Research Article

Modeling the Traveler’s Route Choice Behavior under Unexpected Accidents

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To investigate the route choice behavior of travelers under unexpected accidents, this study designs four different scenarios of travelers’ route choice behavior experiments according to the severity of unexpected accidents. The bounded rationality characteristics of travelers, such as the time perception difference coefficient, psychological threshold effect coefficient, and scale effect, are introduced into the generalized random regret minimization (GRRM) model. An improved generalized random regret minimization (IGRRM) model is constructed based on travelers’ route choice behavior under unexpected accidents. The collected data of travelers’ route choice results under four different congestion-level scenarios are analyzed by the IGRRM model. The study finds that with the increase in congestion level, travelers are more willing to change the route; during the commute, travelers tend to choose the route with less travel time and angular cost; in the moderate and serious congestion scenarios, travelers no longer reject the detour route; attribute perception difference, scale effect, and psychological threshold effect affect travelers’ route choice behavior. The IGRRM model based on the route choice behavior of travelers can more accurately characterize the route choice behavior of travelers under unexpected accidents, provide a basis for traffic flow distribution under unexpected accidents, and benefit traffic management departments to take traffic control and guidance measures to ease the traffic congestion caused by unexpected accidents.

1. Introduction

Unexpected accidents are road traffic accidents that travelers suddenly encounter during a trip and whose information cannot be obtained in advance. Unexpected accidents are the leading cause of urban road congestion and threaten urban road traffic participants’ lives and property safety [1–3]. When an unexpected accident occurs in a road unit and generates congestion, drivers in the distant areas keep their travel routes unchanged because they do not perceive congestion, while drivers on the roads around the accident section may change their route choices according to their perception of congestion [4]. If the roads around the accident cannot bear the traffic flow that changes the travel route due to the unexpected accident, new congestion will occur. With the increase in accident duration, the scope of traffic congestion will gradually expand [5, 6]. Therefore, the study of the route choice behavior of travelers is necessary to improve the efficiency of emergency organization [7, 8] and ease the road congestion caused by unexpected accidents.

Variable message signs (VMS) can provide drivers with spatiotemporal information about traffic and network conditions, where driver route choice behavior is heterogeneous after obtaining the same information [9]. Imants et al. [10] focused on the conflicting traffic information from various sources and described how en-route traffic information affects route choice with the Bayesian model. Kusakabe et al. [11] described the driver route choice behavior when traffic accident information is provided on VSMs in an urban highway network. However, when a traffic accident suddenly occurs on the road ahead during the trip, the drivers need to make a route choice by perceiving the congestion level of the road ahead when they cannot obtain traffic information through mobile devices. The study of
route choice under sudden traffic accidents has been little explored thus far.

The objective of this study is to explore the effects of different congestion levels on travelers’ route choice behavior under unexpected accidents. This study designed four types of congestion-level scenarios under unexpected accidents and selected the measurement indices of travelers’ route choice from two dimensions of time and space: travel time and angular cost [12, 13]. To accurately characterize the route choice rules of travelers under unexpected accidents, it is necessary not only to profoundly understand the psychological dynamic change process of travelers but also to select a suitable model to characterize the travelers’ route choice behavior.

In this study, two regret functions of travel time and angular cost are constructed based on the generalized random regret minimization (GRRM) model. The improved generalized random regret minimization (IGRRM) model shows the bounded rationality characteristics of travelers, such as attribute perception differences, psychological threshold effects, and scale effects. The advantage of the improved model is that it can accurately characterize and predict the route choice behavior of travelers in complex decision environments.

The rest of the article is organized as follows. Section 2 reviews traveler route choice behavior during daily trips in previous studies and identifies the gaps in research. Section 3 discusses the IGRRM model under unexpected accidents and describes the design of the route choice experiment under unexpected accidents to determine the route choice preferences of travelers. Section 4 discusses the results of the model analysis and gives the crucial findings. Finally, conclusions, gaps in the current study, and future research directions are discussed in Section 5.

2. Literature Review

Current research on traveler choice behavior is mainly based on utility theory (UT) [14], prospect theory (PT) [15], and regret theory (RT) [16].

UT assumes that users always have perfect rationality during travel, and they will always choose the route with the highest utility to travel. In 1974, UT began to be widely used in transportation, and McFadden [17] proposed the multinomial logit model (MNL), which further refined the theory of random utility maximization (RUM). Subsequently, the form of MNL models has been gradually expanded to more flexible nested logit (NL) models [18], mixed logit (ML) models [19], latent class logit models (LCM) [20], and so on. Currently, UT is often applied to travel route choice behavior in transportation travel behavior. Nakayama and Chikaraishi [21] developed a new internally consistent adaptive route size logit model with a route size contribution factor based on the ratio of choice probabilities between routes, thus ensuring that the impractical routes in the route choice scheme are exactly the routes with low choice probabilities. Papola et al. [22] proposed a combination of nested logit route choice model based on the principle of locating correlations between routes based on their topological overlap. The model algorithm automatically provides the route choice specification and the corresponding route choice probability over enumerated routes. The model was tested for performance on various networks, and satisfactory results were obtained.

During the actual trip, travelers do not always have perfect rationality due to individual differences, external factors, and psychological effects [23]. Bounded rationality is more consistent with the actual trip of travelers. Therefore, PT began to describe travelers’ bounded rationality decision-making behavior. PT was first proposed in 1977 by Handa [24], who argued that people do not make risky decisions based on expected utility when making decisions. After further development, Tversky and Kahneman [25] improved PT and proposed cumulative prospect theory (CPT) in 1992, which retains the main components of PT without violating the first-order stochastic advantage. The main difference between PT and CPT is that the subjective decision weights are assigned based on the cumulative probabilities rather than the probabilities themselves. In recent years, scholars’ research on PT has been distributed to describe the route choice behavior of travelers under uncertainty and the equilibrium flow allocation of traffic networks. Zhang et al. [26] used bounded rationality theory and CPT to construct a user daily route choice model. Ghaderi et al. [27] analyzed the influence of travel time reliability on route choice behavior and used CPT to build a route choice model considering decision preferences and time reliability. Based on empirical tests, many scholars have begun to apply PT to the equilibrium flow allocation process of transportation networks. Ye and Yang [28] constructed a bounded rational user equilibrium (UE) model to study travelers’ evolutionary process states under different bounded rationality thresholds and different initial values. Wang and Sun [29] studied travelers’ heterogeneity and decision dependence and established a UE model based on CPT. The UE model is based on CPT and takes the random perception errors of travelers into account.

RT was first proposed by Loomes and Sugden [30] in 1982 to describe people’s decision-making behavior in unknown environments. In the last decade or so, RT has started to appear in the field of transportation because it can be used as a decision theory for describing traffic behavior and is favored by many experts and scholars. RT was first introduced into the transportation field by Chorus et al. [31] in 2008, who pioneered the random regret minimization (RRM) model, which applies to unknown risk environments. The application of RT in the transportation field has only a history of more than ten years. Scholars’ current research on RT mainly focuses on improving the model, travelers’ route choice behavior, and equilibrium flow allocation models. Chorus [32] introduced regret weighting coefficients in the model to reflect the weight of regret in the decision-making process and constructed the GRRM model. Van Cranenburgh et al. [33] proposed the μ-RIM model and added parameters such as “regret level” to the model, which makes the RUM model, pure RRM, and RRM model exceptional cases of the μ-RIM model. In terms of travelers’ route choice behavior, Li and Huang [34] proposed a stochastic user equilibrium (SUE) route choice model based on...
RT by introducing a regret aversion parameter to reflect travelers’ regret level, which showed that regret aversion attitude did affect travelers’ route choice behavior. Jang et al. [35] considered the undifferentiated band of regret sentiment, where decision-makers have a certain tolerance for regret. The difference in regret in different solutions can be negligible within a specific interval, thus constructing an RRM model considering decision-maker tolerance and undifferentiated bands. RT can reflect the psychological characteristics of travelers during their route choice behavior and is able to consider multiple attributes of routes in the equilibrium traveling time, in which the traveler’s goal is to minimize the equilibrium (BRminUE) model with monetary cost and travel time, in which the traveler’s goal is to minimize the regret value. Wang et al. [38] combined the route choice behavior of urban rail transit passengers based on RT to simulate the nonintervention passenger flow redistribution process.

UT, PT, and RT can all be used to construct the route choice model for travelers. UT believes that travelers are perfectly rational and that the “value” of a route depends on the attributes of the route itself. The original planned route may not work when disturbed due to the travel environment under unexpected accidents being full of uncertainties. Therefore, the utility-theoretic decision-making approach is unsuitable for describing the traveler’s route choice behavior under unexpected accidents. PT believes that the “value” of the route depends on the choice of the reference point, and the formation of the reference point is a complex psychological process. The choice of the reference point is closely related to the subjective perception of the decision-maker. When the reference point is taken too high or too low, it will have a more significant impact on the traveler’s route decision results, with certain decision-making defects. RT, as a decision-making method in an uncertain environment, is particularly prominent in evaluating the “value” of the routes between travelers under the scenario of unexpected accidents. When the “value” of the route chosen by the traveler is lower than the original planned route, the traveler will feel regretful, and when the opposite is true, the traveler will feel joyful. To review, there exists a research gap in evaluating the effect of experiencing a sudden accident on the urban road network on travelers’ route choice. Previous studies have focused on expressing route choice behavior after obtaining information about an accident. However, travelers on urban road networks usually do not have access to traffic information in advance when they encounter a sudden accident, and they can only judge that a traffic accident has occurred on the front road after perceiving the congestion and thus making a route choice, which has been less-researched. Different severity levels of unexpected traffic accidents can cause different levels of congestion. Previous studies have not considered the route choice rules of travelers under different congestion levels. To fill this gap, this paper assumes different congestion levels caused by unexpected accidents and considers not only the effect of time attributes on route choice but also the effect of topological attributes of the road network on route choice. Using the regret model to analyze the route choice characteristics in an uncertain environment can overcome decision defects such as the perfect rationality of users in UT and the subjectivity of reference point selection in PT. Moreover, the regret model can fully consider the comparison of travelers’ assessments of the value of each route under unexpected accidents, which is more suitable for modeling in this study.

3. Method

3.1. Route Choice Model Framework under Unexpected Accidents. In this section, the GRRM model is introduced to model the route choice behavior of travelers under unexpected accidents with bounded rationality.

3.1.1. Generalized Random Regret Minimization Model. The GRRM model is an evolution of the RRM model, which was first proposed by Chorus et al. [31] as the first theoretical measure of regret to be applied to transportation research, making it an alternative decision model corresponding to the RUM model. Equation (1) gives the RRM model.

\[ R_{l \rightarrow k}^m = \max \{ 0, \beta^m (X_{l}^m - X_{k}^m) \}, \]

where \( X_{l}^m \) is the value of attribute \( m \) of solution \( l \); \( X_{k}^m \) is the value of attribute \( m \) of solution \( k \); \( \beta^m \) characterizes the preference parameter of the attribute, representing the contribution of the \( m \) attribute in the solution.

Because there are some unobservable errors in the regret value measurement, Chorus adds error terms \( \xi_{lm} \) and \( \xi_{Xlm} \) to the base regret model [39], which is given in the following equation:

\[ R_{l \rightarrow k}^m = \max \{ 0 + \xi_{lm}, \beta^m (X_{l}^m - X_{k}^m) + \xi_{Xlm} \}. \]

Then, Chorus again accumulates the dichotomous choice regret values of \( m \) attributes, conducts a two-by-two comparison of the attributes after the regret value accumulation, and selects the maximum value as \( R_l \) given by the following equation:

\[ R_l = \max_{l \neq k} \left\{ \sum_{m=1}^{M} \max \{ 0, \beta^m (X_{l}^m - X_{k}^m) \} \right\}. \]

On this basis, assuming that the error terms obey the Gumbel distribution with an identical independent distribution, the expectation of \( R_{l \rightarrow k}^m \) is deduced as \( R_{l \rightarrow k}^m \), which is given in the following equation:

\[ R_{l \rightarrow k}^m = \ln [1 + \exp \{ \beta^m (X_{l}^m - X_{k}^m) \}]. \]

The advantage of using this equation is that it makes the function curve of the regret model smooth and allows to easily estimate the parameters; on the other hand, it can express people’s regret emotions: when \( \beta^m (X_{l}^m - X_{k}^m) < 0 \), people are joyful; when \( \beta^m (X_{l}^m - X_{k}^m) > 0 \), they are regretful.
and when $\beta_m (X_i^m - X_k^m) = 0$, they are neither joyful nor regretful.

Then, Chorus included all abandoned scenarios in the regret model in the regret metric, which is given in the following equation:

$$
\hat{R} = \sum_{l=k}^{L} \sum_{m=1}^{M} \ln \{1 + \exp [\beta_m (X_i^m - X_k^m)]\}. 
$$

(5)

Based on these models, Chorus reintroduced the idea of decision-theoretic heterogeneity and proposed the GRRM model in 2014 [32], which replaced 1 in equation (4) with a regret weight parameter $\alpha$, depending on the degree of regret avoidance, and its regret expression is given by the following equation:

$$
R_{i-k}^m = \ln \{\alpha + \exp [\beta_m (X_i^m - X_k^m)]\}. 
$$

(6)

In this equation, the regret value reflected by the GRRM model changes from the value of the regret weight parameter $\alpha$. The universality of the model lies in the organic unity of the RRM theory and the RUM theory. Adjusting the regret weight parameter reflects the travelers’ tendency toward utility maximization psychology and regret minimization psychology. When $\alpha$ is 0, the model is transformed into a RUM model; when it is greater than 0, it shows that travelers have a greater tendency to regret minimization in this decision. The RRM model is dominant, and when it is 1, the model becomes a RRM model.

The model’s universality lies in the organic unity of the RRM theory and the RUM theory.

3.1.2. Behavior Characteristics of Route Choice under Unexpected Accidents. The perfect rationality of decision-makers has always been a critical premise assumption in early decision-making theory research. However, with the deepening of behavioral science research and the continuous development of bounded rationality research, the concept of decision-making behavior based on perfect rationality is no longer realistic. The travel environment under unexpected accidents has great uncertainty. Travelers often have different psychological states when facing the same congestion; thus, their utility perceptions of the current route are different. Travelers’ tolerance for travel time and travel inertia affects the route choice outcome to different degrees [40]. Some travelers have a certain degree of tolerance for the unexpected congestion on the current route. When the degree of tolerance is higher, they are more willing to keep driving on the original route, thus reducing the negative emotions brought by traffic congestion and mitigating the perceived negative utility of the current decision. Some travelers will have a strong sense of discomfort or disappointment because of the congestion caused by the current route due to unexpected circumstances. In this case, travelers will ignore the overall situation and become more concerned about the current congestion situation, strengthening the negative emotions caused by traffic congestion and increasing the perception of the current negative utility of decision-making. To explore the influence of the heterogeneity of travelers’ perceived psychological utility on route choice in the context of unexpected accidents, this study defines the aforementioned two types of psychological states as psychological threshold effects and proposes a psychological threshold function for travel time under unexpected accidents based on different traffic states under accidents, as shown in the following equation:

$$
F(k) = \eta^\text{time}_k \Delta_k, 
$$

(7)

where $\eta^\text{time}_k$ is 1 when the route is the original planning route and 0 otherwise; $\Delta_k$ is the psychological threshold coefficient of the current route.

(3) Scale Effect. The traveler’s perception of a route’s attributes is generated when the route is compared with routes in the set of feasible routes. At different attribute orders of magnitude, the same attribute difference produces different perceptions in the traveler. In this study, we borrow a principle from cognitive psychology to characterize the scale effect on a traveler’s route choice behavior. It argues that when the original stimulus is higher, the stimulus increment required for an individual to maintain the same perceived difference is also higher. Later, Guilford [41] and other scholars found that when the external stimulus is too large or too small, the individual’s sensitivity to the stimulus change decreases; thus, the required stimulus increment is larger than that calculated by Weber’s law. For this reason, researchers add a power factor between 0 and 1 to the initial stimulus, called the attribute perceived difference factor, as shown in the following equation:

$$
C = \frac{\Delta I}{I^\delta}. 
$$

(8)

where $C$ is a constant, $\Delta I$ is the attribute difference between the remaining replacement routes and the current route, $I$ is the attribute value of the current route, and $\delta$ is the attribute perceived difference coefficient.
3.1.3. Improved Generalized Random Regret Minimization Model. In this study, we consider the characteristics of travelers' decision-making behavior under unexpected accidents and construct a route choice model for travelers under unexpected accidents based on the GRRM model by introducing bounded rationality features such as the perceived coefficient of difference in attributes and psychological threshold effect of travelers in route choice. The time-dimensional regret function selects travel time as a variable, and the spatial-dimensional regret function selects angular cost [12, 13] as a variable indicator to measure the deviation degree of different routes relative to the origin and destination directions.

The angular cost describes the penalty effect on the utility of route choice. While the feature that the value increases with an increasing angle of deviation from the route reflects the degree of regret of the traveler with an increasing deviation of the route from the direction of the trip, the rate of change of the value decreases with increasing deviation from the direction. The trend of the angular cost value should increase with the increasing angle of deviation. The angular cost function is first-order derivable, and the derivative function is further introduced into the travel time attribute regret function; as shown in the following equation:

\[ x_{i}^{\text{angle}} = \sum_{a} S_{a} \times \tan \left( \frac{\theta}{4} \right), \quad (9) \]

where \( x_{i}^{\text{angle}} \) is the angular cost of the \( i \) th route between point \( O \) and point \( D \); \( N_{a} \) is the number of nodes in route \( i \); \( S_{a} \) is the distance between adjacent nodes, and the deviation angle between the section between adjacent nodes and the line between OD is denoted by \( \theta, \theta \in [0, \pi] \).

The regret function in the GRRM model is constructed similar to the utility function in the RUM model, both consisting of a random term and a fixed term, where the fixed term of the regret function is the difference between the attribute of one option of the route and the corresponding attribute of the rest of the route, and the random term is the difference between the error or other neglected attributes. Equation (10) gives the regret function for the travel time attribute of the routes.

\[ \lambda_{lk}^{\text{time}} = \ln \{ y_{1} + \exp \left[ \beta^{\text{time}} \cdot \left( X_{l}^{\text{time}} - X_{k}^{\text{time}} \right) \right] \}, \quad (10) \]

where \( \beta^{\text{time}} \) is the parameter to be estimated at the travel time attribute; \( y_{1} \) is the regret weighting factor in the time regret function; \( X_{l}^{\text{time}} \) and \( X_{k}^{\text{time}} \) are the travel times of routes \( l \) and \( k \), respectively.

The time perception difference coefficient, the psychological threshold effect coefficient, and the scale effect are further introduced into the travel time attribute regret function, as shown in the following equation:

\[ \lambda_{lk}^{\text{time}} = \ln \left\{ y_{1} + \exp \left[ \beta^{\text{time}} \cdot \left( X_{l}^{\text{time}} - X_{k}^{\text{time}} \right) \right] + \eta_{lk}^{\text{time}} \Delta_{k} \right\}, \quad (11) \]

where \( \delta \) is the coefficient of perceived difference in travel time attributes; \( \eta_{lk}^{\text{time}} \) is 1 when the traveler chooses the accident section and 0 otherwise; \( \Delta_{k} \) is the coefficient of psychological psychological threshold effect of the current route.

Therefore, the IGRRM model of the traveler under the unexpected accident based on the GRRM model is given in the following equation:

\[ \begin{align*}
\lambda_{lk}^{\text{time}} &= \ln \left\{ y_{1} + \exp \left[ \beta^{\text{time}} \cdot \left( X_{l}^{\text{time}} - X_{k}^{\text{time}} \right) \right] \right\}, \\
\lambda_{lk}^{\text{angle}} &= \ln \left\{ y_{2} + \exp \left[ \beta^{\text{angle}} \cdot \left( X_{l}^{\text{angle}} - X_{k}^{\text{angle}} \right) \right] \right\}, \\
\eta_{lk}^{\text{angle}} &= \lambda_{lk}^{\text{angle}} \cdot \left( \lambda_{lk}^{\text{time}} \cdot \left( X_{l}^{\text{angle}} - X_{k}^{\text{angle}} \right) \right), \\
\epsilon_{k} &= \sum_{l \neq k} \left( X_{l}^{\text{angle}} - X_{k}^{\text{angle}} \right),
\end{align*} \quad (12) \]

where \( y_{1} \) is the regret weight coefficient in the angular cost regret function; \( \beta^{\text{angle}} \) is the parameter to be estimated for the angular cost attribute; \( X_{l}^{\text{angle}} \) and \( X_{k}^{\text{angle}} \) are the angular cost of routes \( l \) and \( k \), respectively; \( \lambda_{lk}^{\text{angle}} \) is the attribute difference between the current routes \( l \) and \( k \); \( \lambda_{lk}^{\text{time}} \) is the attribute difference between the current routes \( k \) and \( l \) in the travel time; \( H_{k} \) is the regret value of the current route; \( h_{k} \) is the fixed term of the regret function; \( \epsilon_{k} \) is the random error term of the regret function.

Based on the conditional probability equation, equations (13)–(16) provide the probability \( P_{k} \) calculation of the traveler's choice of route \( k \).

\[ P_{k} = P \left( \bigcap_{l \neq k} H_{k} < H_{l} \right), \quad (13) \]

\[ P_{k} = \prod_{l \neq k} P(h_{k} + \epsilon_{k} < h_{l} + \epsilon_{l}), \quad (14) \]

\[ F(x) = P(x \leq X) = e^{-e^{-x}}, \quad (15) \]

\[ P_{k} = \frac{e^{-h_{k}}}{\sum_{i} e^{-h_{i}}}. \quad (16) \]

3.2. Route Choice Experimental Design

3.2.1. Scheme of the Experiments. To obtain the observed sample data needed to estimate the IGRRM model, this study designs a traveler route choice experiment for four different congestion scenarios under unexpected accidents, concerning the severity of the unexpected accidents.

The experimental part of this study selects the actual road network of a certain area in Tianjin, where \( O \) is the origin and \( D \) is the destination. The travel routes between origin and destination will be screened according to the effective
route concept [42]. Figure 1 shows the topological structure and travel routes of the experimental road network. The video material of the selected actual road network is collected, and the objective traffic flow data during video recording are collected by the car-following method.

In this study, K-means clustering was performed on the collected traffic flow video materials according to the interval speed, and the best clustering result was determined by the elbow method when the number of clusters $K = 4$. There were a total of 20 videos, each with a duration of 20 s, and the sequence of videos was arranged according to the interval speed, from small to large. Before the experiment, 254 respondents were recruited to score the congestion of the sorted video materials according to their subjective perception. The congestion score is a percentage system, which can be divided into four levels corresponding to smooth [0, 25], mild congestion [25, 50], moderate congestion [50, 75], and serious congestion [75, 100]. Based on the scoring results, the video with the highest number of people selected in each congestion level is selected as the representative video for the experimental video material for the congestion-level scenario. Four different congestion scenarios are determined in this way. Figure 2 shows the traffic flow state in the representative video materials of four congestion-level scenarios. Table 1 presents the traffic flow parameters for the four congestion-level scenarios.

This experiment assumes that four route choice scenarios with different congestion levels will occur in the accident section, and the travelers have planned their travel routes and are driving motor vehicles for urban commuting. There is an unexpected accident on the road ahead during the trip, and the traveler needs to choose between the original planned route (daily travel route) and other alternative routes. The collected representative traffic flow videos of four scenarios were imported into the questionnaire in this experiment. During the experiment, the respondents watched a video of the traffic flow state to simulate drivers’ subjective perceptions of different levels of congestion during an actual trip and make route choices. The attribute levels of the travel routes in the experimental road network will be expressed by two dimensions: time and topology. The attribute parameters of each travel route are shown in Table 2. Scenarios 1 to 4 are smooth, mild congestion, moderate congestion, and serious congestion, respectively.

3.2.2. Data Collection. The respondents in this study were all private-car commuters who had a motor vehicle license and had driven to work in the morning for at least one year. The experimental data were collected using the Questionnaire Star online survey site, and the experimental procedure was explained using the necessary text. According to the experimental content, the respondents completed the experiment and submitted the questionnaire. Each respondent was required to repeat the experiment three times, and the data were considered valid if the respondents’ three route choice results were the same twice or more; otherwise, the data were deemed invalid and excluded. After removing invalid questionnaires, we finally collected 637 valid experimental results for a total of 2548 route choice sample data.

4. Results and Analysis

4.1. Preliminary Analysis of Experiment Data. At different congestion levels, the proportion of travelers choosing each route is different. Figure 3 provides the proportion of respondents’ route choices in different congestion-level scenarios under unexpected accidents during the survey.

In the smooth traffic scenario, nearly 90% of the travelers prefer to keep the original route (i.e., route 1), indicating that the congestion level of the S4 section does not affect the travelers’ route choice under the unexpected accident in the smooth traffic condition. Because the damage to the traffic state under this scenario is low, route 1 still has more obvious advantages than other alternative routes in both time and space dimensions; thus, the travelers under the scenario of unexpected accidents are willing to keep the original route.

In the scenario of mild congestion, the probability of choosing route 1 starts to slightly decrease, and the probability of choosing routes 6 and 7 starts to increase. This indicates that under light congestion traffic conditions, the congestion level of the S4 section starts to affect the route choice results of travelers under unexpected accidents, and travelers are beginning to show a slight willingness to change their routes. Furthermore, because the travel time of routes 6 and 7 has significant advantages compared with other routes except route 1, travelers on route 1 begin to shift to routes 6 and 7.

In the moderate congestion scenario, the choice probability of route 1 sharply decreases, and the choice probabilities of routes 6 and 7 increase, indicating that under the moderate congestion condition, the congestion level of the S4 section has a significant impact on the route choice of travelers under unexpected accidents. Due to travelers’ showing a stronger willingness to change their routes, the travelers of route 1 obviously turned to routes 6 and 7.

In the serious congestion scenario, only approximately 5% of the travelers still keep the original route, indicating that the congestion level of the S4 section has tremendously influenced the route choice of travelers under serious traffic congestion. Because the unexpected accident in this scenario caused grievous damage to the traffic state, travelers showed a solid tendency to change the route, and the probability of choosing the remaining route observably increased. In addition, although the congestion on S4 is so serious, a small number of travelers are still willing to maintain the original route, probably due to the psychological threshold effect.

In summary, different congestion-level scenarios caused by unexpected accidents have different degrees of effect on travelers’ route choice results. As the congestion level improves, travelers show a stronger willingness to change their routes, and they tend to choose the route with less travel time and angular cost. The number of travelers who keep their original routes gradually declines as the congestion level improves, and the number of travelers on their original routes sharply declines in the moderate and serious congestion scenarios.
Traffic accident sections:
Route 1:
Route 2:
Route 3:
Route 4:
Route 5:
Route 6:
Route 7:
Route 8:
Route 9:

Figure 1: Experimental network topology and travel routes.

Figure 2: Traffic flow status of different congestion levels: (a) smooth, (b) mild congestion, (c) moderate congestion, and (d) serious congestion.
4.2. Estimation Results. The parameter estimation of the model will adopt the maximum likelihood estimation method. Due to the complexity of the likelihood function form of the model, the conventional gradient-based solution method easily falls into the local extremum cycle and cannot solve the real maximum. In this study, the improved non-dominated sorting genetic algorithm (NSGA-II) with an elite strategy is used to find the extreme value of the likelihood function.

To reflect the effectiveness of the IGRRM model in describing the route choice behavior under unexpected accidents, we used experimental data to estimate the parameters of both the RUM model and the GRRM model, and the evaluation results of different models were compared by the goodness of fit ($\rho^2$), adjusted rho-squared ($\bar{\rho}^2$), and Bayesian information criterion (BIC), as shown in Table 3.

The model evaluation results show that the goodness of fit and adjusted rho-squared of the IGRRM model and the GRRM model are greater than 0.2 for the four different congestion scenarios, indicating that these two models have better testing effects. By comparing the test indices of the three models under different congestion scenarios, the IGRRM model proposed in this study performs better than the GRRM model and the RUM model in the three dimensions of goodness of fit, adjusted rho-squared, and Bayesian information criterion. However, the GRRM model also outperforms the RUM model under moderate and serious congestion scenarios, indicating that the IGRRM model and the GRRM model can better explain the route choice behavior of travelers under unexpected accidents. Moreover, the IGRRM model proposed in this study can more accurately describe the route choice behavior of travelers under unexpected accidents.

The estimation results show that these values are statistically highly significant at the 95% confidence level. A particularly interesting result emerges in the estimation of the angular cost parameter, where both the GRRM model and the RUM model have negative values for different congestion levels, while the IGRRM model proposed in this study has negative values for the angular cost parameter in the smooth and mild congestion scenarios and positive values in the moderate and serious congestion scenarios.
negative angular cost means that travelers generally prefer a route with less deviation relative to the origin and destination directions. However, in the context of serious traffic congestion caused by unexpected accidents, commuters’ time sensitivity is maintained at its highest state throughout the day. From the perspective of commuters, the detour route is no longer rejected to avoid long delays that affect the arrival at work within the time limit. At the same time, combined with the fact that the IGRRM model proposed in this study outperforms both the GRRM model and the RUM model in terms of test indices, and the emergence of such evaluation results further proves that the IGRRM model proposed in this study has stronger applicability for such scenarios with more uncertainties under unexpected accidents. For the travel time parameter, the evaluation results of all three models are negative, indicating that the longer the travel time of the route, the lower the probability of being chosen. For the regret weight coefficients, the regret weight coefficients of the IGRRM model and the GRRM model proposed in this study are both greater than 0, which confirms that the route choice behavior of travelers under unexpected accidents is the product of combining RUM and RRM. The coefficient of perceived difference in travel time is greater than 0 for the IGRRM model, which confirms that there is a scale effect in the traveler’s route choice behavior under unexpected accidents. Regarding the psychological threshold effect coefficient, the positive results of the IGRRM model in the smooth and mild congestion scenarios may indicate that some people may feel discomfort or disappointment when their daily routes are slightly congested, leading to an increase in the regret value of the current route. In contrast, the negative results in the moderate and serious congestion scenarios may indicate that some people have a certain degree of tolerance to the serious congestion of their daily routes, which leads to a decrease in the regret value of the current route.

Above all, the IGRRM model proposed in this study shows its potential advantages in describing the route choice behavior of travelers under unexpected accidents. It shows that introducing bounded rationality features such as time-perceived difference coefficients, psychological threshold effect coefficients, and scale effects into the model improves the accuracy of the original GRRM model in describing the route choice behavior of travelers under unexpected

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Parameters</th>
<th>IGRRM model</th>
<th>GRRM model</th>
<th>RUM model</th>
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<td></td>
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<td>Estimation</td>
<td>Sig.</td>
<td>Estimation</td>
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<td>( \gamma )</td>
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<td>( \Delta_k )</td>
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<td></td>
<td>( \rho_1^2 )</td>
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<td>637.636</td>
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<td>Mild congestion</td>
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<td>( \theta_\text{time} )</td>
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<td>0.0000</td>
<td>-0.1361</td>
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<tr>
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<td></td>
<td>( \Delta_k )</td>
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<td>-</td>
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<tr>
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<td>BIC</td>
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</table>

Note: — denotes the parameter not involved in the model.
accidents. It also illustrates that the decision process of traveler route choice behavior under unexpected accidents is complex, and multiple decision rules will have a collective impact in the case of a changing decision environment. In a complex decision environment, the integration of various decision principles can better describe and predict the behavior of travelers’ route choices under unexpected accidents.

5. Conclusions

This study explores the route choice behavior of travelers under different congestion levels by constructing a model of travelers’ route choice behavior under unexpected accidents based on the IGRRM model. The IGRRM model reveals the relationship between the route attributes and bounded rationality characteristics of travelers’ and their route decision behavior patterns, which has potential advantages in predicting travelers’ route choice behavior and lays the foundation for traffic flow redistribution under unexpected accidents.

The IGRRM model proposed in this study is better than the GRRM model and the RUM model in three dimensions (i.e., the goodness of fit, adjusted rho-squared, and Bayesian information criterion) and can more precisely characterize the route choice behavior of travelers under unexpected accidents.

The results of travelers’ route choices are different under different congestion levels of unexpected accidents. As the congestion level increases, travelers’ willingness to change their travel routes is stronger, and it is extremely significant in moderate and serious congestion.

Route attributes have a notable impact on travelers’ route choice behavior; the higher the travel time of a route, the lower the probability of it being chosen; under smooth and mild congestion scenarios, travelers are more inclined to choose routes with better direct access; under moderate and serious congestion scenarios, travelers no longer reject detour routes.

The estimation results of the coefficient of perceived difference in travel time indicate that there is a scale effect in travelers’ route choice behavior; the estimation results of the coefficient of psychological threshold effect indicate that some people feel discomfort or disappointment when facing mild congestion on daily routes, which leads to an increase in regret value; while in moderate and serious congestion situations, some people have a certain degree of tolerance for serious congestion on daily routes, which leads to a decrease in regret value.

However, the actual trip purpose is diverse, and this work only considers the case in which travelers are commuters in the experimental design. In addition, different travelers have different degrees of bounded rationality, which is not quantified in this work. Future research can consider taking the socioeconomic attributes and travel characteristics of travelers into account when evaluating the route choice behavior. From travelers’ physiological and psychological perspectives, the degree of bounded rationality of travelers is quantified to investigate the impact of different degrees of bounded rationality on route choice behavior. In the route choice experiment, the driving simulator can simulate the driver’s route choice in a real-life travel scenario so that the collected experimental data are more accurate.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References


