Wiley
Journal of Advanced Transportation
Volume 2025, Article ID 3607727, 21 pages
https://doi.org/10.1155/atr/3607727

WILEY

Research Article

On the Application of Probabilistic Route Choice Models to Urban Rail Transit Networks Containing Small-Scale OD Trip Data

Wei Zhu,[1,2] Changyue Xu,[1,2] Amr M. Wahaballa,[3] Wenbo Fan ,[4] and Seham Hemdan[3]

[1]*College of Transportation, Tongji University, 4800 Cao'an Road, Shanghai 201804, China*
[2]*Shanghai Key Laboratory of Rail Infrastructure Durability and System Safety, Tongji University, 4800 Cao'an Road, Shanghai 201804, China*
[3]*Civil Engineering Department, Aswan University, Aboelreesh Kebly, Aswan 81542, Egypt*
[4]*Department of Electrical and Electronic Engineering, The Hong Kong Polytechnic University, Hong Kong SAR, China*

Correspondence should be addressed to Wenbo Fan; wenbo.fan@polyu.edu.hk

Received 13 January 2025; Revised 22 May 2025; Accepted 30 July 2025

Academic Editor: Mohammad Rezwan Habib

Modeling passenger route choices is crucial for analyzing and predicting public transportation demand. One of the most popular methods is to use probabilistic route choice (PRC) models (also known as discrete choice models in general), which have broad applications in transportation, economics, politics, and other fields. However, its performance varies depending on the characteristics of the origin–destination (OD) trip data and should be examined carefully. This paper proposes a framework for validating the PRC model on its application to urban rail transit (URT) networks containing small-scale OD trip data. The concept of small-scale data is defined at first for each OD pair considering the desired confidence level and the variance of route choices. Then, a travel time range (TTR)-based method is put forward to deduce passengers' actual route choices as a benchmark for verifying PRC models. The difference and regularity analysis between the actual route choices and the model predictions are also performed with a twofold comparison. A case study on the Nanchang metro in China shows that the actual daily passenger volumes on routes of small-scale OD pairs diverge remarkably from the estimations of the PRC model. The PRC model's performance is further discussed when the small-scale OD trip data accumulate to a larger scale over multiple days (e.g., several months). This study reveals the inherent limitation of PRC models in estimating the travel behaviors of passengers in a small-scale population. Several practical implications are discussed to improve the route choice model and passenger flow analysis.

Keywords: applicability; probabilistic route choice model; small-scale trips; urban rail transit; validation

1. Introduction

The urban rail transit (URT) system, serving as a high-capacity transportation system, has emerged as a crucial component of urban passenger transportation, undergoing remarkable progress from a solitary line to a complex network in many major cities around the world. It is known in the literature that the passenger flow in the network is the foundation for the operation plan of a URT system. Estimating passengers' route choices on transit networks plays a pivotal role in analyzing, predicting, and simulating passenger flows. Over the years, numerous transit route choice models have been developed, both in theory [1–5] and in practice [6–10]. Comprehensive surveys are available in several review papers [11–15].

In the field of transit route choice modeling, the shortest-route principle is first used to estimate the route choices of URT passengers. From the analyst's perspective, it assumes that all the passengers between an origin–destination (OD) pair take the "shortest route," which is usually the route with fastest travel time (TT) (or lowest cost/shortest distance). As the network expands and becomes more complex, there are more alternative routes between an OD pair, and passengers may not choose the shortest route due to various reasons (e.g., unfamiliarity, residual habits, and group traveling). Accurately modeling passengers' route choice behaviors is also more challenging, considering the complexity of human behavior representation, the lack of passengers' knowledge about the network composition, the uncertainty of passengers' perceptions of route characteristics, and the unavailability of precise information about passengers' preferences. Thus, probabilistic choice models are introduced, of which discrete choice models have been widely adopted in the last few years. Recently, emerging techniques have been applied to route choice data mining. Using automatic train supervision (ATS) and automatic fare collection (AFC) data, analysts can deduce passengers' train choices, thereby estimating passenger route choices and flow distribution on the network. Other techniques estimate passengers' route choices with mobile phone signaling (MPS) data, Wi-Fi probing data, closed-circuit television (CCTV) data, and other sources. However, these techniques cannot take undetected passengers into account and are not effective without historical data. Therefore, probabilistic route choice (PRC) models still remain necessary and are described in detail below.

When it comes to PRC models, Manski's [16] paradigm for predicting choice which provided the models' essential part is very helpful for simplicity. This paradigm states the probability formula for an actor choosing an alternative from the choice set. In terms of passenger route choice, the probability of the passenger i choosing the route r for a given OD pair od from the route choice set US_i can be expressed as the following expression:

$$P_i\left(r_{\mathrm{od}}\middle|\mathrm{US}_i\right) = \sum_{\mathrm{CS}_i \in \mathrm{PS}_i} p_i\left(r_{\mathrm{od}}\middle|\mathrm{CS}_i\right) \cdot p\left(\mathrm{CS}_i\middle|\mathrm{US}_i\right), \tag{1}$$

where $p_i(r_{\mathrm{od}}|\mathrm{US}_i)$ is the choice probability of route r for a given OD pair od from the universal set US_i of all routes available to the passenger i; $p_i(r_{\mathrm{od}}|\mathrm{CS}_i)$ is the conditional probability of passenger i chooses route r for a given OD pair od in his/her consideration set CS_i, which is a subset of US_i; $p(\mathrm{CS}_i|\mathrm{US}_i)$ is the probability that CS_i is the consideration set of passenger i given his/her universal set US_i.

PRC models follow the law of large numbers [17, 18], which means that as the sample size grows, the average tends to approach the expected value. A coin flipping is a classic example of this principle. Each time a coin is flipped, the probability of heads is 50%. Thus, in an infinite sequence of coin flips, the anticipated ratio of heads is gradually equivalent to 1/2. However, when we flip the coin only 10 times, we may find that heads appear only three times. Due to the small sample size of 10 flips, there is no guarantee that the proportion of heads observed will be anywhere near 50%. If the PRC models are applied to the average of a large number of passengers, its prediction results will be accurate. However, it may not be reliable to predict the choices of a limited number of passengers. This issue is evident in URT networks containing OD pairs with small-scale trips. In the case of the Shanghai Metro, one of the largest metro systems in the world, statistics on AFC transaction data show that there are more than 50% of OD pairs with less than 30 passenger trips per day[1], accounting for over 30% of total trips between these OD pairs within the network [19]. Therefore, exploring the reliability of PRC models for OD pairs with small-scale trips is an intriguing and significant issue, both theoretically and practically, which has not been comprehensively addressed in the literature.

Given the widespread presence of small-scale OD pairs and the potential for PRC model misalignment under such conditions, the research problem addressed in this study can thus be stated more formally as follows: consider one URT network represented as a directed graph $G = (N, A)$, where N is the set of nodes (stations) and A is the set of arcs (direct connections between stations). Let W be the set of all OD pairs within the network, where each OD pair $w \in W$ is associated with a daily passenger flow volume d_w. We define a subset $W_s \subset W$ as small-scale OD pairs, where $d_w < \theta$ for all $w \in W_s$, with θ representing a threshold. For each OD pair $w \in W_s$, let R_w be the set of all feasible routes connecting the origin to the destination. Under a PRC model, the probability of route $r \in R_w$ being chosen is given by P_r^w, as expressed in Equation (1). The model predicts that approximately $d_w \cdot P_r^w$ passengers will select route r. However, given the law of large numbers, this prediction becomes increasingly unreliable as d_w decreases. We aim to investigate the reliability gap and evaluate the relationship between predicted route flow distribution $\{d_w \cdot P_r^w | r \in R_w\}$ from PRC models and actual route choices $\{f_r^w | r \in R_w\}$ observed in the system (where $\sum_{r\in R_w} f_r^w = d_w$). For small-scale OD pairs where $d_w < \theta$, we hypothesize that the discrepancy between predicted and actual route flows exceeds acceptable error margins. Furthermore, we examine how this discrepancy evolves when data are accumulated over multiple days, effectively increasing the sample size to $T \cdot d_w$ (where T is the number of days).

To address these questions, we propose a validation framework specifically tailored for small-scale OD pairs and also investigate how model performance evolves when trip data accumulate over multiple days. In addition to filling a clear modeling gap, this study supports more informed decisions about when and how such models can be applied in practice effectively—particularly in short-term forecasting and in identifying scenarios where model modifications or supplementary data collection may be needed. It also helps guide the application of PRC models in medium- and long-term planning tasks, such as capacity design, service optimization, and strategic investments in urban rail systems.

The main contributions of this paper are put forward in advance:

1. A validation framework for PRC models is proposed, which includes three successive tasks and completes the validation with a twofold comparison.

2. The definition of OD pairs with small-scale trips is discussed in the context of URT systems, and the judge criterion is provided.
3. A travel time range (TTR)-based method is developed for deducing URT passengers' actual route choices. It is customized for the OD pairs with small-scale trips, and the results are taken as a benchmark to assess the validation of PRC models.
4. A detailed case study on the Nanchang metro in China is conducted, with several results, and their implications are discussed.

The remainder of this paper is organized as follows: Section 2 reviews relevant studies. Section 3 proposes a validation framework including three successive works. Section 4 presents the application of the proposed approach to the Nanchang metro in China, followed by discussions in Section 5. The final section summarizes the conclusions and their practical implications.

2. Literature Review

This study focuses on the applicability of probabilistic models for passengers route choices in rail transit. In this section, we briefly review related literature on the historical application of probabilistic models in the field of transportation and highlight our contributions to the applicability of PRC models at different demand levels.

2.1. PRC Models in Urban Transportation. Historically, discrete route choice models have been utilized to address passenger route choice issues, with generalized cost functions widely used in current research. Bayesian techniques and Logit-based models [3, 20, 21] have been suggested to estimate passenger route preferences. However, these models must consider the total cost associated with each route, including factors such as waiting time, TT in the vehicle, station dwell time, transfer time, and choice patterns (such as transfer frequency, comfort level, and transfer penalties). Some models attempted to incorporate how the similarity between alternative route options affects passenger decisions. These range from more sophisticated models grounded in generalized extreme value theory, such as the paired combinatorial logit, cross-nested logit (CNL), and generalized nested logit, and error components and logit kernel models. The multinomial logit (MNL) model is adjusted to capture these similarities by introducing additional terms [22]. Sensitivity to the effective route threshold is a limitation of these strategies. The quantity of effective routes between OD pairs determines this to a large extent.

Similarly, route choice estimation in URT relies on those models where passengers choose their transfer station thoroughly based on the train schedules and personal travel experiences. This also presents a typical issue raised by the networked operation of URT in the real-world scenarios [23]. Wu and Liu [24] constructed an equilibrium model based on equilibrium theory and resolved it using the frank-wolf algorithm, drawing inspiration from road traffic flow assignment methods. Si et al. [25] developed a passenger-integrated travel impedance function to enhance the equilibrium model, highlighting the distinctions between URT and road networks. The primary methods for calculating route choice probabilities include the improved logit model [26] and the probability distribution model based on normal distribution [27]. In both models, the likelihood of route choices increases as travel impedance decreases. While initial passenger flow assignment results can be obtained using the methods above, their accuracy has to be further improved. The passenger travel impedance needs to be more specifically described, and qualitative elements influencing passenger route choice need to be converted into quantitative indicators to increase model accuracy and make findings more realistic [28].

Typically, the traditional logit approach may produce some irrational outcomes, particularly due to its neglect of routes interdependencies, which would affect result accuracy. Most existing literature on route choice behavior analysis using the logit models does not account for this aspect. Considering the route relevance in URT networks, Zhang [14] recommended using the C-logit or path size logit model [29] for researching route choice behavior in practice. Gleason et al. [30] utilized the C-logit model to explore how sociodemographics, network structure, and passenger perceptions of transfers affect route choice behavior. Additionally, the cumulative prospect theory was found to be more effective and realistic than the expected-utility-based approach in testing the effectiveness of route choice behavior [31].

2.2. PRC Models for Variable Demand Levels. It is widely known in the literature that stochastic user equilibrium (SUE) flow patterns come close to those provided by the deterministic user equilibrium (DUE) solution at very high demand levels. However, for moderate to high demand levels, SUE flows may differ significantly from DUE flows depending on the specific route choice model employed [22]. A deeper characterization of passenger route choice behavior is necessary, for example, the effects of morning-peak and evening-peak passenger flows, to accurately comprehend how passenger demand changes influence the distribution of passenger flow in the URT network.

According to the changing degrees of travel demand, passengers would be grouped together to mitigate errors and oscillations that arise from insufficient data [32]. Zhang [14] proposed a time-switching topologies approach to dynamically update the URT network representation based on varying passenger loads. This considers the time-variance nature of URT network passenger load, such as peak-hour congestion and off-peak uncongested conditions. They also suggested a function for the computation of general travel costs in the URT network when passenger flow exceeds permissible overcrowding limits. Xue et al. [33] developed a control strategy for station-level passenger flow control in URT networks based on train marshaling plans. Their findings concluded that a suitable size of arrangement scheme can be determined by the spatial and temporal characteristics of large passenger flows due to the short duration and the limited passenger flow packed section.

However, these studies overlooked the situation involving low-demand OD pairs. Bekhor et al. [22] compared path flows generated using path-based SUE assignments with the MNL and CNL models in real-size networks. They examined how the choice set size affected issue convergence, running duration, and particular results, highlighting the prospective adoption of selected route choice models as loading methods in SUE assignments. They found that increasing the choice set size (leading to OD pairs with very low-demand proportions) caused an increase in the route choice estimation error. This may occur as the number of routes in the choice set grows (and is comparable to the situation of low-demand OD pairs).

2.3. The Contribution of the Study in This Paper to the Existing Research Literature. In recent years, scholars have started to notice and investigate the unreliability of traditional PRC models for rail transit passenger route choices from different perspectives. Most studies focused on influence factors such as map topology [34–36], service level [37–39], and passenger travel experience [40–42]. Additionally, investigations were also conducted on abnormal travel behaviors, including denied boarding [43–46], taping in and out at the same station [47], go-and-back travel [48–50], and group-based travel [51].

Despite some enhancements, adjusting existing PRC model parameters alone remains insufficient to fully explain a certain proportion of behaviors and phenomena to achieve accurate estimation, which can influence the passenger flow assignment and rail transit operations. Rail transit agencies have also begun to acknowledge the limitations of PRC models. Important and necessary for industry, validation works for the PRC models based on field data have initiated to be carried out [52, 53]. These studies revealed that a great number of OD pairs witness remarkable deviations between actual passenger flows and the values estimated by the models. For example, an investigation of the Shanghai metro in China showed that more than 7000 OD pairs had deviations based on the traditional PRC model, contributing an average of more than 260,000 passengers per day [19]. Beyond the aforementioned spatial dimension, several inconsistencies also exist in the temporal dimension, typically such as peak hour dislocation [54, 55]. Moreover, PRC models struggle to accurately calculate and grasp actual passenger flow distribution during large-scale or unexpected events, making passenger flow control and network guidance more challenging.

To the best of the authors' knowledge, previous research studies on comparing and evaluating route choice models are limited (Table 1). Existing studies rely either on traditional manual-based methods or approaches dependent upon another route choice model whose applicability is also uncertain. To fill the research gap, this study empirically explores the OD pairs with small-scale trips in terms of the model prerequisites, providing a more comprehensive understanding and insights into the applicability of PRC models. This work is theoretically and practically necessary and essential.

3. Methodology

3.1. Overview of Validation Procedure. Our study is based on an assumption that the PRC models have been calibrated using data from the whole URT network, as is customary in practice [56, 57]. The detailed calibration steps are documented in previous studies and are not included in this paper.

To validate the built PRC models, we propose a framework with three successive major tasks, as shown in Figure 1: (1) identifying the OD pairs with small-scale trips, (2) deducing passengers' actual route choices between the OD pairs, and (3) comparing the actual choices to those estimated by the PRC models. The detailed steps are as follows:

Step 1. Identifying the set of OD pairs of study. For convenient validation, we select OD pairs according to two criteria: (i) OD pairs associated with only two route options; and (ii) OD pairs that satisfy the small-scale definition, which will be described in detail in Section 3.2.

Step 2. Deducing passengers' actual route choices as a benchmark for comparison. A TTR-based method, which is customized for OD pairs with small-scale trips, is proposed in Section 3.3 to deduce passengers' actual route choices and the resulting route flows.

Step 3. Comparing the actual results to those estimated by the PRC model. The comparison is made at two levels, respectively: daily and monthly. At each level, differences between passengers' actual and estimated route choices and their regularity are analyzed in detail.

Remark 1. On the definition of small-scale data, our study presents a criterion based on the sample size formula, as given in Section 3.2, which considers the URT system's characteristics and the desired confidence intervals. Using this criterion, we calculate threshold values for all OD pairs that entail different variances of route choices and delineate small-scale ones.

Remark 2. The proposed TTR-based method for deducing actual route choices is customized for the OD pairs with small-scale trips. Generally speaking, TTRs of routes between a given OD pair may overlap with each other, making it difficult to deduce passengers' route choices according to TTRs. However, it becomes possible, as shown in Section 3.3, when discussing the OD pairs with small-scale trips.

Remark 3. The proposed validation procedure examines the effectiveness of applying PRC models to OD pairs with small-scale trips at both daily and multiday levels. Note that over a longer period (e.g., a month), the number of trips for the same OD pair accumulates and may surpass the

Table 1: Comparison of existing research for model adaptability in metro route choice.

Ref. No.	Focus	Approach	Model/Algorithm	Data				Application
				Survey	AFC	ATS/AVL	CCTV	
[34–42]	Influence factor	Empirical analysis Variable quantification Behavioral experiment	Discrete choice model Travel time chaining	✓	✓			Service planning Policy adjustment
[43–51]	Abnormal behavior	Anomaly detection Probability estimation Individual inference	Machine learning Discrete choice model Travel time chaining		✓	✓	✓	Security guarantee Demand management
[39, 40, 43, 44]	Parameter calibration	Data fusion Statistical fitting Simulation-based optimization	Regression model Bayesian model Heuristic algorithm	✓	✓	✓		Flow assignment Scenario modeling
[19, 52–55]	Field evaluation	Manual-based examination Spatial clustering Temporal matching	Discrete choice model Machine learning Travel time chaining Clustering algorithm	✓	✓	✓	✓	Operational feedback Policy validation
Ours		Empirical analysis Individual inference Performance measurement	Discrete choice model Travel time chaining		✓	✓		

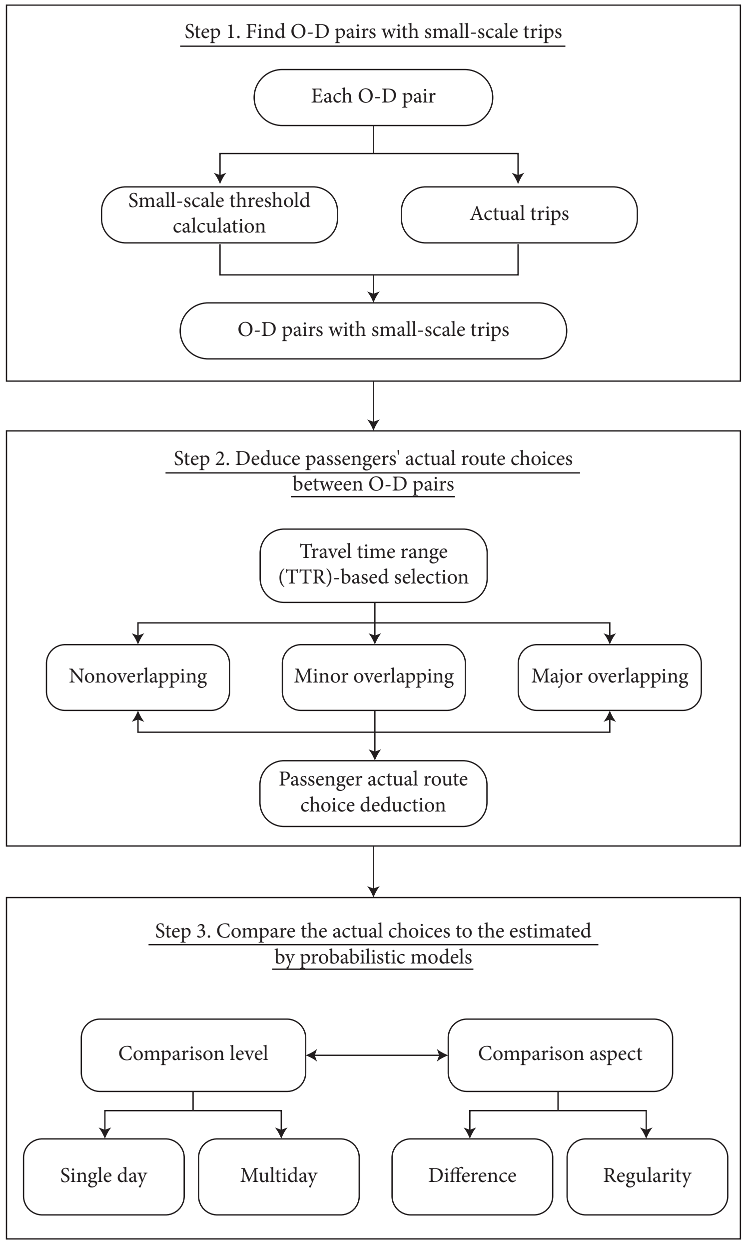


Figure 1: Overall framework of three-step validation procedure.

threshold of small-scale data. Our study aims to conduct comparisons for both scenarios.

3.2. Definition of OD Pairs With Small-Scale Trips. The definition of OD pairs with small-scale trips is the prerequisite and key for the identification. Some practitioners have adopted the principle of a sample size larger than 30 as a universally applicable criterion for large-scale samples [58, 59], which implies the small scale with data records less than 30. Meanwhile, to obtain a more detailed and generalized criterion, researchers in the fields of medicine and control engineering have proposed several sample size estimation formulas according to their professional data and assumptions, such as those based on the Central Limit Theorem or Confidence Interval Theory [60–64].

Our study tries to give a calculation criterion considering the characteristics of the URT system and consequently focuses on the sample size estimation formula based on confidence interval. We introduce it into the context of URT networks to calculate the threshold of small-scale trips for a given OD pair. The calculation formula is as follows:

$$n^{\mathrm{od}} \leq n_0^{\mathrm{od}} \equiv \frac{Z_{\alpha/2}^2 \times V(p)}{\triangle^2}, \quad \mathrm{od} \in W, \tag{2}$$

where n_0^{od} is the threshold of the small scale, implying OD pair od is small-scale if $n^{\mathrm{od}} \leq n_0^{\mathrm{od}}$ and vice versa, and W denotes the set of OD pairs. The $Z_{\alpha/2}$ represents the $1-\alpha/2$ quantile of the standard normal distribution, and usually, α takes the value 0.05, and then, $Z_{\alpha/2}$ is 1.96. The $\triangle$ indicates the precision and can be determined based on the 95% confidence interval reported in the previous literature [65, 66]. Generally, the precision is no more than half the width of the confidence interval. The $V(p)$ represents the variance of choice probability.

To compute the threshold n_0^{od} using this formula in the URT system, we follow these steps: (1) the route choice probability p is obtained using the PRC model; (2) whether the variance $V(p)$ follows a binomial or multinomial form based on the number of significant routes is determined; (3) the precision $\triangle$ and quantile $Z_{\alpha/2}$ based on standard statistical practice are assigned; and (4) these values are substituted into Equation (2) to compute the OD-specific threshold.

As we can see from the above equation, given the parameters ($\triangle$ and$\triangle$) are unified, the threshold of small-scale trips for a given OD pair depends only on the route choice probability value (p) obtained from the PRC model. The primary objective of the proposed method is to identify the limitations of PRC models and quantify their estimation errors. To achieve this, the two-route scenarios serve as a clear and well-defined testbed. For OD pairs with dual routes[2], the route choice probability approximately satisfies the binomial distribution, then $V(p) = p(1-p)$. Since this probability varies across OD pairs depending on network structure and passenger behavior, OD pairs with different route choices will get different threshold values of small-scale trips. Thus, to select those OD pairs with small-scale trips, we need to calculate the threshold value and compare it with the actual trips for each OD pair in the whole URT network.

3.3. TTR-Based Method for Deducing Passengers' Actual Route Choices Between OD Pairs. We propose a TTR-based deduction method as follows. First, we construct and calibrate the TTDs of different route options according to the URT schedules and the distributions of passengers' walking time between AFC gates and platforms. Second, we distinguish AFC records falling into the non-overlapping parts and identify them as different route choices, as illustrated in Figures 2(a) and 2(b). A special case occurs for route options with no overlapping TTDs, as shown in Figure 2(c), under which all passengers' route choices are completely distinguishable.

To further ensure the confidence of deduction, we apply the TTR-based method to OD pairs with only two route options. Doing so significantly reduces the work of deduction and facilitates the verification of PRC models. The following subsections describe these two steps in further detail.

3.3.1. TTD. It is a complete travel process where passengers swipe their cards in and out of a station from their origin (O) to destination (D) stations. The time difference between the two swipes is the actual TT of each passenger. This route TT varies among passengers. For multiroutes OD pairs, the TT of passengers on different routes will also vary. To deduce the actual choices more precisely, we need to parse the internal components of the TT on each route for the OD pairs. In a typical URT network, it mainly contains six parts that can be calibrated from historical data as follows (Figure 3):

a. Walking time from the entry gate at the origin station to the platform, $t_{o,\mathrm{ewt}}$;
b. Waiting time from the arrival at the platform to the departure of the train, $t_{o,\mathrm{wt}}$;
c. TT on the train, t_{od} (can be obtained from ATS system data);
d. Walking time from the platform of the transfer origin line to the platform of the transfer destination line, $t_{\mathrm{ts,tswt}}$;
e. Waiting time from the arrival at the platform of the transfer destination line to the departure of the next train, $t_{\mathrm{ts,wt}}$;
f. Walking time from the platform to the exit gate at the destination station, $t_{d,\mathrm{ewt}}$.

Thus, TT for a passenger's complete travel process can be estimated by the following equation:

$$\mathrm{TT} = t_{o,\mathrm{ewt}} + t_{o,\mathrm{wt}} + t_{\mathrm{od}} + t_{\mathrm{ts,tswt}} + t_{\mathrm{ts,wt}} + t_{d,\mathrm{ewt}}. \tag{3}$$

However, TT always fluctuates among different passengers on the same route of one OD pair due to individual differences and environmental disturbance in the travel process. In other words, TT on one route of the OD pair is usually presented as a range of values, rather than a fixed value (Figure 4).

For this reason, an essential concept that assists us in deducing the passenger route choice is TTR. It is defined as a range of TT that passengers can travel on a given route, from the shortest TT $\mathrm{TT_{min}}$ to the longest TT $\mathrm{TT_{max}}$, as shown below. Specifically, the lower bound is defined theoretically by considering scheduled train arrival and departure times combined with the maximum realistic walking speeds, which represents an ideal, delay-free scenario. For the upper bound, it is determined from AFC and AVL data and captured real-world variability, by including the minimum walking speed and maximum waiting time due to delays. Delays such as those caused by being left behind during peak hours naturally lead to longer observed TTs, we accounted for potential waiting time impacts by incorporating an additional waiting time equivalent to one or two headways into the upper bound based on actual station situations.

$$\mathrm{TTR} = \left[\mathrm{TT_{min}}, \mathrm{TT_{max}}\right]. \tag{4}$$

3.3.2. Route Choice Deduction. Based on the above-mentioned TT inference, the TTRs of routes for OD pairs may overlap to different degrees (non-overlapping, minor overlapping, and major overlapping). For OD pairs with non-overlapping ranges, the actual TT of each passenger is compared with the TTR. A passenger can be deduced to

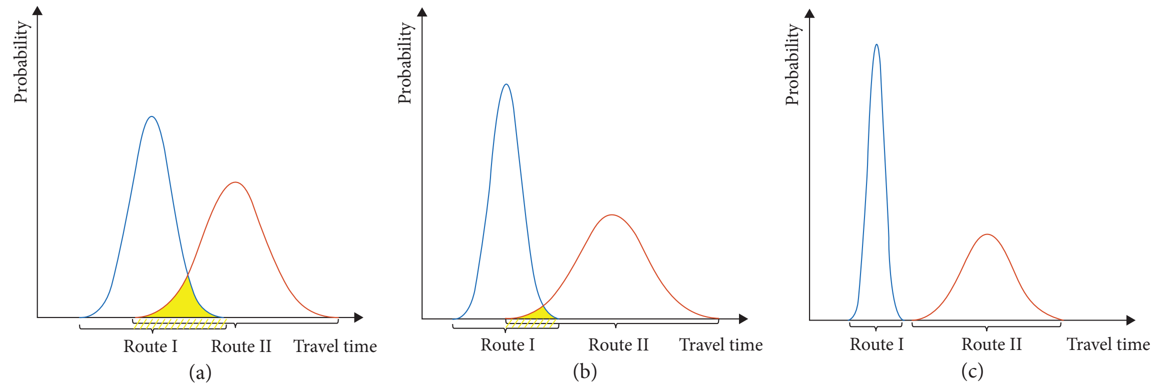


Figure 2: Three overlapping types of route travel time distributions for OD pairs. (a) Major overlapping. (b) Minor overlapping. (c) Non-overlapping.

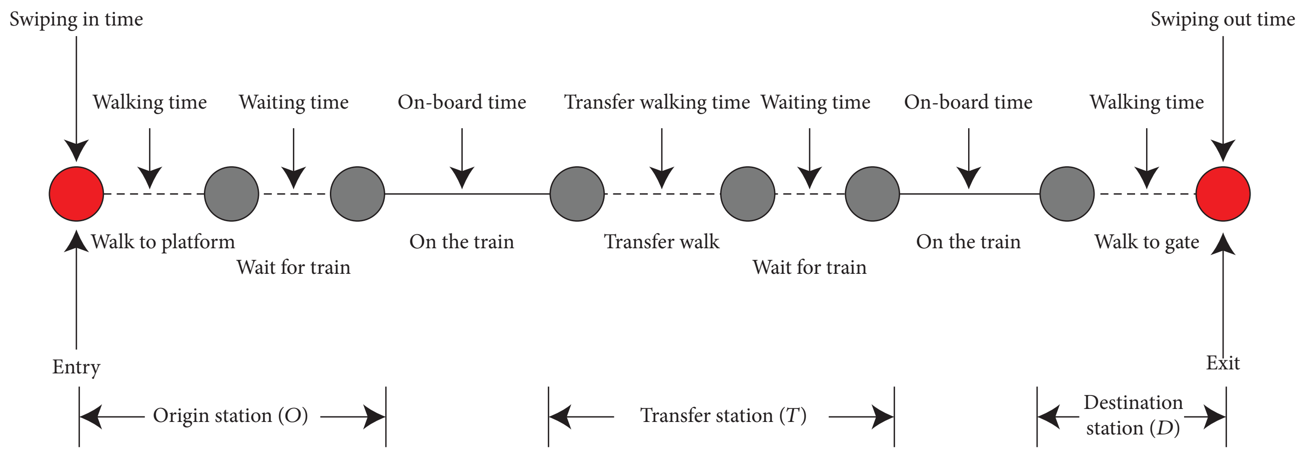


Figure 3: The composition of route travel time (TT) between a given OD pair.

a route if his/her actual time falls into the range of the route. For OD pairs with overlapping ranges (minor overlapping or major overlapping), the dates with trips falling into the overlapping part need to be eliminated, and accordingly, the trips in the remaining dates are in the non-overlapping parts. Therefore, the corresponding deduction for these remaining passenger route choices is consistent with the previous non-overlapping process. In all, the actual route choices of passengers can be deduced with certainty. The deduction diagram is shown in Figure 5.

3.3.3. Twofold Comparison of Passengers' Actual and Estimated Route Choices. In this paper, we carry out a twofold comparison approach (Figure 6): First, the comparison is conducted at the single-day level and multiday level, respectively; second, at each level (single-day or multiday), differences between passengers' actual and estimated route choices and their regularity are analyzed in detail. At the single-day level, the trips of a given OD pair may be classified as small scale, while at the multiday level (e.g., for a month), the trips of the same OD pair may raise and exceed the threshold and become a large sample. We try to complete the comparisons on both of them.

3.3.3.1. Single-Day and Multiday. At the single-day level, the trips of a given OD pair after the abovementioned filtering are small scale and cannot meet the threshold. It would be easy to understand if this would lead to model inaccuracy. But at the multiday level, when accumulating trips by days (e.g., for a month), the count of trips may exceed the threshold and meet the criteria of large scale (large population), and the situation will be changed. Therefore, it is necessary to make comparisons at both levels to analyze the difference between passengers' actual and estimated results to check model applicability. If the choices of such trips are inherently volatile, then they should not be described using a fixed model value, but the regularity between actual passenger choices needs to be explored.

3.3.3.2. Difference and Regularity Analyses. The difference and regularity analyses are conducted at both single-day and multiday levels. Difference analysis aims to know the magnitude of numerical variances between the actual

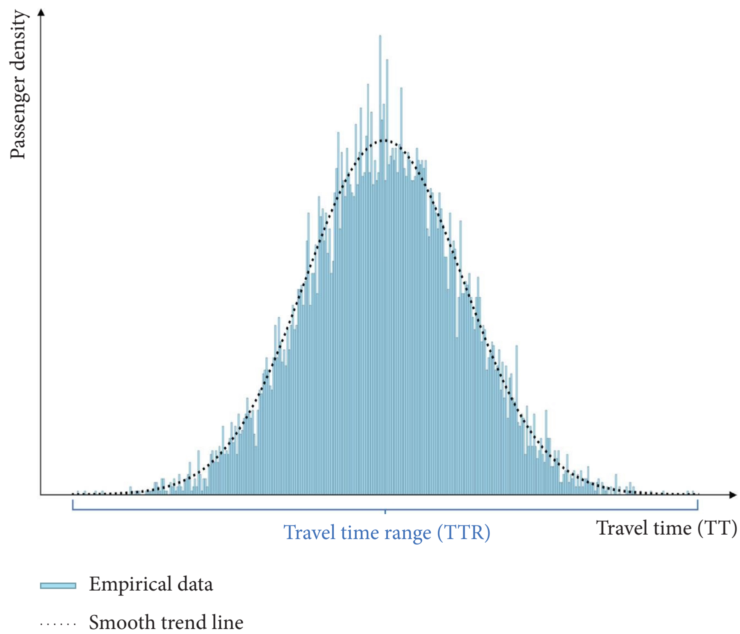


FIGURE 4: Illustration of a route's travel time distribution between a given OD pair.

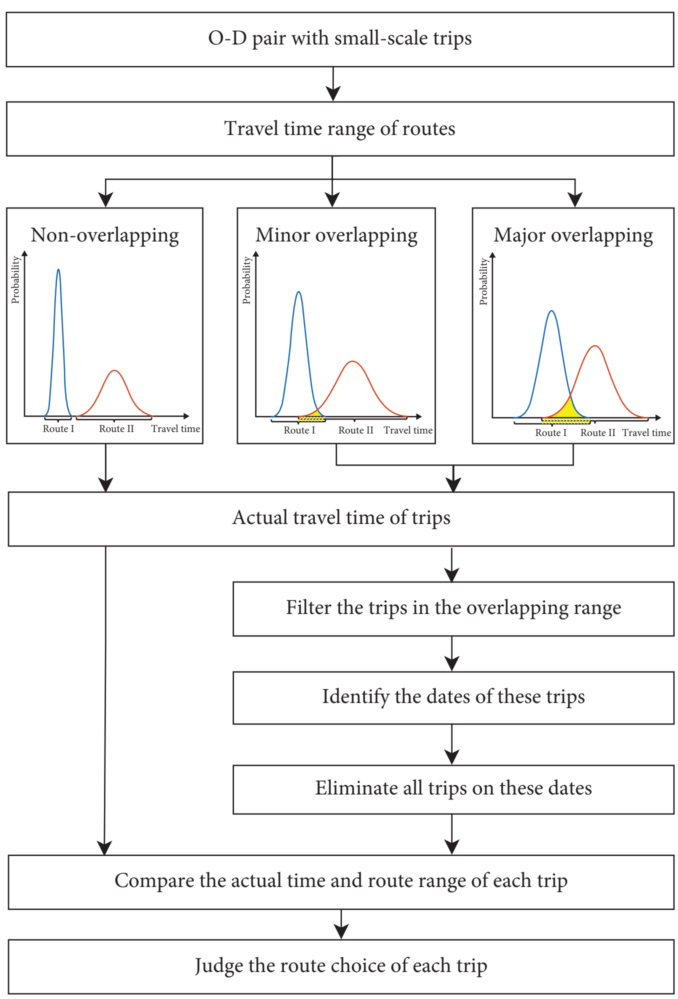


FIGURE 5: Illustration of route choice deduction rules.

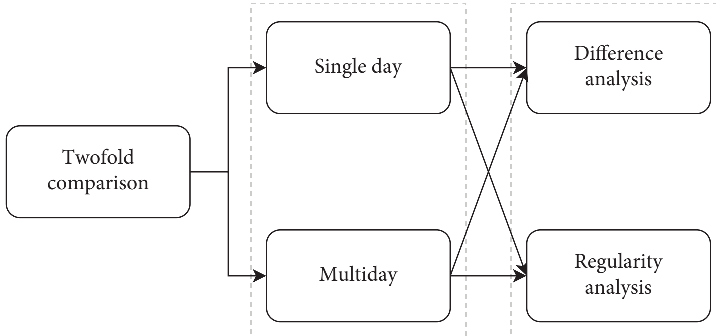


FIGURE 6: Twofold comparison of the actual and estimated passengers' route choices.

choices and the estimated results, while regularity analysis seeks to explore whether the actual choices themselves have a certain regularity and stability.

Two indicators are selected to assist our analysis, the relative percentage difference (RPD) and the root means square error (RMSE). RPD is commonly employed to calculate and observe whether there exists a significant gap between two values and what the size of the gap is, while RMSE helps measure the degree of deviation between a data series and the true value [67]. The larger the RPD is, the more significant the numerical gap is. The larger the RMSE is, the more discrete, unstable, and disordered the data series itself is. In the difference and regularity analysis, the data chosen for the indicator formula are different, and a more detailed description is given below.

In terms of difference analysis, the main focus is on comparing the model result with the actual proportion for each day. Then, RPD and RMSE are calculated as Equations (5) and (6).

$$\mathrm{RPD}_{\mathrm{dif}} = \frac{\left|v_a - v_m\right|}{\left|\left(\left(v_a + v_m\right)/2\right)\right|} \times 100\%, \tag{5}$$

where v_a refers to the actual proportion on a given day, and v_m refers to the estimated by PRC model.

$$\mathrm{RMSE}_{\mathrm{dif}} = \sqrt{\sum_{j=1}^{N} \frac{\left(v_j^a - v_m\right)^2}{N}}, \tag{6}$$

where N means the number of days for comparison, and v_j^a means the actual proportion on the j^{th} day.

In terms of regularity analysis, the main focus is on exploring the self-regularity of the actual proportions. Then, Equations ((5) and (6)) can be applied again by replacing the variable v_m with v_e, which refers to the average of the actual proportions over N days. The resulting values are noted as $\mathrm{RPD}_{\mathrm{reg}}$ and $\mathrm{RMSE}_{\mathrm{reg}}$, respectively.

4. Case Study

4.1. Study Area and Data Collection

4.1.1. The Nanchang Metro Network. The case study conducted in this paper is based on the Nanchang metro in China. Its network (Figure 7) consists of 4 lines (Line No. 1–4), with a total of 94 stations (including 9 transfer stations). For subsequent analysis, each station is numbered, where the transfer stations are generated with different numbers on different lines.

4.1.2. Multisource Data to Be Used. The data we used come from three different sources, including the AFC system, the ATS system, and crowd walking speed (CWS) statistics. The AFC transaction data and ATS timetable data for five months in 2022 were used. Investigations into passenger walking speed were conducted in a comprehensive reference to several literature studies [68, 69].

The station's entry and exit gates can record relevant data when passengers swipe their smart cards, including passenger's ticket number, ticket type, card swipe date and time, travel amount, origin station, and destination stations, etc. We select six types of information relevant to this study, as shown in Table 2.

The train timetable data include the date, line number, line terminal, train number, arrival, and departure time of each train at each station, and the train running direction. We extract the following information from ATS data (Table 3).

The CWS varies depending on individual differences. According to different kinds of people, walking speeds are usually considered for three categories: the ordinary (the medium), the elderly (the low), and the young (the high). The walking speed intervals of the three groups of people may have some overlaps. The average values are taken as the basis of the later calculation. In this study, a simplified example of walking speed value is shown in Table 4.

4.2. Results and Analysis. The proposed approach is applied to the Nanchang metro network. In particular, three OD pairs are used for demonstration. Their daily trips meet the criteria of small scale, and more importantly, their actual route choices can be accurately deduced on certain days using the TTR method. This enables high-confidence benchmarking. Difference and regularity analysis are given based on the deduction results of these three OD pairs.

4.2.1. Typical OD Pairs to Be Selected. The typical OD pairs are selected not for their extremity but because their route configurations allow us to confidently deduce actual passenger route choices. Our focus is on leveraging high-

Figure 7: The Nanchang metro network.

Table 2: AFC data used in this study.

Field	Example
Ticket number	00000111F774108B
Date	20,220,922
Exit time	074,203
Exit station number	0121
Entry time	072,702
Entry station number	0245

Table 3: ATS data used in this study.

Field	Example
Train number	01
Train run number	09
Station name	Qiushui square
Station number	0128
Train arrival time	113,308
Train departure time	113,338

Table 4: A simplified example of walking speed data.

Crowd category	Walking speed value (m/s)
Medium speed	1.35
Low speed	1.28
High speed	1.50

certainty cases to uncover limitations in the PRC model, and other OD pairs covering across the entire network can be included in future work, especially as more granular or sensor-based data become available to improve inference accuracy.

To make the cases more comprehensive and convincing, we divided the OD pairs into three categories based on the degree of TTR overlap. As the overlap increases, fewer dates can be fully presumed for each OD pair and the greater the difference between the actual and the estimated results.

Table 5 summarizes the information of one example in each category, namely, 0438-0425, 0437-0222, and 0244-0227. The locations of the OD pairs in the metro network are also shown in Figures 8(a), 8(b), and 8(c).

4.2.2. Deduction Results. For the OD① (0438-0425), there are 1950 trips during the studied five months. After excluding 23 abnormal records, the actual route choices of the passengers are deduced for each day. The corresponding proportions for the two routes are illustrated in Figure 9, where the red solid line is the prediction of the PRC model and the yellow solid line is the average of the actual proportions. It can be found that most passengers tend to choose the shorter route (Route I) on most days, and more specifically, 54 days or 35.2% of the 5-month data are focused entirely on Route I.

For the OD② (0437-0222), it has 1585 trips during the studied five months. After excluding 29 abnormal records and 19 trips in the overlapping part, 138 days remain to fully deduce the actual route choices of passengers. The corresponding proportions for the two routes are shown in Figure 10, where the red solid line is the prediction of the PRC model and the yellow solid line is the average of the actual proportions. In contrast to the model probability, there are 59 days that all passengers choose the shorter route (Route I), accounting for 42.7%. The longer route (Route II) also has more passenger choices on some dates, with more passengers choosing Route II on 3 days and the same number for both routes on 20 days.

For the OD③ (0244-0227), 909 trips are recorded during the studied five months. After excluding 41 abnormal records and 348 data in the overlapping zone, a total of 23 days is available to fully deduce the actual choice of passengers. The corresponding proportions for the two routes are shown in Figure 11, where the red solid line is the prediction of the PRC model and the yellow solid line is the average of the actual proportions. The actual proportions of passenger choices differ significantly from the model probability, with 15 days (65.2%) that are completely contrary to the trend of the model.

4.2.3. Single-Day Analysis. For the non-overlapping OD pair, we take the week from 07/24/2022 to 07/30/2022 as an example shown in Table 6. The convergence between the actual and the estimated is consistent, with the shorter route chosen more. Comparing the actual proportions with each other for each day, there are occasionally different trends in the proportions, and it is hard to summarize a clear regularity of changes.

For the minor overlapping OD pair, we take the week from 01/01/2022 to 01/07/2022 as an example shown in Table 7. The convergence between the actual and the estimated is gradually becoming different, which means that passengers did not overwhelmingly tend to the shorter route as the model indicates. The general trend is consistent when comparing the actual proportions within each other on most dates, there are still occasional disparities.

For the major overlapping OD pair, we take all deducted dates as an example shown in Table 8. The convergence between actual and estimated values varies significantly on most dates. The trend of actual proportions per day is not regular to each other, with almost no dates closer to obvious patterns.

In summary, at the single-day level, when the trips are below the small-scale threshold, the actual proportions of passenger route choices per day are distinctly different from the estimated by the model for all three types of OD pairs. The difference between the actual proportions and the estimated can be significant to a great extent even inverted as the TTRs overlap more. When the TTRs are completely overlapping, the uncertainty in passenger route choices is more pronounced. In other words, probabilistic models cannot describe passenger route choices between OD pairs when the trips are small scale, and the choices themselves are with little regularity.

4.2.4. Multiday Analysis. For the non-overlapping OD pair, we take the monthly data as demonstrated in Table 9. The comparison from the monthly dimension is conducted. The actual proportions after accumulating multiple days are again compared with the model probability, and it can be found that they are nearly similar. Meanwhile, the proportions are also close to each other among months. The change in the difference is relatively stable, with no large deviations.

For the minor overlapping OD pair, we take the monthly data as demonstrated in Table 10. The actual proportions after monthly accumulation remain predominantly similar to the model probability, and the actual proportions converge from month to month. The change of the difference is still relatively stable, especially in the comparison between the actual proportions.

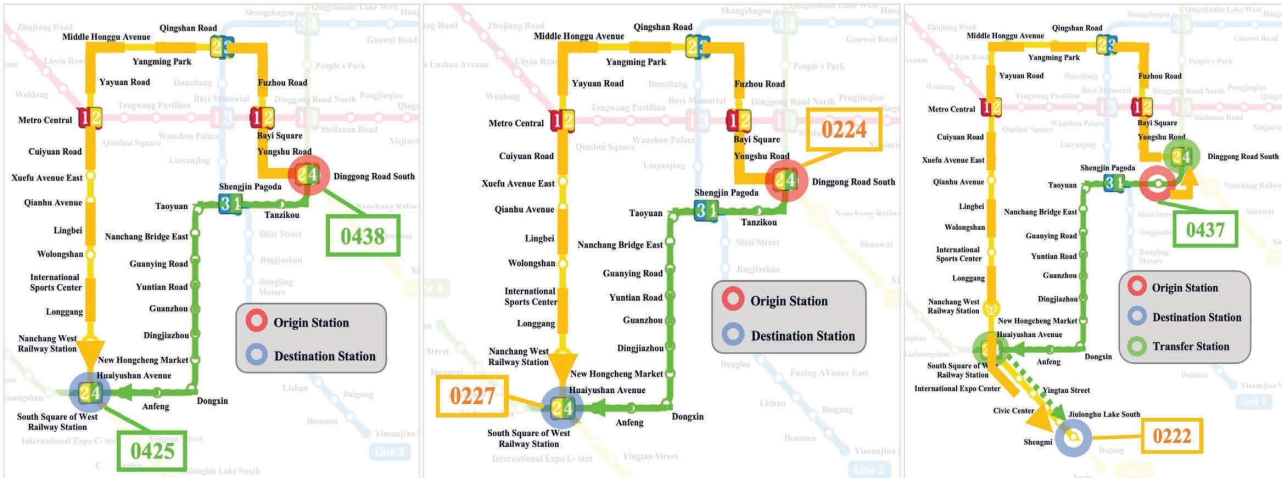
For the major overlapping OD pair, we take the monthly data as demonstrated in Table 11. The monthly actual proportions after accumulation are very different from the model probability, and they even all appear to be reversed. In contrast, the actual proportions of these 5 months after accumulating are very similar. The change of the difference with the model is greater than the change in own difference.

Building on the previous discussion, it is evident that at the multiday level, even when the trips surpass the small-scale threshold, passenger route choices may deviate from the PRC models in some cases. Specifically, when TTRs do not overlap or overlap minimally, passenger choices tend to align with model predictions. Conversely, when TTRs exhibit substantial or complete overlap, notable differences between actual proportions and model estimates become evident, sometimes even resulting in reversed trends. In this case, it is intriguing that passenger route choices seem to exhibit their own patterns, which sheds light on future studies concerning passenger choices for OD pairs with small-scale trips.

In summary, the variance of passengers' actual route choices on OD pairs with small-scale trips is more significant as the overlap of TTRs between routes increases. This may

Table 5: The OD pairs used in the case study.

Type of OD pairs	Non-overlapping				Minor overlapping				Major overlapping			
OD pairs	0438–0425				0437–0222				0244–0227			
Daily trips	13				10				6			
Small-scale threshold	57				53				57			
Routes	Line 4 nonstop		Line 2 nonstop		Transfer in 0425&0227		Transfer in 0438&0244		Line 4 nonstop		Line 2 nonstop	
Station count	13		17		18		24		13		17	
Model probability	82.03%		17.97%		83.40%		16.60%		82.03%		17.97%	
Walking-in time (s)	53	63	153	180	63	74	63	74	160	188	90	105
Waiting time I (s)	0	390	0	390	0	390	0	390	0	390	0	390
On-board time I (s)	1896	1896	1896	1896	1777	1777	115	115	1896	1896	2259	2259
Transfer time (s)	—	—	—	—	113	133	153	242	—	—	—	—
Waiting time II (s)	—	—	—	—	0	390	0	390	—	—	—	—
On-board time II (s)	—	—	—	—	656	656	3020	3020	—	—	—	—
Walking-out time (s)	80	94	87	102	100	117	100	117	153	180	93	109
Travel time range (s)	[2029, 2442]	[2499, 2930]	[2710, 3537]	[3452, 4349]	[2166, 2602]	[2426, 2844]						
Overlapping length (s)	0	85	177									



(a) (b) (c)

FIGURE 8: The specific locations of the case study OD pairs in the Nanchang metro network. (a) OD① (b) OD② (c) OD③.

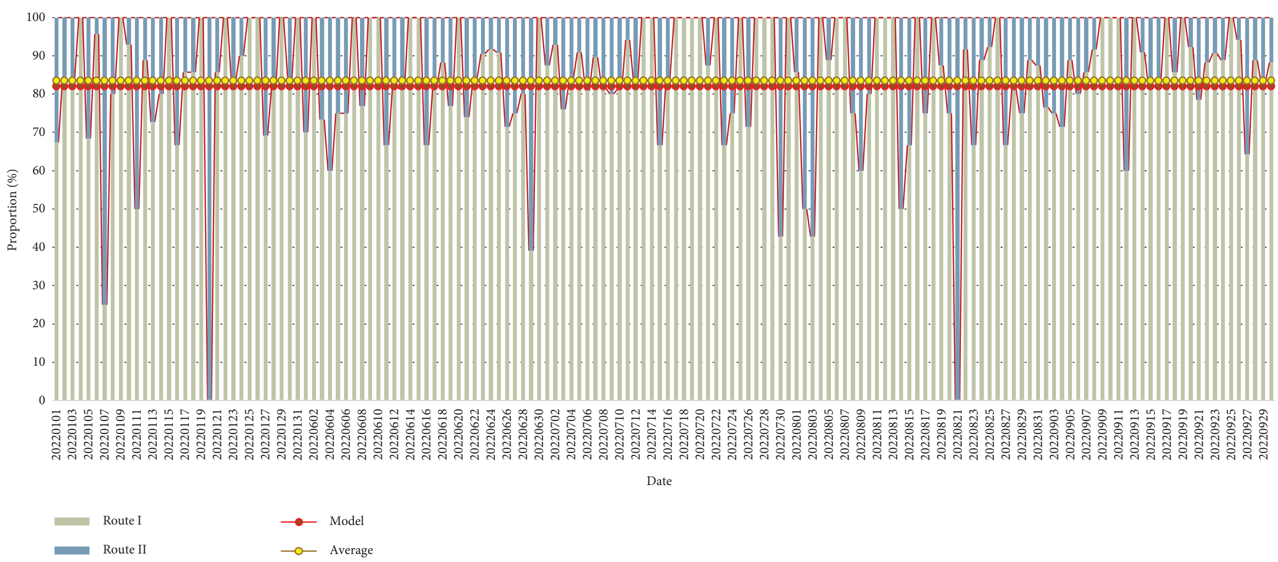


FIGURE 9: Choice proportions of the two routes between OD① (0438-0425).

have some degree of impact on the result accuracy and create analytical disturbances in the overall network. Pending further validation analysis is necessary and valuable.

4.3. Discussions. Several results are further discussed in the following subsections to inspire the application and improvement of the existing route choice models as well as passenger flow calculations.

i. *The variance in passengers' actual route choices among single days for OD pairs with small-scale trips*

At the single-day level, it can be found that passenger route choices lack stability when compared across different days. The actual *proportions* fluctuate a lot from date to date (as shown in record No. 1 to No. 7 of Table 12) and can even appear distinctly opposite on the days before and after (as shown in record No. 2 to No. 3 of Table 11). These findings are not surprising, given that passenger flow distribution in the URT network is a macroscopic emergence from individual route choices at the micro level. To discern distribution patterns clearly, a large-scale dataset is required. In situations with limited samples, passenger flow exhibits higher volatility compared to regularity, amplifying the variance in passenger choices.

ii. The variability in model applicability among multidays for OD pairs with small-scale trips

At the multiday level, the passenger route choices themselves present stable proportions to an extent when those single-day trips are accumulated and meet the criteria of large-scale (large population). Nevertheless, these actual proportions of passenger route choices may either conform to (as shown in

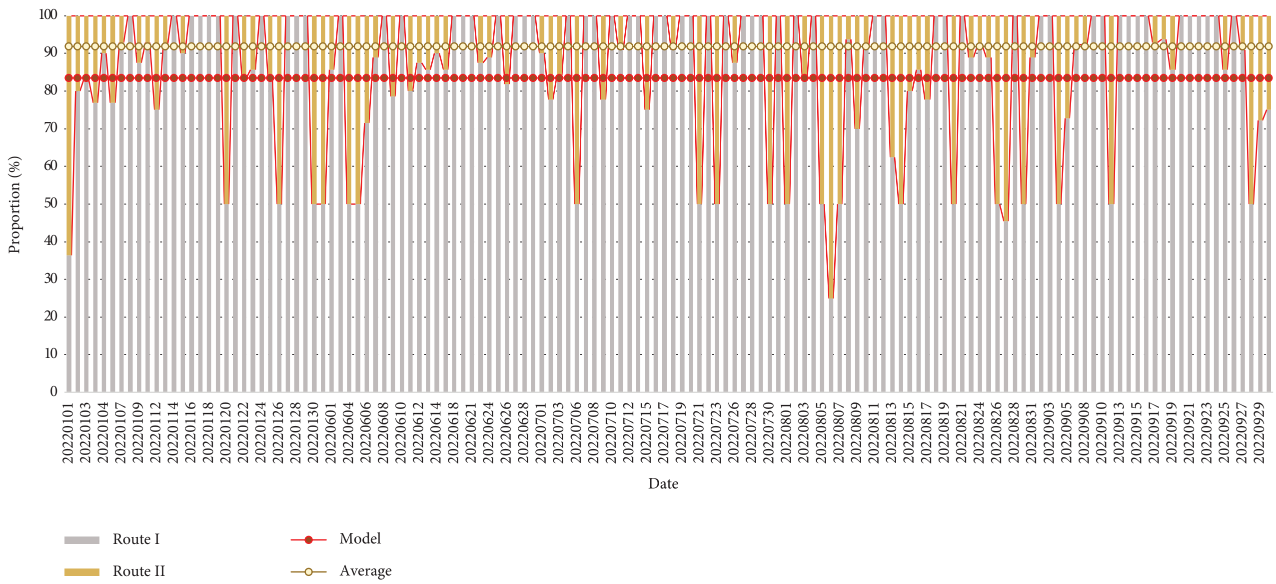


Figure 10: Choice proportions of the two routes between OD② (0437-0222).

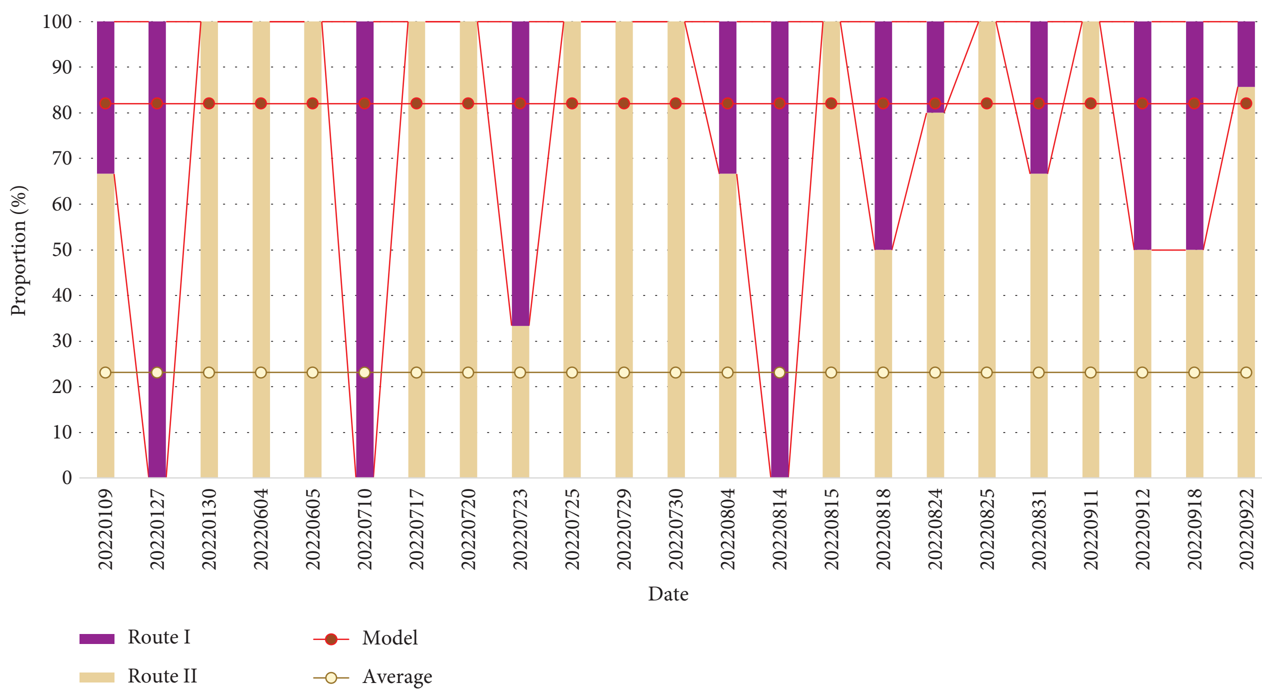


Figure 11: Choice proportions of the two routes between OD③ (0244-0227).

records No. 1 and No. 2 of Table 12) or deviate from (as shown in record No. 3 of Table 13) the probabilistic model. On the one hand, due to the expansion of sample size, it exceeds the threshold of large scale, and thus, the probabilistic model can be generally consistent with actual proportions in some cases. On the other hand, there are also some special cases where several same passengers travel every day. These passengers have solidified their travel habits; that is, they choose the same route every time. Therefore, even though the large sample is satisfied, it does not meet the premise assumption of independent identical distribution (IID) in the probabilistic model.

Table 6: Weekly results for OD① (0438-0425).

Date	Actual trips of route I	Actual trips of route II	Proportion of route I (%)	Proportion of route II (%)	RPD_{dif} (%)	RPD_{reg} (%)
20220724	3	1	75.00	25.00	−8.95	−11.54
20220725	8	0	100.00	0.00	19.74	17.17
20220726	5	2	71.43	28.57	−13.82	−16.39
20220727	2	0	100.00	0.00	19.74	17.17
20220728	3	0	100.00	0.00	19.74	17.17
20220729	5	0	100.00	0.00	19.74	17.17
20220730	3	4	42.86	57.14	−62.73	−65.06
Small-scale threshold	57	Model probability	82.03	17.97	—	—

Table 7: Weekly results for OD② (0437-0222).

Date	Actual trips of route I	Actual trips of route II	Proportion of route I (%)	Proportion of route II (%)	RPD_{dif} (%)	RPD_{reg} (%)
20220101	4	7	36.36	63.64	−78.55	−71.27
20220102	20	4	83.33	16.67	−4.16	4.30
20220103	5	1	83.33	16.67	−0.08	8.38
20220104	9	1	90.00	10.00	7.61	16.05
20220105	10	3	76.92	23.08	−8.08	0.38
20220106	10	3	76.92	23.08	−8.08	0.38
20220107	13	1	92.86	7.14	10.73	19.15
Small-scale threshold	53	Model probability	83.40	16.60	—	—

Table 8: Weekly results OD③ (0244-0227).

Date	Actual trips of route I	Actual trips of route II	Proportion of route I (%)	Proportion of route II (%)	RPD_{dif} (%)	RPD_{reg} (%)
20220109	1	2	33.33	66.67	−84.42	16.33
20220127	1	0	100.00	0.00	19.74	111.76
20220130	0	4	0.00	100.00	−200.00	−200.00
20220604	0	2	0.00	100.00	−200.00	−200.00
20220605	0	7	0.00	100.00	−200.00	−200.00
20220710	3	0	100.00	0.00	19.74	111.76
20220717	0	1	0.00	100.00	−200.00	−200.00
20220720	0	1	0.00	100.00	−200.00	−200.00
20220723	2	1	66.67	33.33	−20.66	80.79
20220725	0	3	0.00	100.00	−200.00	−200.00
20220729	0	4	0.00	100.00	−200.00	−200.00
20220730	0	2	0.00	100.00	−200.00	−200.00
20220804	1	2	33.33	66.67	−84.42	16.33
20220814	1	0	100.00	0.00	19.74	111.76
20220815	0	4	0.00	100.00	−200.00	−200.00
20220818	1	1	50.00	50.00	−48.52	55.42
20220824	1	4	20.00	80.00	−121.59	−34.38
20220825	0	1	0.00	100.00	−200.00	−200.00
20220831	1	2	33.33	66.67	−84.42	16.33
20220911	0	1	0.00	100.00	−200.00	−200.00
20220912	1	1	50.00	50.00	−48.52	55.42
20220918	1	1	50.00	50.00	−48.52	55.42
20220922	1	6	14.29	85.71	−140.67	−65.82
Small-scale threshold	57	Model probability	82.03	17.97	—	—

Table 9: Monthly results for OD① (0438-0425).

Month	Actual trips of route I	Actual trips of route II	Proportion of route I (%)	Proportion of route II (%)	RPD_{dif} (%)	RPD_{reg} (%)
202201	301	69	81.35	18.65	−0.83	−2.71
202206	384	86	81.70	18.30	−0.40	−2.28
202207	266	45	85.53	14.47	4.18	2.29
202208	194	41	82.55	17.45	0.64	−1.25
202209	316	48	86.81	13.19	5.67	3.78
Total	1461	289	83.49	16.51	1.76	—
Small-scale threshold	57	Model probability	82.03	17.97	$RMSE_{dif}$ 0.1761	$RMSE_{reg}$ 0.1754

Table 10: Monthly results for OD② (0437-0222).

Month	Actual trips of route I	Actual trips of route II	Proportion of route I (%)	Proportion of route II (%)	RPD_{dif} (%)	RPD_{reg} (%)
202201	240	31	88.56	11.44	5.63	−3.45
202206	198	19	91.24	8.76	8.98	−0.10
202207	262	19	93.24	6.76	11.14	2.07
202208	252	26	90.65	9.35	8.33	−0.75
202209	334	24	93.30	6.70	11.20	2.13
Total	1243	111	91.80	8.20	9.08	—
Small-scale threshold	53	Model probability	83.40	16.60	$RMSE_{dif}$ 0.1451	$RMSE_{reg}$ 0.1118

Table 11: Monthly results for OD③ (0244-0227).

Month	Actual trips of route I	Actual trips of route II	Proportion of route I (%)	Proportion of route II (%)	RPD_{dif} (%)	RPD_{reg} (%)
202201	2	6	25.00	75.00	−106.57	16.71
202206	0	9	0.00	100.00	−200.00	−200.00
202207	5	12	29.41	70.59	−94.43	32.70
202208	5	14	26.32	73.68	−102.85	21.79
202209	3	9	25.00	75.00	−106.57	16.71
Total	15	50	23.08	76.92	−112.17	—
Small-scale threshold	57	Model probability	82.03	17.97	$RMSE_{dif}$ 0.6388	$RMSE_{reg}$ 0.3455

Table 12: Comparison of the actual proportions of passengers' route choices among multiple days.

No.	OD	Date	Actual trip		Actual proportion		Model probability	
			Route I	Route II	Route I (%)	Route II (%)	Route I (%)	Route II (%)
1	0244-0227	20220804	1	2	33.33	66.67	82.03	17.97
2		20220814	1	0	100.00	0.00		
3		20220815	0	4	0.00	100.00		
4		20220818	1	1	50.00	50.00		
5		20220824	1	4	20.00	80.00		
6		20220825	0	1	0.00	100.00		
7		20220831	1	2	33.33	66.67		

Table 13: Comparison of the actual proportion and the estimated by model for large-scale trips of multiple days.

No.	OD	Month	Actual trip		Actual proportion		Model probability	
			Route I	Route II	Route I (%)	Route II (%)	Route I (%)	Route II (%)
1	0438-0425	5 months in 2022	1461	289	83.49	16.51	82.03	17.97
2	0437-0222	5 months in 2022	1243	111	91.80	8.20	83.40	16.60
3	0244-0227	5 months in 2022	15	50	23.08	76.92	82.03	17.97

iii. Application of PRC models for short-, medium- and long-term prediction

Performed analysis shows that caution is needed when applying PRC models on a daily or weekly basis. Before *application*, the scale of the passenger trip data should be evaluated, and modification is needed for those small-scale OD pairs. One potential approach is to combine the data-driven deduction method with PRC models. Routine surveys are also suggested for the small-scale OD pairs. While applying PRC models in short-term predictions may encounter a considerable amount of small-scale OD pairs, which may cause notable errors, the medium- and long-term applications with time horizons of months or years would likely address the small-scale issue. Such predictions serve as invaluable tools for facilitating strategic planning tasks, including resource investment and network designs. In summary, when it comes to passenger route choices for OD pairs with small-scale trips, the probabilistic model proves inadequate in providing accurate descriptions. Additionally, it is worth noting that passenger route choices exhibit varying behavior at different scale levels. There is a lack of consistency in route choices when comparing every single day. When aggregated over multiple days, resulting in trips that meet the large-scale threshold, these choices can align with the probabilistic model in some cases. However, in some other cases, this alignment is absent, and the behavior does not conform to the model. While the PRC model exhibits the aforementioned errors in single-day scenarios, it still maintains partial applicability in large-scale contexts, making it suitable for medium and long-term predictions. This complex interplay underscores the need for a more nuanced understanding of passenger route choices and their relationship with trip scale and temporal factors.

Overall, the results presented in this section offer practical value for both transit planners and model developers. By distinguishing where PRC models succeed and where they fail based on trip volume, temporal scale, and user behavior consistency, this study supports more context-aware applications of modeling tools. These findings also point to the need for adaptive strategies, such as integrating supplementary data sources or modifying model assumptions, to improve accuracy in small-scale OD scenarios. In doing so, it helps bridge the gap between theoretical model design and operational decision-making in real-world URT systems.

5. Conclusion and Practical Implications

This study sets out to address a fundamental modeling challenge in URT system: evaluating the reliability of PRC models when applied to OD pairs with small-scale trip data. While PRC models are widely used in transit demand modeling, their limitations under sparse data conditions remain insufficiently understood. This research fills that gap by proposing and testing a validation framework tailored for such contexts, aiming to clarify when and how these models should be applied in practice. First, the concept of "small scale" is defined, enabling the identification of OD pairs with small-scale trips in the network. Second, a TTR-based method is proposed to infer passengers' actual route choices. Third, a twofold comparison, at single-day and multiday levels, is conducted to analyze the corresponding difference and regularity between the estimations and actual results. In the case of the Nanchang metro in China, we found that OD pairs with small-scale trips exhibit significant variations in the daily passenger route choices, leading to notable errors. While the model becomes applicable again in some instances when the trips of OD pairs accumulate and reach the large-scale threshold over a monthly period, limitations still persist in certain cases, revealing complex dynamics that challenge traditional probabilistic assumptions.

The results of this study also have several practical implications for URT operation agencies regarding route choice modeling to improve passenger flow analysis.

1. There are OD pairs on the URT network where passengers' route choices cannot be appropriately estimated by existing PRC models. URT operation agencies need to recognize that PRC models may not be suitable for certain OD pairs, even if their trip data accumulates to a large-scale population. Therefore, it is important for URT operation agencies to exercise caution when estimating route choices using PRC models.
2. The operation of URT should be able to withstand a certain degree of inaccuracies in passenger flow predictions. It is not economically viable to accurately detect and record the actual behaviors of URT passengers in practice. Therefore, further research is necessary to investigate the impact of small-scale data issues on the entire network and incorporate this information into robust modeling.
3. New approaches to estimating URT passengers' route choices are necessary for operation agencies seeking more precise passenger flow analysis. There may be situations where the impact of PRC models'

inapplicability becomes larger due to different URT network structures or different stages of development. When it becomes too large to harm the whole network operation, new approaches or even paradigms need to be considered to replace the existing PRC models, such as retrospective route choice models, and multisource data fusion (cell phone signaling data, Wi-Fi data, CCTV data, etc.).

In light of the aforementioned, it is imperative that more URT operation agencies take note of the inapplicability of PRC models in practice. We contend that our research focus remains relevant, and our analytical framework offers valuable insights, particularly for cities with more extensive and intricate URT networks. By grouping less-used alternatives into an aggregated category, multiroute OD pairs can be approximated within a binary framework, retaining methodological simplicity while enabling broader applicability. Building on this, future research should delve deeper into understanding how OD pairs with small-scale trips may lead to adverse consequences in diverse network configurations. Investigating how network structure and development scale influence the generalizability of our conclusions holds great interest. Ultimately, developing new paradigms tailored to refined URT operations is also essential for exploring and evaluating the performance in comparison to PRC models.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

Author Contributions

Wei Zhu and Changyue Xu contributed equally.

Funding

This study was supported by the National Natural Science Foundation of China (NSFC, Grant No. 72071147); the Fundamental Research Funds for the Central Universities of China (Grant No. 22120220628); and the Research Program of Nanchang Metro Co., Ltd. (Grant No. 2021HGKYC005).

Endnotes

[1]A more rigorous definition of small scale will be given in Section 3.

[2]This structure forms a practical basis for future extension to multiroute scenarios, which are not discussed here.

References

[1] H. Spiess and M. Florian, "Optimal Strategies: A New Assignment Model for Transit Networks," *Transportation Research Part B: Methodological* 23, no. 2 (1989): 83–102, https://doi.org/10.1016/0191-2615(89)90034-9.

[2] S. H. Lam and F. Xie, "Transit Path-Choice Models That Use Revealed Preference and Stated Preference Data," *Transportation Research Record: Journal of the Transportation Research Board* 1799, no. 1 (2002): 58–65, https://doi.org/10.3141/1799-08.

[3] Y. Sun and R. Xu, "Rail Transit Travel Time Reliability and Estimation of Passenger Route Choice Behavior: Analysis Using Automatic Fare Collection Data," *Transportation Research Record: Journal of the Transportation Research Board* 2275, no. 1 (2012): 58–67, https://doi.org/10.3141/2275-07.

[4] P. Kumar, A. Khani, and Q. He, "A Robust Method for Estimating Transit Passenger Trajectories Using Automated Data," *Transportation Research Part C: Emerging Technologies* 95 (2018): 731–747, https://doi.org/10.1016/j.trc.2018.08.006.

[5] Y. Zhu, H. N. Koutsopoulos, and N. H. Wilson, "Passenger Itinerary Inference Model for Congested Urban Rail Networks," *Transportation Research Part C: Emerging Technologies* 123 (2021): 102896, https://doi.org/10.1016/j.trc.2020.102896.

[6] N. Eluru, V. Chakour, and A. M. El-Geneidy, "Travel Mode Choice and Transit Route Choice Behavior in Montreal: Insights From McGill University Members Commute Patterns," *Public Transport* 4, no. 2 (2012): 129–149, https://doi.org/10.1007/s12469-012-0056-2.

[7] F. Zhou, J. Shi, and R. Xu, "Estimation Method of Path-Selecting Proportion for Urban Rail Transit Based on AFC Data," *Mathematical Problems in Engineering* 2015 (2015): 1–9, https://doi.org/10.1155/2015/350397.

[8] W. Zhu, W. Wang, and Z. Huang, "Estimating Train Choices of Rail Transit Passengers With Real Timetable and Automatic Fare Collection Data," *Journal of Advanced Transportation* 2017 (2017): 1–12, https://doi.org/10.1155/2017/5824051.

[9] C. Li, X. Liu, Y. Bai, B. Wang, J. Huang, and Y. Chen, "Route Choice Model of the Major Passenger Group in Urban Rail Transit: A Case Study of Beijing, China," *2020 IEEE 5th International Conference on Intelligent Transportation Engineering (ICITE)* (2020): 8–13, https://doi.org/10.1109/icite50838.2020.9231366.

[10] B. Mo, Z. Ma, H. N. Koutsopoulos, and J. Zhao, "Ex Post Path Choice Estimation for Urban Rail Systems Using Smart Card Data: An Aggregated Time-Space Hypernetwork Approach," *Transportation Science* 57, no. 2 (2023): 313–335, https://doi.org/10.1287/trsc.2022.1177.

[11] J. N. Prashker and B. Shlomo, "Route Choice Models Used in the Stochastic User Equilibrium Problem: A Review," *Transport Reviews* 24, no. 4 (2004): 437–463, https://doi.org/10.1080/0144164042000181707.

[12] C. G. Prato, "Route Choice Modeling: Past, Present and Future Research Directions," *Journal of Choice Modelling* 2, no. 1 (2009): 65–100, https://doi.org/10.1016/S1755-5345(13)70005-8.

[13] M. Pelletier, T. Martin, and M. Catherine, "Smart Card Data Use in Public Transit: A Literature Review," *Transportation Research C* 19, no. 4 (2011): 557–568, https://doi.org/10.1016/j.trc.2010.12.003.

[14] J. Zhang, "A Review on Route Choice Behavior and Volume Control of Passengers in Urban Rail Transit Network," *IOP Conference Series: Materials Science and Engineering*, 677, no. 4 (IOP Publishing, 2019), 042047, https://doi.org/10.1088/1757-899x/677/4/042047.

[15] T. J. Tiam-Lee and R. Henriques, "Route Choice Estimation in Rail Transit Systems Using Smart Card Data: Handling Vehicle Schedule and Walking Time Uncertainties," *European*

Transport Research Review 14, no. 1 (2022): 31–16, https://doi.org/10.1186/s12544-022-00558-x.

[16] C. F. Manski, "The Structure of Random Utility Models," *Theory and Decision* 8, no. 3 (1977): 229–254, https://doi.org/10.1007/BF00133443.

[17] E. L. Lehmann, *Introduction to Large-Sample Theory* (Springer, 1999).

[18] R. O. Kuehl, *Design of Experiments: Statistical Principles of Research Design and Analysis*, 2nd ed. (Duxbury Press California, 2000).

[19] R. Xu, W. Zhu, and F. Song, *Research on Validation and Optimization of Clearing Model of Shanghai metro Network* (Tongji University, 2014).

[20] B. Si, M. Zhong, J. Liu, Z. Gao, and J. Wu, "Development of a Transfer-Cost-Based Logit Assignment Model for the Beijing Rail Transit Network Using Automated Fare Collection Data," *Journal of Advanced Transportation* 47, no. 3 (2013): 297–318, https://doi.org/10.1002/atr.1203.

[21] B. Si, L. Fu, J. Liu, S. Shiravi, and Z. Gao, "A Multi-Class Transit Assignment Model for Estimating Transit Passenger Flows—A Case Study of Beijing Subway Network," *Journal of Advanced Transportation* 50, no. 1 (2016): 50–68, https://doi.org/10.1002/atr.1309.

[22] S. Bekhor, T. Toledo, and J. N. Prashker, "Effects of Choice Set Size and Route Choice Models on Path-Based Traffic Assignment," *Transportmetrica* 4, no. 2 (2008): 117–133, https://doi.org/10.1080/18128600808685682.

[23] B. Mao, Z. Zhang, and Z. Chen, "A Review on Operational Technologies of Urban Rail Transit Networks," *Journal of Transportation Systems Engineering and Information Technology* 17, no. 6 (2017): 1–9.

[24] X. Wu and C. Liu, "Traffic Equilibrium Assignment Model Specially for Urban Railway Network," *Journal of Tongji University* 32, no. 9 (2004): 1158–1162.

[25] B. Si, B. Mao, and Z. Liu, "Passenger Flow Assignment Model and Algorithm for Urban Railway Traffic Network Under the Condition of Seamless Transfer," *Journal of the China Railway Society* 29, no. 6 (2007): 12–18.

[26] J. Liu, "Passenger Flow Distribution Model of Urban Rail Transit Network Based on Data Obtained IC card Usage," *Logistics Technology* 8 (2010): 64–67.

[27] R. Xu, Q. Luo, and P. Gao, "Passenger Flow Distribution Model and Algorithm for Urban Rail Transit Network Based on Multi-Route Choice," *Journal of the China Railway Society* 31, no. 2 (2009): 110–114.

[28] K. Qiao, P. Zhao, and Z. Qin, "Passenger Route Choice Model and Algorithm in the Urban Rail Transit Network," *Journal of Industrial Engineering and Management* 6, no. 1 (2013): 113–123, https://doi.org/10.3926/jiem.595.

[29] M. Ben-Akiva and M. Bierlaire, "Discrete Choice Methods and Their Applications to Short Term Travel Decisions," *Handbook of Transportation Science* 1 (1999): 1–29.

[30] J. Gleason, S. Richter, and C. Sundberg, "A Behavioral Comparison of Route Choice on Metro Networks: TIME, Transfer, Crowding, Topology and Socio-Demographics," *Transportation Research A* 66, no. 1 (2014): 185–195.

[31] H. Xu, J. Zhou, and W. Xu, "A Decision-Making Rule for Modeling Travelers' Route Choice Behavior Based on Cumulative Prospect Theory," *Transportation Research Part C: Emerging Technologies* 19, no. 2 (2011): 218–228, https://doi.org/10.1016/j.trc.2010.05.009.

[32] J. Wu, Y. Qu, H. Sun, H. Yin, X. Yan, and J. Zhao, "Data-Driven Model for Passenger Route Choice in Urban Metro Network," *Physica A: Statistical Mechanics and Its Applications* 524 (2019): 787–798, https://doi.org/10.1016/j.physa.2019.04.231.

[33] H. Xue, P. Yang, H. Zhang, and E. Jing, "Study on the Control Strategy of Urban Rail Transit Passenger Flow Under the Condition of Large Passenger Flow," in *IOP Conference Series: Earth and Environmental Science*, 234, no. 1 (IOP Publishing, 2019), 012001, https://doi.org/10.1088/1755-1315/234/1/012001.

[34] Z. Guo, "Mind the Map! The Impact of Transit Maps on Path Choice in Public Transit," *Transportation Research Part A: Policy and Practice* 45, no. 7 (2011): 625–639, https://doi.org/10.1016/j.tra.2011.04.001.

[35] S. Raveau, J. C. Muñoz, and L. Grange, "A Topological Route Choice Model for Metro," *Transportation Research A* 45, no. 2 (2011): 138–147, https://doi.org/10.1016/j.tra.2010.12.004.

[36] S. Raveau, Z. Guo, J. C. Muñoz, and N. H. Wilson, "A Behavioral Comparison of Route Choice on Metro Networks: Time, Transfers, Crowding, Topology and Socio-Demographics," *Transportation Research A* 66 (2014): 185–195, https://doi.org/10.1016/j.tra.2014.05.010.

[37] D. V. Lierop, G. B. Madhav, and M. E. Ahmed, "What Influences Satisfaction and Loyalty in Public Transport? A Review of the Literature," *Transport Reviews* 38, no. 1 (2018): 52–72, https://doi.org/10.1080/01441647.2017.1298683.

[38] A. Tirachini, H. Ricardo, D. Thijs, and A. D. Ricardo, "Estimation of Crowding Discomfort in Public Transport: Results From Santiago de Chile," *Transportation Research A* 103, no. 9 (2017): 311–326, https://doi.org/10.1016/j.tra.2017.06.008.

[39] X. Xu, L. Xie, H. Li, and L. Qin, "Learning the Route Choice Behavior of Subway Passengers From AFC Data," *Expert Systems With Applications* 95, no. 4 (2018): 324–332, https://doi.org/10.1016/j.eswa.2017.11.043.

[40] Y. Zhang, E. Yao, J. Zhang, and K. Zheng, "Estimating Metro Passengers' Path Choices by Combining Self-Reported Revealed Preference and Smart Card Data," *Transportation Research Part C: Emerging Technologies* 92, no. 7 (2018): 76–89, https://doi.org/10.1016/j.trc.2018.04.019.

[41] Y. Asakura, I. Takamasa, N. Yoshiki, and K. Takahiko, "Estimation of Behavioral Change of Railway Passengers Using Smart Card Data," *Public Transport* 4, no. 1 (2012): 1–16, https://doi.org/10.1007/s12469-011-0050-0.

[42] T. Kusakabe, T. Iryo, and Y. Asakura, "Estimation Method for Railway Passengers' Train Choice Behavior With Smart Card Transaction Data," *Transportation* 37, no. 5 (2010): 731–749, https://doi.org/10.1007/s11116-010-9290-0.

[43] E. Miller, E. S. Gabriel, and N. Neema, "Estimation of Passengers Left Behind by Trains in High-Frequency Transit Service Operating Near Capacity," *Transportation Research Record: Journal of the Transportation Research Board* 2672, no. 8 (2018): 497–504, https://doi.org/10.1177/0361198118794291.

[44] C. Sipetas, A. Keklikoglou, and E. J. Gonzales, "Estimation of Left Behind Subway Passengers Through Archived Data and Video Image Processing," *Transportation Research Part C: Emerging Technologies* 118, no. 9 (2020): 102727, https://doi.org/10.1016/j.trc.2020.102727.

[45] Y. Zhu, H. N. Koutsopoulos, and N. H. Wilson, "Inferring Left Behind Passengers in Congested Metro Systems From Automated Data," *Transportation Research Procedia* 23 (2017): 362–379, https://doi.org/10.1016/j.trpro.2017.05.021.

[46] Z. Ma, H. N. Koutsopoulos, Y. Chen, and N. H. Wilson, "Estimation of Denied Boarding in Urban Rail Systems: Alternative Formulations and Comparative Analysis," *Transportation Research Record: Journal of the Transportation Research Board* 2673, no. 11 (2019): 771–778, https://doi.org/10.1177/0361198119857034.

[47] G. Xue, S. Liu, and D. Gong, "Identifying Abnormal Riding Behavior in Urban Rail Transit: A Survey on "In-Out" in the Same Subway Station," *IEEE Transactions on Intelligent Transportation Systems* 23, no. 4 (April 2022): 3201–3213, https://doi.org/10.1109/TITS.2020.3032843.

[48] Y. Li, F. Zhou, L. Hong, and W. Zhu, in *Empirical Analysis of Failing to Board and Traveling Backward in an Overcrowded Urban Rail Transit System* (American Society of Civil Engineers, 2018).

[49] C. Yu, H. Li, X. Xu, and J. Liu, "Data-Driven Approach for Solving the Route Choice Problem With Traveling Backward Behavior in Congested Metro Systems," *Transportation Research Part E: Logistics and Transportation Review* 142, no. 10 (2020): 102037, https://doi.org/10.1016/j.tre.2020.102037.

[50] R. Xu, Y. Li, W. Zhu, and S. Li, "Empirical Analysis of Traveling Backwards and Passenger Flows Reassignment on a Metro Network With Automatic Fare Collection (AFC) Data and Train Diagram," *Transportation Research Record: Journal of the Transportation Research Board* 2672, no. 8 (2018): 230–242, https://doi.org/10.1177/0361198118781395.

[51] Y. Liu, Y. Zhao, and W. Zhu, "Abnormal Travel Behaviors and Their Impacts on Route Choice Modeling for Metro Passengers," *Traffic & Transportation* no. 01 (2023): 51–55.

[52] W. Zhu, F. Zhou, J. Huang, and R. Xu, "Validating Rail Transit Assignment Models With Cluster Analysis and Automatic Fare Collection Data," *Transportation Research Record: Journal of the Transportation Research Board* 2526, no. 1 (2015): 10–18, https://doi.org/10.3141/2526-02.

[53] C. Monterola, F. L. Erika, P. Di, K. L. Kee, and G. H. Gih, "Non-Invasive Procedure to Probe the Route Choices of Commuters in Rail Transit Systems," *Procedia Computer Science* 80 (2016): 2387–2391, https://doi.org/10.1016/j.procs.2016.05.459.

[54] Y. Zhang, E. Yao, K. Zheng, and H. Xu, "Metro Passenger's Path Choice Model Estimation With Travel Time Correlations Derived From Smart Card Data," *Transportation Planning and Technology* 43, no. 2 (2020): 141–157, https://doi.org/10.1080/03081060.2020.1717135.

[55] W. Zhu, J. Wei, and C. Xu, "Evaluating Rail Transit Assignment Models in the Temporal Dimension: The Problem and Its Solution," *International Journal of Transportation Science and Technology* 18 (2025): 96–114, https://doi.org/10.1016/j.ijtst.2024.05.008.

[56] W. Zhu, H. Hu, and Z. Huang, "Calibrating Rail Transit Assignment Models With Genetic Algorithm and Automated Fare Collection Data," *Computer-Aided Civil and Infrastructure Engineering* 29, no. 7 (2014): 518–530, https://doi.org/10.1111/mice.12075.

[57] B. Mo, Z. Ma, H. N. Koutsopoulos, and J. Zhao, "Calibrating Path Choices and Train Capacities for Urban Rail Transit Simulation Models Using Smart Card and Train Movement Data," *Journal of Advanced Transportation* 2021 (2021): 1–15, https://doi.org/10.1155/2021/5597130.

[58] S. Y. Assele, M. Meulders, and M. Vandebroek, "Sample Size Selection for Discrete Choice Experiments Using Design Features," *Journal of Choice Modelling* 49 (2023): 100436, https://doi.org/10.1016/j.jocm.2023.100436.

[59] W. Wang, H. Xiang, W. Gong, and Z. Shi, "Research of the Applicable Sample Size of Common Distribution Central Limit Theorem," *Journal of Science of Teachers' College and University* 41, no. 07 (2021): 20–25.

[60] J. Li and J. Fine, "On Sample Size for Sensitivity and Specificity in Prospective Diagnostic Accuracy Studies," *Statistics in Medicine* 23, no. 16 (2004): 2537–2550, https://doi.org/10.1002/sim.1836.

[61] K. Hajian-Tilaki and Karimollah, "Sample Size Estimation in Diagnostic Test Studies of Biomedical Informatics," *Journal of Biomedical Informatics* 48 (2014): 193–204, https://doi.org/10.1016/j.jbi.2014.02.013.

[62] N. A. Obuchowski, "Computing Sample Size for Receiver Operating Characteristic Studies," *Investigative Radiology* 29, no. 2 (1994): 238–243, https://doi.org/10.1097/00004424-199402000-00020.

[63] Z. Zhang, "On Wireless Location Equipped Probe Vehicle Sample Sizes," *Control Engineering China* 17, no. S2 (2010): 171–172, https://doi.org/10.14107/j.cnki.kzgc.2010.s2.002.

[64] G. Feng, "Sample Size Estimation for Diagnostic Test Evaluation," *Chronic Pathematology Journal* 23, no. 11 (2022): 1657–1660, https://doi.org/10.16440/J.CNKI.1674-8166.2022.11.15.

[65] G. Casella and R. L. Berger, *Statistical Inference* (Duxbury Press California, 2002).

[66] H. Blaker, "Confidence Curves and Improved Exact Confidence Intervals for Discrete Distributions," *Canadian Journal of Statistics* 28, no. 4 (2000): 783–798, https://doi.org/10.2307/3315916.

[67] D. C. Montgomery and G. C. Runger, *Applied Statistics and Probability for Engineers* (Wiley, 2018).

[68] W. H. K. Lam and C. Cheung, "Pedestrian Speed/Flow Relationships for Walking Facilities in Hong Kong," *Journal of Transportation Engineering* 126, no. 4 (2000): 343–349, https://doi.org/10.1061/(asce)0733-947x(2000)126:4(343).

[69] H. Yang, M. Wu, and H. Zhang, "A Modeling Study of the Walking Speed of the Passengers in Different Areas of a Subway Station for Transfer," *Journal of Transportation Systems Engineering and Information Technology* 11, no. S1 (2011): 140–145, https://doi.org/10.16097/j.cnki.1009-6744.2011.s1.001.