

Research Article

Commuting in the Storm: Adaptation of Transit Riders and Measures for Transit Operator—A Case in Shanghai

Kun Bo ^{1,2,3} Jing Teng ^{1,2,4} Cen Zhang ⁵ and Dahai Han ⁶

¹College of Transportation Engineering, Tongji University, Shanghai 201804, China

²Key Laboratory of Road and Traffic Engineering of the Ministry of Education, Tongji University, Shanghai 201804, China

³College of Higher Technical, Shanghai Maritime University, Shanghai 201306, China

⁴Shanghai Key Laboratory of Rail Infrastructure Durability and System Safety, Shanghai 201804, China

⁵Department of Urban Management, Kyoto University, Kyoto 615-8540, Japan

⁶Department of Civil and Environmental Engineering, University of Wisconsin-Milwaukee, PO Box 784, Milwaukee, WI 53211, USA

Correspondence should be addressed to Jing Teng; tengjing@tongji.edu.cn and Cen Zhang; zhang.cen@trans.kuciv.kyoto-u.ac.jp

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Adverse weather has been recognized as an important factor to affect travelers' activity plans in departure time, transport mode, route taken, or cancellation. In the storm, road waterlogging degrades the capacity of road networks and the service quality of transit systems, which further may affect the supply and demand for transit. Based on a typical case in Shanghai that commuters have no easy access to metro service, this paper aims to explore how transit passengers adapt to different situations in the storm and what emergency plans should be taken accordingly. Derived from the revealed preference (RP) and stated preference (SP) survey results for experienced transit commuters, a nested logit (NL) model was developed to describe the travel behavior of transit commuters. Six alternatives, Direct Bus, Bus + Bus, Metro, Bus + Metro, Taxi, and Cancel Trip, and three storm scenarios were set for transit commuters in this case. Estimated parameters indicate that, in storm weather, crowdedness is less considered by transit commuters, and transfer times, walking time, in-vehicle time, and waiting time have negative effects on the selection of the corresponding alternative, whereas the impact of taxi fare is positive since the higher fare is usually accompanied by worse weather and traffic condition. Sensitivity analysis shows that walking time to metro station, in-vehicle time, and waiting time at a bus stop are the most critical factors leading to transit ridership reduction in the storm. According to this, three possible plans for the transit operator, shuttle bus to the metro station (P1), information announcement (P2), and route adjustment (P3), are simulated and compared. We recommend adopting P2, P2 + P3, and P1 + P2 + P3 in turn with the increase of road waterlogging. These findings have important practical implications for developing transit emergency management plans and serve as references for the transit agencies and operators.

1. Introduction

Weather is recognized as a critical factor in transportation system operation. Inclement weather can significantly decrease traffic speed and road capacity, cause traffic congestion or disruption, and affect traffic safety. Public transport, a vital component of urban transport systems serving commuting trips, may also be largely affected by the inclement weather. It has been proved that inclement weather can degrade the bus service, affect passengers' travel choices, and reduce transit ridership [1]. As reported in the

Intergovernmental Panel on Climate Change (IPCC) [2], a significant increase in extreme weather and climate events has been observed since the 1950s on a global scale. Facing increasing days with inclement weather, transit operators and government should provide powerful emergency management plans to guarantee commuting travel.

It is of great importance to understand the impact of transport system performance in adverse weather and how travelers adapt to it. There exist some studies investigating the influence of weather on the travel behavior of passengers, including travel demand, modal shift, departure time, and

route/destination choices [3–6]. The most common method of examining inclement weather's impact on travel has involved collecting and analyzing traffic data and ridership data in conjunction with weather variables, such as temperature, rainfall, and wind speed. Recently, more temporally and spatially disaggregated analyses are proposed to increase the explanatory power of results [7–9]. Besides, some studies pay attention to identify the impact of more issues in adverse weather, such as setting of infrastructure, traveler segments, and trip purpose [10–13]. The results of studies show the heterogeneous impacts of adverse weather on travel behavior due to discrepancies in the overall settings of studies.

According to our understanding, the influence of adverse weather on travel behavior can be decomposed into two parts: the negative impacts of extreme weather on transportation services and the corresponding adjustment of travel behavior by travelers. In essence, ridership is directly affected by the performance of the travel services (e.g., accessibility, reliability, convenience, comfort, and travel time) rather than weather. Several studies have investigated the influence of weather on the performance of transport systems, such as road capacity, vehicle moving speed, bus dwell time, and transit service reliability [14, 15]. From our point of view, in addition to the settings of infrastructure and meteorological elements, the management level is also a decisive factor in the impact of adverse weather on transport services. We believe that good measures can reduce the negative impact and improve performance effectively. For transit operators, to know what measures should be taken, it is necessary to understand the influence of the transit service performance on travel choices under various situations. However, the limited research on adaptation of travelers to the change of transit service quality in adverse weather may be not supportive to conduct effective emergency measures.

To fill this gap, this paper aims to explore the adaptation of transit commuters to different situations and provide feasible measures for the transit operators accordingly. Firstly, the revealed preference (RP) and stated preference (SP) surveys were conducted, and then the relationship between travel mode choice and transit service performance in the storm was established. Derived from the statistic and sensitivity analysis, three possible plans, shuttle bus to the metro station, information announcement, and routine adjustment, are simulated and compared. These results could have implications for developing bus emergency management plans and serve as references for the public transit agency.

The remainder of this paper is organized as follows. Section 2 reviews related studies and provides the literature background for the present study. Section 3 introduces the data and the study area. Analytical approaches are also elaborated on in this section. Section 4 presents and discusses the analysis results and research findings. Section 5 proposes and then simulates some emergency plans for the transit operator. Section 6 summarizes the research findings and points out limitations and future work.

2. Literature Review

The impacts of weather on transportation have received substantial research attention. Studies can be identified as two major parts: impacts on physical and operational aspects and impacts on travel demand and traveler behavior. In this section, we shall review the relevant studies, outline the major findings, and identify research gaps.

2.1. Impacts on Physical and Operational Aspects.

Weather has a direct impact on the performance of transportation infrastructure [6]. Heavy rainfall, storms, snow, and fog all can result in deterioration of traffic conditions, like low visibility, wet roads, and waterlogging. Regarding different travel modes, previous studies have shown a negative impact on travel speeds [3, 16–19]. Some studies indicate that wet roads can reduce the average vehicle speed by 6–7% in urban areas and even 8–12% when it rains [20]. And the reduction of travel speed can even lead to a 20% decrease in road capacity in the urban network [21], resulting in traffic congestion or disruptions [1], the unreliability of the transportation system [22], and more traffic accidents [23]. For transit services, the impact of weather is more complex than private and nonmotorized transport. In one aspect, it has negative impacts on bus operation in terms of service frequency, headway regularity, and travel time variability [1]; in the other aspect, it increases the difficulty and time on the way to/from transit stations for passengers [7].

2.2. Impact on Travel Demand and Traveler Behavior.

Aside from its impact on the physical and operational aspects of transport systems, adverse weather may affect travelers' decisions. A lot of studies highlighted travel behavior changes due to weather conditions, like model shift [4, 6], changes in destination and route [3], and put-off or cancel trips [24]. Transit riders are often directly subject to adverse weather while waiting or walking to/from the station, and they are indirectly affected by the deterioration of in-vehicle transit services [7]. Both direct and indirect effects influence riders' behavior as well as transit ridership.

In most previous studies, adverse weather, such as rain, has been found to exert a negative influence on transit ridership [1, 25]. Nevertheless, some empirical studies report different results on the rain-transit ridership relationship, which shows that it is positively associated with public transit share [17, 26]. Further studies indicate that transit ridership has a slight decline during light rainfall, then increases with rain becomes heavier, and eventually drops sharply in heavy rain [27]. The heterogeneous impacts show the complexity of the relationship between adverse weather and transit ridership. Therefore, some studies pay attention to identify specific impacts of adverse weather with more detailed issues. For example, senior passengers [28], lower-income travelers [29], and occasional users [10] are more sensitive to adverse weather. Additionally, adverse weather has more impact on recreational travel than commuter travel [12], bus trips than

metro trips [13], weekend trips than weekday trips [7], and long commuting trips in winter than that in summer [11]. Besides the adverse weather's impact on transit, ridership also varies on the type, location, facilities, and routes of stations [8] and time of day [9].

In short, most of these studies examined inclement weather's impact on ridership in conjunction with amount variables, weather elements (e.g., temperature, rainfall, and wind speed), time (day of week, time of day, and seasonality), facility (e.g., weather protection of palm, accessibility of station, and connecting bus routes), and individual attributions (e.g., age, gender, income, experience, and travel purpose). Less attention was paid to explore how transit passengers adapt to transit service in storm according to service performance, such as travel time variability, service frequency, reliability, accessibility, and comfort. We believe that it helps improve transit management for infrastructure as well as transit service adjustment for transit operator and agency.

3. Data and Analytical Methods

In this section, we will introduce a case study, including data collection and analytical methods, to describe the dynamics of travel choice behavior in adverse weather.

3.1. Data Collection. As shown in Figure 1, the data adopted in this study are originated from surveys in a largely residential area with over 15,000 residents near the middle ring roads in Shanghai, China. This residential area covers nearly 10 bus stops, but no metro station. A passenger from the center of this area needs to walk over 1 km to the nearest metro station. There exist large commuting demands between the residential area and the central business district nearly 6 km away. However, road waterlogging and disruption occur recurrently in storm weather within this area, causing terrible bus service.

It is a representative case to reflect the dilemmas of transit commuters without convenient metro service. They have to make a compromise between time, comfort, and economic loss since there is no convenient and reliable transit service in adverse weather. Based on this case, later we will have a detailed analysis of travel behavior in different conditions and propose some possible measures accordingly.

The questionnaire, designed for RP and SP survey, was conducted in the weekday morning peak hours in September 2016, targeting passengers leaving their homes to take public transit. The RP survey collected sociodemographic information, for example, gender, age, occupation, and monthly income, as well as travel-related information, for example, travel purpose, travel mode, travel time and transfer time, and commuting experience in the storm. The SP survey asked respondents to make travel choices in hypothetical scenarios.

Three hypothetical road waterlogging scenarios (S1–S3) are assumed to have different impacts on road conditions and transit operation in storm weather (see Figure 2):

S1: in the slight storm (beyond 20 mm rainfall), the small-scale ponding occurs, causing walking time increase, vehicle speed decline, and slight bus delay

S2: in the medium storm (around 50 mm rainfall), several parts of roads are waterlogging, leading to inconvenient walking, traffic congestion, and serious bus delays

S3: in the heavy storm (over 100 mm rainfall), roads within some regions are waterlogging seriously, resulting in walking difficulties, partial road closure, and bus detours

Through on-the-spot investigation in a storm, we found that in this case there are six reasonable travel alternatives for transit commuters, which specifies five possible combinations of travel modes and another option to cancel the trip. The performance of services under six travel alternatives is settled according to the investigation data. The details are shown as follows (see Figure 1 and Table 1):

A1: taking a bus with no transfer (Direct Bus Service, DB)

A2: riding a bus and then transferring to another bus in a different routine (Bus + Bus, B + B)

A3: walking to a metro station and then taking a metro (Metro, M)

A4: riding a bus and then transferring to a metro (Bus + Metro, B + M)

A5: taking a taxi (Taxi, Tx)

A6: cancelling the trip (Cancel Trip, CT)

Based on these, we design the SP survey, which contained twelve different conditions derived from three hypothetical road waterlogging scenarios and four crowded scenarios. For each case, respondents were offered the above six travel alternatives and their performances (see Table 1). It is assumed that the respondents have enough knowledge from experience and can make choices accordingly.

In our designed scenarios, Direct Bus, the most convenient way in normal weather, was largely affected by the storm in walking time, waiting time, and in-vehicle travel time. Metro operation is less affected by storm, whereas the need for long time walking to the metro station may reduce their willingness. Taking a bus and then transferring to metro or bus, there could be alternatives to keep short walking time and relatively low delay. Traveling by taxi can avoid long walking time, large travel delay, and possible crowdedness in transit service effectively, and yet the fare of taxi, increasing with road waterlogging due to congestion and detouring, is much higher than that of all alternatives in public transportation in all scenarios.

To ensure that the samples were representative, some trap questions and logical judgments were used in preliminary selection. 185 questionnaires that have enough knowledge of commuting by transit in storm weather are selected, and 162 among them are transit commuters choosing bus or metro as their major travel mode. Totally,



FIGURE 1: Shanghai, the study context.



FIGURE 2: Hypothetical road waterlogging scenarios in the storm. (a) Scenario 1, (b) Scenario 2, and (c) Scenario 3.

1944 valid travel choices gathered from these 162 experienced transit commuters in the SP survey are used to calibrate the parameters of the model in this study. Table 2 presents the descriptive statistics of these participants. Some key features of the participants in this study are as follows:

- Most of the respondents are working-age adults in the normal sense, ranging from 16 to 60 years old. Since the government is trying to create incentives for people to work longer, the elderly also make up a large proportion of commuters.
- The monthly income of more than 80% of respondents ranges from 2000 yuan (about 300 US dollars) to 10,000 yuan (about 1500 US dollars). The proportion of high-income people is just over 10%,

which is only half of 20.6% in the Shanghai Statistical Yearbook [30].

- More than 90% of respondents who have transit commuting experience in a storm choose bus or metro as their major travel mode.
- About half of respondents' travels in the RP survey, which was carried in the weekday morning peak, are commuting trips.
- The expected travel time of near 80% of the respondents is over 60 minutes.
- Above 40% of the respondents need transfers.

In sum, the data revealed that the majority of the respondents are transit passengers with long commuting time,

TABLE 1: Performance of services in scenarios.

Performance of services	Scenarios	Alternatives				
		A1	A2	A3	A4	A5
Walking time (minute)	S0	9	5	15	6	0
	S1	10	5	20	7	0
	S2	12	6	25	8	0
	S3	15	8	30	10	0
Waiting time (minute)	S0	15	12	3	15	5
	S1	20	15	3	15	10
	S2	30	25	5	20	20
	S3	45	40	9	30	30
In-vehicle travel time (minute)	S0	25	25	15	25	15
	S1	30	30	15	30	20
	S2	40	40	15	35	25
	S3	60	60	20	45	30
Overall travel time (minute)	S0	49	42	33	46	20
	S1	60	50	38	52	30
	S2	82	71	45	63	45
	S3	120	108	59	85	60
Fare (yuan)	S0					35
	S1					40
	S2	2	3	4	5	60
	S3					100
Transfer	S0-S3	0	1	0	1	0

Note: S0 is the normal weather; S1-S3 are three hypothetical scenarios of the storm.

TABLE 2: Survey profile.

Respondent characteristic	Variables	Percentage	Trip characteristic	Variables	Percentage
Gender	Male	41.98	Travel purpose	Commute	49.38
	Female	58.02		Business	6.17
Age	16-	0.62		Leisure	11.73
	16-24	14.20		Hospital	7.41
	25-34	33.95		Visiting friend	10.49
	35-44	16.05		Others	14.81
	45-60	11.73	Bus	51.85	
	60+	23.46	Metro	41.36	
Monthly income (yuan)	2000-	9.26	Travel mode	Taxi	1.85
	2000-5000	38.89		Bike	1.85
	5000-10,000	41.36	Walk	3.09	
	10000+	10.49	0-30	9.88	
Occupation	Government official	1.23	Travel time (minutes)	30-60	12.35
	Company staff	37.65		60-90	20.37
	Student	4.94		90+	57.41
	Freelancer	8.64	Transfer	One or more transfer	43.21
	Others	47.53		None transfer	56.79

medium income, and working age, which make sure that they are our targeted group in this study.

3.2. Analytical Methods. Generally, researchers adopt the discrete choice model (DCM) [31-35] or structural equation model (SEM) [17] to estimate the travel mode choice using the RP and SP survey data. The combination of RP and SP data covers both the existing absolute attribute levels and a much wider range of attributes; thus, it is beneficial to build a more robust model. In this study, the RP data can help us select our target respondents and decision variables. And the SP data is used to estimate the critical factors of that in the

storm weather with road waterlogging. Multinomial logit (MNL) model has been proved to be suitable for modeling discrete choice outcomes under mixed traffic conditions [31]. One inherent assumption of the MNL model is the independence of irrelevant alternatives (IIA), which means that the alternatives are uncorrelated. Considering the similarity of A1~A4, it may lead to the fact that IIA assumption cannot hold; in this case, the nested logit (NL) models were adopted to link the probabilities of choice for commuting travelers to explanatory variables.

In this study, we aim to explore the relationship between the performance of alternatives and the choice probability of transit commuters in different storm scenarios. It is different

from most previous studies, linking weather variables, such as temperature, rainfall, and wind speed with travel choices. To achieve it, three main types of effects are considered in our model. The first one is the direct impact of weather on the accessibility of stations, mainly affected by walking time to/from stations or between transfer stations. The second one is the indirect impact of weather, mainly affected by the degradation of service performance, such as variations of waiting time, in-vehicle travel time, and crowdedness. The third one is the travel cost; travel fare varies with different transport modes and route choices. Besides, individual attributes, for example, age, gender, income, and travel purpose, may differ in sensitivity to the three effects. Travel purpose is set as commuting in this study.

Overall, the details of the decision variables are as follows:

- (a) Crowdedness (CD) refers to the crowding level in terms of transit passenger's feeling (4 levels: 0, 0.3, 0.6, and 0.9)
- (b) Walking time (WT) refers to the time spent by the transit passenger to walk from the departure point to the transit station
- (c) Transfer times (TT) refers to the times of a passenger moving from one vehicle to another, which is fixed in one alternative
- (d) Waiting time (OWT) refers to the time spent for the arrival of the vehicle
- (e) In-vehicle travel time (IT) refers to the time from boarding to alighting
- (f) Travel fare (TF) refers to the fare paid for alternatives
- (g) Monthly income (MI) refers to the scaled parameter which reflects the ability to pay (4 levels, 0, 1, 2, and 3)
- (h) Gender (GE) refers to the gender of the commuter (0, male; 1, female)
- (i) Age (AG) refers to the age group the commuter belongs to (6 levels, 0, 1, 2, 3, 4, and 5)

Among these variables in various scenarios, MI is fixed for a specific commuter, and TT is fixed for a specific alternative. Travel time, including WT, OWT, and IT, varies with scenarios and alternatives. Fare in A1 to A4 (public transportation alternatives) is fixed, while fare in A5 (taxi alternative) varies according to scenarios. CD is an uncertain variable related to the supply and demand of transit service; for taxi mode, it usually can be treated as 0. A1 to A4 belong to public transportation nest (nest 1) which have low fare cost, A5 is taxi nest (nest 2) with high fare cost, and A6 which stops traveling is in cancel nest (nest 3). Suppose that the choice set includes j alternatives ($j = 1, 2, \dots, 6$) belonging to nest i ($i = 1, 2, 3$) and the utility that individual n ($n = 1, 2, \dots, N$) gains from alternative j is formulated as

$$U_{j,n}^k = \alpha_j + \beta_j X_n^k + \varepsilon_{jn}, \quad (1)$$

where $U_{j,n}^k$ is the utility of individual n for choosing alternative j in scenario k , X_n^k is the vector of observable attributes of individual n in scenario k , β_j is the coefficient associated with X_n^k for alternative j , α_j is the intercept of utility function of alternative j , and ε_{jn} is the random error term.

The probability formulation of the NL model (a two-level NL model) can be expressed as follows:

$$\begin{aligned} P_{j,n}^k &= P_{i,n}^k \cdot P_{j|i,n}^k, \\ P_{j|i,n}^k &= \frac{\exp(U_{j,n}^k/\lambda_i)}{\sum_{j' \in S_i} \exp(U_{j',n}^k/\lambda_i)}, \\ V_{i,n}^k &= \ln \left(\sum_{j' \in S_i} \exp(U_{j',n}^k/\lambda_i) \right), \\ P_{i,n}^k &= \frac{\exp(\lambda_i V_{i,n}^k)}{\sum_{i'} \exp(\lambda_{i'} V_{i',n}^k)}, \end{aligned} \quad (2)$$

where $P_{j,n}^k$ is the probability that individual n chooses alternative j in a scenario k , $P_{i,n}^k$ is the probability that individual n chooses nest i in a scenario k , $P_{j|i,n}^k$ is the probability that individual n chooses alternative j if nest i is chosen, S_i is the set of all alternatives included in nest i in a scenario k , $V_{i,n}^k$ is the log sum variable of nest j in scenario k , and λ_i is the dissimilarity parameter for nest i .

4. Results Analysis

In this section, to better understand the behavior changes of transit commuters in adverse weather, we further analyze the statistical results, estimated parameters, and sensitivity based on the choice model and collected data in Section 3.

4.1. Statistical Results. According to Table 3, there are three nests in alternatives: Public transportation, Taxi, and Cancel. From the SP survey in designed scenarios, one may expect that the proportion of public transportation mode decreases sharply from S1 to S3 while choosing probabilities of taxi and cancel increase significantly. It is obvious that storm weather has a huge effect on the travel choice of commuters, and overall, with walking time, waiting time, and in-vehicle time increasing, the willingness to choose public transportation will diminish. Specifically, the probability of DB and B+B modes in S1–S3 has fallen sharply, while increasing from S1 to S2 in M mode and S2 to S3 in B+M mode occurred. It suggests that metro service is less affected and considered as a good substitution for bus service in the storm, which is consistent with previous studies [36]. Even if taxi fare exceeds 20 times of bus fare in S3, the number of people who choose to commute by public transport was almost the same as people choosing taxi, which shows that the travel fare is not decisive for transit commuters in the storm. Meanwhile, over one-third of commuters decide to

TABLE 3: Selection of transit commuters in the storm.

Scenarios	Alternatives					Cancel CT (%)
	Public transportation				Taxi	
	DB (%)	B + B (%)	M (%)	B + M (%)	Tx (%)	
S1	22.53	31.02	19.29	9.26	11.42	6.48
		82.10				
S2	14.66	16.20	23.92	6.17	22.38	16.67
		60.96				
S3	1.23	4.94	14.97	9.88	30.86	38.12
		31.02				

cancel trips and be absent from work which may have a great impact on travel demand and bring huge losses to society.

4.2. Estimated Parameters. The nested logit model was used to test the effects of walking time, waiting time, in-vehicle travel time, crowdedness, and income on commute choices of transit passengers in the storm. Walking time (WT), waiting time (OWT), in-vehicle travel time (IT), fare (TF), and income (MI) were kept in the final model. Though slight impacts of crowdedness (CD), gender (GE), and age (AG) existed in tests, they are not significant at a 95% confidence level. Adding these variables will lead to a rise of *R*-square but the decline of AIC, BIC, and adjusted *R*-square. Further, in addition, some interaction items, such as MI * WT, MI * OWT, MI * IT, and MI * TF, were also tested, but none was significant even at 90% confidence level. We emphasized that the value of time and cost are treated as the same for a certain individual; the coefficients of the time and cost variables were set as generic in our model. The weights and significances of decision variables and performance of the final model are shown in Table 4. Next, we would like to have a detailed analysis of that.

4.2.1. Intercept. Initially, we set different intercepts for all alternatives (the cancel nest as a fixed item is 0). However, we found that alternatives in public transportation nest (A1–A4) have similar estimated values of the intercept. According to our tests, a universal intercept for alternatives in public transportation nest, which is adopted in the final model, can improve the AIC and BIC but will not significantly reduce the *R*-square. A generic intercept for public transportation nest can improve the AIC and BIC but not decrease the *R*-square obviously. It shows that transit commuters have no obvious preference difference in alternatives in public transportations nest.

4.2.2. Transfer. The coefficient of transfer for public transportation nest is -1.88 ; that means the transfer largely reduces the choice probability for alternatives. In taxi and cancel nests, no transfer behavior is considered in the travel process. We suggest that usually multitransfer travel plans are not attractive for commuters, and even in an emergency, transit agency should avoid providing passengers plans more than one transfer.

4.2.3. Income. The coefficients of income for A1, A3, and A4 are negative, whereas for A2, A5, and A6 are positive. It is reasonable that the high-income group has a preference for A5 and A6. If one chooses taxi (A5), he/she needs to pay much more on travel fare, and if one chooses to cancel trip (A6), he/she needs to bear economic loss due to the absence from work. For A2 in our case, the passenger has the shortest walking distance. Therefore, commuters with higher income may be more concerned with the performance of walking time. Overall, it seems that high-income individuals may care about comfort issues more than economic issues and travel time.

4.2.4. Waiting Time and In-Vehicle Time. The coefficients of waiting time and in-vehicle time are both negative, which shows that longer travel time will decrease the choice probability for alternatives. From estimated parameters, in this case, it seems that in-vehicle time has a greater influence than waiting time, which may be a little different from normal weather. It can be explained that, as in storm weather, wetted travelers' crowd in vehicles may feel more uncomfortable than individuals waiting at the station.

4.2.5. Walking Time. Compared with a coefficient of waiting time (-0.059) and in-vehicle time (-0.042), the coefficient value of *walking time* (-0.174) is 3 to 4 times larger, which shows the huge influence of walking time on travel choice in storm. It seems that walking difficulty due to the rain and waterlogging significantly decreases the travel willingness. When walking time exceeds personal tolerance, passengers have to change travel options. It is the decisive factor of commuting in the storm weather.

4.2.6. Fare. The coefficient of fare is positive; it seems to be not reasonable since usually higher cost means less attractiveness to traveler. However, our designed scenario is highly based on real condition; transit fare is constant in different scenarios, while taxi fare is based on travel time and distance which is highly related to storm and road condition. When the traffic condition and weather get worse, the taxi costs more, and to reduce the impact of the storm, taxi, in turn, has a higher attraction. For taxi mode, traffic gets worse, and fare goes higher. When the negative impacts exceed the tolerance, commuter becomes more eager to guarantee commuting even at a higher cost.

4.2.7. Crowdedness. Unexpectedly, there is no obvious effect of crowdedness on all passengers. One possible explanation is that transit commuters in a metropolis, like Shanghai, are used to the crowdedness environment in bus or metro in daily commuting. Compared with normal days, the obvious changes, such as heavy rain, road waterlogging, bus delay, longer walking, and waiting time, are more likely to be concerned in the storm. Therefore, crowdedness is not the key factor affecting commuting in storm weather.

TABLE 4: Estimation results.

Explanatory variables	Alternatives					
	Direct Bus	Public transportation nest Bus + Bus	Metro	Bus + Metro	Taxi nest Taxi	Cancel nest Cancel Trip
Intercept		6.48*			1.31*	0 (fixed)
Transfer		-1.88*			—	—
Dissimilarity of nest		0.787*			1 (fixed)	1 (fixed)
Income	-0.477*	1.06*	-0.501*	-0.256	0.306*	0.58*
In-vehicle travel time			-0.0587*			—
Walking time			-0.174*			—
Waiting time			-0.0418**			—
Fare			0.028*			—
Sample size	1944					
Number of parameters	14					
Final log-likelihood	-3134					
Likelihood ratio	698					
R-square	0.201					
Adjusted R-square	0.196					
AIC	6296					
BIC	6374					

**Significant at 0.01 level; *significant at 0.05 level.

4.3. Sensitivity Analysis

4.3.1. Definition of Sensitivity. In the NL model, the estimated coefficients, which are the odds ratio of the specific travel mode to the reference level, cannot reflect the overall impact of a particular variable directly since it also depends on the magnitudes of all other variables. Therefore, a “strict impact” for a given variable cannot be determined due to the diversity of combinations with other variables. The objective is to anticipate the influence of value changes of variables on the choice of certain individual and subsequently on the share of alternatives. In this case study, sensitivity is defined based on the elasticity with an infinitesimal change, which is called point elasticity. Since the variables of operation performance are continuous, we assume that the relative change of one variable is the same for every individual in the population and the disaggregate direct point elasticity of the model with respect to the variable $x_{m,k}^n$ is defined as

$$\begin{aligned}
 \Delta p_{jmk}^n &= \frac{\partial p_{jmk}^n}{\partial x_{m,k}^n} \cdot x_{m,k}^n, \\
 e_{mjk}^n &= \frac{\Delta p_{jmk}^n}{p_{jmk}^n}, \\
 p_{jmk}^n &= f_j(x_n^k, \hat{\gamma}), \\
 E_{mjk} &= \frac{\sum_{n \in A} \Delta p_{jmk}^n}{\sum_{n \in A} p_{jmk}^n} = \frac{\sum_{n \in A} e_{mjk}^n \cdot p_{jmk}^n}{\sum_{n \in A} p_{jmk}^n} \\
 &= \frac{\sum_{n \in A} (\partial f_j(x_n^k, \hat{\gamma}) / \partial x_{m,n}^k) \cdot x_{m,n}^k}{\sum_{n \in A} f_j(x_n^k, \hat{\gamma})},
 \end{aligned} \tag{3}$$

where E_{mjk} is the aggregate point elasticity of the model of travel mode j in choice set A. $p_{i,n}$ is the estimated probability of individual n choosing travel mode j with variables X_n^k in a scenario k . A is the set containing all relevant samples. $f_j(\cdot)$ is the probability mass function for evaluating $p_{i,n}$, which is obtained from the estimated NL model. $\hat{\gamma}$ is the estimated coefficients from the NL.

4.3.2. Sensitivity Analysis of Single Variable. Table 5 reports the sensitivity for each variable according to the estimated NL model. The numbers in the tables present the percentage change in the probability of an alternative with respect to the changes in one variable in a certain situation. As shown in Table 5, red values indicate an increase in the probability, whereas blue values indicate the opposite. Five variables, for example, transfer times, walking time, waiting time, in-vehicle time, and fare, indicate the performance of transport operation. In storm weather with road waterlogging, the quantitative values of indicators can directly reflect the bus service quality at that time and indirectly reflect the severity level of impact by weather. The sensitivity analysis results were interpreted from the mode share shift responding to single variable change.

4.3.3. Walking Time. In our case, we assume that passengers can be taken to their destination by taxi without walking. Therefore, WT5 is set as 0, and sensitivity is also estimated as 0 here. For WT1 to WT4, with walking time of certain alternative getting longer, the probabilities of this alternative are expected to decrease while the probabilities of other alternatives all increase. Specifically, in all scenarios, WT3 has the largest impacts (0.7 to 0.9) on A5 and A6, which prove the key influence of walking time to metro station.

TABLE 5: Sensitivity for each variable.

Variables	Scenario	A1	A2	A3	A4	A5	A6	Variables	Scenario	A1	A2	A3	A4	A5	A6
WT1	1	-1.626	0.520	0.584	0.575	0.417	0.410	IT1	1	-1.642	0.525	0.590	0.580	0.421	0.414
	2	-2.319	0.297	0.332	0.327	0.222	0.219		2	-2.927	0.375	0.420	0.413	0.281	0.276
	3	-3.164	0.135	0.149	0.147	0.077	0.075		3	-4.260	0.182	0.201	0.198	0.103	0.102
WT2	1	0.311	-0.734	0.310	0.319	0.255	0.261	IT2	1	0.627	-1.481	0.625	0.643	0.515	0.528
	2	0.301	-1.183	0.300	0.309	0.229	0.235		2	0.579	-2.279	0.578	0.595	0.442	0.453
	3	0.133	-1.604	0.133	0.137	0.076	0.078		3	0.336	-4.050	0.335	0.346	0.192	0.196
WT3	1	1.018	0.904	-3.398	1.002	0.727	0.714	IT3	1	0.257	0.228	-0.858	0.253	0.183	0.180
	2	1.450	1.293	-4.070	1.428	0.969	0.952		2	0.293	0.261	-0.822	0.288	0.196	0.192
	3	1.515	1.368	-5.110	1.495	0.779	0.765		3	0.340	0.307	-1.147	0.335	0.175	0.172
WT4	1	0.121	0.113	0.121	-1.426	0.088	0.087	IT4	1	0.175	0.162	0.175	-2.057	0.127	0.126
	2	0.225	0.210	0.225	-1.544	0.153	0.152		2	0.331	0.309	0.332	-2.274	0.226	0.223
	3	0.238	0.225	0.239	-1.972	0.124	0.123		3	0.361	0.341	0.361	-2.987	0.188	0.186
WT5	1	0.000	0.000	0.000	0.000	0.000	0.000	IT5	1	0.145	0.148	0.145	0.145	-1.028	0.147
	2	0.000	0.000	0.000	0.000	0.000	0.000		2	0.304	0.310	0.304	0.305	-1.161	0.308
	3	0.000	0.000	0.000	0.000	0.000	0.000		3	0.728	0.732	0.728	0.729	-1.619	0.730
OWT1	1	-0.780	0.249	0.280	0.276	0.200	0.197	TF1	1	0.052	-0.017	-0.019	-0.018	-0.013	-0.013
	2	-1.390	0.178	0.199	0.196	0.133	0.131		2	0.062	-0.008	-0.009	-0.009	-0.006	-0.006
	3	-2.277	0.097	0.107	0.106	0.055	0.054		3	0.068	-0.003	-0.003	-0.003	-0.002	-0.002
OWT2	1	0.223	-0.528	0.223	0.229	0.183	0.188	TF2	1	-0.030	0.071	-0.030	-0.031	-0.025	-0.025
	2	0.258	-1.015	0.257	0.265	0.197	0.202		2	-0.021	0.082	-0.021	-0.021	-0.016	-0.016
	3	0.160	-1.924	0.159	0.164	0.091	0.093		3	-0.008	0.097	-0.008	-0.008	-0.005	-0.005
OWT3	1	0.037	0.033	-0.122	0.036	0.026	0.026	TF3	1	-0.033	-0.029	0.109	-0.032	-0.023	-0.023
	2	0.070	0.062	-0.195	0.069	0.046	0.046		2	-0.037	-0.033	0.105	-0.037	-0.025	-0.024
	3	0.109	0.098	-0.368	0.108	0.056	0.055		3	-0.032	-0.029	0.109	-0.032	-0.017	-0.016
OWT4	1	0.062	0.058	0.062	-0.733	0.045	0.045	TF4	1	-0.014	-0.013	-0.014	0.164	-0.010	-0.010
	2	0.135	0.126	0.135	-0.926	0.092	0.091		2	-0.023	-0.021	-0.023	0.155	-0.015	-0.015
	3	0.172	0.162	0.172	-1.419	0.090	0.088		3	-0.019	-0.018	-0.019	0.158	-0.010	-0.010
OWT5	1	0.052	0.053	0.052	0.052	-0.366	0.052	TF5	1	-0.138	-0.141	-0.138	-0.139	0.982	-0.140
	2	0.173	0.177	0.173	0.174	-0.662	0.176		2	-0.291	-0.296	-0.290	-0.291	1.109	-0.294
	3	0.389	0.391	0.389	0.390	-0.865	0.390		3	-0.696	-0.699	-0.696	-0.696	1.546	-0.697

Besides, in S1, when WT1 increased by 1%, the selection probability of A5 and A6 increased by 0.417% and 0.410%, respectively. It also shows that, in slight storm, walking time to bus stop cannot be ignored. Overall, to reduce ridership decline of public transportation, WT3 in all scenarios and WT1 in S1 are of significant importance.

4.3.4. Waiting Time. Similar to walking time, the probability of one alternative declines as its waiting time becomes longer. However, compared with walking time, the impact would be much less. Specifically, for a 1% increase in waiting time (OWT), the probabilities of A5 and A6 are expected to increase by 0.197% and 0.39% at most, while for 1% increase in walking time (WT), the increase can reach 0.97% and 0.95%, respectively. OWT1 in S1, OWT2 in S1 and S2, and OWT5 in S3 which obviously affect the Cancel Trip should be of concern.

4.3.5. In-Vehicle Time. Similar to walking time and waiting time, the rise of in-vehicle time decreases the choice probability of the respective alternative and increases that of CT. From the results in Table 5, the choice probability of CT is sensitive to changes of IT1 and IT2 in S1, IT2 and IT5 in S2, and IT5 in S3. These results showed that transit commuters can benefit most from reducing the in-vehicle time of A1 and A2 before the weather becomes terrific.

4.3.6. Fare. Since fare of A1~A4 in our designed scenarios is constant, the sensitivity for them does not make any sense. The fare of taxi which is related to travel distance and in-vehicle time road reflect the severity of road waterlogging, leading detouring, and congestion. It can be treated as a variable combination of environment and cost. The impacts of fare are opposite to other variables. Specifically, a 1% increase in taxi fares will increase the selection probability of taxi by 1.5%, while other alternatives will decrease by nearly 0.7% in S3.

Overall, when we compared the absolute direct elastic which measures the impact of a change of an attribute of alternative i on the choice probability of the same alternative, for OWT and IT, there is the same order from high to low: A1, A2, A4, A5, and A3, while for WT, the order becomes A3, A1, A4, A2, and A5. For bus services A1 and A2, the performance of the waiting time and in-vehicle time is needed to be improved. For metro service A3, the key point changes to the walking time.

Since one of our goals is to reduce the choice of Cancel Trip in storm weather, a comparison of Absolute Cross Elasticities to Cancel Trip (A6) is made. We found that the key factors (value > 0.15) vary with scenarios. In S1, the main factors with the order from high to low are WT3, WT1, IT5, IT2, IT1, OWT5, OWT2, and OWT1, while in S2, it becomes WT3, IT2, IT5, IT1, IT4, WT2, WT1, and OWT2, and in S3, it changes to WT3, IT5, BF5, OWT5, IT2, IT4, and IT3. It shows that WT3 is the most critical issue in all scenarios. Besides, WT, IT, and OWT impacts are under balance in S1, but when the condition gets worse, influence of IT of bus

may take the major part, and later when it becomes a terrible storm, attributes of taxi IT5, BF5, and OWT5 have a great influence on Cancel Trip.

In summary, increase of attributes of one alternative, such as walking time, waiting time, and in-vehicle time, has negative impacts on probability choice but positive impacts on other alternatives, while fare is the opposite. Walking time is the key factor for all alternatives. In-vehicle time is similar to waiting time to some extent, with a larger value of sensitivity. When the weather is not so bad, reducing time in all aspects can take effects. When it gets worse, reducing in-vehicle time may still work. If the weather becomes terrible, metro and taxi rather than bus are the preferred choices for most commuters. Reducing the walking time to metro or guaranteeing high-quality taxi service may be feasible.

5. Simulation

In this section, based on information of the case and data analysis, we propose possible plans for transit operators accordingly and simulate the ridership share dynamics in different scenarios. According to the simulation results, we recommend suitable measures in this case for transit operators in different conditions.

5.1. Simulation Method. Once the choice model has been estimated, we hope to use it to simulate the response of transit commuters to emergency measures and evaluate the performance of schemes in promoting transit ridership. The method of simulation is as follows.

Consider a choice model p_{jk}^n providing the probability that individual n chooses alternative j within the choice set C_n in Scenario k , given the explanatory variables X_n^k . To calculate the ridership share in the population of size N , a sample of N_s individuals is drawn. As it is rarely possible to draw from the population with equal sampling probability, it is assumed that stratified sampling has been used and that each individual in the sample is associated with a weight w_n correcting for sampling biases. To achieve it, w_n can be presented by a ratio of proportion in sample and target population for personal attributes of individual n . In this case, we use monthly income distribution in the population derived from official demographic information in Shanghai Statistical Yearbook to correct bias. If $MI_n = c$ for individual n , w_n can be estimated as

$$w_n = \frac{\rho'_c}{\rho_c} \quad (4)$$

$$MI_n = c,$$

where ρ'_c and ρ_c are proportion target population and in sample, respectively. In this case, ρ'_c came from the official demographic information in Shanghai Statistical Yearbook 2016.

The weights are normalized such that

$$N_s = \sum_{n=1}^{N_s} W_n. \quad (5)$$

The normalized weight of individual n , W_n , is formulated as

$$W_n = \frac{w_n N_s}{\left[\sum_{n'=1}^{N_s} w_{n'} \right]}. \quad (6)$$

An estimator of the ridership share of alternative j in the population R_j^k is

$$R_j^k = \sum_{n=1}^{N_s} W_n P_n^k(j|X_n^k). \quad (7)$$

5.2. Simulation of Possible Plans. According to the above analysis, it was found that increase in walking time to metro station, waiting time at bus stop, and in-vehicle time are the main obstacles for transit commuters in storm weather. To cope with the impacts of the storm on transit service, three feasible emergencies are proposed:

P1: shuttle bus, connecting bus stations and metro station near the residential area

P2: information announcement, such as real-time arrival and transfer information for bus service

P3: route adjustment, slightly adjusting the bus routine to avoid serious section with waterlogging and congestion

Parameters after taking emergence plan are different from original plan. Therefore, reasonable setting of all alternatives is shown in Table 6 and explained as follows:

P1. Due to shuttle bus between bus stops and metro station, there exist new choice A7 for commuters which is taking shuttle bus and then transferring by metro, noted as S+M. Compared to A3, passenger who chooses A7 must transfer one time which increases IT and OWT to gain shorter WT. Compared to the existing transfer plan A4, since shuttle only services for connecting nearby bus stops and metro station and can avoid road waterlogging, choosing A7 can have shorter OWT and IT and similar WT for commuters. In emergence plan P1, passengers have alternatives A1 to A7.

P2. If real-time information for bus service is available for passengers, according to previous studies, the expected waiting time can decrease up to 30% [37]. Therefore, OWT in A1, A2, and A4 is settled as 70% of values after the information announcement is taken.

P3. Temporarily change the route of bus lines to avoid road sections with serious road waterlogging section, but lengthen bus line slightly. In this case, according to investigation and data analysis, nearly 50% of delay occurs in road waterlogging sections; we may expect that adjust bus line can reduce 50% delay. Therefore, IT of A1 and A2 will have a significant decline in P3.

Besides, we combined the changes due to different plans together to form four combined plans: P1 + P2, P1 + P3, P2 + P3, and P1 + P2 + P3. Therefore, in the next, 7 plans are simulated and compared in each scenario.

5.3. Simulation Results Analysis. The detailed simulation results of ridership share of alternatives with adoption of plans are shown in Table 7. The aggregation of passengers who choose the main mode as bus (DB, B + B), metro (M, B + M, S + M), and public transportation, is listed as Bus, Metro, and PT, respectively. Value of Bus/Metro reflects the ridership ratio of Bus to Metro in different situations. Further, Table 8 exhibits the ridership share changes to normal weather and the benefits of strategies with a combination of plans. Red and green indicate positive values and negative values, respectively.

Generally, emergency plans will increase the ridership of public transportation and decrease that of taxi and cancel. In single plan strategy (1-P), P1 provides S + M mode which decreases walking time compared to M and waiting time compared to B + M, while P2 aims to decrease bus waiting time and P3 tries to reduce in-vehicle time. Obviously, P1 may increase the attraction of Metro, and P2 and P3 can improve bus ridership, resulting in low Bus/Metro in P1. Besides, we note that, with the deterioration of weather, more benefits can be gained for one certain plan, but the effect varies on plans. Considering a single plan, P1, P2, and P3 perform best in S3, S1, and S2, respectively. Analysis indicates that P2 has a general effect on all scenarios, P1 and P3 are more suitable in a worse situation in the storm.

In 2-Plan strategy, P2 + P3 which is concentrated in bus service performs better than the balanced solutions P1 + P2 and P1 + P3 in all scenarios. We must emphasize that P2 + P3 can greatly increase bus ridership in storm weather, but the cost of reducing metro passengers needs to be carefully considered in the final decision. When it comes to multiplan strategy, as one may expect, the more the plans adopt, the better the performance is. 3-P strategy adopting all three plans is more effective than 2-P strategy, which is also better than 1-P strategy. However, with the adoption of more plans, the margin benefit that brought by one more plan declines. Taking S3 as an example, 1-P strategy can bring 11.42% ridership share rise compared to no plan taking; the margin benefit of 1-P is 11.42%. If one more plan is adopted, in 2-P strategy the rise can reach 19.44% which is much higher than 1-P, but the margin benefit of 2-P decreases to 8.02%. In 3-P, the value further declines to 4.79%. Therefore, considering the margin benefit of emergency plans, we recommend 1-P strategy P2 or original plan P0 in scenario S1, 2-P strategy P2 + P3 in scenario S2, and 3P strategy P1 + P2 + P3 in scenario S3.

Overall, all emergency plans are effective in increasing public transportation ridership and decreasing cancel choice probability. In scenario S1, the impact of the light storm on public transportation is not serious. Therefore, taking no measure or just publishing bus arrival information can be acceptable in this condition. When weather gets worse, P2 + P3 can guarantee bus service and maintain bus

TABLE 6: Parameters of emergence plans.

Performance of services	Scenarios	Alternatives												
		A1	A1-P2	A1-P3	A1-P23	A2	A2-P2	A2-P3	A2-P23	A3	A4	A4-P2	A7-P1	A5
Walking time (minute)	S0	9	9	9	9	5	5	5	5	15	6	6	6	0
	S1	10	10	10	10	5	5	5	5	20	7	7	7	0
	S2	12	12	12	12	6	6	6	6	25	8	8	8	0
	S3	15	15	15	15	8	8	8	8	30	10	10	10	0
Waiting time (minute)	S0	15	10	15	10	12	8	12	8	3	15	11	8	5
	S1	20	14	20	14	15	11	15	11	3	15	11	8	10
	S2	30	21	30	21	25	18	25	18	5	20	16	10	20
	S3	45	32	45	32	40	28	40	28	9	30	23	14	30
In-vehicle travel time (minute)	S0	25	25	30	30	25	25	30	30	15	25	25	25	15
	S1	30	30	32	32	30	30	32	32	15	30	30	25	20
	S2	40	40	35	35	40	40	35	35	15	35	35	27	25
	S3	60	60	42	42	60	60	42	42	20	45	45	35	30
Overall travel time (minute)	S0	49	44	54	49	42	38	47	43	33	46	42	39	20
	S1	60	54	62	56	50	46	52	48	38	52	48	40	30
	S2	82	73	77	68	71	64	66	59	45	63	59	45	45
	S3	120	107	102	89	108	96	90	78	59	85	78	59	60
Transfer	S0-S3	0	0	0	0	1	1	1	1	0	1	1	1	0

TABLE 7: Simulation results in different scenarios.

Scenario	Plan	Public transportation								Taxi	Cancel	
		DB (%)	B + B (%)	Bus (%)	M (%)	B + M (%)	S + M (%)	Metro (%)	Bus/ Metro	PT (%)	TX (%)	CT (%)
S1	P0	24.12	28.82	52.94	21.02	7.28	—	28.29	1.871	81.24	12.42	6.34
	P1	21.82	26.26	48.08	19.01	6.59	8.88	34.48	1.394	82.56	11.55	5.90
	P2	27.74	30.55	58.30	17.59	7.73	—	25.32	2.303	83.61	10.85	5.54
	P3	26.15	31.09	57.24	18.92	6.54	—	25.46	2.248	82.70	11.45	5.84
	P1 + P2	25.73	28.57	54.30	16.31	7.17	6.69	30.18	1.799	84.48	8.95	4.57
	P1 + P3	26.15	29.01	55.16	16.58	5.74	6.81	29.13	1.894	84.29	9.11	4.66
	P2 + P3	29.78	32.66	62.44	15.68	6.88	—	22.57	2.767	85.01	8.96	4.57
	P1 + P2 + P3	27.84	30.77	58.60	14.66	6.44	6.02	27.11	2.161	85.72	8.23	4.20
S2	P0	10.70	18.58	29.28	22.39	11.03	—	33.43	0.876	62.70	20.89	16.41
	P1	8.64	15.20	23.84	18.08	8.92	16.97	43.97	0.542	67.81	18.02	14.18
	P2	14.17	22.59	36.75	18.41	12.45	—	30.86	1.191	67.61	18.14	14.24
	P3	17.59	25.10	42.69	17.51	8.61	—	26.12	1.634	68.81	17.47	13.71
	P1 + P2	12.08	19.59	31.67	15.70	10.64	12.94	39.28	0.806	70.95	16.26	12.79
	P1 + P3	12.48	20.20	32.69	16.22	8.00	13.37	37.59	0.870	70.27	16.64	13.09
	P2 + P3	22.11	29.01	51.12	13.66	9.23	—	22.89	2.233	74.01	14.56	11.42
	P1 + P2 + P3	19.63	26.11	45.74	12.13	8.21	10.00	30.33	1.508	76.07	13.40	10.53
S3	P0	2.94	5.42	8.36	14.91	7.14	—	22.05	0.379	30.42	31.07	38.51
	P1	2.14	4.00	6.14	10.82	5.19	19.69	35.70	0.172	41.84	25.94	32.22
	P2	5.13	8.69	13.82	12.72	9.81	—	22.53	0.614	36.35	28.42	35.23
	P3	8.32	15.03	23.35	11.49	5.49	—	16.98	1.376	40.33	26.66	33.01
	P1 + P2	4.02	6.98	11.01	9.97	7.71	15.95	33.64	0.327	44.64	24.69	30.67
	P1 + P3	4.18	7.24	11.42	10.36	4.97	16.58	31.91	0.358	43.34	25.27	31.39
	P2 + P3	12.94	21.46	34.40	8.74	6.72	—	15.46	2.226	49.86	22.41	27.73
	P1 + P2 + P3	11.00	18.62	29.62	7.43	5.72	11.88	25.03	1.183	54.65	20.25	25.11

P0 is the plan without taking any emergency plans.

ridership share in commuting in S2. If things get worse, in S3, one way is trying our best to guarantee both metro and bus service, adopting all three plans at huge cost and difficult to carry out in practice. Besides, since the metro service is less affected than bus service in the storm, giving up the main

bus service and providing shuttle buses to connect residential areas and metro stations to guarantee the accessibility of metro could be another possible choice in S3. However, it has some limitations, only suitable for areas with highly developed metro networks.

TABLE 8: Performances of plans in ridership compared with original plan.

Scenario	Plan	Bus (%)	Metro (%)	Public transportation (%)	Taxi (%)	Cancel (%)	Strategy	Transit share increase (%)	Margin benefit (%)
S1	P1	-4.86	6.18	1.32	-0.88	-0.44	1-P	2.37	2.37
	P2	5.35	-2.98	2.37	-1.57	-0.80			
	P3	4.30	-2.83	1.46	-0.97	-0.50			
	P1 + P2	1.35	1.88	3.24	-3.47	-1.77	2-P	3.77	1.40
	P1 + P3	2.22	0.83	3.05	-3.31	-1.68			
	P2 + P3	9.50	-5.73	3.77	-3.46	-1.77	3-P	4.48	0.71
	P1 + P2 + P3	5.66	-1.18	4.48	-4.19	-2.14			
S2	P1	-5.44	10.54	5.10	-2.87	-2.23	1-P	6.11	6.11
	P2	7.48	-2.56	4.91	-2.75	-2.16			
	P3	13.41	-7.30	6.11	-3.42	-2.70			
	P1 + P2	2.39	5.85	8.25	-4.63	-3.62	2-P	11.31	5.20
	P1 + P3	3.41	4.16	7.57	-4.25	-3.32			
	P2 + P3	21.84	-10.53	11.31	-6.33	-4.99	3-P	13.37	2.06
	P1 + P2 + P3	16.46	-3.09	13.37	-7.49	-5.88			
S3	P1	-2.23	13.65	11.42	-5.13	-6.29	1-P	11.42	11.42
	P2	5.46	0.47	5.93	-2.65	-3.28			
	P3	14.99	-5.08	9.91	-4.41	-5.50			
	P1 + P2	2.64	11.58	14.22	-6.39	-7.84	2-P	19.44	8.02
	P1 + P3	3.06	9.86	12.92	-5.80	-7.12			
	P2 + P3	26.04	-6.60	19.44	-8.66	-10.78	3-P	24.23	4.79
	P1 + P2 + P3	21.25	2.98	24.23	-10.82	-13.40			

The values in the tables are presented by the ratio to transit ridership under normal weather.

6. Discussion and Conclusions

Our paper aims to describe travel behavior dynamics of transit commuters in the storm and provide possible emergency plans for transit operator/agency to guarantee transit trips of commuters. First of all, this study conducted RP and SP surveys on the impact of storms on travel behavior, focusing on the relationship between travel choice changes of transit commuters and transit service performance. To achieve it, we established a choice model by considering gender, age, income, walking time, waiting time, in-vehicle time, crowdedness, transfer, and fare. From results' analysis, it shows that, in storm weather, walking time, waiting time, and in-vehicle time have obvious negative impacts on the choice probability of alternatives; high-income commuters prefer Bus + Bus, Taxi, and Cancel Trip; age, gender, and crowdedness have limited impacts on storm weather. Through sensitivity analysis, we further found that, in a light storm, reducing travel time, including walking time, waiting time, in-vehicle time, can have effects. When it gets worse, the decline of in-vehicle time may be more sensitive, and therefore Metro becomes the most popular choice. When the weather is terrible, walking becomes more difficult, and thus most commuters give up Metro and choose Taxi or Cancel Trip. Accordingly, three possible emergency plans, information announcement, route adjustment, and shuttle bus to metro station, are simulated in different scenarios. The simulation results can provide references for public transit agencies by suggesting important implications for future public transport development. A strategic proposal of transit agency is to work out detailed emergency plans in conjunction with meteorological departments, road management bureaus, telecommunications companies, and transit

operators, including information release, operation adjustment, and traffic management. Specifically, real-time information should be provided, including weather condition, the emergency state and duration, temporary route plan and timetable, and estimated delay or arrival time at stops, to guide passengers to adjust their travel plans under all scenarios in the storm. Further, according to weather data from the meteorological department and risk analysis of road congestion by road management department, bus operators can adjust bus routes in time to avoid high-risk sections. When weather getting worse and maintenance of normal bus operation becomes difficult, metro system which is less affected by heavy storms can be a reliable substitute for bus service. Thus, it is necessary to put forward a temporary feeder bus scheme, including temporary route, bus stops, and schedule, to bridge the residential areas and metro stations.

Despite these promising implications, there are still some limitations that need to be addressed. Firstly, due to lack of enough data to assess time reliability of alternatives in storm, this study does not directly consider the reliability which may play important roles in making travel decisions. Secondly, to narrow the scope of the study, recreational travel which is more likely to be affected than commuter travel is out of consideration in this study. Thirdly, to reduce the complexity of methodology and focus on transit service, private car, which has some differences from the alternative Taxi, was not listed as an alternative for transit commuters. Thus, more issues should be taken into account to provide a refined profile of how adverse weather affects travel choice. Finally, this study exhibits the adaptation of transit commuter to the storm and provides possible countermeasures for transit agency by the case study in a specific small zone. A general application would require further verification in more areas. Further research should be undertaken to

investigate the spatiotemporal heterogeneity of the influence by adverse weather, simulate transit ridership dynamics in different areas over time, and evaluate the performance of feasible emergency plans.

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.

Authors' Contributions

Teng, Bo, and Zhang contributed to study conception and design. Teng and Bo contributed to data collection. Zhang and Bo contributed to methodology, analysis and interpretation of results, and draft manuscript preparation. All authors reviewed the results and approved the final version of the manuscript.

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