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Research Article

Influence of Expressway Construction Area Information on Drivers' Route Choice Behaviours

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Expressway traffic information is important for guiding driving routes and alleviating traffic congestion. However, the current research on expressway guidance information focuses on existing expressways. In this study, strategies for providing expressway guidance information under reconstruction and expansion scenarios are investigated. Multiple factors of expressway reconstruction and expansion, such as the length of construction areas and the number of lanes occupied by construction areas, are extracted. A panel latent class logit model considering individual heterogeneity is established to fit the survey data collected by 825 respondents. The results show that the proposed panel latent class logit model fits the data best, and the studied drivers could be categorized into three classes, i.e., the information provision time-sensitive class, the information promotion detour class, and the information suppression detour class. The research results can support expressway operators in designing appropriate traffic information provision strategies, providing personalized guidance to drivers, and ensuring the safe operation of expressways in construction areas.

1. Introduction

With the increasing number of motor vehicles, more attention has been given to traffic congestion, air pollution, and traffic accidents [1]. A large number of quality improvement and reconstruction projects on existing expressways have sprung up to alleviate the traffic congestion caused by the large numbers of vehicles, and expressway reconstruction and expansion projects are gradually becoming essential in the field of infrastructure construction [2]. The proportion of reconstruction and expansion projects for existing expressway networks is increasing annually, especially in economically developed areas. However, most expressways that need to be rebuilt and expanded are the main traffic lines in the area where they are located. Therefore, the negative impacts of fully enclosed construction are unacceptable, and the mode of opening to traffic while rebuilding is generally adopted in the reconstruction and expansion of expressways to reduce the impact on travel. During the construction period of the reconstruction and expansion project of an expressway, the traffic capacity of the road section in the operation area is reduced. A dangerous and complicated traffic environment is then generated by construction personnel and machinery, roadside construction guardrails, and passing vehicles. Therefore, the reconstruction and expansion operation area of an expressway can easily become a bottleneck and induce traffic congestion [3]. Studies have shown that road construction can cause serious delays and congestion. According to a Federal Expressway Administration (FHWA) report [4], the congestion caused by construction areas accounts for approximately 10% of the total congestion and approximately 24% of the nonrecurring congestion. In addition, expressway reconstruction and expansion projects last for a long time, causing a large impact on travel. Therefore, to ensure normal operation of traffic during the reconstruction and expansion period, it is necessary to divert the affected vehicles.

In recent years, the development of information and communication technology has promoted the continuous development of active traffic management systems (ATMS), which consist of road sensors, traffic information navigation, and communication transmission. In an active traffic management system, vehicle drivers are guided by traffic guidance information. Research shows that drivers who receive traffic guidance information are more likely to take alternative routes. Therefore, the impact of traffic guidance information on congestion management is closely related to the information utilization of travellers [5].

Existing measures in construction areas include forcible diversion of vehicles or one-way closure of construction [6] without considering means to guide travellers to actively detour around construction areas through information provision. The urban section of an expressway not only undertakes the traffic function of the main transit channel but also serves to collect and distribute traffic entering and leaving a city. Therefore, normal road passage during the implementation of reconstruction and expansion projects is difficult. In addition, Schmid et al. showed that the existence of construction areas affects train dispatchers' choice of train travel routes [7]. Therefore, it is necessary to study how the strategy of providing traffic guide information in construction areas affects drivers' route choice behaviours and to further analyse the probability of drivers changing their route choice due to construction. The research results will help ATMS operators design scientific traffic information provision strategies to ensure the operational benefits and safe operation of expressways in construction areas.

With the continuous development of transit travel demand, a large number of expressway reconstruction and expansion projects are emerging. Therefore, it is essential to study the strategies of expressway guidance information provision under reconstruction and expansion scenarios. However, multiple challenges associated with providing expressway guidance information remain which are detailed as follows:

(1) For the research scenario, expressway guidance information provision in reconstruction and expansion scenarios is lacking. Previous studies have focused mostly on providing information for existing expressways. However, the traffic environment in reconstruction and expansion scenarios is more complicated than that in existing expressways. Therefore, studies on expressway guidance information provision in reconstruction and expansion scenarios are essential.

(2) For the influencing factor analysis model, individual heterogeneity is usually not considered. The logit model is commonly used for influencing factor analysis. However, when the logit model is used, there are no obvious differences between individuals in the sample, which ignores individual heterogeneity under different guidance information.

(3) For the influencing factors, the interaction effects between individual attributes and the characteristics of construction areas are usually not considered, and it is difficult to provide personalized traffic information and alleviate traffic congestion in reconstruction and expansion scenarios.

To fill the abovementioned research gaps, this study introduces the latent class logit (LCL) model to investigate expressway guidance information provision in reconstruction and expansion scenarios. On the one hand, the LCL model is a semiparametric approximation model that can avoid assumptions about the subjective distribution of unobserved heterogeneity. On the other hand, several interaction terms are introduced to reflect the interaction effects between individual attributes and the characteristics of the construction area, which supports personalized traffic information provision.

The incremental contributions of this paper lie in the following three aspects:

(1) Traffic information provision strategies in reconstruction and expansion scenarios are investigated.

(2) Individual heterogeneity is considered by introducing the LCL model.

(3) The interaction effects between individual attributes and the characteristics of the construction area are considered.

The remainder of this paper is organized as follows. Section 2 reviews the literature on drivers' route choice behaviours. Section 3 details the questionnaire design, data collection, and modelling framework. Section 4 presents the model and explains the results. The differences in individuals' willingness to transfer are analysed in Section 5. Finally, Section 6 summarizes the findings and provides potential policy implications.

2. Literature Review

We conducted a literature review from three main perspectives: (1) expressway information in construction areas, (2) factors influencing drivers' route choice behaviours, and (3) model methods used to explore the mechanism of each factor's influence on drivers' route choice behaviours.

2.1. Expressway Construction Area Information. The information about the Chinese expressway construction area includes the construction position, construction time, construction motivation, and traffic control strategies during construction. The methods used to release construction area information include traffic information electronic display screens, mobile phone applications, radio stations, and onsite instructions [8, 9]. At present, China requires the placement of signs and markings in road operation areas, the placement of different signs, and the layout of safety facilities. Then, drivers can take measures in advance according to the prompts to avoid traffic accidents. In addition, the Manual on Uniform Traffic Control Devices (MUTCD) published by the Federal Highway Administration (FHWA) simulates driver behaviours through dynamic simulation experiments and analyses the influence of traffic sign text pattern size on drivers [10–12].

For information release and route guidance in construction areas, existing works focus on special events, such as accidents, congestion, and construction, which can affect the operation of roads and cause interruptions to a road network. Previous studies have investigated changes in travel behaviours caused by network interruptions, which could lead to short-term and long-term changes in traveller behaviours [13]. Kattan et al. investigated the impact of traffic capacity reduction caused by light rail line construction on travellers' route choice behaviours, and the results showed that commuters in the morning and evening peak hours and travellers who received information before travel are more inclined to choose alternative routes [14]. Yi et al. proposed an adaptive adjustment method for driving routes under expressway construction, which improved construction efficiency and reduced the probability of traffic accidents in construction areas. The results highlight the role of building information modelling (BIM) in improving information management for construction projects, especially in terms of safety and efficiency [15]. However, only a few studies have evaluated the impact of releasing different information on travellers' behaviours after interruption events. Al-Deek et al. [16] and Sharples et al. [17] analysed drivers' route choice behaviours in the case of congestion emergencies and found that obtaining detailed information on the cause of congestion is more acceptable to drivers than simply providing congestion or accident information. Zhao et al. used the decision tree of the CHAID algorithm to classify drivers into five classes and found that construction, congestion, and accident information all impact the route choice behaviours of the five classes of drivers. Compared with road construction and congestion, accident information has a greater impact on drivers' route choice behaviours [18].

2.2. Influencing Factors. With more drivers following the guidance information, the traffic status will be easier to detect and manage from the perspective of system optimization. To improve the compliance rate of drivers with guidance information, it is highly important to analyse the impact of user preferences on the route choice [19]. With the development and integration of related disciplines, such as economics, psychology, ethology, and statistics, interdisciplinary disciplines and a large number of econometric and statistical analysis models have emerged. Based on these results, scholars in the field of transportation have begun to use expected utility theory to describe drivers' route choice behaviours more reasonably. A large number of studies have shown that the factors influencing travel route choice behaviours include socioeconomic, demographic, travel characteristics, road operation conditions, and traffic guidance information [20, 21].

Compared with female drivers, male drivers have a lower tolerance for congestion. Therefore, male drivers are more willing to follow alternative routes recommended by dynamic traffic information [22]. Younger drivers prefer to make choices based on their own experience rather than recommended routes. However, these findings are not consistent across all studies [23, 24]. For example, Jou's study drew different conclusions: increasing age could imply a greater likelihood of establishing travel habits and preferences. Older drivers are less inclined to choose alternative routes due to a lower willingness to take risks when choosing alternative routes [25]. In addition, other studies have explored the influences of an individual's educational background, income, and occupation on route choices [24, 26]. Moreover, expressway infrastructure also impacts drivers' travel behaviours. Abdel-Aty and Huang et al. discussed drivers' choices when entering or leaving an on-ramp, and the results showed that in addition to the spacing between ramps, drivers' choices are influenced by factors such as trip purpose, vehicle occupancy, driver income level, and E-Pass use [27]. Liao et al. also considered the impact of service areas on expressway congestion [28].

Moreover, the characteristics of traffic guidance information are also important for drivers. Khattak et al. reported that some drivers refuse to change their normal routes, especially when travelling from home to work [29]. However, if the traffic information provided by ATISs is accurate and quantitative, the information is more likely to change the travel paths of drivers [30]. Zhu et al. investigated the interplay between travel-time reliability and route choice based on a generalized Bayesian flow model [31]. Using route choice data from questionnaires and field observations, Shen et al. concluded that drivers' route choice decisions are related to their average daily driving times and attention given to the VMS when the VMS showed "moderate traffic congestion." When the VMS shows "severe traffic congestion," the influencing factors include sex, age, average number of daily driving trips, and the driver's attention to the VMS [32]. In addition, fuel is another important factor that travellers are concerned about. Dai et al. considered the heterogeneity of drivers in terms of fuel consumption and travel time, and a multiagent simulation method was used to explore the impact of drivers' route choice behaviours. The simulation results showed that the performance of the traffic state is better when enough drivers emphasize fuel consumption, and the optimal percentage of such drivers is approximately 60% [33]. Ashkrof et al. found that classic route attributes, vehicle-related variables, and charging characteristics can significantly influence battery-electric vehicle drivers' route choices and charging behaviour through a stated preference survey [34].

In addition, COVID-19 has had a significant impact on traffic modes and driving behaviours. Public health guidelines during the pandemic changed people's travel behaviours, which indirectly affected drivers' route choices, such as the frequency of drivers' travel and their preference for travel modes. Amin et al. evaluated the impact of COVID-19 on elderly people's travel mode choices and reported that the epidemic led to a decrease in the average frequency of travel per week but an increase in the share of walking and cycling [35]. Luan et al. investigated how COVID-19 impacted travel mode choice and car purchasing intention and reported that public transport is strongly related to long trips, while the ride-hailing service industry has sharply affected travel style [36]. Muhammad explored people's choice of travel mode during the COVID-19 pandemic. Respondents were more likely to choose solo travel than public transport during the pandemic. Gender, income, education, profession, trip frequency, car ownership, motorbike ownership, and an underlying factor that was defined as "safety precautions" were found to be significant predictors of public transport choice relative to solo travel [37]. Luo et al. analysed residents' willingness to choose travel modes for middle- and long-distance travel. Based on the multinomial logit model of individual risk perception, they concluded that residents were more inclined to choose expressway self-driving than aviation or railway under the influence of greater self-risk perception [38]. Parr et al. used expressway flow data to characterize residents' activities and social contact in Florida and reported that a decrease in expressway traffic was positively correlated with an increase in confirmed cases of COVID-19 [39].

2.3. Methods. The discrete choice analysis is a method for analysing and predicting travel decisions, and the stochastic utility maximization theory is the commonly used theory for studying travellers' route choice behaviours. The theory holds that all decision-makers are perfectly rational and always choose the most efficient or desirable route among their perceived route choices [40, 41]. In early-stage route choice studies, the parameters related to each influencing factor were assumed to be fixed values during the analysis process, resulting in heterogeneity not being considered. Therefore, researchers first started with the parameter distribution. Fosgerau and Bierlaire proposed the idea of random parameters for the discrete choice model, and a mixed logit model was constructed. This method allows the model parameters to change randomly according to a certain distribution on different road sections. Therefore, it is also called the random parameter logit model and is also used to include factors such as road characteristics, environmental factors, and driver behaviours [42]. Yan et al. fitted commuting mode choice behaviours using the RP-MNL model, the SP mixed logit model, and the RP-SP mixed logit model. The fitting results showed that the mixed logit model was better than the MNL model, and the SP mixed logit model was better than the RP-SP mixed logit model [43]. Currently, the LCL model has become a popular alternative to the mixed logit model. Qi et al. and Bansal et al. compared the effects of the latent class logit model and other models on route choice behaviours and found that the latent class logit model performed better [44, 45].

Several scholars have used structural equation modelling to evaluate the relationship between traffic information characteristics and personal characteristics by measuring the relationship between latent variables and explicit variables and to explore people's preferences for future traffic guidance information [46, 47]. In recent years, machine learning methods have emerged as a new approach to route choice modelling [48, 49]. Like discrete choice models, machine learning methods are based on statistical theory, but they are more suitable for big data environments that require high predictive accuracy. Therefore, some studies have combined machine learning methods with discrete choice methods to improve the parameter estimation accuracy and prediction accuracy of route choice models [38, 50]. While machine learning algorithms can improve the prediction accuracy of models, discrete choice models can effectively capture driver heterogeneity [7] with fewer data requirements.

Previous studies have focused mostly on emergencies, such as congestion and accidents. However, the impacts of long-duration planning events, such as construction maintenance, on drivers' route choice behaviour have seldom been explored. Therefore, drivers' preferences for information provision strategies in construction areas are not considered. Moreover, studies on the interactions among individual characteristics, trip characteristics, and road characteristics are lacking. Furthermore, although some researchers have used mixed MNL models to take unobserved heterogeneity into account, such models require specific distributional assumptions for unobserved heterogeneity, which is somewhat subjective.

Therefore, to understand drivers' preferences in the route choice process in construction areas and to analyse the impact of traffic information provision in construction areas on drivers' route choice behaviour on the basis of considering the heterogeneity of drivers, this paper first designed and carried out a joint survey of SP and RP. The survey data were subsequently analysed by a panel mixed logit model and a panel latent class logit model. In addition, we analysed the transition probability to determine the driver's transition probability under different information provision situations and proposed corresponding suggestions for ATIS designers.

3. Methods

3.1. Questionnaire Survey. To investigate drivers' preferences regarding route choice, 1,338 Chinese drivers were surveyed from February to March 2023. Questionnaires were distributed and disseminated via QR codes on smartphones or tablets.

The questionnaire consisted of three parts: (1) demographic and socioeconomic information (including gender, age, occupation, income, and years of driving experience), (2) expressway driving experience (including frequency of trips on expressways, average daily trip distance on expressways, driving type, and whether there is a travel time limit), and (3) hypothetical scenarios related to the construction area.

This survey focused on designing simulated scenarios to determine respondents' route choices. Table 1 lists multiple factor characteristics in the SP design, which is widely used in route choice analysis. The definitions and the different levels of the seven survey characteristics are given in Table 1. To reduce the number of survey scenarios, we applied an orthogonal fractional factorial design. Then, we checked the generated scenes and deleted scenes containing dominant alternatives; ultimately, 24 scenes were retained. To avoid overwhelming information for respondents, each

Table 1: Characteristics' levels for scenarios.

Attribute	Definition	Characteristics' level
Availability of traffic information	The provision stage of traffic information	Two characteristics' levels defined as Pretrip On-trip
Weather	Weather conditions of the expressway	Two characteristics' levels defined as Sunny Snowy/Foggy/Rainy
Time	Travel time	Two characteristics' levels defined as Morning and evening peak hours Other hours
Day	Travel dates	Two characteristics' levels defined as Nonworking days Workdays
Length of construction area (km)	The length of construction areas	Continuous variable
Destination distance (km)	The distance between the construction area and the destination	Continuous variable
Number of lanes (km)	The number of lanes occupied by construction areas	Continuous variable
Length information release	Whether to release length information of the construction areas	Two characteristics' levels defined as Yes No

respondent was provided with seven scenarios using a randomized block design approach. Figure 1 shows an example of a simulated scenario. Repeated and logical trap questions were set in the questionnaires. Moreover, the minimum time required to complete the questionnaire was set to 3 minutes. Finally, only those questionnaires with correct answers to repeated and logical trap questions and a duration longer than the minimum time limit were retained. We also set up a red envelope reward for each questionnaire, and we provided 2 CNY to each respondent who completed the questionnaire carefully to encourage the respondent to finish the questionnaire as required.

3.2. Demographic Profile. A total of 1,338 questionnaires were recovered. A total of 513 questionnaires with incorrect trap question responses or short completion times were eliminated, and 825 questionnaires remained. Since each respondent was shown 7 choice scenarios, there were $825 * 7 = 5{,}775$ observations in the dataset.

Table 2 summarizes the descriptive statistics of the respondents. Among the 825 respondents, males accounted for 58.1% (51.19% of the Chinese population) and females accounted for 41.9% (48.81% of the Chinese population). From the perspective of age distribution, approximately half of the respondents were 26–35 years old, and only 1.3% of the respondents were older than 55 years. The age distribution of the obtained sample is similar to that of the drivers. Among the drivers surveyed, 80.2% were company employees, followed by 8.6% who were students. In addition, the vast majority of respondents travelled by private car, and the proportion of large trucks were less than that of actual expressways. However, due to safety considerations in construction areas, large trucks are generally forced to divert mandatorily. More than 65% of the people had more than 3 years of driving experience, and 10.1% of the respondents were currently novice drivers. More than 65% of the respondents took at least one expressway trip a month, and the kilometres driven were generally concentrated in medium- and long-distance trips of 60–200 km.

In the survey, we also asked the respondents how they generally obtain road condition information about expressways. The vast majority (more than 90%) of respondents obtained road condition information through mobile phone navigation. Moreover, to better design detour routes for drivers, we investigated the maximum detour distance and time acceptable to drivers. Figure 2 shows that the drivers are more sensitive to travel distance, and more than 40% of drivers would accept only an additional 15 km of travel and an additional 30 minutes of travel time.

3.3. Modelling Framework. The modelling framework is shown in Figure 3. In our questionnaire survey, drivers made a binary choice when choosing whether to detour. In this section, we explain the econometric framework of the panel mixed logit model and panel LCL model based on the utilized binary logit model.

According to the random utility theory, the utility function of traveller i choosing branch j is shown in the following equation:

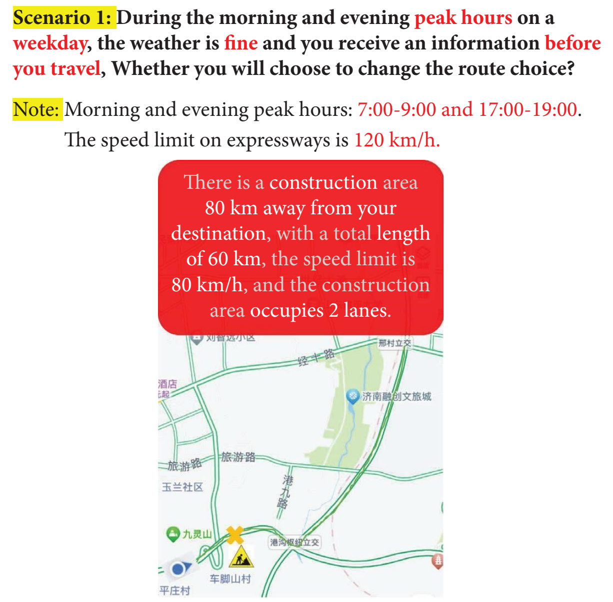

Figure 1: Sample scenario in the survey.

$$U_{ij} = V_{ij} + \varepsilon_{ij}, \tag{1}$$

where V_{ij} is the fixed utility and ε_{ij} is an unobservable random item.

When the random term is biexponentially distributed, the model is a logit model. For route choice setting J, the probability that traveller i chooses j is

$$P(y_i = j) = \frac{\exp(\alpha_{ij} + \beta_j' x_{ij})}{\sum_{q=1}^{J} \exp(\alpha_{iq} + \beta_q' x_{iq})}, i = 1, 2, \ldots, N, \tag{2}$$

where x_{ij} is an explanatory variable that changes with the traveller, β_j' is the corresponding parameter vector to be estimated, and α_{ij} is a fixed constant term.

In the mixed logit model, it is assumed that some parameters are random and obey a certain probability distribution. That is, the mixed logit model expands the parameters β_j' as

$$\beta_{ki} = \beta_k + \sigma_k \nu_{ik}, \tag{3}$$

where β_k is the overall average of all individual characteristics k, ν_{ik} is the individual heterogeneity with an average of 0 and a variance of 1, and σ_k is the standard deviation of the β_{ki} distribution. Since the probability function of the mixed logit model is nonclosed, it cannot be solved directly by calculating integrals; instead, an approximate solution is obtained by means of computer simulation.

The mixed logit model can be used to describe complex heterogeneity because it assumes that heterogeneity varies by individual. However, the mixed logit model assumes that the parameters to be estimated obey a random distribution. In practical applications, the mixed logit model may not be able to capture random parameters. Therefore, in 1989, Kamakura et al. proposed a new heterogeneity model, the latent class logit model [51]. The latent class logit model rejects the assumptions of mixed logit models. Latent class

Table 2: Characteristics' levels for scenarios.

Form	Considerations	Hallmark	Quantities	Proportion (%)
Demographics	Gender	Male	479	58.1
		Female	346	41.9
	Age	18–25 years	135	16.4
		26–35 years	509	61.7
		36–45 years	143	17.3
		46–55 years	27	3.3
		>55 years old	11	1.3
Social property	Occupation	Student	71	8.6
		Company employees	662	80.2
		Self-employed person	52	6.3
		Civil servants	16	1.9
		Retiree	4	0.5
Driving characteristics	Years of driving experience	Fewer	83	10.1
		1–3 years	193	23.4
		3–5 years	234	28.4
		More than 5 years	315	38.2
	Driving vehicle type	Private car	724	87.8
		Small passenger cars	35	4.2
		Medium passenger cars	15	1.8
		Large passenger cars	13	1.6
		Lorry	13	1.6
		Medium truck	18	2.2
		Large truck	14	1.7
Expressway travel characteristics	Frequency of trips on expressways	Almost everyday	36	4.4
		1–4 times a week	126	15.3
		1–3 times a month	391	47.4
		Fewer trips using expressways	272	33.0
	Average daily trip distance on expressways	Less than 20 km	50	6.1
		20–60 km	259	31.4
		60–200 km	387	46.9
		Greater than 200 km	129	15.6

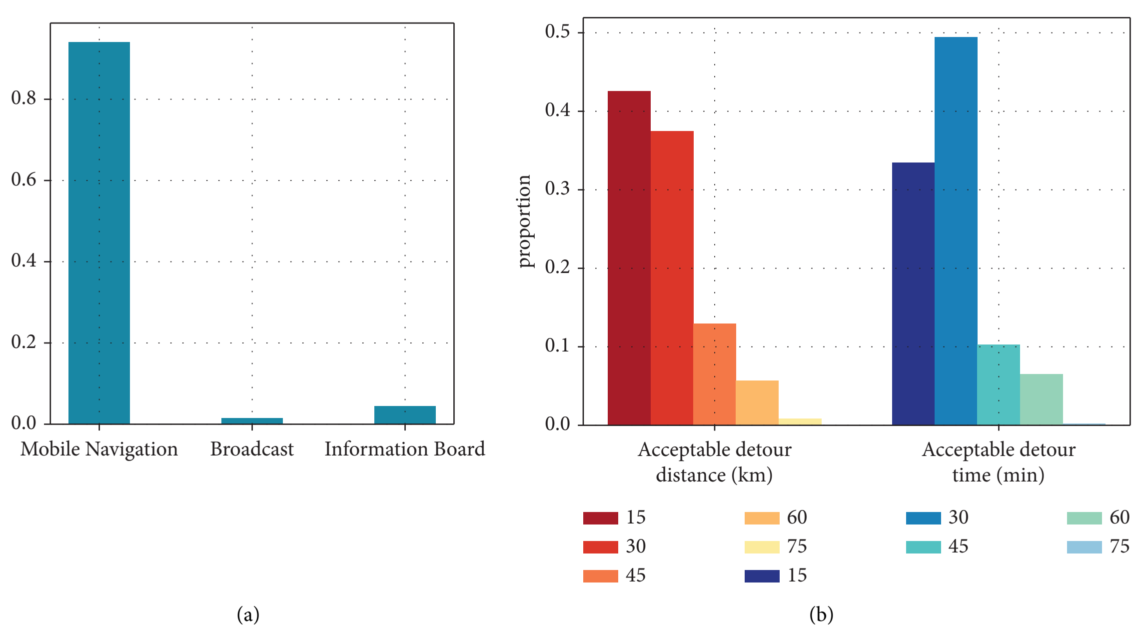

Figure 2: Variation in the variables influencing route choice: (a) the way expressway road condition information is obtained and (b) maximum acceptable detour distance and time for drivers (compared to continuing to travel on the original expressway).

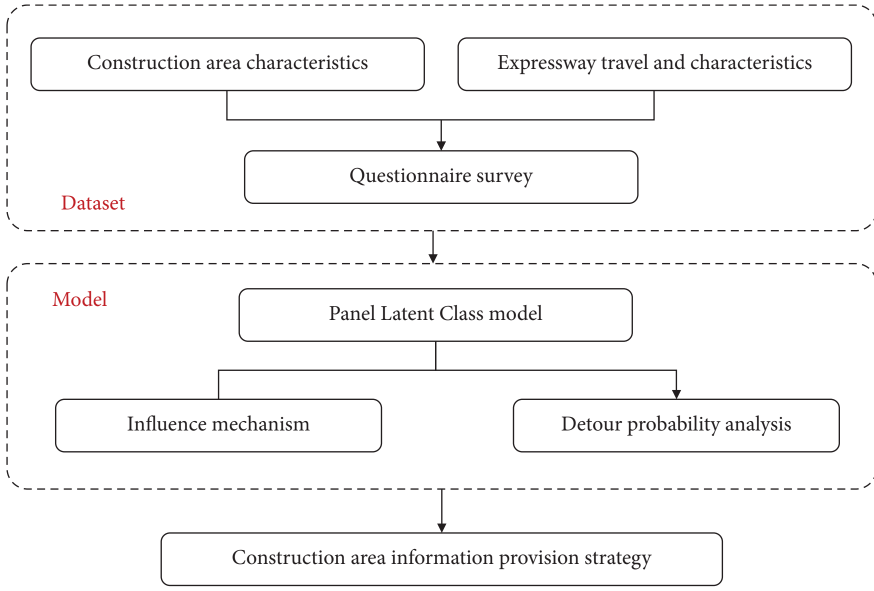

FIGURE 3: Modelling framework.

logit models assume that the dependent variable is influenced by independent variables with potentially unobservable heterogeneity. Heterogeneity is reflected by dividing the total population (respondents) into C classes (subgroups), and C is unknown. Before statistical modelling, the value of C must be set artificially. The choice probability form of traveller i under each class C is the standard logit model, that is,

$$P\left(y_i = j \mid \text{class} = \text{c}\right) = \frac{\exp\left(\alpha_{ij|c} + \beta_{j|c}' x_{ij}\right)}{\sum_{q=1}^{J} \exp\left(\alpha_{iq|c} + \beta_{q|c}' x_{iq}\right)}, \tag{4}$$

where $\beta_{j|c}'$ is the parameter vector to be estimated corresponding to class C and $\alpha_{\text{ij|c}}$ is a fixed constant item for class C.

The class probability can also be defined in a similar form as

$$P\left(\text{class} = \text{c}\right) = \frac{\exp\left(\theta_c' z_i\right)}{\sum_{c=1}^{C} \exp\left(\theta_c' z_i\right)}, \theta_C = 0, \tag{5}$$

where z_i denotes a set of respondent characteristics with an invariant situation and θ_c' is a parameter relating to class C. The probability that traveller i chooses branch j can be derived through equations (4) and (5). That is, the total probability equation is

$$P\left(y_i = j\right) = \sum_{c=1}^{C} P\left(y_i = j \mid \text{class} = \text{c}\right) \times P\left(\text{class} = \text{c}\right). \tag{6}$$

The parameters in the LCL model can be estimated via the expectation-maximization algorithm.

4. Results

To determine the model that best fits our survey data, the parameters of the mixed logit model and the LCL model were estimated separately. A normal distribution was assumed for each random parameter because the model fits best in this case. All the characteristics were tested with random parameters, and only important characteristics were included in the model. Moreover, the parameters of the LCL model were estimated to determine the number of driver classes. Therefore, the number of latent classes was varied from 2 to 5, and the AIC/N and LL values were calculated for different numbers of latent classes. Figure 4 shows that when the number of latent classes C was equal to 3, the value of AIC/N was the smallest, and the value of LL was the largest.

Table 3 lists the estimated results of the detour behaviour in the construction area. To better compare the performance of the models, we first estimated the parameter values and goodness-of-fit of the traditional binary logit model. The AIC/N and LL values were 1.135 and −8,838.32, respectively. In addition, Table 3 shows that the AIC/N and LL values of the other two models were 0.979 and −7,620.51 for the panel mixed logit model and 0.840 and −6,426.88 for the panel LCL model. From the perspective of the AIC/N and LL values, the panel LCL model was the most suitable. A possible reason is that the LCL model considers unobserved individual heterogeneity by dividing the 825 respondents into three classes (42.7%, 38.7%, and 18.5%). Moreover, this means that there is unobserved homogeneity among the respondents, so they are classified into the same class. These results are consistent with those of Qi et al. [44]. Therefore, the following analysis is based on the results of the panel LCL model.

Variables that were not significant at the 90% confidence level were removed to generate the final model. Furthermore, to better explain the driver's route choice behaviours in construction areas, several interaction effects were considered, for example, the interactions among travel time, the number of lanes occupied by the construction area, and the distance between the construction area and the destination.

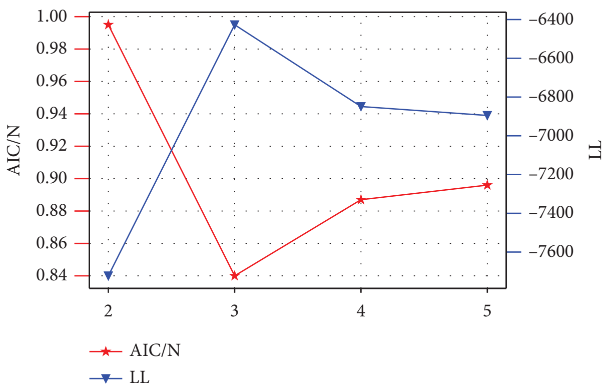

Figure 4: Comparison of AIC/N and LL values.

4.1. Characteristics. Compared with females, male drivers have a greater degree of acceptance of construction areas. Therefore, male drivers are less willing to follow traffic information when choosing detour routes, and the results of congestion correlation analysis are the opposite [24, 25, 52]. Younger drivers are more inclined to choose detour roads. Marginal utility analysis revealed that the transition probability of 26–35-year-olds increased by 3.7%, and the transition probability of 36–45-year-olds increased by 1.9%, indicating that young drivers are more likely to be affected by the complex traffic environment in construction areas. This finding is similar to the conclusion of Jou's research, i.e., an increase in age may mean that the possibility of establishing travel habits and preferences is greater [25] and that the acceptance of complex traffic environments is greater. Therefore, younger drivers are more inclined to choose detour routes. In addition, large passenger cars and large trucks tend to choose to detour. In addition, drivers who use expressways less frequently are more willing to choose detours as recommended by the traffic guidance information.

4.2. Results of the Latent Class Model. To better provide personalized traffic guidance information, differences among the three classes of drivers were further analysed (Figure 5). To compare the parameter distributions more intuitively, the values of the two parameters were expanded by a factor of 10 in Figure 5, i.e., the length of the construction area and the distance between the construction area and the destination. Obtaining more information on the construction area has a positive impact on the second class of drivers but a negative impact on the third class of drivers, indicating that the second class of drivers is more likely to be influenced by traffic guidance information and choose detours. However, obtaining more information about construction areas decreases the likelihood of making detours for class 3 drivers. Moreover, the impact of information provision time on drivers in class 1 is greater than that on drivers in the other two classes, and it is the most influential among all the factors in class 3. Therefore, the drivers were divided into three classes: the provision time-sensitive class, the information promotion detour class, and the information suppression detour class. Figure 6 shows the distribution of personal characteristics of the three classes of drivers. The results show that the proportion of male drivers in class 3 was significantly greater than that in the other two classes, and the proportion of people aged 26–35 years in class 2 was relatively large. These results are consistent with the fact that male drivers are more accepting of construction areas, and their transition probability is lower. Younger drivers are more likely to choose detours, which is consistent with the analysis of the increased transition probability of 26–35-year-olds.

4.3. Construction Area Information. Sunny days have a negative impact on drivers' detour behaviours. Weekdays, morning peaks, and evening peaks have a positive impact on drivers' detour behaviours. The reasons could be that the traffic conditions in construction areas are complicated, and the traffic volume on expressways is large. Therefore, drivers are more willing to follow the detour road guidance. In addition, drivers are more sensitive on workdays. From the perspective of marginal utility, the transfer probability of drivers on weekdays increases by 3.02%, whereas it increases by 6.70% for the morning and evening peak hours. In contrast to expectations, providing length information about a construction area has a negative impact on drivers' detour behaviours. This may be because the drivers are more aware of the specific information about the construction area and have a more accurate assessment of the risk of the construction area, thereby reducing their willingness to bear the risk of choosing alternative routes. Compared with the provision of construction area information before drivers' departure, the provision of construction area information during a trip has a negative impact on drivers' detour behaviours.

4.4. Interaction Effects. According to the previous analysis, multiple variables, such as weather, travel time, information provision time, length of construction area, and number of lanes occupied by the construction area, have significant impacts on drivers' route choice behaviours. In addition, we considered several interaction terms, such as the interaction between the driver's personal characteristics and construction area characteristics.

4.4.1. Time-Limited × Number of Lanes. A positive coefficient means that drivers with time-limited travel are less sensitive to the number of lanes occupied by the construction area than are drivers without time-limited travel. This means that as the number of lanes occupied by the construction area increases, drivers with time-limited travel are less likely to turn to other roads. One possible reason is that drivers without time limits for travel have more time to think carefully about different information and thus are more sensitive to the number of lanes occupied by the construction area.

4.4.2. Fewer Trips Using Expressways × Length of Construction Area and Fewer Trips Using Expressways × Number of Lanes. Note that, the coefficient of fewer trips using

Table 3: Model estimation results (*T*-test results in parentheses).

Form	Considerations	Attribute level	Mix logit	LCL Class 1	LCL Class 2	LCL Class 3
	Constant		1.55*** (12.99)	1.81*** (6.10)	4.11*** (13.84)	−3.00*** (−8.16)
Demographic characteristics	Gender	Male	−0.12** (−2.47)	—	−0.54*** (−4.66)	−0.23** (−2.08)
	Age	26–35 years		0.64*** (3.80)	—	—
		36–45 years	0.16*** (2.59)	—	0.43*** (2.77)	0.35** (2.20)
		46–55 years	−0.38** (−2.81)	−1.02*** (−2.00)	—	—
Driving characteristics	Driving model	Large passenger cars	−1.10*** (−2.66)	−2.03** (−2.10)	—	−2.66** (−2.26)
		Large truck	−1.34*** (−4.76)	−1.84*** (−2.86)	−3.02*** (−6.32)	—
Expressway travel characteristics	Frequency of trip on expressways	1–3 times a month	−0.31*** (−4.76)	−0.82** (−4.79)	—	−0.29** (−2.00)
		Fewer	−0.42*** (−5.68)	—	−0.37** (−2.29)	−0.60*** (−3.49)
	Average daily trip distance on expressways	60-200 km	−0.11** (−2.32)	−0.72** (−6.12)		—
	Time-limited	Travelling with time limit	—	−0.56*** (−4.23)	0.26** (2.43)	—
Construction zone characteristics	Weather	Sunny	−0.42*** (−6.68)	—	−1.12*** (−8.00)	
	Time	Morning and evening peak hours	0.41*** (4.55)	1.74*** (3.96)	—	
	Day	Workdays	0.97*** (10.60)	1.78*** (3.73)	2.55*** (10.16)	
	Length information release	Yes	−0.78*** (−4.69)			−1.26*** (−4.06)
	Availability of traffic information	On-trip	−0.63*** (−7.56)	−0.70*** (−4.16)	−0.46*** (−2.84)	−1.27*** (−4.44)
	Length of construction area	Mean	0.10*** (22.60)	0.11*** (12.13)	0.12*** (14.85)	−0.07*** (−11.53)
		Std	0.05*** (17.02)	—	—	—
	Destination distance	Mean	0.05*** (21.12)	0.08*** (15.42)	0.08*** (21.06)	−0.04*** (−19.74)
		Std	0.04*** (18.79)	—	—	—
	Number of lanes		0.44*** (6.35)	—	2.76*** (16.12)	—
Interaction variable	Time-limited × number of lanes		0.42*** (4.99)	0.92** (2.15)	—	0.76*** (3.55)
	Fewer trips using expressways × length of construction area		—	—	—	−0.01*** (−2.68)
	Fewer trips using expressways × number of lanes		0.40*** (3.34)	—	0.61*** (2.71)	—
	Workdays × number of lanes		0.42*** (2.82)	0.75** (1.98)	2.86*** (12.25)	1.00** (2.46)
	Male × length of construction area		—	—	—	0.03*** (5.62)
	Male × number of lanes		—		0.40** (1.98)	—
	Large trucks × number of lanes		—		−0.61*** (−2.71)	—

***Statistically significant at the 1% level; **statistically significant at the 5% level.

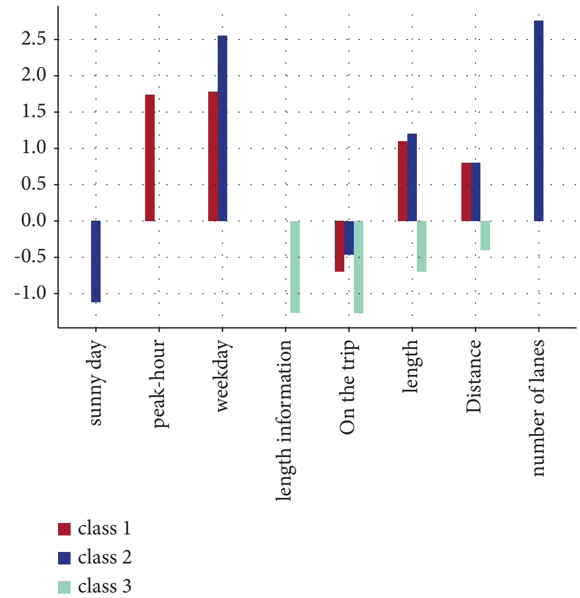

FIGURE 5: The differences between the three classes.

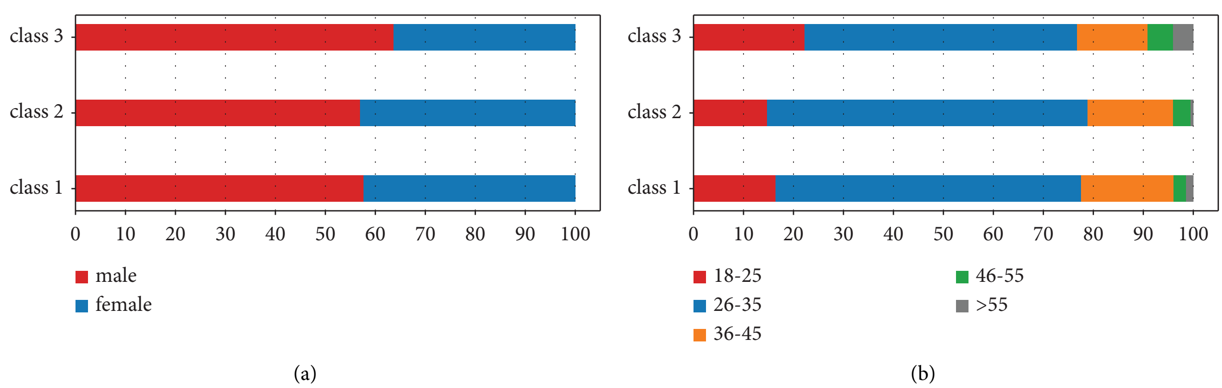

FIGURE 6: Distribution of personal characteristics of three classes of drivers: (a) gender and (b) age.

expressways × length of construction area is different from that of fewer trips using expressways × number of lanes. The coefficient of fewer trips using expressways × length of construction area is negative, while the coefficient of less highway trip frequency × length of construction area is positive. As reported by Qi et al. [44] and Harms et al. [53], drivers familiar with road networks prefer easy-to-drive routes to minimize complex manoeuvres. This indicates that for drivers who use the expressway more frequently, the increase in the number of lanes occupied by the construction area means that the roads are more complicated, so they are more inclined to choose other routes. A reasonable explanation is that drivers with more driving experience might have more unsatisfied experiences caused by congestion and delay, so they prefer to avoid road delays as much as possible.

4.4.3. Male × Length of Construction Area and Male × Number of Lanes. The coefficients of male × length of construction area and male × number of lanes are both positive, which means that male drivers are less sensitive than female drivers are to changes in the length of the construction area and the number of lanes occupied by the construction area. That is, as the length of the construction area changes or the number of lanes occupied by the construction area changes, females are more inclined to choose detour roads. In the route choice experiments conducted by Knorr et al., females were also found to have a strong preference for choosing easy-to-drive routes [54]. In addition, related studies have shown that females tend to avoid risks in both route choice experiments and other economic experiments [55]. Therefore, an increase in the length of the construction area and the number of lanes occupied by the construction area will increase the risk of the construction area. To avoid this risk, female drivers choose to detour.

4.4.4. Large Truck × Number of Lanes. A negative coefficient suggests that the drivers of large trucks are more sensitive to the number of lanes occupied in the construction area. That is, as the number of lanes occupied in the construction area increases, the probability of large trucks detouring increases.

One possible reason is that as the number of lanes occupied in the construction area increases, the risk in the construction area also increases. When encountering risks, the operation of large trucks is more complicated, and there is a greater probability of accidents. Therefore, large trucks tend to choose easy-to-drive routes. In addition, as the number of lanes occupied by the construction area increases, the number of passable lanes decreases. In order to ensure safety, large trucks will be forced to divert in some construction areas. Therefore, some large trucks will be worried about being forced to divert when approaching the construction area, so they could actively choose other routes in advance.

4.5. Detour Probability Analysis. The analysis of the driver's detour probability is shown in Figure 7, with the characteristic variable as the abscissa and the detour probability as the ordinate. When analysing the detour probability of each influencing factor, the other factors are averaged. Compared with the statistical description of survey data, the results of variable sensitivity analysis can accurately reflect the change in route choice probability with each characteristic variable.

Figure 7 shows that as information-promoting detour classes, the first and second classes of drivers are more sensitive to the number of lanes occupied by the construction area. With an increase in the length of the construction area and the number of occupied lanes in the construction area, the driver's transition probability greatly improves. When the length of the construction area increases from 40 km to 80 km, the detour probabilities of the first and second classes of drivers increase by 0.23 and 0.15, respectively. The third class of drivers is the information suppression detour class, and an increase in the length of the construction area decreases the probability of choosing a detour. One possible reason is that an increase in the length of the construction area leads to an increase in the detour distance. The third class of drivers believes that the longer the detour is, the greater the risk. Therefore, they are unwilling to choose a detour.

In addition, the second class of drivers is most affected by the number of lanes occupied by the construction area, and the first and third classes of drivers are more affected by the length of the construction area. Therefore, to increase the transition probability of drivers, information on the number of lanes occupied by the construction area can be given to the second class of drivers, and information about the length of the construction area can be given to the first and third classes of drivers.

5. Discussion

5.1. Characteristic. The significant characteristics captured by the employed latent class logit (LCL) model are consistent with those of the commonly used mixed logit model. For instance, the random parameters of both the length of the construction area and the length of the construction area to the destination are significant in the mixed logit model. The parameters of classes 1, 2, and 3 in the LCL model are different, indicating individual heterogeneity among drivers.

However, the employed LCL model could also capture the potential characteristics influencing the detour probability of drivers. For instance, the effect of travelling with a time limit is difficult to capture by using the mixed logit model, while the results of the latent class logit model show that travelling with a time limit is a reasonable and essential parameter. In addition, the coefficient values of the first class (provision time-sensitive class) and the second class (information promotion detour class) in the LCL model are different, which has a negative effect on the first class of drivers and a positive effect on the second class of drivers. This finding confirms the individual heterogeneity among drivers.

5.2. Policy Analysis. The results of the model can help traffic operators and expressway managers design traffic information provision strategies in construction areas, guide drivers to detour, improve expressway levels of service, and reduce potential risks in construction areas. Moreover, the results provide support for traffic information provision in construction areas during the traffic organization design stage, improve the accuracy of traffic information, and ensure the safe operation of traffic in construction areas.

Since a driver's personality characteristics significantly affect his or her preference for route and navigation information, mobile phone navigation applications can provide personalized information for drivers by identifying their personality characteristics.

First, the results of the present study shed light on the provision time of traffic information. On the one hand, the provision of construction area information during a trip will have a negative impact on drivers' detour behaviours compared with the provision of construction area information before departure. The marginal utility results reveal that providing information during a trip will reduce drivers' transition probability by 1.2%, indicating that the release of construction zone information during a trip may inhibit drivers' detour behaviours. Therefore, mobile navigation apps could provide drivers with route information as early as possible and try to provide construction area information to drivers before a trip rather than during a trip. On the other hand, travellers are more likely to accept induction information and are more sensitive to the number of lanes occupied by the construction area during travel-limited time spans, such as workdays, morning peak hours, and evening peak hours. During these time spans, the urban sections of expressways also accommodate part of the commuter flow, resulting in a greater traffic flow. To alleviate traffic congestion in the construction areas of urban expressways, information on the number of lanes occupied by expressway construction areas could be released more frequently, which could contribute to the traffic volume of construction areas diverting during morning and evening peak hours.

Second, the present study contributes to the literature on information release in expressway construction zones. Studies have shown that large truck drivers are more sensitive to the number of lanes occupied by the construction

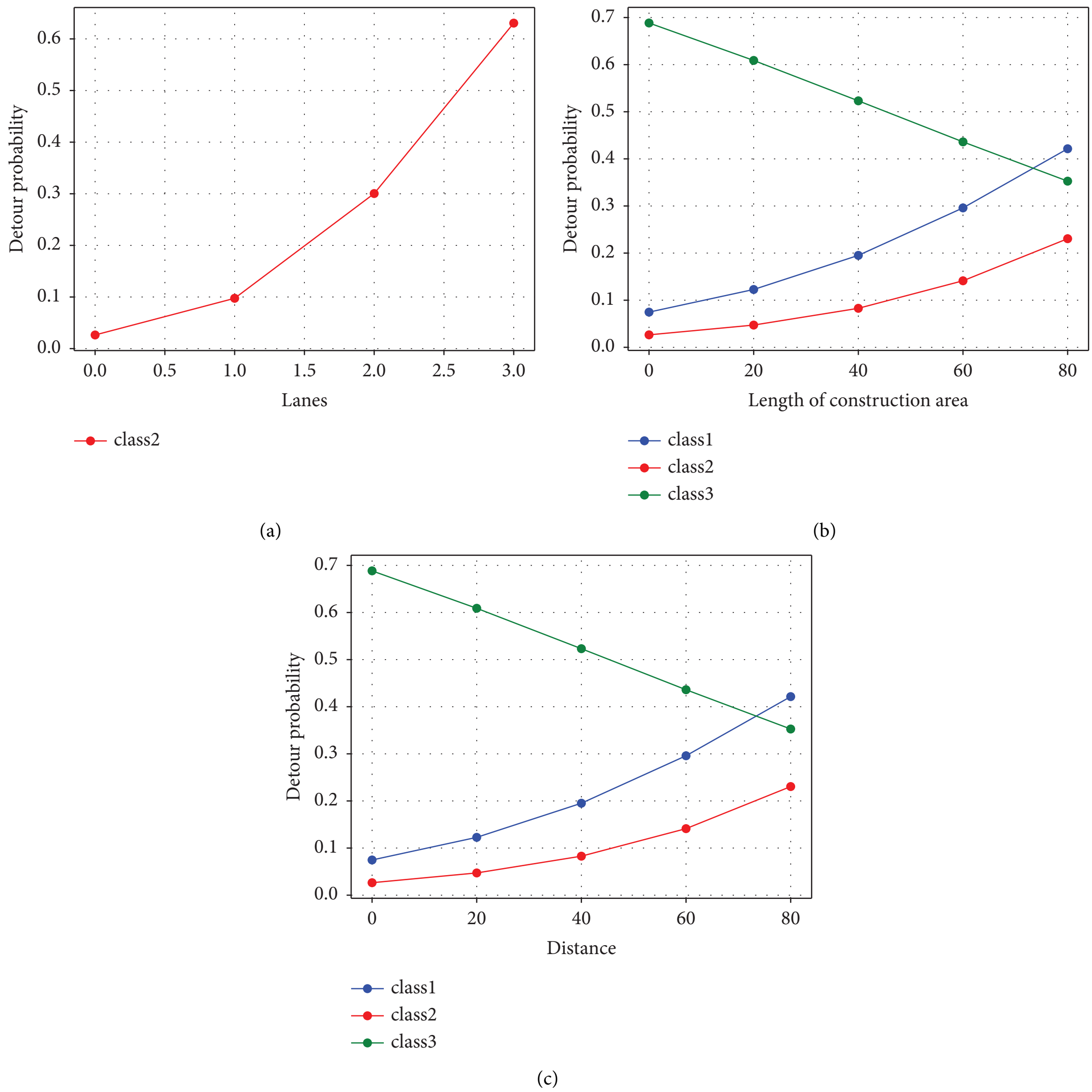

Figure 7: Marginal effects of independent variables: (a) number of lanes, (b) length of the construction area, and (c) the distance between the construction area and the destination.

area, and the potential risk of large trucks in the construction area is greater. Therefore, information on expressway construction areas should be provided in a timely manner for drivers of large trucks. Moreover, the results show that expressways with low risk and comfortable driving conditions are more attractive to female drivers and drivers who are unfamiliar with the expressway network. This implies that more information about expressway construction areas can be provided to female drivers and drivers who are unfamiliar with expressway networks and who tend to drive in a safer way. Note that, information on construction areas may not cause drivers to detour. For drivers with information suppression detours, sufficient information provision would inhibit their detours.

6. Conclusions

During the reconstruction and expansion period, the traffic capacity of expressways decreases substantially. The reasonable provision of real-time traffic guidance information to drivers can help drivers better follow recommended routes and alleviate traffic congestion on expressways. The present study aims to provide suggestions for traffic information in construction areas by investigating the factors influencing drivers' route choices in construction areas and the interactions between traffic information and individual characteristics. Based on the RP and SP data of drivers in Shandong Province, China, this study established a mixed logit model and an LCL model considering drivers' personal characteristics, travel characteristics, driving characteristics, and construction area characteristics. The results show that multiple variables, such as gender, age, weather, time, information provision time, length of the construction area, and number of lanes occupied by the construction area, could impact drivers' detour behaviours. Several interaction terms are also considered, including the interaction between the driver's personal characteristics and construction area characteristics. The results reveal that female drivers and drivers of large trucks are more sensitive to construction area characteristics, drivers with higher travel frequencies on expressways are more sensitive to the length of construction areas, and drivers with lower travel frequencies on expressways are more sensitive to the number of lanes occupied by construction areas.

Based on the transition probability analysis of the LCL model, the studied drivers are divided into three classes: the provision time-sensitive class, the information promotion detour class, and the information suppression detour class. Most of the drivers belong to the provision time-sensitive class or information promotion detour class. That is, most trips occur during peak periods or when the probability of a detour occurring on workdays is high, and providing sufficient information further promotes travellers' detour choices. However, for the information suppression detour class, the proportion of males is relatively high, and the proportion of young people is relatively low. Providing traffic guidance information may inhibit the detour behaviours of drivers in the information suppression detour class.

In addition, this paper discusses the driver detour probability under different construction area attributes to support expressway managers in predicting traffic flow in construction areas to help them identify bottleneck sections in project impact areas and develop traffic organization and induced diversion strategies in construction areas. The findings of the present study may provide valuable insights for transport operators and expressway managers. Expressway managers and developers of mobile navigation applications can design customized information provision strategies and make personalized route recommendations based on the analysis of drivers' route choice behaviours.

This study is limited by the use of questionnaire data, which may be affected by choice bias. Only a fixed set of scenarios is considered in the survey, which cannot fully simulate real-world dynamic route choice behaviours. Therefore, using experimental methods such as driving simulators to explore the real-time behaviours of drivers in terms of route characteristics and traffic conditions to obtain more comprehensive and realistic behavioural data is worthy of further research. In addition, the survey collected less data on elderly drivers and large-vehicle drivers. Therefore, there may be bias in the estimation results for elderly individuals and large-vehicle drivers.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this article.

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