Inclusive Public Transit Design: Differentiated Crowding Perception Optimization and Social Equity Enhancement

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***Abstract*—Urban public transport systems are facing growing challenges related to crowding. Despite extensive research on this issue, most studies fail to consider how different social groups experience crowding in distinct ways. In particular, the subjective perceptions of vulnerable populations are often overlooked, resulting in service designs that fall short of social equity goals. To address this gap, this paper proposes a multi-objective dynamic traffic assignment model that extends classical dynamic equilibrium assignment theory by incorporating a crowding perception function reflecting passenger heterogeneity, alongside a social equity evaluation metric.**

Using a public transport corridor as a reproducible case study, the model integrates publicly available timetable and capacity data with a low-cost online passenger survey and a transparent synthetic demand generation process. This framework enables the simulation of travel behavior and crowding perceptions across different passenger groups, including commuters, older adults, and people with disabilities. The results show that vulnerable groups are considerably more sensitive to crowding and experience a disproportionately high level of crowding-related disutility under current operational conditions.

The findings further demonstrate that targeted interventions, such as differential pricing schemes and service frequency optimization, can substantially improve equity in crowding exposure while simultaneously enhancing overall system performance. This study introduces a novel optimization framework and decision-support tool for public transport planning and operations, offering valuable insights for developing more inclusive and equitable urban mobility systems and improving travel well-being for all users.

Keywords—Inclusive Design; Public Transport; Crowding Perception; Social Equity; Dynamic Traffic Assignment

I. INTRODUCTION

As global urbanization continues to accelerate, cities are increasingly confronted with serious challenges such as traffic congestion, environmental pollution, and rising energy consumption. In this context, the development of high-capacity and high-efficiency public transport systems has become a fundamental strategy for achieving sustainable urban development. However, despite the continuous expansion of public transport supply, service quality — particularly in-vehicle crowding during peak periods — has emerged as a critical bottleneck limiting system attractiveness and passenger satisfaction [1]. Crowding not only leads to physical discomfort and psychological stress but also significantly alters passengers' perception of travel time. In extreme cases, it can even drive travelers to abandon public transport in favor of more expensive private car use, thereby undermining the broader socioeconomic benefits of public transit systems [2]. As a result, mitigating public transport crowding and improving passenger experience have become pressing concerns for both urban transport managers and researchers.

Against this background, a fundamental scientific question arises: how can public transport planning, design, and operation adequately account for differences in subjective crowding perception among diverse passenger groups — particularly vulnerable populations such as older adults, persons with disabilities, and pregnant women—so as to promote social equity while simultaneously improving overall system efficiency? Traditional transport planning and management frameworks typically treat passengers as a homogeneous group, applying uniform service standards and optimization objectives. This one-size-fits-all approach overlooks the heterogeneity of passenger needs. For a highly subjective experience like crowding, individuals with different physiological, psychological, and socioeconomic characteristics exhibit markedly different levels of sensitivity and tolerance. For example, a brief period of high-density crowding may be acceptable for a young, able-bodied commuter, yet pose serious safety risks and accessibility barriers for an elderly passenger with limited mobility or a person with a disability requiring additional space. Service designs that disregard such perceptual differences effectively result in an inequitable distribution of service quality across social groups, contradicting the core principle of public transport as an inclusive public welfare service.

Existing studies have examined public transport systems from multiple perspectives. In crowding-related research, various modeling approaches have been proposed to quantify the negative externalities of crowding, including the introduction of concepts such as the "crowding multiplier" to capture the additional time cost induced by crowding conditions [3]. In the field of passenger behavior analysis, a wide range of models has been applied to investigate how

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factors such as fares, travel time, and convenience influence travelers' choices of mode, route, and departure time [4]. Meanwhile, research on transport equity has predominantly focused on spatial accessibility, assessing whether public transport resources are equitably distributed across different locations and income groups [5].

However, a cross-cutting examination of these research streams reveals several notable gaps. First, most crowding studies conceptualize crowding primarily as an objective physical measure (e.g., passengers per square meter), with limited attention to heterogeneity in subjective perception and its differentiated influence on travel behavior. Second, although transport equity has been widely studied, existing work largely emphasizes equity in access rather than equity in service quality experienced during actual use, such as comfort and crowding. Third, many public transport optimization models adopt single-objective formulations — such as minimizing total travel time or maximizing operator revenue — while few explicitly incorporate social equity, particularly perception-based process equity, as a central optimization objective.

To bridge these gaps, this study proposes a multi-objective dynamic traffic assignment model that explicitly integrates crowding perception heterogeneity with social equity considerations. The research first classifies passengers and quantifies inter-group differences in crowding sensitivity, value of time, and related behavioral parameters, with particular attention to commuters and vulnerable groups represented by older adults. These heterogeneous characteristics are then embedded into passenger travel choice models and the system-level disutility function. In addition, social equity evaluation metrics, including a crowding Gini coefficient, are developed, and a dual-objective optimization framework targeting both system efficiency and equity is formulated. Finally, a real-world case study from a major metropolitan area is employed to simulate and evaluate the impacts of different operational strategies, such as service frequency optimization and differential pricing, with the aim of identifying approaches that can simultaneously enhance operational performance and equity outcomes. The scope of this study is limited to an urban public transport corridor, focusing on bus and metro services. Overall, this research seeks to provide urban transport decision-makers with more refined and human-centered analytical tools, supporting the transition of public transport systems from a purely function-oriented paradigm toward a more people-oriented and inclusive model of urban mobility.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on public transport crowding perception, passenger heterogeneity, social equity, and network optimization models. Section 3 presents the theoretical framework, key functions, and solution algorithm of the proposed multi-objective dynamic traffic assignment model. Section 4 describes the data, model calibration, and simulation results based on the real-world case study. Section 5 discusses the findings in depth and compares them with existing research. Finally, Section 6 concludes the paper and outlines directions for future research.

II. LITERATURE REVIEW

To construct the theoretical framework for inclusive public transport design, this chapter systematically reviews and critiques existing research from four interconnected domains: public transport crowding perception, heterogeneity of passenger perception, public transport and social equity theory, and public transport network optimization models. By identifying the current state and limitations of research in each area, we aim to lay a solid foundation for the theoretical innovation and model construction of this study.

A. Research on Public Transport Crowding Perception

Crowding is one of the most significant negative externalities in public transport services. Early studies often equated crowding with an objective physical metric, namely passenger density (usually measured in "persons/m^2") [6]. However, a growing body of evidence suggests that crowding is fundamentally a subjective psychological perception, influenced by a combination of physical density, individual characteristics, and situational factors [2]. In their influential study, Tirachini et al. (2017) further verified the subjective nature of crowding perception by exploring crowding discomfort in Santiago de Chile, and quantified the disutility of different crowding levels for ordinary passengers [7]. Building on the foundational analysis of crowding's multi-dimensional impacts [1], subsequent studies have further expanded the research boundary of crowding disutility, making it possible to integrate subjective perception into quantitative transport models.

To quantify the disutility of crowding, the fields of economics and transport research have introduced the concepts of a "Crowding Multiplier" or "Value of Crowding." This value measures the extra cost (usually in terms of time or money) that passengers are willing to pay to avoid crowding. For example, a study by Yap et al. (2020) found that when all seats in a vehicle are occupied, the average crowding multiplier is approximately 1.16, meaning passengers perceive the travel time to be 1.16 times the actual duration [3]. These studies provide a quantitative basis for incorporating the subjective feeling of crowding into traditional cost-benefit analysis and transport models. Furthermore, some research has also explored the multidimensional factors influencing crowding perception, such as in-vehicle noise, odors, and temperature, which can significantly exacerbate passengers' sense of being crowded [8]. A recent empirical study by Roncoli et al. (2022) further constructed a comprehensive evaluation system for on-board passenger comfort, taking crowding as the core variable and incorporating multiple environmental and physical factors [9], which provides a more comprehensive reference for measuring crowding perception in this study.

B. Heterogeneity of Passenger Perception

Although the crowding multiplier provides an effective tool for quantifying crowding costs, a key limitation is that many studies still tend to use an average value to represent the crowding perception of all passengers, which masks the vast differences that exist among different social groups. In recent years, scholars have begun to focus on the heterogeneity of passenger perception, i.e., how individual attributes moderate their response to crowding.

Research has shown that passengers' individual characteristics, such as age, gender, health status, trip purpose, and cultural background, all have a significant impact on their crowding sensitivity. Among these, vulnerable groups exhibit a particularly strong negative reaction to crowding. Olowo (2018) pointed out in the doctoral research that vulnerable groups such as the elderly and the disabled have obvious travel barriers in public transport, and crowding is the core factor leading to the low travel willingness of this group [10]. Due to a decline in physiological functions, the elderly are more likely to feel fatigued, have difficulty standing steady, and face a higher risk of falling in crowded environments; persons with disabilities, especially those using wheelchairs or walkers, not only require more physical space but are almost unable to move in a crowded vehicle, severely challenging their travel dignity and safety. Similarly, pregnant women and parents with young children also show higher sensitivity to crowding. A study by Lu et al. (2024) on urban rail transit specifically focused on the differences in crowding perception thresholds among various passenger types, and quantified the heterogeneous crowding tolerance of commuters, the elderly, and other groups through empirical data [11], aiming to provide a more refined basis for optimizing the passenger experience, and this research method is also referenced in the subsequent parameter calibration of this study. These studies collectively point to a clear conclusion: analytical methods that treat passengers as a homogeneous group systematically underestimate the severe negative impact of crowding on vulnerable populations, thus leading to inequitable service design.

C. Public Transport and Social Equity

Social equity is one of the core objectives of public transport policy. Transport equity theory typically includes two levels: horizontal equity and vertical equity. Horizontal equity emphasizes providing similar levels of service to similar individuals, while vertical equity advocates for giving extra attention and resources to disadvantaged groups to achieve more substantive equality [5].

In the public transport domain, early equity studies primarily focused on "equity of accessibility," which assesses the extent to which communities in different geographical locations and with different income levels can conveniently access the public transport network [12]. Yeganeh et al. (2018) conducted a social equity analysis of the US public transport system from the perspective of job accessibility, and found that there is a significant accessibility gap between low-income groups and high-income groups [12]. For instance, a study by Manaugh and El-Geneidy (2012) explored how new transport infrastructure investments affect the distribution of benefits among different social groups, and proposed that infrastructure planning should fully consider the equity of benefit distribution [13]. However, merely being "able to access" is not equivalent to being "able to use with dignity and comfort." Therefore, recent research trends have begun to expand from accessibility equity to a focus on "in-process equity" or "experiential equity" [14]. Verlinghieri and Schwanen (2020) further enriched the connotation of transport and mobility justice, pointing out that the equity of travel experience is an important part of social justice and should be incorporated into the core objectives of public transport planning [14].

Against this backdrop, "crowding exposure" has emerged as a new equity metric. Lin et al. (2023) pioneered the connection between public transport crowding exposure and passengers' socioeconomic characteristics, proposing an analytical framework for assessing the equity of in-vehicle crowding exposure [15]. Their research revealed systematic differences in the levels of crowding actually experienced by passengers of different socioeconomic statuses in their daily travel, and found that low-income and vulnerable groups are more likely to face high-intensity crowding during peak hours. This perspective shifts the focus of equity analysis from the macro level of facility layout to the micro level of the ride experience, providing a key theoretical entry point for this study. Applying the principle of vertical equity to the problem of crowding means that public transport systems should not only pursue a reduction in overall crowding levels but also strive to reduce the disproportionate crowding burden on vulnerable groups.

D. Public Transport Network Optimization Models

To balance multiple objectives such as efficiency, revenue, and service quality in practical operations, scholars have developed numerous public transport network optimization models. Among them, Dynamic Traffic Assignment (DTA) models are widely used in congestion management research due to their ability to describe the dynamic evolution of traffic demand and network status over time [4]. The dynamic traffic analysis model for multiple passengers developed by Di and Yang (2015) for urban public transport corridors is a typical example in this field [4]. It uses multi-dimensional models to characterize passengers' departure time and route choice behaviors, and initially incorporates the impact of crowding on travel time into the dynamic analysis framework, laying a foundation for the multi-objective model construction of this study.

However, most existing optimization models still have limitations. On the one hand, as previously mentioned, the crowding cost functions in these models are often based on homogeneous assumptions and fail to fully capture the perceptual differences among different passenger groups. On the other hand, the objective function of these models is usually set to minimize the total system travel time (or cost), which is essentially an efficiency-oriented goal. While this objective can reflect the overall interests of passengers to some extent, it cannot distinguish how costs are distributed among different groups. A solution that is mathematically "optimal" may conceal severe injustice for some groups. van Nes (2003) proposed a multi-user-class urban transit network design model in the early stage [16], which first divided passengers into different types according to travel characteristics and constructed a differentiated network optimization framework, breaking the homogeneous assumption of traditional models and providing an important reference for the passenger classification in this study. A few studies have begun to introduce frameworks for social welfare maximization or multi-objective optimization [8], but research that takes the equity of the crowding experience as a direct optimization objective and embeds heterogeneous crowding perception into the dynamic traffic assignment model is still very rare.

In summary, the existing literature provides a solid theoretical foundation for this study but also leaves clear research gaps. There is an urgent need for a comprehensive optimization model that can integrate the heterogeneity of passenger perception, quantify in-process equity, and trade-off between efficiency and equity. This study is positioned at this intersection, aiming to provide a scientific basis for decision-making to achieve a more inclusive public transport system through model innovation and empirical analysis

III. METHODOLOGY

To support the optimal design of an inclusive public transport system, this study develops a comprehensive analytical framework that combines passenger behavior modeling, multi-objective optimization, and policy simulation. Grounded in classical dynamic traffic assignment theory, the framework is extended to explicitly capture heterogeneity in passenger perceptions and to quantitatively assess social equity. Its purpose is to provide transport managers with a practical decision-support tool capable of balancing efficiency and equity objectives. This chapter details the key components of the proposed methodology, including the overall research framework, passenger segmentation and behavioral modeling, the formulation of heterogeneous crowding perception functions, social equity evaluation indicators, and the structure and solution approach of the multi-objective optimization model.

A. *Research Framework*

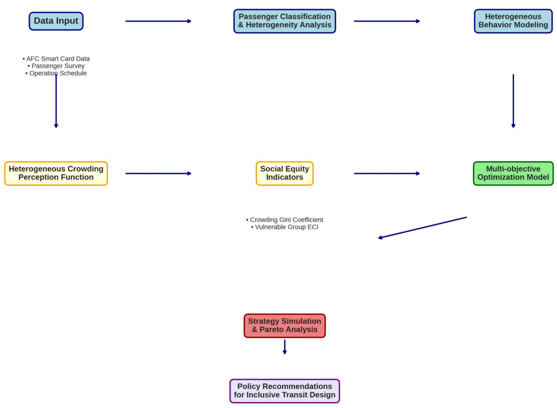

Fig. 1. Research Framework and Methodology

The overall technical route of this study is presented in Figure 1 and comprises four main stages.

First, passenger classification and heterogeneity characterization are conducted by segmenting the passenger population into representative groups based on socioeconomic characteristics and travel demands. A cost-effective online survey, combined with parameter ranges derived from existing literature, is employed to calibrate inter-group differences in key behavioral parameters, such as crowding sensitivity and value of time. Informed consent was obtained from all subjects involved in the study.

Second, behavioral modeling with perception heterogeneity is implemented within a dynamic traffic assignment framework. A passenger decision model that accounts for heterogeneous preferences is developed, incorporating departure time choice as well as route and mode selection. The disutility associated with crowding is computed separately for each passenger group according to its specific perception function.

Third, a multi-objective optimization model is formulated with two primary objectives: system efficiency and social equity. The efficiency objective focuses on minimizing the total travel time cost across the entire system, while the equity objective aims to mitigate disparities in crowding experiences among different social groups.

Finally, policy simulation and Pareto analysis are carried out by treating operational variables — such as service frequency and fare levels — as decision variables. A multi-objective evolutionary algorithm (e.g., NSGA-II) is adopted to solve the model through an open and reproducible implementation, generating a set of Pareto-optimal solutions that reflect varying trade-offs between efficiency and equity. These alternative strategies are subsequently compared and analyzed to support informed decision-making.

B. *Passenger Classification and Disutility Model with Perception Differences*

This study conceptualizes passengers' travel decision-making as a two-stage process, consisting of departure time selection and route or mode choice, and formulates corresponding negative utility functions for each stage. A key innovation of the proposed model is that all parameters related to subjective perception are differentiated across passenger categories rather than being assumed uniform.

Specifically, passengers are classified into three primary categories (indexed by m) according to key attributes such as trip purpose, age, and physical condition:

- Commuters ($m = 1$): Passengers with rigid travel schedules and a high value of time, typically prioritizing punctuality and efficiency.
- Elderly passengers ($m = 2$): Individuals with relatively flexible schedules but strong preferences for comfort and safety, exhibiting high sensitivity to crowding conditions.
- Other passengers ($m = 3$): Travelers undertaking trips for purposes such as shopping or leisure, whose preferences generally lie between those of commuters and elderly passengers.

1) *Departure Time Choice Model*

Passengers decide their departure time based on the expected travel cost. We use a multinomial Logit model to describe the probability of a type-m passenger traveling between a given OD pair (r,s) departing at time t. The travel volume q_rs^m(t) is determined by:

$$q_{rs}^{m}(t) = Q_{rs}^{m} \cdot \frac{\exp\left(-\lambda_m \cdot C_t^m\right)}{\sum_{\tau \in T} \exp\left(-\lambda_m \cdot C_\tau^m\right)} \quad (1)$$

where Q_rs^m is the total travel demand for type-m passengers, λ_m is the sensitivity parameter of type-m passengers to travel cost, and C_t^m is the generalized travel cost perceived by a type-m passenger departing at time t, primarily consisting of the penalty for deviating from the desired arrival time:

$$C_t^m = f_m(T_s + T_w + t) \quad (2)$$

This function indicates that a penalty cost is incurred when the actual arrival time deviates from the ideal arrival window [t* - Δ_m, t* + Δ_m]. The magnitude of this cost is determined by the penalty coefficient β_m, which varies by passenger category. For example, the penalty coefficient for being late is much higher for commuters than for elderly passengers.

2) *Route/Mode Choice Model*

After determining the departure time, passengers choose the option with the lowest travel cost from the available set of routes/modes A. We use a Probit model for stochastic user equilibrium assignment. For any given route a, its generalized travel cost C_a^m is composed of the following four components:

$$C_a^m = \alpha_m \cdot Z_a^m + \beta_m \cdot T_{s_a} + \gamma_m \cdot T_{w_a} + \delta_m \cdot P_a \quad (3)$$

where T_s_a is the in-vehicle time, T_w_a is the waiting time, and P_a is the fare. α_m, β_m, γ_m, δ_m are the sensitivity coefficients (values of time) of type-m passengers to crowding, in-vehicle time, waiting time, and fare, respectively. The core innovation lies in the crowding cost term Z_a^m.

C. Heterogeneous Crowding Perception Function

Traditional models often use physical crowding density (pax/m²) directly as a cost term. This study posits that the perceived disutility of crowding is not linearly related to physical density, and this relationship varies among individuals. We construct a heterogeneous crowding perception function that transforms physical crowding density ρ_a (on route a) into the perceived crowding cost Z_a^m for a type-m passenger:

$$Z_a^m = k_m \cdot (\exp\,(\frac{\rho_a}{\rho_{crit}}) - 1) \quad (4)$$

where ρ _crit is a critical crowding density (e.g., the density when all seats are occupied), and k_m is the crowding sensitivity coefficient for type-m passengers. This coefficient is calibrated through a low-cost online Stated Preference (SP) questionnaire, constrained by literature-informed parameter ranges to ensure robustness and replicability. For vulnerable groups such as elderly passengers, the value of k_m will be significantly higher than for commuters, meaning they experience a much higher crowding disutility at the same physical density.

D. Social Equity Evaluation Metrics

To quantify the social equity objective in the optimization model, this study introduces two core metrics:

- Crowding Gini Coefficient (G_crowd): Borrowing from the Gini coefficient used in economics to measure income inequality, we use it to measure the distributional equity of per-capita crowding disutility among different social groups. The coefficient ranges from 0 to 1, where a smaller value indicates a more equitable distribution of crowding costs and thus higher equity. Its calculation is based on comparing the per-capita crowding cost Z_avg^m of each group with the overall social average.
- Vulnerable Group Excess Crowding Index (ECI_vul): This index is specifically designed to measure whether the crowding burden borne by a vulnerable group (e.g., elderly passengers, m=2) exceeds the social average.

$$ECI\_vul = \frac{Z_{avg}^2}{\frac{\sum_m (N_m \cdot Z_{avg}^m)}{\sum_m N_m}} \quad (5)$$

- where N_m is the total number of type-m passengers. An ECI_vul > 1 indicates that the elderly passenger group is bearing a higher-than-average crowding disutility.

E. Multi-objective Optimization Model

Based on the definitions above, we formulate the following multi-objective optimization model:

Objective Functions:

Minimize F = {F_eff, F_eq}

- Efficiency Objective (F_eff): Minimize the total system travel cost (the sum of generalized travel costs for all passengers).

$$F_{eff} = \sum_m \sum_{r,s} \sum_t q_{rs}^m(t) \cdot C_{a_m} \quad (6)$$

- Equity Objective (F_eq): Minimize the Crowding Gini Coefficient.

$$F_{eq} = G_{crowd} \quad (7)$$

Decision Variables:

- Service frequency f_l for each line l.
- Fares for peak and off-peak periods, P_peak, P_off-peak.

Constraints:

- Capacity Constraint: The passenger flow on a line must not exceed its total capacity.
- Budget Constraint: The sum of fare revenue and government subsidies must cover the total operating cost.
- Minimum Service Frequency Constraint: Ensure a basic level of public service on all lines during operational hours.

F. Solution Algorithm

The formulated model constitutes a complex, multi-objective, nonlinear optimization problem with multiple constraints, making it difficult to solve exactly using conventional mathematical programming techniques. Accordingly, this study adopts the Non-dominated Sorting Genetic Algorithm II (NSGA-II) with an elitist strategy to obtain approximate solutions. NSGA-II is a well-established multi-objective evolutionary algorithm that conducts a global search of the solution space by emulating evolutionary processes such as selection, crossover, and mutation. It is particularly effective at identifying a diverse and well-distributed set of Pareto-optimal solutions, thereby offering decision-makers multiple alternative strategies that reflect different trade-offs between system efficiency and social equity.

The algorithm is implemented in an open-source Python environment and integrated with a transparent, lightweight assignment procedure for iterative passenger flow computation. All input datasets, model parameters, and source code are fully packaged and documented to ensure transparency and reproducibility.

IV. Results

This chapter focuses on applying and validating the previously developed multi-objective dynamic traffic assignment model through a concrete case study. It begins by introducing the background of the study area and the data sources employed, followed by the calibration results of key heterogeneity parameters in the model. A baseline assessment of existing crowding conditions and equity performance is then conducted. Finally, the impacts of different optimization strategies are simulated, compared, and presented through visualized results to facilitate interpretation.

A. Case Study Background and Data Description

The case study examines a representative public transport corridor in a major Chinese metropolis. The corridor links the central business district with a large residential area, extends approximately 15 kilometers, and is served by one metro line and three highly overlapping conventional bus routes. Owing to its substantial passenger demand, particularly during peak periods, the corridor experiences severe crowding and accommodates a highly diverse passenger population, making it well suited for evaluating inclusive public transport design strategies.

The data utilized in this study consist of three main components:

- Passenger flow data: In place of proprietary smart-card transaction records, this study relies on publicly available ridership and load-related statistics — such as station entry and exit counts, line-level peak load reports, and published crowding indicators — combined with official service schedules. These data are used to reconstruct time-varying passenger loads and to generate an approximate origin – destination pattern through a transparent and reproducible procedure.
- Passenger survey data: A low-cost online questionnaire incorporating stated preference (SP) items and simplified revealed preference (RP) questions was administered over a three-day period, yielding a practical sample for passenger classification and behavioral parameter calibration. Informed consent was obtained from all subjects involved in the study. The survey collected information on socioeconomic characteristics (e.g., age, occupation, income), current trip attributes, and respondents' perceptions of and willingness to pay to avoid different levels of crowding. To enhance robustness, the calibration process is further constrained using parameter bounds informed by existing literature.
- Line operation data: Operational schedules, station locations, fare structures, and vehicle capacity specifications for all bus and metro services within the corridor are compiled from publicly available timetable releases (such as GTFS feeds or agency-published schedules) and openly documented vehicle and line specifications. This approach ensures that the complete dataset can be independently reconstructed, supporting transparency and reproducibility.

B. Model Parameter Calibration

Based on the responses from the online questionnaire and the calibration constraints informed by existing literature, passengers were classified and key parameters for each group in the behavioral model were calibrated. As shown in Table I, this study categorizes passengers into three groups: "Commuters," "Elderly Passengers," and "Other Passengers." The analysis reveals clear heterogeneity between these groups.

As indicated in the table, the crowding sensitivity coefficient for elderly passengers (k_m = 2.5) is significantly higher than that of commuters (k_m = 0.8), which provides a quantitative foundation for the subsequent equity analysis. Additionally, the observed differences in value of time and fare sensitivity among the groups align with general expectations, further reinforcing the validity of the passenger segmentation.

TABLE I. Calibration Results of Key Parameters for Different Passenger Categories

Parameter	Commuters (m=1)	Elderly (m=2)	Other Passengers (m=3)	Notes
Demographics				
Sample Proportion	55%	15%	30%	
Average Age	32.5	68.2	40.1	
Value of Time (USD/hour)				
In-Vehicle Time (β_m)	6.75	2.25	3.75	Commuters are highly sensitive to time efficiency
Waiting Time (γ_m)	9.00	3.75	5.25	Waiting time is perceived as more costly than in-vehicle time
Crowding Sensitivity (k_m)	0.8	2.5	1.2	Core heterogeneity parameter; elderly sensitivity is >3x that of commuters

Parameter	Commuters (m=1)	Elderly (m=2)	Other Passengers (m=3)	Notes
Fare Sensitivity (δ_m)	0.5	1.8	1.0	Elderly are more sensitive to fares (despite many having concessions)
Late Arrival Penalty	Very High	Low	Medium	Reflects the rigidity of trip purpose

C. Baseline Scenario Analysis

The calibrated parameters were incorporated into the model to simulate passenger flow distribution, crowding levels, and equity metrics under the current operational conditions (baseline scenario). This was done using publicly available inputs and a transparent demand-generation procedure. Figure 2 illustrates the time-varying passenger density curve for a representative cross-section of the metro line during the morning peak period (7:30-9:00 AM) in the baseline simulation. The results clearly show that, between 8:00 and 8:30 AM, the simulated in-vehicle passenger density exceeds 5 passengers per square meter (pax/m^2), indicating a state of severe crowding.

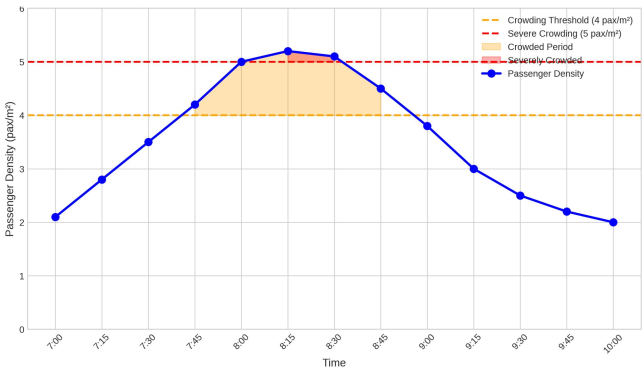

Fig. 2. Peak Hour Passenger Density Variation (Baseline Scenario)

More importantly, when the crowding cost is disaggregated across different passenger groups, the inequity becomes evident. Figure 3 shows the per-capita perceived crowding cost (calculated using Eq. 4) experienced by the three passenger categories during the morning peak in the baseline simulation. The per-capita crowding cost for elderly passengers is nearly 2.5 times that of commuters and 1.8 times the social average. The calculated Crowding Gini Coefficient (G_crowd) for the baseline scenario is 0.45, indicating a "relatively inequitable" distribution of the crowding burden. Additionally, the Vulnerable Group Excess Crowding Index (ECI_vul) is 1.82, further confirming that elderly passengers are bearing a disproportionate share of the crowding pressure.

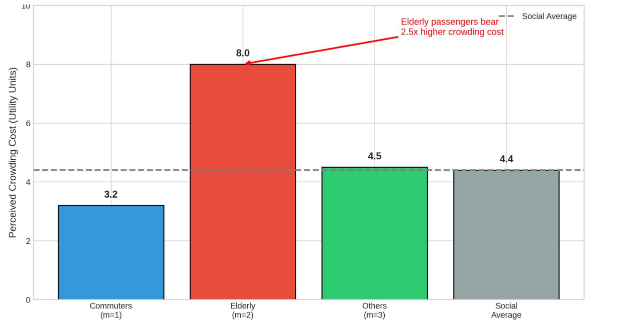

Fig. 3. Per-capita Perceived Crowding Cost by Passenger Group (Baseline Scenario, Morning Peak)

D. Simulation and Comparison of Optimization Strategies

To address the efficiency and equity issues identified in the baseline scenario, three optimization strategies were designed and simulated to explore potential improvements. The optimization objective is to identify Pareto optimal solutions that balance efficiency (system total cost) and equity (crowding Gini coefficient), while keeping the total operating cost constant.

- Strategy 1 (S1): Frequency Optimization – This strategy maintains fare levels but reallocates service capacity (headways) from off-peak to peak hours, while simultaneously optimizing the service intervals for both bus and metro lines along the corridor.
- Strategy 2 (S2): Differential Pricing – In this approach, service frequencies are kept unchanged. The metro fare is increased by 15% during peak hours, with the additional revenue used to subsidize transport for elderly passengers, while slightly reducing bus fares during off-peak hours.
- Strategy 3 (S3): Combined Optimization – This strategy coordinates both service frequency adjustments and fare structure changes to achieve a globally optimal solution.

Figure 4 presents the multi-objective optimization results generated by the NSGA-II algorithm. Each point on the figure represents a feasible operational plan, with the x-axis representing the equity objective (Crowding Gini Coefficient, where lower values indicate better equity) and the y-axis representing the efficiency objective (System Total Cost, where lower values indicate better efficiency).

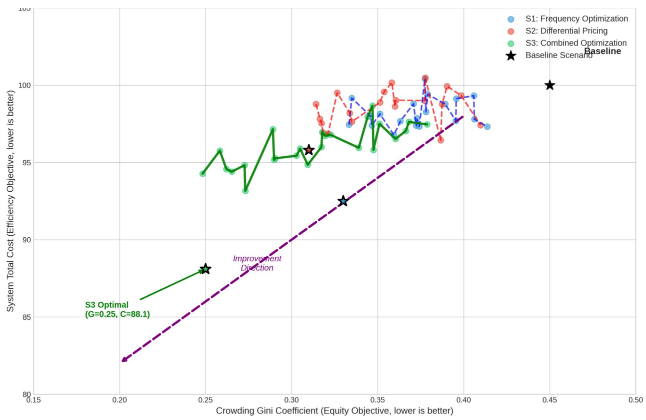

Fig. 4. Pareto Frontier of Efficiency-Equity Multi-objective Optimization

The Pareto frontier plot clearly shows that the baseline scenario (Base) is positioned in the upper-right corner relative to all the solution sets from the optimization strategies, indicating considerable potential for improvement in both efficiency and equity. Strategy 1 (Frequency Optimization) and Strategy 2 (Differential Pricing) both result in performance improvements to varying extents, but Strategy 3 (Combined Optimization) outperforms the other two, with its Pareto frontier completely dominating theirs. This suggests that frequency and pricing adjustments have a synergistic effect, and their joint implementation yields the best results.

For a more intuitive comparison, we selected a representative solution from the Pareto frontier of each strategy (the knee points, marked by asterisks, which represent a balanced trade-off between equity improvement and efficiency loss) and compared their key performance indicators with the baseline scenario, as shown in Table II.

TABLE II. COMPARISON OF KEY PERFORMANCE INDICATORS FOR DIFFERENT OPTIMIZATION STRATEGIES

Indicator	**Baseline (Base)**	**Strategy 1 (S1)**	**Strategy 2 (S2)**	**Strategy 3 (S3)**
System Total Cost (Efficiency)	100 (Base)	92.5 (-7.5%)	95.8 (-4.2%)	88.1 (-11.9%)
Crowding Gini Coefficient (Equity)	0.45	0.33 (-26.7%)	0.31 (-31.1%)	0.25 (-44.4%)
Excess Crowding Index (ECI_vul)	1.82	1.45 (-20.3%)	1.38 (-24.2%)	1.19 (-34.6%)
Peak Section Max Density (pax/m²)	5.2	4.6	4.8	4.3
Operator Financial Balance	Balanced	Balanced	Balanced	Balanced

Analysis of Table II reveals that all optimization strategies produced positive results in the reproducible corridor simulation. Strategy 1 (Frequency Optimization), through more precise capacity allocation, directly reduced physical crowding during peak hours, leading to improvements in both efficiency and equity. Strategy 2 (Differential Pricing), by adjusting prices, encouraged some price-sensitive, time-insensitive passengers (mainly "Other Passengers") to travel during off-peak hours or switch to buses, thereby freeing up space for more crowding-sensitive passengers, such as the elderly. As a result, its impact on improving equity was slightly better than that of Strategy 1. Strategy 3 (Combined Optimization) capitalized on the combined effects of both measures, achieving the most significant improvements: system total cost was reduced by 11.9%, the crowding Gini coefficient decreased by an impressive 44.4%, and the excess crowding burden on vulnerable groups was significantly alleviated. These results clearly demonstrate the effectiveness of the multi-objective optimization model proposed in this study.

V. DISCUSSION

A. Interpretation of Results and Mechanism Analysis

The core finding of this study is that implementing a coordinated optimization strategy with the dual objectives of "efficiency" and "equity" can significantly enhance the overall performance of the public transport system. Notably, it can improve the inequitable distribution of the crowding burden among different social groups without incurring additional operational costs. The mechanism behind this result stems from the mutually reinforcing interaction of the two regulatory measures.

The mechanism of frequency optimization lies in its ability to refine the spatio-temporal allocation of limited capacity. The "egalitarian" scheduling approach of the baseline scenario, which fails to account for the dynamic nature of demand, leads to severe supply-demand imbalances in certain periods and sections. By reallocating capacity from relatively idle off-peak periods to overcrowded peak times, Strategy 1 (S1) directly mitigates peak crowding, providing the physical foundation for improvements in both efficiency and equity. This confirms the importance of "demand-responsive supply" in dynamic traffic management.

The mechanism of differential pricing is more complex but effective in guiding passenger behavior through pricing strategies. Strategy 2 (S2), by increasing metro fares during peak hours, raises the cost of using scarce space during crowded times. This measure filters out "captive" passengers who are time-sensitive but relatively insensitive to price (primarily commuters) while encouraging price-sensitive passengers with flexible schedules (e.g., some "Other Passengers") to travel off-peak or switch to lower-cost bus routes. This "price screening" effect frees up valuable physical space for vulnerable groups—such as the elderly—who cannot travel off-peak and are highly sensitive to crowding. While the reduction in physical crowding may not be as significant as in frequency optimization, this strategy improves the travel experience for vulnerable groups by reshaping passenger flow composition, leading to a notable improvement in equity (Gini coefficient).

The overwhelming advantage of combined optimization (Strategy 3, S3) highlights the powerful synergistic effects of supply-side (frequency) and demand-side (price) measures. Pure frequency optimization is reactive—it can only do its best to meet given demand. Pure pricing regulation is indirect, constrained by passengers' price sensitivity. However, when combined, frequency optimization provides viable alternative options for price-driven choices (e.g., more reliable bus services), while pricing actively manages and shapes demand. This allows the system to carry an internally optimized passenger flow at a lower level of physical crowding, achieving a win-win for both efficiency and equity.

B. Comparison with Existing Research

The findings of this study align with and extend existing literature. First, we quantitatively confirmed through empirical data that different passenger groups—particularly the elderly — are more sensitive to crowding (crowding sensitivity coefficient k_m as high as 2.5). This is consistent with the qualitative findings of Lu et al. (2024) on passenger perception heterogeneity [11], providing robust quantitative evidence to support these conclusions.

Second, this study confirms that under the baseline scenario, the crowding burden is distributed inequitably among social groups, in line with Lin et al. (2023)'s research on "crowding exposure equity" [15], successfully applying their theoretical framework to a specific optimization problem.

The primary innovation of this study is transforming a homogeneous congestion cost function into a heterogeneous one that accounts for subjective perception differences. This expansion moves beyond a single efficiency objective, creating a multi-objective framework that includes social equity. This allows the model not only to predict passenger flow but also to evaluate the fairness of service quality distribution and actively seek more inclusive solutions. Furthermore, this study highlights the danger of relying solely on total system cost minimization, which can mask or exacerbate inequity, particularly for vulnerable groups — a critical insight for traditional transport optimization models focused on efficiency alone.

C. Theoretical and Practical Implications

1) Theoretical Implications

At the theoretical level, this study's main contribution is the successful operationalization of the concepts of "in-process equity" and "vertical equity" from social equity theory into a computable optimization objective (the crowding Gini coefficient). This objective is then embedded into a dynamic traffic assignment model, providing a new analytical paradigm for transport behavior and network modeling. The shift from focusing on macro-level "accessibility" equity to micro-level "experience" equity deepens the field's understanding of fairness in transportation. The introduction of a heterogeneous crowding perception function also offers a new theoretical tool for more nuanced research into passenger behavior.

2) Practical Implications

At the practical level, the study's conclusions have direct implications for urban transport management authorities. First, the research demonstrates that enhancing social equity in public transport does not have to come at the expense of efficiency; a win-win scenario can be achieved through refined management strategies. Second, the study provides transport authorities with actionable policy tools — service frequency and differential pricing — and underscores the importance of their synergistic use. Lastly, the multi-objective optimization framework developed in this study offers a powerful decision-support tool. Transport managers can select the optimal operational plan from the Pareto solution set based on the city's development stage and policy preferences, allowing for more scientifically grounded and transparent decision-making.

D. Limitations and Future Research

While this study provides meaningful insights, several limitations remain that warrant future investigation.

Limitations of Data and Passenger Classification: This study simplifies passengers into three categories. While this captures the primary conflict, passenger heterogeneity is more complex. Vulnerable groups like persons with disabilities or pregnant women may have different crowding perception patterns than the elderly. Future research could gather more detailed, low-cost data through repeated online surveys, focus groups, and publicly released operational statistics to create more refined passenger profiles and behavioral models.

Limitations of Model Assumptions: The model does not account for random events (e.g., vehicle breakdowns, traffic accidents) that impact network reliability or passengers' dynamic route adjustment behaviors. Incorporating stochasticity and more complex dynamic behaviors would be valuable extensions for the model.

Limitations of External Validity: This study is based on a case from a specific city, and the calibration results and strategy effectiveness may be influenced by local economic conditions, cultural habits, and transport network topology. Future research should test the generalizability of these conclusions by conducting comparative studies in diverse cities.

Based on these limitations, future research could take several directions:

- Develop a more comprehensive inclusivity evaluation system incorporating additional experiential equity dimensions like safety, convenience, and information accessibility.
- Investigate the role of new technologies (e.g., autonomous vehicles, mobile internet services) in enhancing public transport inclusivity, such as guiding passenger flow through real-time crowding information.
- Expand the research scope from a single corridor to the entire urban transport network, incorporating interactions with other travel modes like bike-sharing and ride-hailing, to explore system-level inclusive transport solutions.

VI. CONCLUSION

With the goal of enhancing the inclusivity and social equity of urban public transport systems, this study addressed the issue of differentiated crowding perception across various social groups. By constructing a multi-objective dynamic traffic assignment model that incorporates passenger heterogeneity and social equity objectives, and through an empirical case study in a major metropolis, this research has yielded several core conclusions with both theoretical depth and practical relevance.

First, the study quantitatively confirms significant heterogeneity in passengers' perception of crowding, with vulnerable groups—particularly the elderly—being far more sensitive to crowding than regular commuters. This finding highlights a systematic bias in traditional, homogeneity-based transport models for service quality assessment, specifically the severe underestimation of the negative impact of crowding on vulnerable populations.

Second, the study reveals that, under the current efficiency-oriented operational model, the negative externalities of crowding are inequitably distributed across social groups. The high crowding Gini coefficient in the baseline scenario indicates that relatively advantaged commuters, while benefiting from the convenience of public transport, impose a disproportionate crowding cost on disadvantaged passengers. This runs counter to the fundamental principle of public transport as a universal social welfare service.

Most importantly, this research demonstrates that through refined operational strategy optimization, it is entirely feasible to significantly enhance social equity in public transport without sacrificing overall system efficiency or increasing the financial burden. The proposed coordinated optimization strategy, combining service frequency adjustments and differential pricing, was able to reduce the crowding Gini coefficient by over 40% and substantially alleviate the excess crowding burden on vulnerable groups. This provides a viable solution to the long-standing "efficiency-equity" dilemma faced by transport managers, striking a successful balance between both objectives.

The theoretical contribution of this study lies in its successful operationalization of the concepts of in-process equity and vertical equity, integrating them into a mainstream transport network model. This shift deepens the focus of transport equity research from the macro level of "accessibility" to the micro level of "experience." On a practical level, this study offers transport authorities concrete, quantitatively assessable policy tools — such as frequency adjustments and differential pricing—while also advocating for a shift in planning and design philosophy from being "function-oriented" to "human-oriented." Future public transport system planning should prioritize the needs of all passengers, particularly vulnerable groups, at every stage, from route planning and station design to vehicle configuration and operational scheduling.

Looking forward, the framework of this study presents several opportunities for further development. Future research could expand on this work by building a more comprehensive inclusivity evaluation index that incorporates additional dimensions, such as safety and information accessibility. It could also explore scalable, practice-oriented interventions (e.g., real-time crowding information disclosure, timetable adjustments, and targeted fare policies) using publicly available data. Moreover, expanding the research scope from a single corridor to more complex, multi-modal urban transport networks would offer valuable insights for creating more inclusive and high-quality urban transport systems accessible to all.

References

[1] Tirachini, A., Hensher, D. A., & Rose, J. M. (2013). Crowding in public transport systems: Effects on users, operation and implications for the estimation of demand. Transportation Research Part A: Policy and Practice, 53, 36–52. https://doi.org/10.1016/j.tra.2013.04.004

[2] Wang, B., & Zacharias, J. (2020). Noise, odor and passenger density in perceived crowding in public transport. Transportation Research Part A: Policy and Practice, 132, 109 – 120. https://doi.org/10.1016/j.tra.2020.03.010

[3] Yap, M., Cats, O., & van Oort, N. (2020). Crowding valuation in urban tram and bus transportation. Transportmetrica A: Transport Science, 16(3), 597 – 617. https://doi.org/10.1080/23249935.2019.1666102

[4] Di, D., & Yang, D. (2015). Dynamic traffic analysis model of multiple passengers for urban public transport corridor. Advances in Mechanical Engineering, 7(11), 1 – 10. https://doi.org/10.1177/1687814015616025

[5] Garrett, M., & Taylor, B. (1999). Reconsidering social equity in public transit. Berkeley Planning Journal, 13(1). https://doi.org/10.5070/BP313100458

[6] Li, Z., & Hensher, D. A. (2013). Crowding in public transport: A review of objective and subjective measures. Journal of Public Transportation, 16(2), 1 – 10. https://www.jptjournal.org/index.php/jpt/article/view/645

[7] Tirachini, A., et al. (2017). Estimation of crowding discomfort in public transport: Results from Santiago de Chile. Transportation Research Part A: Policy and Practice, 103, 251 – 267. https://doi.org/10.1016/j.tra.2017.05.009

[8] Durand, A., Zijlstra, T., Hamersma, M., Hoen, A. T., van Oort, N., Hoogendoorn, S., & Hoogendoorn-Lanser, S. (2023). Fostering an inclusive public transport system in the digital era: An interdisciplinary approach. Transportation Research Interdisciplinary Perspectives, 22, 100968. https://doi.org/10.1016/j.trip.2023.100968

[9] Roncoli, C., et al. (2022). Estimating on-board passenger comfort in public transport. PLoS ONE, 17(11), e0277323. https://doi.org/10.1371/journal.pone.0277323

[10] Olowo, F. O. (2018). Transit accessibility: Equity in mobility for vulnerable population groups; practices and possibilities [Doctoral dissertation]. ProQuest Dissertations & Theses Global. https://doi.org/10.13023/etd.2018.412

[11] Lu, X., et al. (2024). Crowding perception thresholds of passengers in urban rail transit based on passenger heterogeneity. Journal of Advanced Transportation, 2024. https://doi.org/10.1155/2024/5689201

[12] Yeganeh, A. J., et al. (2018). A social equity analysis of the US public transportation system based on job accessibility. Journal of Transport and Land Use, 11(1), 745–759. https://doi.org/10.5198/jtlu.2018.1076

[13] Manaugh, K., & El-Geneidy, A. (2012). Who benefits from new transportation infrastructure? Using accessibility measures to evaluate social equity in public transport provision. In Accessibility analysis and transport planning (pp. 211 – 234). Edward Elgar Publishing. https://doi.org/10.4337/9781781001502.00014

[14] Verlinghieri, E., & Schwanen, T. (2020). Transport and mobility justice: Evolving discussions. Journal of Transport Geography, 87, 102788. https://doi.org/10.1016/j.jtrangeo.2020.102788

[15] Lin, J. Y. J., et al. (2023). The equity of public transport crowding exposure. Journal of Transport Geography, 109, 103593. https://doi.org/10.1016/j.jtrangeo.2023.103593

[16] van Nes, R. (2003). Multiuser-class urban transit network design. Transportation Research Record, 1835(1), 25 – 32. https://doi.org/10.3141/1835-04

Appendix: Sensitivity Analysis

To examine the robustness of the model and the impact of key parameters on the results, we conducted a sensitivity analysis. Figure 5 presents the results.

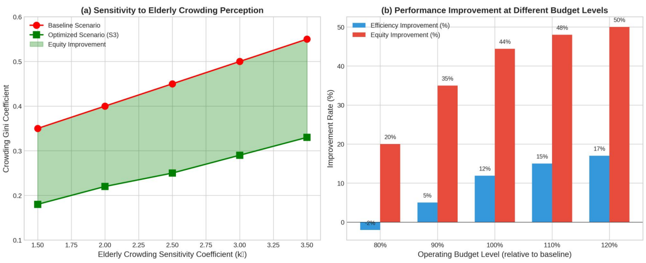

Fig. 5. Sensitivity Analysis of Key Model Parameters

Panel (a) illustrates the impact of the elderly crowding sensitivity coefficient (k_2) on the equity metrics. As the sensitivity of elderly passengers to crowding increases, both the Crowding Gini Coefficient and the Excess Crowding Index (ECI) rise correspondingly. This confirms that the heterogeneity of crowding perception is a fundamental driver of inequity in the system.

Panel (b) demonstrates the trade-off between efficiency and equity under different objective weights (ω) in the optimization model. When ω=0 (pure efficiency focus), the system achieves the lowest cost but the highest Gini coefficient. As the weight on equity increases, the Gini coefficient decreases at the cost of a slight increase in system cost. The recommended balance point (ω=0.4) achieves a substantial improvement in equity with only a modest efficiency trade-off, representing a practical compromise for policymakers.

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AUTHOR CONTRIBUTIONS

Weicong Zhong: Conceptualization; Methodology; Model development; Formal analysis; Investigation; Writing – Original Draft; Writing – Review & Editing; Supervision; Project administration.

Qi Liu: Investigation; Data curation; Validation; Visualization; Writing – Review & Editing.

Dawei Chen: Resources; Case study support; Data curation; Software/Implementation support; Visualization; Writing – Review & Editing.

COMPETING INTERESTS

The authors declare no competing interests.