plan to mitigate negative consequences. However, little attention has been paid to evacuee real decision psychology when developing a strategy. The aim of this paper is to analyze evacuee mode choice behavior considering regret aversion psychology during evacuation. First, the utility-based and regret-based models are formulated to obtain evacuees' preferences on travel mode choice, respectively. According to the data collected from the stated preference (SP) survey on evacuee mode choice, the estimation results show that the regret-based model performs better than the utility model. Moreover, based on the estimates from behavioral analysis, the elasticities of evacuee mode choices are calculated, and transit strategy simulation is undertaken to investigate the influence on evacuee mode switching from private automobile to public transit. The results are expected to help emergency administrators to make a transit-oriented strategy for a sustainable evacuation plan, especially for the benefit of carless people.

Keywords: evacuation; travel mode choice; regret model; utility model; transit-oriented strategy

1. Introduction

With the rapid development of urban society in recent decades, natural disasters (e.g., floods, hurricanes, wild fires, *etc.*) associated with global climate change have been considered a worldwide problem. These disasters lead to huge societal loss and environmental damage and challenge the sustainable development of urban cities. According to global catastrophe recap from Aon Benfield, severe weather caused economic losses near USD 106 billion in 2014. The worst case was USD 16 billion from the river-basin flood in India, followed by USD 11 billion from cyclone Hudhud and USD 6 billion from China's Ludian earthquake. European countries, such as France, Germany and Belgium, suffered strong wind and large hail attacks, and USD 2.7 billion were lost [1]. Another review report in 2014 released by the UN Economic and Social Commission for Asia and the Pacific (ESCAP) said that 6000 fatalities were caused by natural disaster, and an estimated 79.6 million people were affected by natural disaster across Asia and the Pacific. "Such disasters, which may very well be on the rise because of climate change, require improved regional information exchange and the joint coordination of operations for effectively warning and evacuations" [2]. Since these disasters are going to occur frequently, these negative consequences on the economy, society and the environment highlight the importance of enhancing the city's defense capability.

For a sustainable urban development, emergency evacuation has become an effective response to mitigate these adverse effects (e.g., human deaths and property loss) [3–5]. The roles and responsibilities of transportation during emergencies have been formalized in the National Response Framework by the Department of Homeland Security in 2008 [6]. The most important roles of transportation are the management of evacuation and the utilization of mass transit systems. In 2005, Hurricane Katrina caused severe destruction along the Gulf coast from central Florida to Texas. When a hurricane warning and a mandatory evacuation were issued, the estimates claimed that 80% of the 1.3 million residents of the greater New Orleans metropolitan area evacuated. The total damage from Katrina is estimated at USD 108 billion [7]. In 2014, Japan was hit by the strongest flood, causing 95 casualties, and 1.6 million people were evacuated [1]. It is worth noting that in the Katrina evacuation, about 71% of fatalities were elderly people aged over 60, and 47% were over 75 years old. They need transportation aid from an emergency transit agency, family, friends or neighbors [8,9]. Therefore, the focus of evacuation planning is shifting to the carless population without access to a personal vehicle, who cannot self-evacuate in private vehicles, such as the disabled, young, elderly and low-income residents. Although private car is a popular mode during emergency evacuation, the necessity for the transit mode to improve evacuation efficiency is well recognized.

In light of the fact that evacuee decision behavior plays an important role in predicting evacuation demand and evaluating the evacuation strategy, some efforts have been made on a range of issues from an individual perspective, e.g., whether to evacuate, when to evacuate, how to evacuate and where to go [9,10]. Taking the example of a flood, the emergency agency will issue an evacuation warning according to the amount of precipitation and the water level of the river. After receiving the evacuation order, people should make a decision about whether to evacuate or not. It seems easy to choose a destination (e.g., public shelter, relative's house, hotel, *etc.*) once they decide to evacuate. Much effort and thought should be used to select an appropriate mode and a safe route. As for the mode taken to evacuate (e.g., bus, emergency vehicle, taxi, private car, *etc.*), it is assumed that evacuees who are able to take their own cars still take them. This assumption can be regarded as a mode split rule to estimate the evacuation demand. However, the decision process of evacuee mode choice is complex, depending on a wide variety of factors, such as disaster characteristics, the travel distance to a shelter and the accessibility to mode options [6]. Some evacuees were found to give up their own cars to use other travel modes [11]. It is certainly worth investigating evacuees' preference for the mode decision, as well as other influencing factors. As a key aspect of evacuation efficiency, a transit-oriented evacuation plan highly depends on a full understanding of evacuee mode choice behavior.

From the review of previous literature on the choice problem, discrete choice modelling provides a decision paradigm at a disaggregated level in transportation, as well as in evacuation planning. Multinomial logit, the nested logit model and mixed logit models are widely used to investigate daily travel mode choice [12–14]. The decision rule is mainly based on utility theory. There are some aspects of the utility decision rule that make it far from realistic. It postulates that travelers are absolutely rational, should determine the utility of every choice alternative and select the one with the highest utility. This means that the utility function allows a full compensation among the different alternatives. Since the notion of anticipated regret was recognized as a choice-behavioral determinant rule in many fields, e.g., marketing and microeconomics, the regret theory also provides an alternative paradigm to explain travelers' decision behaviors [15–18]. The regret minimization model in transportation was firstly proposed by Chorus, and it assumed that travelers should consider their regret aversion psychology and choose the alternative with the lowest regret [17]. The regret happens when a considered alternative is outperformed by another in terms of one or more attributes. The decision rule is to minimize the regret instead of utility maximization. It is consistent with behavioral intuitions accounting for regret aversion psychology when people face risky choices under uncertainty (*i.e.*, emergency).

Although regret-based models are becoming popular in travel choices, the application of regret-based models in an emergency context is limited. Due to evacuees' regret aversions with bounded rationality, it seems plausible to adopt the regret-based model to describe evacuee mode choice behavior. Therefore, the aim of this paper is to apply the regret-based model in the analysis of evacuee mode choice to reveal different evacuees' decisions considering the regret aversion. Meanwhile, a transit-oriented evacuation strategy simulation is undertaken to investigate the travel mode switch behavior from private automobile to public transit. The improvement of transit service not only considers the needs of the carless population, but also attracts private automobile users. It is helpful for emergency administrators to ensure the overall evacuation efficiency. To the best of the author's knowledge, this is the first attempt to model evacuee mode choice using the regret theory. Typically, the application in the evacuation field can be a new empirical analysis in regret modelling. In this study, evacuee mode choice is described using the utility-based and regret-based models, respectively. A comparison among different models is presented to find the best model to explain the evacuee mode choice behavior. Based on the estimated results, a series of scenarios on strategy simulation assuming that there is an improvement for transit service are undertaken to test the effect of different strategies.

The remainder of this paper is organized as follows. The next section describes previous literature related to behavior modelling. Then, the third section presents the model formulation used in this study. The fourth section describes the stated preference dataset on evacuation mode choice and compares the estimated results from different models. The elasticities are calculated and transit-oriented strategies are simulated in the fifth section. The final section concludes the paper and discusses future research directions.

2. Literature Review

Evacuation behavior modelling is complex and depends on many influencing factors. Many efforts have been made to explain evacuee travel behaviors using the dataset from a revealed preference survey (RP) or a stated preference survey (SP). The selection of survey methods is dependent on the basis of the research purpose. The former data are usually collected by means of telephone and interview survey after an incident. The latter data are designed based on a hypothetical incident. In contrast, RP is a reliable method due to the respondents' real experiences, but the disadvantage is that it can only deal with the incident that occurred. The specified data, such as policy-sensitive data, cannot be collected to test evacuation policies. SP is a flexible scenario-based experiment that can meet different requirements. The survey scale can be controlled well.

The existing studies on modelling evacuees travel behavior are mainly on the background of a hurricane. Murray-Tuite and Wolshon presented a comprehensive review of evacuation modelling over the past decades [6]. Behavioral science was highlighted from evacuation demand forecasting, distribution and assignment. The research focus is at a disaggregated level, including the evacuate/stay decision, when to evacuate, the selection of evacuation destination and evacuation route [19–23].

Extensive research on evacuation vehicle usage has been conducted. Perry *et al.* found that 74% of evacuees used their own vehicles during flood evacuation, 13% rode with other people and 13% took public transit [20]. During Hurricane Lili, Lindell *et al.* gave the average number of 1.6 vehicles per household, ranging from 1.1 to 2.5 across five counties. It was reported that 90% of evacuees traveled in their own vehicles, 9% rode with other people and less than 1% used public transit [24]. Wu *et al.* indicated that the most common mode to evacuate was to take one's own vehicles based on Katrina/Rita data. However, 11% of evacuees were found to leave their own cars, of which 71% rode with other people and 28% used another transportation mode. Older evacuees would prefer a registered shared mode service. The top rate of transit use was 13% from the previous surveys [11].

There is little information about the influencing factors on evacuee mode choice. The decision of evacuate/stay and its influencing factors are frequently investigated. The frequency of response and logistic regression techniques are mainly used to identify the effect of these factors. The factors, such as warning information, distance to the threat, the perceived risk and family gathering, are more likely to show an increased effect on the evacuation decision [10]. Hasan *et al.* proposed a mixed logit model using original data from Hurricane Ivan to reveal the heterogeneities. The factors included household's geographic location, whether or not a member in the household has to go to work during the evacuation, the number of children, the evacuation notice type, previous experiences and whether or not the household has a high income or a post-graduate member [25].

The latest research regarding evacuee mode choice was done by Sadri *et al*. [26]. A nested logit model was developed to explain the evacuee mode choice using survey data from a hypothetical Category 4 hurricane on Miami Beach. The study focused on the evacuees who were likely to use different non-household transportation modes. The mode choice decisions involved five discrete outcomes, such as ride with someone, taxi, special evacuation bus, regular bus and other. Several influencing factors, including determining variables, evacuees' socio-demographics, household characteristics and previous experience, were considered to model evacuees' strategic behavior. The preferences of different evacuees using different modes were found: for example, evacuees are more likely to take special evacuation buses, and higher income people are more likely to take a taxi. Evacuees who arrived at a shelter are less likely to ride with someone else. They are dependent on transportation service from emergency management agencies. For the carless and special needs populations, Deka and Carnegie constructed a model based on the stated preference survey data. The results show that evacuees prefer private vehicles, and the familiarity of the transit options and the unavailability of a personal vehicle are the key influencing factors [7]. Based on the data from a hypothetical incident in the Chicago metropolitan region, Liu *et al.* [27] presented a framework to incorporate both household-gathering behavior and mode choice into an evacuation model in order to examine the effects on evacuation efficiency. A decision tree approach model was employed to model evacuation mode choice. Three mode options, such as driving alone, taking public transit or taxi and carpools, were considered. Individuals' gender, possession of a driver's license and access to a personal car or commute mode were input variables for the decision model.

3. Model Specification

It is recognized that evacuees are regret averse as a special type of traveler when making a decision. They do not want to be caught in the situation that the chosen alternative performs worse than others in terms of one or more attributes, especially on the aspects they value highly. In order to take evacuees' regret aversion psychology into account, the regret-based choice model is established to explain evacuee mode choice behavior, and a utility-based choice model is also constructed as a comparison.

Assume the choice situation: an evacuee faces a set of M mode options, each mode alternative i being described in terms of A travel-related multiple attributes. In a utility-based choice model, evacuees are assumed as utility maximization pursuers, and they will choose the alternative with the highest utility (*i.e.*, the most satisfaction). There is no correlation among different mode alternatives, and the utility of each mode will be calculated separately. The utility-based choice model assigns a utility to each mode alternative, and the utility function is shown as follows [12,28]:

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \sum_{a=1\ldots A} \beta_a \times x_{na} + \varepsilon_{ni} \tag{1}$$

where U_{ni} is the random utility of mode alternative i selected by evacuee n; V_{ni} is the observed utility of mode alternative i selected by evacuee n; ε_{ni} is the unobserved utility of mode alternative i selected by evacuee n; β_a denotes the estimated taste parameter for mode attribute a; x_{na} denotes the value of attribute a for mode alternative i selected by evacuee n.

In contrast, a regret-based choice model postulates that evacuees are regret averse (*i.e.*, to minimize the random regret of the alternatives). When the considered alternative is outperformed by others in terms of one or more attributes, regret will occur. Evacuees should make a trade-off between different mode alternatives on multiple mode attributes to find the alternative with the lowest regret. The generalized random regret function can be formulated as follows [29]:

$$GR_{ni} = R_{ni} + \varepsilon_{ni} = \sum_{a=1,\ldots,A} \sum_{j \neq i} \ln(\gamma_a + \exp[\beta_a \times (x_{nja} - x_{nia})]) + \varepsilon_{ni} \tag{2}$$

where GR_{ni} is the generalized random regret of mode alternative i selected by evacuee n; R_{ni} is the observed regret of mode alternative i selected by evacuee n; ε_{ni} is the unobserved regret of mode alternative i selected by evacuee n; γ_a denotes the regret weight for attribute x_a; β_a denotes the estimated taste parameter for mode attribute a; x_{nia} and x_{nja} are the values of attribute a for mode alternative i,j selected by evacuee n, respectively.

Obviously, due to the different values γ_a for different mode attributes, different regret-based choice models will be constructed. Since γ_a is bounded between zero and one, a binary logit function $\gamma_a = \exp(\delta_a)/(1 + \exp(\delta_a))$ can be used to estimate γ_a. When $\gamma_a = \gamma = 1$, the expression $\ln(1 + \exp[\beta_a \cdot (x_{ja} - x_{ia})])$

represents a basic random regret model. When γ_a varies from zero to one, the above formulation reflects a hybrid paradigm of a random utility model and a basic random regret model. The determinant of regret minimization *versus* utility maximization behaviors for different mode attributes depends on the parameter δ_a [30–32].

It is mathematically recognized that the minimization of the regret is equivalent to maximizing the negative of the regret. When an i.i.d. Extreme Value Type I-distributed error is adopted to represent the heterogeneity for the unobserved utility, the choice probability can be written as the following multinomial logit formulation [12,32]:

$$P(ni|\beta) = \frac{\exp(H_{ni})}{\sum_{j=1\ldots M}\exp(H_{nj})} \tag{3}$$

where when $H_{ni} = V_{ni}$, the function represents the choice probability for the random utility model in Equation (1); when $H_{ni} = -R_{ni}$, the function represents the choice probability for the generalized random regret model in Equation (2).

The parameters related to the attributes can be estimated based on the maximum likelihood method, and the natural logarithm of the likelihood function is as shown [12,32]:

$$LL(\beta) = \ln(\prod_n \prod_i P(ni|\beta)^{y(ni)}) = \sum_n \sum_i y(ni) \times \ln(P(ni|\beta)) \tag{4}$$

where $y(ni)$ equals one if the mode alternative i is chosen by evacuee n, and zero otherwise.

In this study, three available evacuation mode options, including public transit, private automobile and shared automobile (*i.e.*, i, j, k), are provided for evacuees to travel from a dangerous area to a safe destination. Here, public transit mainly denotes the buses organized by the government and emergency management agency. Private automobiles are the cars from a household. Shared automobiles denote the taxis and the cars from another household. Four attributes are assigned to each mode option, such as average travel time (*TRAVEL_TIME*), travel time uncertainty (*TIME_UNC*), waiting time (*WAIT_TIME*), and perceived comfort level (*COMFORT_PER*). The attribute *TRAVEL_TIME* describes the average in-vehicle/mode time along a route under free-flow condition. The attribute *TIME_UNC* reflects the increased time resulting from possible congestion and accidents. The attribute *WAIT_TIME* describes the waiting time before evacuees' departure. The attribute *COMFORT_PER* reflects an overall comfort level perceived by evacuees, such as seat availability and the familiarity with the mode. Evacuees should make a reasonable decision after considering the performance of every mode option on every attribute. Therefore, the probability of choosing an evacuation mode depends on the four key parameters: the coefficient β_t of *TRAVEL_TIME*, the coefficient β_u of *TIME_UNC*, the coefficient β_w of *WAIT_TIME* and the coefficient β_c of *COMFORT_ PER*. These parameters can be estimated based on Equation (4) using Biogeme [33,34].

4. Data and Results

4.1. Data Description

In this study, a stated preference (SP) household survey on evacuee mode choice behavior was used to collect evacuation data. In 2003, Harbin was battling a higher water level situation. Eleven thousand five hundred ninety seven residents along the river were evacuated in advance. One thousand sixty one residents from Harbin city who lived in the Songhua River (one of the seven rivers in China) Basin participated in the survey in 2014. An SP household survey was conducted to investigate the residents' evacuation mode choices if there were a flood. The participant should imagine an evacuation action and complete a questionnaire. The questionnaire contained two parts: one was related to socio-demographic information (e.g., gender, age, education, car ownership experience, *etc.*); the other was an evacuation mode choice task. There are three available travel modes, including public transit, private automobile and shared automobile, provided to leave from home to the safe shelter. The evacuation mode choice task was designed with two sections. The first section was based on different disaster scenarios to discover the distribution of evacuee mode choice. The second section was based on evacuation mode attributes to reveal the influencing factors. The attributes, including average travel time, travel time uncertainty, waiting time and perceived comfort level, were selected due to the significant effects on evacuee mode choice. Finally, a total of 796 valid responses were obtained to explain the evacuee mode choice behavior, and their socio-demographic information is listed in Table 1.

Table 1. Descriptive statistics of the socio-demographic variables for participants (n = 796).

Variable	Variable Description	Mean	SD
Gender			
	Male (1 = yes; 0 = otherwise)	0.52	0.500
Age			
	Person is less than 34 years old (1 = yes; 0 = otherwise)	0.78	0.414
	Person is between 34 and 54 years old (1 = yes; 0 = otherwise)	0.21	0.408
	Person is equal to or more than 55 (1 = yes; 0 = otherwise)	0.01	0.093
Education			
	Level is high school. (1 = yes; 0 = otherwise)	0.11	0.307
	Level is an undergraduate. (1 = yes; 0 = otherwise)	0.57	0.496
	Level is postgraduate. (1 = yes; 0 = otherwise)	0.33	0.469
Experience			
	Have evacuation experiences. (1 = yes; 0 = otherwise)	0.95	0.213
Car ownership			
	Household owns cars. (1 = yes; 0 = otherwise)	0.51	0.500
Kids			
	Household has kids (< age 18). (1 = yes; 0 = otherwise)	0.31	0.461
The elderly			
	Household has elderly members (> age 65). (1 = yes; 0 = otherwise)	0.47	0.499

More specifically, in the first section, with the evolution of the disaster, evacuees were informed of three scenarios of 48 h (Scenario I), 32 h (Scenario II) and 16 h (Scenario III) before flooding. Scenarios I, II and III represented the low-risk, medium-risk and high-risk conditions when there were 48, 32 and 16 h left for evacuation, respectively. With the advance of time, the water level of the river and the amount of the rain were increasing, and the road capacity was decreasing. In Scenario III, the transit service was strengthened in order to ensure the evacuation efficiency. Table 2 lists the frequencies of evacuee mode choice under the three disaster scenarios.

Table 2. Sample profiles of evacuation modes under different disaster scenarios.

Frequencies (%)	Scenario I			Scenario II			Scenario III		
	Transit	Car	Taxi	Transit	Car	Taxi	Transit	Car	Taxi
Gender									
Male	47.6	43.9	8.5	47.6	41.7	10.7	51.5	35.4	13.1
Female	60.2	33.5	6.3	55.9	33.5	10.6	64.2	26.6	9.2
Age									
18–34	57.3	35.1	7.6	53.6	35.4	11.0	58.8	29.2	12.0
35–54	38.7	54.2	7.1	44.0	47.6	8.3	53.0	39.3	7.7
>55	85.7	14.3	0	57.1	14.3	28.6	57.1	14.3	28.6
Education									
High school	51.2	35.7	13.1	48.8	31.0	20.2	59.5	22.6	17.9
Undergraduate	56.4	38.1	5.5	54.9	36.7	8.4	61.1	29.8	9.1
Postgraduate	49.4	41.6	9.0	46.7	42.0	11.4	50.6	36.5	12.9
Experience									
Little	63.2	28.9	7.9	52.6	31.6	15.8	57.9	23.7	18.4
Many	53.1	39.4	7.4	53.5	36.1	10.4	57.6	31.6	10.9
Car ownership									
No car	83.8	3.9	12.3	76.8	4.2	19.1	76.8	4.4	18.8
Own car	25.2	71.8	2.9	27.9	69.4	2.7	39.5	56.4	4.2
Kids									
None	58.4	34.5	7.1	55.1	34.5	10.4	58.0	30.3	11.7
Have	42.8	49.0	8.2	43.6	45.3	11.1	56.6	33.2	10.2
The elderly									
None	52.0	40.0	7.9	51.1	36.9	12.0	58.0	30.5	11.5
Have	55.3	37.7	7.0	52.1	38.8	9.1	57.1	32.0	10.9

In the second section, taking the medium-risk Scenario II as the context, an optimal orthogonal design was used to generate the least amount of scenario sets. The purpose was to investigate the main effects of mode attributes on evacuee choice behavior. There were nine possible scenario combinations according to attribute levels, including *TRAVEL_TIME* (60, 80, 100 min), *TIME_UNC* (5, 10, 15 min), *WAIT_TIME* (0, 15, 30 min) and *COMFORT_PER* (50%, 75%, 100%). Here, the percentage represented the chance that the evacuee was satisfied from a considered mode. A higher percentage reflected a greater comfort perceived from the mode. In order to reduce the survey time, each participant was asked to finish three scenarios randomly, and finally, 2388 choice observations were obtained in the dataset.

As shown in Table 1, most participants had a degree of evacuation experience. Half of them were carless people who did not have a private car. Households that have kids or elderly members might have more difficulty during an evacuation. One-point-five percent of evacuees with experience would stay no matter how the evacuation notice was issued. Nine-point-nine percent of them would wait and observe other people's decisions. Eighty eight-point-six percent of them would evacuate on the recommended or compulsory evacuation notice. Eighty three-point-six percent of experienced evacuees would depart immediately after they arranged their properties. The shelter provided by the government and the houses of relatives and friends were the main evacuation destinations. A descriptive analysis of evacuee mode choice was presented to show an intuitive finding on the correlation between socio-demographic variables and mode preferences. The distributions of three modes are compared under different disaster scenarios, as shown in Table 2. Compared with the males, female evacuees are more likely to choose public transit as an evacuation mode. Middle-aged people have a significant preference for driving a private car. Those who are highly-educated occupied a slightly higher percentage of car-based evacuation. This is probably because many highly-educated people owned a private car. It was found that the carless group is highly dependent on public transit and shared taxis. With the increase of disaster risk, people show an obvious tendency to take public transit. Nearly 15.4% of car-dependent respondents give up their private cars and then select public transit and shared taxis as an evacuation mode, of which 14.3% take transit. This figure is a little higher than what is given by Wu *et al.* [8], 11% of evacuees not taking their own cars, but sharing with other people.

The findings reveal that more attention should be paid on public transit as an evacuation mode, so that: (i) the benefit of carless evacuees can be guaranteed; (ii) those people who switch to the transit mode will benefit from emergency resource savings; and (iii) the overall evacuation efficiency will be improved. The prediction of transit-based evacuation demand can help emergency administrators to develop an effective transit-oriented evacuation plan, especially evacuees' choice response to the change of transit strategy.

4.2. Model Results

In this section, the results from different models are compared to find the best model to explain the evacuee mode choice. Besides the travel attributes of evacuation modes, a car dummy-attribute (*CAR_DUMMY*, the coefficient β_{car}) can reflect the nature of the evacuation mode in line with intuition. Therefore, it was attempted to introduce the variable *CAR_DUMMY* into the choice model, as well as *TRAVEL_TIME*, *TIME_UNC*, *WAIT_TIME* and *COMFORT_PER*.

The utility function can be written as a linear additive expression in Equations (5)–(7):

$$\begin{aligned} V_{\text{public}} = {} & \beta_t \times TRAVEL\_TIME_{public} + \beta_u \times TTIME\_UNC_{public} + \\ & \beta_w \times WAIT\_TIME_{public} + \beta_c \times COMFORT\_PER_{public} \end{aligned} \tag{5}$$

$$\begin{aligned} V_{\text{private}} = {} & \beta_{car} \times CAR\_DUMMY + \beta_t \times TRAVEL\_TIME_{private} + \beta_u \times TIME\_UNC_{private} + \\ & \beta_w \times WAIT\_TIME_{private} + \beta_c \times COMFORT\_PER_{private} \end{aligned} \tag{6}$$

$$\begin{aligned} V_{shared} = {} & \beta_t \times TRAVEL\_TIME_{shared} + \beta_u \times TIME\_UNC_{shared} + \\ & \beta_w \times WAIT\_TIME_{shared} + \beta_c \times COMFORT\_PER_{shared} \end{aligned} \tag{7}$$

The regret function of the private mode can be written as shown in Equation (8):

$$R_{private} = R_{private}^{\text{travel}\_time} + R_{private}^{time\_unc} + R_{private}^{wait\_time} + R_{private}^{comfort\_per} + R_{private}^{car} \tag{8}$$

$$\begin{aligned} R_{private}^{travel\_time} = {} & \ln(\gamma_t + \exp[\beta_t \times (TRAVEL\_TIME_{public} - TRAVEL\_TIME_{private})]) + \\ & \ln(\gamma_t + \exp[\beta_t \times (TRAVEL\_TIME_{shared} - TRAVEL\_TIME_{private})]) \end{aligned} \tag{8a}$$

$$\begin{aligned} R_{private}^{time\_unc} = {} & \ln(\gamma_u + \exp[\beta_u \times (TIME\_UNC_{public} - TIME\_UNC_{private})]) + \\ & \ln(\gamma_u + \exp[\beta_u \times (TIME\_UNC_{shared} - TIME\_UNC_{private})]) \end{aligned} \tag{8b}$$

$$\begin{aligned} R_{private}^{wait\_time} = {} & \ln(\gamma_w + \exp[\beta_w \times (WAIT\_TIME_{public} - WAIT\_TIME_{private})]) + \\ & \ln(\gamma_w + \exp[\beta_w \times (WAIT\_TIME_{shared} - WAIT\_TIME_{private})]) \end{aligned} \tag{8c}$$

$$\begin{aligned} R_{private}^{comfort\_per} = {} & \ln(\gamma_c + \exp[\beta_c \times (COMFORT\_PER_{public} - COMFORT\_PER_{private})]) + \\ & \ln(\gamma_c + \exp[\beta_c \times (COMFORT\_PER_{shared} - COMFORT\_PER_{private})]) \end{aligned} \tag{8d}$$

$$R^{car}_{private} = 2\ln[\gamma_{car} + \exp(-\beta_{car} \times CAR\_DUMMY)] \quad (8e)$$

The above regret function has different types of formulations due to different values of γ_a. In this study, a random utility model is denoted as *U*; four regret-based models are also given a symbol, such as the basic regret model *BR* ($\gamma_a = \gamma = 1$), the generalized regret *GR*-I ($\gamma_a = \gamma = 0$), the generalized regret model *GR*-II (δ) and the generalized regret model *GR*-III (δ_a). All of these models can be estimated using Biogeme, and the estimation results of these models are shown in Table 3.

Table 3. Estimation results for different choice models.

Coefficients (*t*-value)	***U***	***BR***	***GR*-I** $\Gamma = 0$	***GR*-II** δ	***GR*-III** δ_a
CAR_DUMMY	2.37 (*27.15*)	1.85 (*23.46*)	0.79 (*27.15*)	1.85 (*23.46*)	1.33 (*23.43*)
TRAVEL_TIME	−0.0173 (*−12.87*)	−0.0118 (*−12.73*)	−0.00577 (*−12.87*)	−0.0118 (*−12.72*)	−0.0118 (*−11.37*)
TIME_UNC	−0.0403 (*−6.53*)	−0.0257 (*−6.39*)	−0.0134 (*−6.53*)	−0.0256 (*−6.39*)	−0.0130 (*−4.12*)
WAIT_TIME	−0.00867 (*−4.22*)	−0.00587 (*−4.21*)	−0.00289 (*−4.22*)	−0.00587 (*−4.21*)	−0.00588 (*−3.82*)
COMFORT_PER	−0.0174 (*−13.26*)	−0.0123 (*−12.74*)	−0.00581 (*−13.26*)	−0.0123 (*−12.74*)	−0.0123 (*−11.08*)
δ_GENERIC	--	--	--	7.94 (*22.23*)	
δ_CAR	--	--	--	--	0 (*ns* [1])
δ_TRAVEL_TIME	--	--	--	--	7.08 (*13.34*)
δ_TIME_UNC	--	--	--	--	−5.31 (*−6.49*)
δ_WAIT_TIME	--	--	--	--	5.05 (*7.10*)
δ_COMFORT_PER	--	--	--	--	6.98 (*18.01*)
No. of Choices	2388	2388	2388	2388	2388
NULL-Log-Likelihood	−2623.486	−2623.486	−2623.486	−2623.486	−2623.486
FINAL-Log-Likelihood	−2009.629	−2006.581	−2009.629	−2006.581	−2006.431

[1] This parameter was found to be insignificant (robust *t*-value = 0.09). The model was re-estimated with this parameter fixed at zero.

In line with the theoretical proposition established by Chorus, the *GR*-I model has the same log-likelihood and *t*-statistic as the *U* model, and the parameters from the *GR*-I model are three-times smaller than those from the *U* model. The similar estimated results are found from the *BR* model and the *GR*-II model. This is due to $\delta_{generic}$ being a positive value with a significant *t*-value, and the attributes in the *GR*-II model are processed based on the regret minimization rule. In terms of the final log-likelihood, the regret-based models (*i.e.*, *BR*, *GR*-II and *GR*-III) achieve a slightly better model fit than that from the *U* model and the *GR*-I model. This means that compared with the *U* model, regret-based models perform better for explaining the evacuee mode choice data. The best final log-likelihood is obtained by the *GR*-III model with attribute-based values δ_a.

As mentioned above, the question of which rule (*i.e.*, utility maximization or regret minimization) is better to explain the attribute *a* is decided by the value of δ_a. For the *GR*-III model, utility maximization is the approach for the attribute (*i.e.*, *TIME_UNC*) when δ_a is a large negative value; the regret minimization is the approach for the attribute (*i.e.*, *TRVEL_TIME*, *WAIT_TIME*, *COMFORT_PER*) when δ_a is a large positive value. It seems that the mode choice has a regret tendency, indicating that evacuees' regret aversion psychology is relatively strong during an evacuation decision.

Following the estimation results from different models, we try to formulate an evacuee mode choice model in a hybrid paradigm. The attribute of *TIME_UNC* is processed using the utility maximization rule, and other attributes, including *TAVEL_TIME*, *WAIT_TIME* and *COMFORT_PER*, are processed using the regret minimization rule. Therefore, the hybrid function for mode choice can be written as follows:

$$H_{ni} = \sum_{u,car} \beta_a \times x_{na} + \sum_{a=t,w,c} \sum_{j \neq i} \ln(1 + \exp[\beta_a \times (x_{nja} - x_{nia})]) + \varepsilon_{ni} \tag{9}$$

The estimated results of the hybrid mode choice model are reported in Table 4. As expected, the travel-related parameters are all significant at the 95% confidence level. The negative signs of *TAVEL_TIME*, *TIME_UNC* and *WAIT_TIME* imply that evacuees are more likely to choose the mode with smaller average travel time, travel time uncertainty and waiting time. It seems odd that the sign of *COMFORT_PER* is negative. This may be due to the larger choice probability for public transit, and the comfort level of public transit perceived by evacuees is relatively lower in reality. The attribute *TAVEL_TIME* is the most significant influencing factor on evacuee mode choice under an emergency evacuation. Since most evacuees think highly of the attribute *TAVEL_TIME*, the attribute *TAVEL_TIME* should be considered as one of the key determinants for evacuation strategy development.

Table 4. Estimated results for the hybrid mode choice model.

	Coefficients (*t*-Value)	Model Fit	
CAR_DUMMY	2.40 (*26.81*)	No. of Choices	2388
TRAVEL_TIME	−0.0118 (−*12.73*)	NULL-Log-Likelihood	−2623.486
TIME_UNC	−0.0388 (−*6.38*)	FINAL-Log-Likelihood	−2006.428
WAIT_TIME	−0.00590 (−*4.23*)	Rho-square [1]	0.235
COMFORT_ PER	−0.0123 (−*12.85*)	Adjusted Rho-square	0.233

[1] This parameter reflects the goodness of fit for the model.

5. Elasticities and Simulation Test

The transit-oriented evacuation plan is becoming more and more popular in urban cities. Therefore, it is meaningful to conduct a simulation scenario test on different strategies for evacuation demand management and strategy development [35]. In this section, direct elasticity and cross elasticity are both calculated at a disaggregated level in order to reflect the sensitivity of evacuee mode choice probability on mode attributes. Moreover, the simulated results will be obtained based on the scenarios of the travel-related attributes' change arising from transit-oriented strategies. The empirical results are used to verify the influence of transit strategy on evacuation mode switching behavior due to a change in public transit service.

The direct elasticity and cross elasticity of the hybrid mode choice model in Equations (10) and (11) are presented in Table 5. Direct elasticity represents the variation in an evacuee's choice probability due to one percentage change of the attribute from this mode. Cross elasticity represents the variation in an evacuee's choice probability due to one percentage change of the attribute from other modes. The elasticities of the hybrid choice model can be calculated as follows [36,37]:

$$direct\text{-}elasticity = \frac{\partial P_i}{\partial x_{ia}} \times \frac{x_{ia}}{P_i} = \begin{cases} \beta_a & a = car, u \\ \beta_a \sum_{j \neq i}^{J} \dfrac{\exp[\beta_a (x_{ja} - x_{ia})]}{1 + \exp[\beta_a (x_{ja} - x_{ia})]} & a = t, w, c \end{cases} \tag{10}$$

$$cross\text{-}elasticity = \frac{\partial P_i}{\partial x_{ka}} \times \frac{x_{ka}}{P_i} = \begin{cases} 0 & a = car, u \\ -\beta_a \dfrac{\exp[\beta_a (x_{ka} - x_{ia})]}{1 + \exp[\beta_a (x_{ka} - x_{ia})]} & a = t, w, c \end{cases} \tag{11}$$

Tables 5 and 6 present the direct elasticity and cross elasticity about travel-related attributes. The direct elasticity of the attribute from private car is larger than that from public transit and shared mode. This shows that evacuees who choose a private car are more sensitive than those that select other modes. In other words, this indicates that evacuees choosing a private car are more likely to change their choices due to the attribute change arising from the evacuation strategy. It is found that the cross elasticity of the attribute *TIME_UNC* for private car and shared modes are both equal to 1.444. This means that one percentage of *TIME_UNC* decrease for public transit would lead to a 0.144 percent increase in choice possibility for private car and shared modes. It is also found that the most sensitive attributes are *TRAVEL_TIME* and *COMFORT_PER*. This means that evacuation strategies about *TRAVEL_TIME* change are more likely to produce a significant effect.

Table 5. Direct elasticity with travel-related attributes.

Travel mode	Public	Private	Shared
TRAVEL_TIME	−3.121	−4.083	−3.202
TIME_UNC	−0.243	−0.300	−0.247
WAIT_TIME	−0.058	−0.044	−0.079
COMFORT_ PER	−2.972	−4.030	−2.991

Table 6. Cross elasticity with travel-related attributes.

Travel mode	Public		Private		Shared	
Based mode	**Private**	**Shared**	**Public**	**Shared**	**Public**	**Private**
TRAVEL_TIME	1.321	1.341	2.363	2.332	1.253	1.272
TIME_UNC	0.144	0.144	0.087	0.087	0.143	0.143
WAIT_TIME	0.039	0.037	0.015	0.016	0.039	0.040
COMFORT_PER	1.330	1.443	1.327	1.332	1.320	1.156

The calculation of direct elasticity and cross elasticity is at a disaggregated level from a random evacuee. It reflects the responsiveness of the mode attributes' change. Seeing that the aggregate results are of great help for making a strategy, it is meaningful to generate the aggregate shares to test the evacuation strategy. In order to solve the issues of traffic congestion and vehicle emissions, one way is to affect travelers' mode choice behavior by means of improving the level of service indicators. For example, the construction of bus rapid transit (BRT) aims to reduce the average travel time of the public transit mode. Bus lanes are also designed to improve public transit service (*i.e.*, avoiding traffic congestion).

In an emergency context, travel mode plays an important role in the overall evacuation efficiency. Here, a series of strategy simulations is implemented from the viewpoint of public transit, assuming that there is a travel time improvement of public transit arising from the usage of the BRT strategy, the bus lane strategy and other transit priority strategies during an evacuation.

Sample enumeration is employed as the aggregate forecasting technique. Based on the estimated parameters presented in Table 4, the mode choice probability for each evacuee is calculated using the data samples from Scenario II. A list of simulated choices can be obtained based on Monte-Carlo simulation. The correct predicted probabilities for all mode alternatives are produced based on the previous simulated choice [38]. It is meaningful to generate the aggregate shares of evacuation modes. The simulated results of transit travel time savings due to a transit-oriented strategy are listed in Table 4. As expected, the simulated results in Table 7 show that the mode choice probability of public transit increases with the decrease of the average travel time. In the situation of a 10% transit travel time savings, there are 1.1% car-dependent evacuees who probably switch to public transit. In the situation of a 20% transit travel time savings, there is nearly a 6.2% increase from evacuees who choose public transit. The strategy of transit travel time savings shows a significant effect for car-dependent evacuees. This echoes the phenomenon that several car-dependent respondents switch to taking public transit in our survey. Therefore, it is necessary to provide an effective public transit mode during an emergency evacuation.

Table 7. Predicted shares based on the different strategy scenarios.

Scenario Group (%)	Public Transit	Private Cars	Shared
Base scenario (*TRAVEL_TIME*)	0.514	0.376	0.110
10% time saving of transit	0.545	0.365	0.090
20% time saving of transit	0.576	0.354	0.070
30% time saving of transit	0.605	0.343	0.052

6. Conclusions

This paper contributes to analyzing evacuee mode choice behavior using the utility-based and regret-based models in an emergency context. The random utility model, the basic random regret model, the generalized regret model without regret weight, the generalized regret model with a generic regret weight and the generalized regret model with attribute-specific regret weight were formulated and estimated, respectively. Compared with the utility-based model, the regret-based models show a slightly better model fit due to accounting for evacuees' regret aversion psychology.

Furthermore, based on the analysis of evacuee mode choice behavior, evacuation strategy simulations using sample enumeration are conducted to predict the aggregate mode choice shares. The results show a significant switching effect from private mode to pubic mode. The behavioral characteristic of evacuee mode choice is an important consideration when developing an evacuation strategy. A transit-oriented strategy about transit time improvement may achieve a good mark on evacuation efficiency.

The study is expected to give a better understanding of evacuee mode choice behavior and help to make a transit-oriented evacuation plan for carless people, as well as other car-dependent evacuees. The regret-based model appears to have the potential to model evacuee decision behavior in evacuation modeling. Future research can be conducted in a few directions. The application of the regret-based model can be conducted in other travel behavior analyses, such as evacuation departure time, route choice, and so on. Meanwhile, the heterogeneity of the evacuees should be considered to explain mode choice behavior, for example kids and elderly people probably have different behaviors from others. The elasticity with regard to evacuation demand should be calculated.

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Author Contributions

The paper represents an effort from three authors. Shi An designed the study. Ze Wang analyzed the data and drafted this manuscript. Jianxun Cui collected the data.

Conflicts of Interest

The authors declare no conflict of interest.

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