Transportation Research Part A 206 (2026) 104918

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Airport accessibility assessment and shuttle bus scheduling across socioeconomic groups

Tinghe Zhang [a], Ang Li [a,*], Lingxiao Wu [a], Changmin Jiang [b]

[a] Department of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong SAR, China
[b] Department of Logistics and Maritime Studies, The Hong Kong Polytechnic University, Hung Hom, Hong Kong SAR, China

ARTICLE INFO

Keywords:
Transport accessibility
Bus scheduling
Two-stage optimization
Fairness-aware transit planning

ABSTRACT

Airport accessibility is a critical factor influencing air travel behavior, particularly for low-income travelers who face both economic and transit-related constraints. This study proposes the Fairness Airport Accessibility Metric (FAAM), a novel measure that captures disparities in accessibility across income groups by incorporating variations in travel options and behavioral responses. Building on this metric, we develop a dual-perspective, two-stage Airport Bus Scheduling and Allocation Model that reflects the differing priorities of public stakeholders. The government-led model first maximizes accessibility to ensure fair transit access across income groups, then minimizes operational costs under fairness constraints. The operator-led model, in contrast, begins by minimizing costs while maintaining baseline accessibility, and subsequently improves accessibility within those budgetary limits, capturing the trade-off between fairness and efficiency from both policy and operational standpoints. To validate the framework, we conduct a case study in Hong Kong, using actual flight schedules from Hong Kong International Airport (HKIA) combined with a synthetically constructed public transit network. The case study confirms significant spatial and income-based disparities in current airport accessibility and demonstrates the necessity of differentiated planning for diverse socioeconomic groups. Numerical experiments reveal that over-prioritizing low-income users can lead to underutilized system capacity, while favoring high-income users may improve overall efficiency but widen accessibility gaps. A balanced, fairness-driven weighting scheme provides inclusive service delivery without compromising operational feasibility. The findings highlight the importance of integrating income-responsive transit planning, fairness-aware scheduling algorithms, and targeted fare policies. Together, these strategies provide a scalable and adaptable framework for designing airport ground access systems that are both socially inclusive and operationally sustainable.

1. Introduction

Air travel accounts for more than three-quarters of long-distance trips (BTS, 2017), establishing aircraft as a vital mode of transportation for regional and global mobility. Airports play a crucial role as hubs that connect people from diverse backgrounds, serving as gateways to economic and social opportunities. The accessibility of airports significantly influences travelers' choices (Handy and Niemeier, 1997). Many individuals, especially those facing economic constraints, may opt for airports farther away or reduce travel altogether due to the higher costs or limited connectivity of local airports (Grubesic and Wei, 2012; Fuellhart, 2007). This challenge

* Corresponding author.
E-mail address: ang-joy.li@polyu.edu.hk (A. Li).

https://doi.org/10.1016/j.tra.2026.104918
Received 26 August 2025; Received in revised form 14 December 2025; Accepted 3 February 2026
Available online 12 February 2026

is further exacerbated by the dominance of traditional carriers, as low-cost flights remain limited. Globally, low-cost carriers account for only 36% of scheduled airline seats, and in Asia their penetration is even higher, reaching 63% of air capacity in South Asia and around 52% in Southeast Asia (OAG, 2024). The restricted availability of affordable flight options, combined with accessibility barriers, highlights the dual challenge of ensuring both physical access to airports and fair access to affordable air travel opportunities.

Improving airport accessibility is therefore essential not only to enhance mobility and connectivity but also to address socioeconomic disparities. Public transit, particularly buses, offers a practical and economical way to bridge the gap for underserved communities (Mutiganda et al., 2023). By providing affordable first- and last-mile connections to airports, public transit reduces barriers that disproportionately impact low-income travelers. Recognizing this need, Hong Kong has implemented a range of transport policies aimed at improving accessibility and fairness in mobility. In public transportation, recent priorities include smoother and more accessible commuting through the implementation of HKeToll and station upgrades (Wikipedia, 2025a). At the airport level, efforts have focused on enhancing inclusive access, such as improved wheelchair facilities, expanded internal transit systems like the Automated People Mover (APM), and major infrastructure investment in the Three-Runway System (HKIA, 2025d; Wikipedia, 2025b,c). These initiatives reflect a growing commitment to ensuring that airport access is fair, efficient, and responsive to diverse user needs.

Despite these investments, substantial barriers remain. Inadequate transportation options (Ryerson and Kim, 2018), high travel costs (Hess et al., 2007), and uneven public transit coverage continue to restrict access, especially for lower-income groups (Bhadra, 2004). These barriers force many travelers to either forgo air travel altogether or incur additional burdens by accessing more distant airports. Fairness in airport accessibility requires targeted strategies that prioritize the needs of vulnerable populations, ensuring that the ability to fly is not determined by income level or residential location.

However, existing research reveals several gaps. Most airport accessibility metrics are based on spatial or infrastructural features, such as travel time or distance, and assume a homogeneous user population (Pan et al., 2023; Rahardja et al., 2022). Few models incorporate socioeconomic diversity or behavioral preferences that influence how different groups experience and evaluate transit options (Karam et al., 2022; Yoo et al., 2024, 2025). Additionally, airport bus scheduling models often prioritize system-level efficiency or cost minimization, with limited attention to how these choices affect vulnerable travelers.

To address these gaps, this study proposes a fairness-aware optimization framework that combines behavioral modeling with operational planning. We begin by introducing the Fairness Airport Accessibility Metric (FAAM), a utility-based measure that captures differences in travel preferences, constraints, and perceived utility across income groups. Building on this metric, we formulate a Two-Stage Airport Bus Scheduling and Allocation Model, constructed from two complementary stakeholder perspectives.

From a policy and operational standpoint, addressing airport accessibility involves multiple stakeholders with distinct priorities. On one hand, government agencies focus on enhancing overall urban accessibility, ensuring equitable mobility for all income groups and promoting transportation fairness. Governments prioritize policies that improve transit accessibility for underserved populations while maintaining an efficient and sustainable transportation system. On the other hand, bus companies must operate under government regulations, balancing their social responsibility of providing accessible transportation with the economic imperative of maintaining operational efficiency. Under this dual influence, two distinct decision-making approaches naturally emerge:

1. Accessibility-Driven Approach (Government-Led): The primary objective is to maximize accessibility for all income groups while incorporating economic considerations. In this framework, the first stage of decision-making focuses on maximizing accessibility, ensuring equitable access across different socioeconomic demographics. Then, in the second stage, cost efficiency is optimized while maintaining the accessibility constraints set in the first stage.
2. Cost-Driven Approach (Transit Operator-Led): The primary objective is to minimize operational costs while ensuring that a minimum level of accessibility is met. In this approach, the first stage focuses on minimizing operational costs while ensuring a baseline level of transit service. Then, in the second stage, the accessibility of the system is optimized within the cost constraints established in the first stage.

To validate the FAAM metric and demonstrate the effectiveness of our proposed models, we first conduct a case study in Hong Kong. Using real-world flight and transit data from all 18 administrative districts, we quantify substantial disparities in airport accessibility across income groups. Low-income districts face longer travel times, weaker service frequency, and misalignment with flight schedules, confirming the need for fairness-oriented planning tools. We then simulate a virtual transit network to conduct numerical experiments that integrate flight schedules, passenger demand, and service constraints. Sensitivity analyses across both the government-led and operator-led models demonstrate that a balanced trade-off between fairness and operational cost is achievable. Our results also show that excessive prioritization of either income group leads to inefficiencies or increased disparities. In contrast, balanced income weighting combined with targeted interventions, such as income-based fare subsidies or expanded service windows, significantly enhances accessibility without inflating costs.

The rest of the paper is structured as follows. Section 2 summarizes existing work and identifies key research gaps. Section 3 presents the FAAM metric and formalizes the two-stage optimization models. Section 4 applies the FAAM metric to assess real-world disparities across Hong Kong districts. Section 5 presents numerical experiments and sensitivity analyses evaluating trade-offs and policy levers. Conclusions will be presented in Section 6.

2. Literature review

Accessibility refers to the ease of reaching desired destinations and is influenced not only by spatial distance (Rossolov et al., 2021), but also by factors such as transportation mode, the quality of infrastructure (Coppola and Silvestri, 2018), travel time, and cost (El-Geneidy et al., 2016). In the context of air travel, airport accessibility captures how effectively airports connect users to local and global networks (Lenaerts, 2021). Common measures include quickest-path travel time (Burghouwt and Redondi, 2013), gravity-based interactions (Stacherl and Sauzet, 2023), and market potential indicators (Kompil et al., 2019), which collectively inform strategies to improve multimodal integration, service coverage, and regional connectivity. Beyond these, existing airport accessibility metrics can be broadly categorized into operational metrics, such as number of destinations served, flight frequency, and network centrality measures (e.g., degree and closeness), and spatio-temporal metrics, including travel costs, remoteness, routing feasibility, and link quality. While these approaches offer important insights into system-level performance and economic impact, they primarily adopt aggregate, network-wide perspectives. Consequently, they often fail to capture the individual traveler's experience and needs, limiting their ability to inform user-centered or fairness-aware accessibility assessments (Karam et al., 2022).

While these metrics provide valuable insights into network efficiency, they are typically developed using spatial and infrastructural data, often without accounting for differences in socioeconomic status or user behavior. Most models assume a homogenous traveler population, overlooking the fact that low-income travelers frequently face distinct challenges, such as limited access to affordable airport transit, compared to higher, income groups with more resources and flexibility (Pan et al., 2023; Rahardja et al., 2022). Furthermore, studies on long-distance air accessibility (e.g., Yoo et al., 2024; Avogadro et al., 2021) remain largely spatial, with limited attention to traveler perceptions or the behavioral dimensions of accessibility (Karam et al., 2022; Yoo et al., 2025).

Recent developments in airport access modeling have increasingly emphasized the need to account for heterogeneity in travelers' preferences, particularly in light of socioeconomic disparities. Discrete Choice Models, grounded in random utility theory, provide a robust analytical framework to capture individual-level trade-offs among travel time, cost, convenience, and service attributes (Choi et al., 2019; Prentice and Kadan, 2019; Bergantino et al., 2020; Kalakou and Moura, 2021; Hess et al., 2007; Hess and Polak, 2006). These findings highlight the necessity of complementing spatial analyses with critical individual and contextual variables in accessibility assessments, particularly income levels, trip purposes, and group composition. Accessibility manifests heterogeneously across populations, as identical transportation infrastructure can generate substantially different outcomes among socioeconomic groups (Karam et al., 2022). This evidence establishes that discrete choice modeling offers a principled and empirically grounded approach for constructing behaviorally sensitive accessibility metrics, ultimately enhancing both policy relevance and fairness in transit and airport planning.

Given the critical role of ground access in shaping airport accessibility, particularly for low-income travelers, airport bus services represent a vital mode whose planning directly impacts fairness in accessibility outcomes. Various research strands have emerged to optimize different aspects of airport bus scheduling and operations. Foundational studies focus on vehicle routing and scheduling under capacity and time-window constraints, as seen in the Airport Shuttle Bus Scheduling Problem, which formulates the task as a profit-maximizing assignment problem solved via mixed-integer programming and hybrid metaheuristics (Öner et al., 2020). Subsequent work extends to dynamic and uncertain contexts. For example, airport bus timetables have been optimized by incorporating passenger airport choice behavior and using multi-objective evolutionary algorithms to accelerate market share growth during early service phases (Lu et al., 2016). In lower-density suburban areas, bus routing models minimize access time through optimized stop selection and visit sequences, employing dynamic programming and nature-inspired heuristics (Chen et al., 2017). Recent research reflects evolving mobility needs by integrating airport buses with last-mile ride-sharing services. These studies jointly address stop selection, passenger assignment, and routing through decomposition-based heuristics, yielding improvements in both ride time and operational efficiency (He et al., 2024). Other efforts model hotel-to-airport transfers with uncertain demand using stochastic programming and recourse strategies like backup vehicles (Abdelaziz et al., 2017).

While bus scheduling plays a key role in providing economical access to airports, much of the existing research emphasizes cost-efficiency and service optimization, often overlooking accessibility from a fairness perspective. As a result, the transportation needs of underserved communities, particularly those with low income, are frequently unmet, exacerbating disparities in airport access.

This study builds upon and extends the current literature in several key ways:

1. Development of a novel accessibility metric: Unlike conventional accessibility measures that emphasize aggregate travel times and costs, our Fair Airport Accessibility Metric incorporates income-sensitive constraints and travel behavior to more accurately capture disparities in airport access.
2. Fairness-oriented bus scheduling optimization: Whereas existing airport bus scheduling models primarily optimize for cost and operational efficiency, we propose a Two-Stage Airport Bus Scheduling and Allocation Model that explicitly embeds fairness considerations, ensuring that travelers across different income groups can access airport transit on comparable terms.
3. Policy implications for fair and inclusive transportation planning: This study offers actionable insights for policymakers and transit agencies, emphasizing the importance of fairness-aware scheduling, demand-responsive services, and targeted fare interventions to close access gaps and promote inclusive airport connectivity for all socioeconomic segments.

3. Fairness-oriented accessibility modeling and optimization pipeline

This study introduces a dual-perspective optimization framework that systematically integrates fairness considerations into airport shuttle bus planning. The framework aims to reconcile the policy-driven objective of equitable access with the operational goal of cost efficiency. At its foundation is the Fairness Airport Accessibility Metric (FAAM), a utility-based measure that captures heterogeneity in traveler behavior, income-specific constraints, and perceived service utility.

Building on this metric, we formulate a Two-Stage Airport Bus Scheduling and Allocation Problem that reflects the divergent priorities of two key stakeholders: government agencies and public transit operators. The government-led model emphasizes maximizing

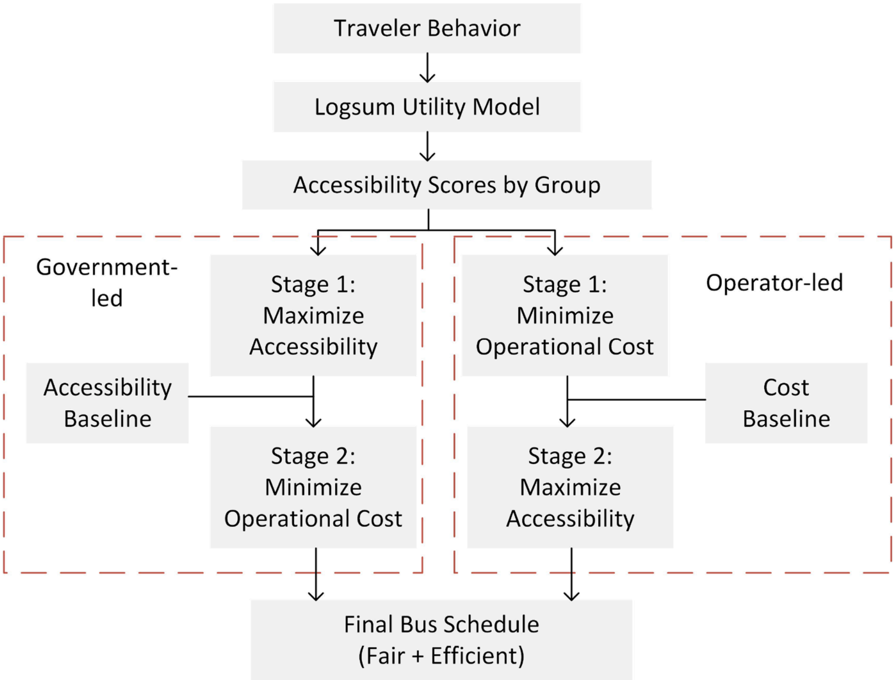

Fig. 1. Dual-perspective optimization framework for fair and efficient airport bus scheduling.

accessibility across socioeconomic groups before minimizing cost, whereas the operator-led model first seeks operational efficiency and then allocates accessibility gains within budget limits.

Fig. 1 illustrates the overall architecture of this framework. It begins with traveler behavior modeling through a logsum utility function, which generates income-stratified accessibility scores. These scores feed into two separate but complementary two-stage optimization pathways. In the government-led track, the first stage maximizes accessibility, establishing a fairness baseline, followed by cost minimization that preserves these fairness gains. Conversely, the operator-led pathway begins with cost minimization to establish a budget baseline, and the second stage then enhances accessibility within those constraints.

3.1. *Fairness-oriented airport accessibility metric design*

3.1.1. *Fairness airport accessibility metric*

This section introduces the Fairness Airport Accessibility Metric (FAAM), a behaviorally grounded indicator designed to address the limitations of traditional airport accessibility measures. Conventional metrics often emphasize spatial or temporal coverage at an aggregate level, neglecting the nuanced constraints and preferences of individual travelers, particularly those from economically disadvantaged groups. In contrast, FAAM is developed from a fairness perspective, evaluating accessibility as it is perceived and experienced by individuals across different income levels. The metric advances both theoretical and practical dimensions of transportation planning: theoretically, it provides a framework for researchers to integrate individual utility, behavioral sensitivity, and income-based variation into accessibility assessment; practically, it equips policymakers with a granular tool to identify and mitigate systemic inequities in airport transit systems.

Our design begins with a realistic user decision process: passengers have already purchased flights and must now select a suitable bus connection. For airport-bound bus users, accessibility hinges on two key decisions: (1) selecting a pre-flight bus that arrives at the airport within the required timeframe for check-in and boarding, and (2) selecting a post-flight bus that departs the airport shortly after landing, ensuring a timely transfer to their final destination.

Based on this behavioral analysis, airport accessibility for bus users can be categorized through three dimensions:

1. Time Accessibility captures the temporal alignment between bus schedules and flight operations. This dimension is operationalized through the concept of a *service window*, which defines the acceptable time range within which a bus trip can effectively serve a given flight. For arriving flights, the service window starts after a buffer period following landing, accounting for deboarding, baggage claim, and walking time to the bus stop. For departing flights, the service window represents the time when passengers should reach the airport to check in, clear security, and board without being too early or late. Buses arriving within this window are considered feasible. As shown in Fig. 2, service windows can overlap across flights. For instance, Bus Trip 1 can serve both Flight 1 and Flight 2 due to overlapping windows, while Bus Trip 2 serves only Flight 2. This mapping helps quantify time-based

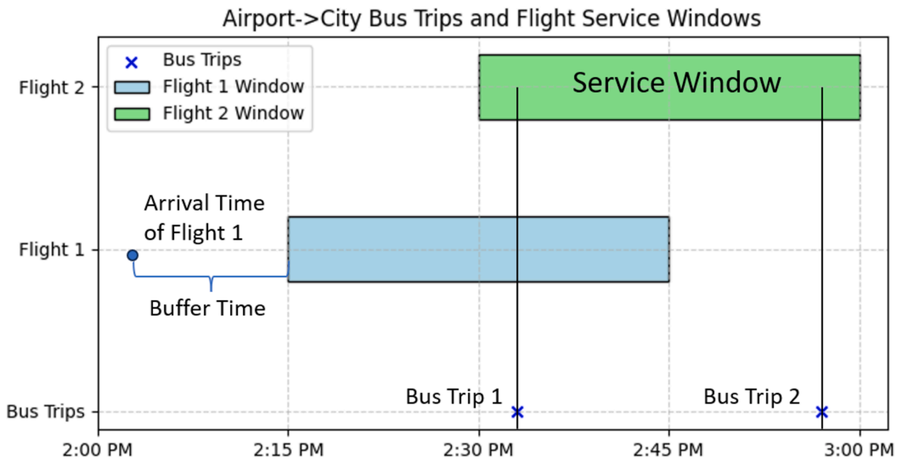

Fig. 2. Example of service window for flights.

accessibility and optimize bus departure times and frequencies. By maximizing service window coverage, transit planners can reduce wait times and improve airport bus connectivity.

2. Spatial accessibility refers to the convenience of bus stop locations relative to passengers' places of origin. This is especially critical for ensuring service coverage in underserved residential areas, where proximity to public transit strongly influences airport access.
3. Behavioral accessibility considers how passengers plan their trips, factoring in preferences such as waiting time, total travel time, flight frequency and cost. These personal choices influence the perceived quality of access.

To quantitatively evaluate these dimensions, we embed them within the Fairness Airport Accessibility Metric (FAAM) through a logsum-based utility framework that aggregates the perceived benefits of all feasible bus trip options across income groups. The metric is defined as:

$$\text{FAAM} = \sum_{q\in\text{groups}} \text{weight}_q \cdot \log\left(\sum_{k\in K}\sum_{l\in L} \text{availability}_{lk} \cdot e^{U_{qlk}}\right) \tag{1}$$

whether bus trip k is a viable option for flight l. The utility function U_{qlk} is the perceived utility of choosing bus k for flight l by income group q. where weight_q represents the accessibility weight of income group q; K denotes the set of bus trips; Availability_{lk} indicates whether bus trip k is feasible for flight l; and U_{qlk} is the perceived utility of choosing bus k for flight l by income group q.

The FAAM formulation is derived from a Multinomial Logit (MNL) framework, in which the logsum represents the expected maximum utility across feasible bus–flight alternatives. All access alternatives are treated as belonging to a single choice nest, and the associated independence-from-irrelevant-alternatives (IIA) assumption is therefore appropriate in this context

To operationalize income-based segmentation in a scalable and privacy-preserving manner, we classify passengers using census tract-level income data rather than individual-level records. Each bus stop is spatially mapped to its corresponding census tract, and passengers boarding at that stop are assigned the average income of that tract. This method offers several advantages. First, it ensures that income-based accessibility disparities are captured without relying on individual-level data, which can be difficult to obtain and subject to privacy concerns. Second, by integrating census-tract-based classification into the utility function, the model effectively differentiates accessibility experiences between high-income and low-income regions, reflecting variations in transit dependency, affordability concerns, and travel behavior. Lastly, the optimization model's constraints incorporate these distinctions, enabling bus schedules to be designed in a way that equally prioritizes accessibility for diverse socioeconomic groups, ensuring an equitable distribution of transit resources. This geographically aggregated approach enhances the model's applicability and accuracy in addressing income-based transportation inequalities while maintaining computational efficiency and policy relevance.

This structure enables FAAM to holistically integrate all three dimensions of accessibility. Time accessibility is captured via Availability_{lk} and the utility function U, which reflects schedule compatibility. Spatial accessibility is embedded through tract-level income classification based on passengers' boarding locations. Behavioral accessibility is directly represented in U_{qlk}, which includes user-sensitive variables such as waiting time, travel cost, and flight attributes. Together, these components ensure that FAAM not only quantifies access in technical terms but also reflects the lived realities of diverse user groups, making it an effective foundation for fairness-oriented airport bus scheduling.

3.1.2. Utility function specification

When choosing how to access the airport, travelers evaluate a combination of factors that influence their perceived benefit or cost of each option. These include not only tangible aspects like travel time and fare, but also subjective perceptions of convenience and schedule reliability. Importantly, the influence of these factors varies by socioeconomic group due to differences in income, opportunity cost of time, and sensitivity to financial constraints.

The utility function U measures the perceived benefit of selecting a specific travel option, accounting for multiple factors that influence airport accessibility. It integrates personal preferences and trade-offs across variables such as airfare, travel time, and socioeconomic factors, enabling a nuanced view of accessibility across income groups. The utility function is defined as:

$$U = \beta_1 \cdot \text{Airfare} + \beta_2 \cdot \text{Travel Time} + \beta_3 \cdot \text{Waiting Time} + \beta_4 \cdot \text{Flight Frequency} + \beta_5 \cdot \text{Access Time} + \beta_6 \cdot \text{Access Cost} + \kappa \tag{2}$$

where the coefficients β_i represent systematic sensitivities to observable attributes, and κ captures unobserved preferences. This error term κ is assumed to be independently and identically distributed extreme-value noise across observations, discrete choice events, and alternatives, consistent with the multinomial logit (MNL) framework.

The deterministic portion of utility is therefore defined as:

$$U = \beta_1 \cdot \text{Airfare} + \beta_2 \cdot \text{Travel Time} + \beta_3 \cdot \text{Waiting Time} + \beta_4 \cdot \text{Flight Frequency} + \beta_5 \cdot \text{Access Time} + \beta_6 \cdot \text{Access Cost} \tag{3}$$

This specification follows the attribute structure used in Hess and Polak (Hess and Polak, 2006), who estimate airport and airline choice models using formulations. Their empirical findings motivate the inclusion of cost-, time-, and frequency-related components, as well as income-group-specific sensitivity parameters.

For the full ground–air alternative defined by bus trips and flights for income group q, we express utility as: $U = V +$ error term.

Together, this structure provides a behaviorally grounded representation of travelers' airport access decisions. The airfare component reflects ticket costs, with low-income groups being more sensitive to price fluctuations, while high-income groups exhibit lower cost sensitivity. Travel time negatively affects all passengers, as longer durations reduce attractiveness while waiting time further decreases utility by increasing travel uncertainty. Flight frequency improves accessibility, offering greater flexibility, particularly for time-sensitive groups. Access time is more critical for high-income travelers who prioritize efficiency, whereas low-income groups weigh it against cost constraints. Similarly, access cost significantly impacts low-income groups, for whom affordability is a primary concern, while high-income groups prioritize convenience. Together, these components capture diverse income-based preferences, allowing the model to provide a comprehensive analysis of airport accessibility across different socioeconomic groups.

3.2. Two-stage airport bus scheduling and allocation problem

This study formulates the airport-accessible bus timetabling and vehicle scheduling challenge as a two-stage optimization framework that jointly considers passenger accessibility and operational efficiency. The goal is to design a fair and cost-effective scheduling system that guarantees all flights are adequately served while preserving fair transit access across socioeconomic groups. Two complementary modeling paradigms are introduced: a government-led model prioritizing fairness and a transit-operator-led model focusing on cost efficiency.

3.2.1. Problem description

The problem involves bi-directional bus transport between the city and the airport: (1) City to Airport direction – Passengers travel from the city to the airport to catch their departing flights, and (2) Airport to City direction – Passengers arrive at the airport and return to the city.

The bus line follows a fixed route from the city to the airport, passing through a set of census tracts $Q = \{1, 2, \dots, N\}$ in sequence. The airport is denoted as stop $N + 1$, and the extended set of all stops is given by $\bar{Q} = Q \cup \{N + 1\}$.

The set of flights departing from and arriving at the airport is denoted as $l \in L$. The set $L^{\text{out}} \subseteq L$ represents flights departing from the airport, and $L^{\text{in}} \subseteq L$ represents flights arriving at the airport. Each census tract $q \in Q$ has a demand h_{lq} for flight $l \in L$. Flights are uniquely identified by their origin or destination, scheduled time, and a flight ID. Although flights vary in temporal and spatial attributes, their acceptable bus service time windows may overlap, allowing passengers from different flights to share the same bus trip if timing permits.

The scheduling involves a set of bus trips $k \in \bar{K}$, where $\bar{K} = K \cup \{0\}$ includes all scheduled trips $k \in K$, along with the initial trip from the depot (stop 0) to the first stop and the final return trip to the depot. Each bus trip has a passenger capacity of c_k. The arrival time of bus trip k at each stop q is represented as t_{kq}. For each flight $l \in L$, there is a corresponding set of candidate bus trips K_l, where each bus trip can potentially serve flight l within the service window. The set L_k includes only those flights that fall within the feasible service window for trip k. All buses $b \in B$ begin and end their routes at the depot, with depot trips now incorporated in $\bar{K}$.

In the Fig. 3, three flights (Flight 1, Flight 2, and Flight 3) have service windows defined as $[1{:}05, 1{:}35]$, $[1{:}20, 1{:}50]$, and $[1{:}30, 2{:}00]$, respectively. Correspondingly, three candidate bus trips are considered with departure times at 1:10, 1:20, and 1:30. These times are mapped against the flight service windows, and the inclusion relationships are depicted:

$K_{l_1} = \{\text{Bus Trip 1}\}$: Bus Trip 1 is the only feasible candidate for Flight 1, as it departs at 1:10, falling squarely within the flight's service window.

$K_{l_2} = \{\text{Bus Trip 2}, \text{Bus Trip 3}\}$: Flights 2 and 3 share overlapping windows with Bus Trips 2 and 3, making them valid candidates.

$K_{l_3} = \{\text{Bus Trip 3}\}$: Only Bus Trip 3, departing at 1:30, lies within the service window for Flight 3.

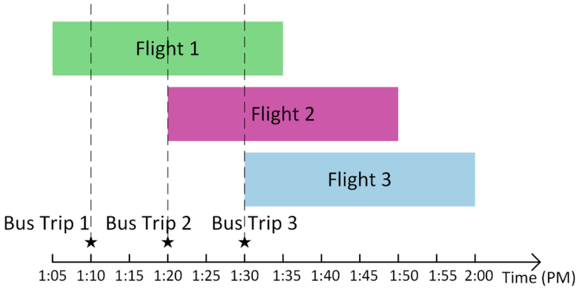

Fig. 3. Illustration of feasible assignment sets K_l and L_k.

From the bus trip perspective:

$L_{k_1} = \{\text{Flight } 1\}$: Bus Trip 1 can only serve Flight 1.

$L_{k_2} = \{\text{Flight } 1, \text{Flight } 2\}$: Bus Trip 2 is compatible with the service windows of both Flights 1 and 2.

$L_{k_3} = \{\text{Flight } 2, \text{Flight } 3\}$: Bus Trip 3 aligns with Flights 2 and 3.

Decision variable $y_{lk} = 1$ indicates that bus trip k serves flight l; otherwise, $y_{lk} = 0$. Every flight must have at least one bus trip assigned to serve its passengers. If a bus trip k is scheduled, the decision variable $x_k = 1$ is used; otherwise, $x_k = 0$. The decision variable $z_{kb} = 1$ indicates that bus b is assigned to bus trip k; otherwise, $z_{kb} = 0$. If bus b is used, then $w_b = 1$; otherwise, $w_b = 0$. Additionally, the variable $g^b_{k_0k_1} = 1$ indicates that bus b serves trips k_0 and k_1 in succession without any intervening trips; otherwise, $g^b_{k_0k_1} = 0$.

The goal is to optimize bus schedules such that all flights are served by the required number of bus trips, while also minimizing the operational costs of the bus system. This involves making decisions about which buses should serve which trips and ensuring that bus capacities and time constraints are respected.

The proposed optimization framework determines the optimal allocation of bus trips and bus assignments to strike a balance between maximizing accessibility for passengers and minimizing operational costs for the transit system.

3.2.2. Model structure: Government-led vs. Transit operator-led perspectives

To balance fairness and efficiency in airport shuttle bus scheduling, this study adopts two complementary planning perspectives: a government-led model and a transit operator-led model. Each reflects distinct institutional priorities and operational philosophies, informing how accessibility goals and cost-efficiency can be harmonized through optimization.

The Government-Led Model prioritizes fair access to airport transit services across socioeconomic groups. It emphasizes the inclusion of underserved populations by ensuring sufficient coverage in low-income areas, while maintaining fiscal discipline. This approach aligns with broader public policy goals, such as reducing mobility disparities, promoting inclusive transport planning, and advancing transportation justice.

In contrast, the Transit Operator-Led Model centers on operational sustainability, aiming to optimize schedules that minimize system costs while adhering to baseline fairness standards. This perspective focuses on the strategic allocation of limited resources to enhance service delivery without compromising financial viability.

Although grounded in different institutional roles, both models share a common analytical foundation: they apply optimization techniques to quantify trade-offs between fairness and efficiency. Collectively, they demonstrate how socially inclusive and fiscally responsible objectives can be jointly pursued in the design of accessible airport transportation systems.

3.2.3. Mathematical formulation

To operationalize the proposed framework, we develop a two-stage optimization model that captures the interaction between traveler preferences, transit schedules, and resource constraints. The modeling approach hinges on the Fairness Airport Accessibility Metric (FAAM), which evaluates user-perceived utility and accessibility across income groups. An overview of all model parameters and decision variables is provided in Table 1.

At the core of both government-led and operator-led models is the utility function, which quantifies the perceived benefit U_{lkq} of a traveler from census tract q selecting bus trip k to connect with flight l. For modeling purposes, each census tract is represented by its corresponding bus stop q. The utility incorporates key components that influence mode and schedule preference:

$$U_{lkq} = V_{lkq} + \kappa_{lkq} \tag{4}$$

$$V_{lkq} = \begin{cases} \alpha_q \cdot r_l + \beta \cdot t_l + \theta \cdot (d_l - t_{kq} - a_q) + \delta \cdot \log(f_l) + \gamma_q \cdot a_q + \zeta_q \cdot c, & \forall q \in Q, \forall l \in L^{out}, \forall k \in K_l \\ \alpha_q \cdot r_l + \beta \cdot t_l + \theta \cdot (t_{k,(N+1)} - b_l) + \delta \cdot \log(f_l) + \gamma_q \cdot \bar{a}_q + \zeta_q \cdot c, & \forall q \in Q, \forall l \in L^{in}, \forall k \in K_l \end{cases} \tag{5}$$

where V_{lkq} is the deterministic component obtained by substituting the corresponding attributes (airfare, flight time, access time, waiting time, etc.) for alternative (l, k), and κ_{lkq} denotes an alternative-specific constant (ASC) capturing systematic differences across bus–flight combinations that are not explained by observable variables.

Table 1
Notation for model formulation.

Sets	
Q	Set of census tracts
$\bar{Q}$	Extended set of tracts
L	Set of flights
L^{out}	Set of departing flights
L^{in}	Set of arriving flights
K	Set of candidate bus trips across the day
K_l	Candidate bus trips that can serve flight l
L_k	Flights in the feasible service window for trip k
B	Set of available buses
Parameters	
c	Passenger cost to travel via bus
α_q	Airfare coefficient for census tract q
β	Air travel time coefficient
θ	Wait time coefficient
δ	Flight frequency coefficient
γ_q	Access time coefficient for census tract q
ζ_q	Access cost coefficient for census tract q
λ_q	Destination and census tract specific weight
$p_{k_0k_1}$	Operating cost from the start of trip k_0 to the start of trip k_1, including depot-to-k travel cost or empty travel cost when k_0 and k_1 are in the same direction
o_b	Operating cost of bus b
u	Maximum allowable operating cost for both bus trips and buses
r_l	Average airfare for flight l
t_l	Average air travel time for flight l
f_l	Number of nonstop scheduled departures for flight l
d_l	Departure time of flight l
b_l	Arrival time of flight l
t_{kq}	Arrival time of bus trip k at stop q
a_q	Access time from the bus station in census tract q to the airport
$\bar{a}_q$	Access time from the bus station in the airport to census tract q
h_{lq}	Demand from a census tract q to the airport in a day for flight l
c_k	Capacity of bus trip k
$\phi_{\min}$	Minimum demand threshold for flight l as a percentage
$s_{k_0k_1}$	1 if bus trip k_0 ends before k_1 departs; else, 0
N_l	Maximum number of feasible trips for flight l, where $N_l = \lvert K_l \rvert$
μ	Scaling coefficient for accessibility
Auxiliary Variables	
y_{lk}	1 if bus trip k serves flight l; else, 0
ϵ	The difference between the first and second stage accessibility
Decision Variables	
x_k	1 if bus trip k is scheduled; else, 0
z_{kb}	1 if bus b serves bus trip k; else, 0
w_b	1 if bus b is used; else, 0
$g^b_{k_0k_1}$	1 if bus b serves trips k_0 and k_1 consecutively, with k_0 first; otherwise, 0
f_{ln}	1 if flight l is served by exactly n bus trips; else, 0
U_{lkq}	Utility for income group q from selecting bus trip k to serve flight l

This comprehensive structure allows the model to capture heterogeneous travel preferences and quantify accessibility across different socioeconomic profiles. It includes: airfare ($\alpha_q \cdot r_l$), average air travel time ($\beta \cdot t_l$), wait time, frequency effect ($\delta \cdot \log(f_l)$), access time ($\gamma_q \cdot a_q$ or $\gamma_q \cdot \bar{a}_q$), and bus access cost ($\zeta_q \cdot c$). The utility function U_{lkq} captures the perceived benefit of choosing a particular bus-trip–flight combination for travelers originating from census tract q. For modeling purposes, each census tract is represented by its corresponding bus stop q. The utility incorporates key components that influence mode and schedule preference, including airfare ($\alpha_q \cdot r_l$), average air travel time ($\beta \cdot t_l$), and waiting time (either between bus arrival and flight departure, or between flight arrival and bus departure). The term $\delta \cdot \log(f_l)$ reflects the influence of flight availability (measured by biweekly nonstop departure frequency) on traveler utility. Access time to the airport ($\gamma_q \cdot a_q$ or $\gamma_q \cdot \bar{a}_q$) and bus access cost ($\zeta_q \cdot c$) are also included to account for first/last-mile travel burdens, especially relevant to lower-income groups.

1) Government-led accessibility-first model

The government-led model prioritizes fairness in airport accessibility by first maximizing traveler utility across all socioeconomic groups and then minimizing the operational cost required to implement that accessibility plan. The first stage is formulated as follows:

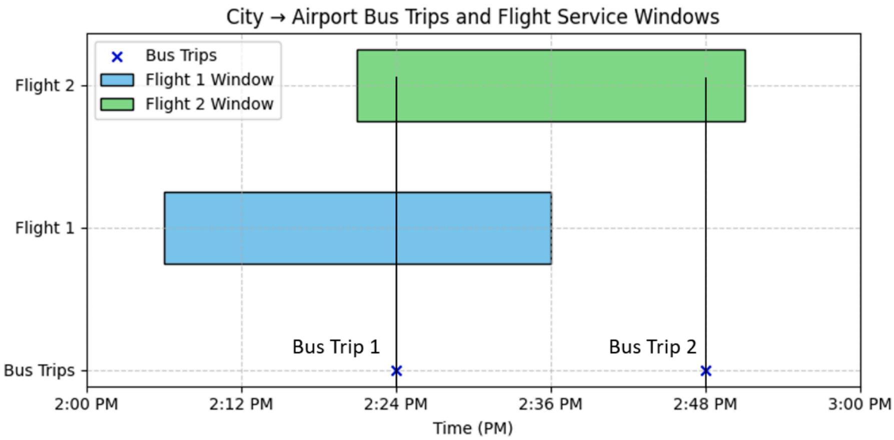

Fig. 4. Example of capacity allocation.

Stage 1: Maximize accessibility.

The first stage prioritizes accessibility across all income groups:

$$\max L(u) = \sum_{q \in Q} \lambda_q \cdot \log \left(\sum_{k \in K_l} \sum_{l \in L} y_{lk} \cdot e^{U_{lkq}} \right) \tag{6}$$

This objective aggregates the logsum-based accessibility of all census tracts, weighted by income group priority λ_q. It reflects the perceived accessibility at the population level, accounting for the availability of bus–flight connections.

Subject to:

(a) Flight-service assignment.

To ensure full flight coverage and operational consistency, the following constraints are imposed:

$$\sum_{k \in K_l} y_{lk} \geq 1, \qquad \forall l \in L \tag{7}$$

$$y_{lk} = x_k, \qquad \forall k \in K_l, \forall l \in L_k \tag{8}$$

Constraint (7) ensures that every flight $l \in L$ is served by at least one compatible bus trip $k \in K_l$, where K_l denotes the set of bus trips whose schedules align with the flight's service window. Constraint (8) enforces a logical coupling: a bus trip can only serve a flight if it is activated (i.e., $x_k = 1$). Once a bus trip is scheduled, it automatically serves all flights $l \in L_k$ whose time windows are feasible for that trip. This strategy maximizes operational efficiency by fully utilizing the available capacity of each bus trip and consolidating service across overlapping flights. The sets K_l and L_k are preprocessed to ensure schedule feasibility, thereby simplifying implementation while enhancing model realism.

(b) Capacity constraints.

To ensure operational feasibility, the model incorporates capacity constraints that regulate how passenger demand is distributed across scheduled bus trips. These constraints ensure that no bus is overloaded and that each flight's passenger demand is appropriately allocated.

$$\phi_{\min} \sum_{l \in L} \sum_{q \in Q} \sum_{n \in N_l} h_{lq} \cdot \frac{1}{n} \cdot f_{ln} \leq c_k \cdot y_{lk}, \qquad \forall k \in K, \forall l \in L \tag{9}$$

$$\sum_{n \in N_l} f_{ln} = 1, \qquad \forall l \in L \tag{10}$$

$$\sum_{k \in K_l} y_{lk} = \sum_{n \in N_l} n \cdot f_{ln}, \qquad \forall l \in L \tag{11}$$

Constraint (9) ensures that the total number of passengers assigned to bus trip k, aggregated across all census tracts and flights, does not exceed the bus's capacity c_k. Here, demand from each flight l is evenly distributed across n selected bus trips, with each trip bearing a proportion $1/n$ of the total passenger volume h_{lq}. The binary variable f_{ln} indicates whether exactly n bus trips are chosen to serve flight l, and M is a large constant used to deactivate the constraint when bus trip k is not assigned to flight l. Constraint (10) enforces that a unique number of bus trips n is selected for each flight. Constrain (11) links this value to the actual number of trips assigned to that flight, ensuring consistency between declared allocation size and scheduled service.

Fig. 4 provides a simple illustration of how these constraints govern passenger allocation. In the example, two flights have overlapping service windows and are served by two candidate bus trips. Bus Trip 1 is compatible with both flights, while Bus Trip 2 can only serve Flight 2. As a result: All passengers for Flight 1 are assigned to Bus Trip 1, which is the only feasible option. Passengers for Flight 2 are evenly divided between Bus Trip 1 and Bus Trip 2, yielding a 50–50 split. This example demonstrates how the model ensures demand-responsive and capacity-feasible allocation. By distributing passengers proportionally across feasible bus trips, the framework supports efficient resource utilization and aligns with the broader fairness and accessibility objectives of the scheduling system.

A simple numerical illustration helps clarify how these constraints prevent overload. A simple numerical illustration helps clarify how these constraints regulate demand allocation and prevent overload. Consider four flights ($l_1 - l_4$), each carrying 30 passengers, and three candidate bus trips ($k_1 - k_3$), each with a capacity of 40 seats. Suppose the feasible service sets are

$$K_{l_1} = \{k_1\}, \quad K_{l_2} = \{k_2, k_3\}, \quad K_{l_3} = \{k_2, k_3\}, \quad K_{l_4} = \{k_3\}.$$

In this configuration, all passengers of l_1 must be assigned to k_1, as it is the only feasible option. Flights l_2 and l_3, however, can be served by both k_2 and k_3. The model therefore splits their passengers evenly, allocating 15 passengers per flight to each of the two trips, in accordance with Constraints (9)– (11). Finally, flight l_4 contributes an additional 30 passengers to k_3. If the resulting load on any trip exceeds its capacity, the model is forced to activate an additional trip or adjust allocations to restore feasibility. For instance, should k_2 be assigned more than 40 passengers, this rule would be triggered. This mechanism ensures that capacity limits are never violated.

Together, the constraints guarantee a demand-responsive and capacity-feasible assignment structure. Passenger volumes are distributed proportionally across feasible trips, resource utilization is balanced, and the scheduling framework remains aligned with the system's broader fairness and accessibility objectives.

(c) Fleet assignment.

$$\sum_{b \in B} z_{kb} = x_k, \qquad \forall k \in K \tag{12}$$

$$z_{kb} \le w_b, \qquad \forall k \in K,\ \forall b \in B \tag{13}$$

Constraint (12) ensures that each active bus trip k (i.e., $x_k = 1$) is assigned to exactly one bus from the available fleet. Constraint (13) enforces a bus b to be assigned to a trip only if it is activated (i.e., $w_b = 1$).

(d) Bus routing.

$$g^b_{k_0 k_1} \le s_{k_0 k_1}, \qquad \forall b \in B,\ \forall k_0, k_1 \in K,\ k_0 \ne k_1 \tag{14}$$

$$\sum_{k_0 \in \bar{K} \setminus \{k_1\}} g^b_{k_0 k_1} = z_{k_1 b}, \qquad \forall b \in B,\ \forall k_1 \in K \tag{15}$$

$$g^b_{0k_1} + \sum_{k_0 \in K \setminus \{k_1\}} g^b_{k_0 k_1} = \sum_{k_2 \in K \setminus \{k_1\}} g^b_{k_1 k_2} + g^b_{k_1 0}, \qquad \forall b \in B,\ \forall k_1 \in K \tag{16}$$

$$\sum_{k \in K} g^b_{0k} = w_b, \qquad \forall b \in B \tag{17}$$

$$\sum_{k \in K} g^b_{k0} = w_b, \qquad \forall b \in B \tag{18}$$

Constraint (14) ensures that any two bus trips k_0 and k_1 can only be consecutively assigned to the same bus 4 if they are temporally feasible. The condition $s_{k_0 k_1} = 1$ is defined such that the pair of trips (k_0, k_1) can feasibly be served consecutively by the same bus b, based on timing and direction. With $s_{k_0 k_1} = 1$, we confirm that the sequence (k_0, k_1) is feasible for consecutive service by bus b, as the timing and operational constraints are satisfied. Therefore, $g^b_{k_0 k_1} = 1$ implies a feasible solution, as it ensures that each bus can proceed continuously from trip k_0 and k_1 without violating any constraints.

Constraint (15) enforces that each scheduled bus trip k_1 must have exactly one immediate predecessor trip when assigned to bus b. Constraint (16) guarantees route continuity through a flow balance condition. For any trip k_0, the number of incoming arcs (i.e., prior trips assigned to the same bus) must equal the number of outgoing arcs (i.e., trips that follow k_1 on the same bus). Constraints (17) and (18) ensure that each active bus route begins and ends at the depot. These conditions formalize complete bus routes and prevent partial sequences.

A small example illustrates how these feasibility checks work in practice. Consider three candidate bus trips with start times: k_1 at 08:00, k_2 at 08:55, and k_3 at 09:30. Suppose k_1 and k_2 operate in the same direction and require a minimum layover of $T_1 = 30$ min. If k_1 ends at 08:30, then it cannot precede k_2 because 08:30 plus the layover exceeds the start time of k_2. Now assume that k_2 and k_3 operate in opposite directions with a turnaround time of $T_2 = 5$ min. If k_2 ends at 09:25, then it can precede k_3 since 09:25 plus the turnaround time is no greater than the start time of k_3. These feasibility results are reflected by setting $s_{k_1 k_2} = 0$ and $s_{k_2 k_3} = 1$.

This example demonstrates how the model systematically constructs valid bus sequences and prevents infeasible chaining of trips. The preprocessing of $s_{k_0 k_1}$ greatly reduces computational complexity and ensures that all resulting bus routes are operationally sound, continuous, and compliant with layover and directional rules.

Remark 1. Trip sequencing feasibility and assignment compatibility

The parameter $s_{k_0 k_1}$ is a binary indicator, precomputed to determine whether two bus trips k_0 and k_1 can be consecutively assigned to the same bus b. This parameter is derived through a preprocessing step that evaluates temporal and directional feasibility, allowing the model to efficiently exclude incompatible trip pairs during optimization.

Two key conditions govern the feasibility of consecutive service:

1. **Opposite direction trips:** If trips k_0 and k_1 are scheduled in opposite directions (e.g., from the city to the airport and vice versa), the time interval between them must exceed the required preparation time for the bus to load and unload passengers and complete the turnaround. This condition is mathematically expressed as:

$$\text{End Time of } k_0 + \text{Preparation Time} \leq \text{Start Time of } k_1$$

2. **Same direction trips:** When both trips are in the same direction, the interval between them must be at least the time required for the bus to return to the starting point before proceeding. This condition is formulated as:

$$\text{End Time of } k_0 + \text{Return Time} \leq \text{Start Time of } k_1$$

If either of these conditions holds, then $s_{k_0 k_1} = 1$; otherwise, $s_{k_0 k_1} = 0$. This constraint structure ensures logical continuity in scheduling and prevents infeasible sequencing of trips.

(e) Budget constraint.

$$\&sum_{b\in B} \sum_{k_0 \in \bar{K}\setminus\{k_1\}} \sum_{k_1 \in \bar{K}\setminus\{k_1\}} p_{k_0 k_1} \cdot g^b_{k_0 k_1} + \sum_{b \in B} o_b \cdot w_b \leq u \tag{19}$$

$$x_k, y_{lk}, z_{kb}, w_b, g^b_{k_0 k_1}, f_{ln} \in \{0,1\}, \forall l \in L,\ \forall b \in B,\ \forall k, k_0, k_1 \in K,\ k_0 \neq k_1,\ n \in N_l \tag{20}$$

Constraint (19) imposes an upper bound u on total system-wide operating cost, including the cost of serving consecutive trip pairs (via $p_{k_0 k_1}$) and fixed costs per active bus (o_b). Constraint (20) defines the domain of decision variables.

Remark 2. Operational Cost Parameter $p_{k_0 k_1}$ and Cost Efficiency

The parameter $p_{k_0 k_1}$ represents the operational cost of assigning two trips k_0 and k_1 consecutively to a bus. It is derived based on trip direction and scheduling feasibility:

1. **Depot to first trip / last trip to depot:** If $k_0 = 0$, $p_{k_0 k_1}$ is the cost of dispatching a bus from the depot to the starting point of k_1. Similarly, if $k_1 = 0$, it indicates the cost of returning the bus to the depot after k_0.
2. **Same direction trips:** $p_{k_0 k_1}$ includes the operating cost of k_0 and the repositioning cost to the start of k_1 (same direction).
3. **Opposite direction trips:** $p_{k_0 k_1}$ also accounts for turnaround and repositioning costs if k_0 and k_1 are in reverse directions.

To ensure realistic accounting of operational movements, all deadheading, layover, and depot-related repositioning activities are explicitly costed within $p_{k_0 k_1}$. The transition cost combines a fixed departure component, a variable cost proportional to operating time, and, where applicable, an added repositioning cost reflecting direction changes or empty travel. This formulation guarantees that both in-service operations and non-revenue movements are captured within the optimization, enabling the model to generate operationally feasible and cost-consistent bus schedules.

By integrating $p_{k_0 k_1}$ into the objective function, the model seeks to maximize passenger utility while minimizing total operational cost, thus achieving a balanced trade-off between accessibility and resource efficiency. This formulation allows the optimization to internalize real-world cost structures, ensuring that bus scheduling decisions not only enhance service fairness but also remain operationally viable.

Stage 2: Minimize operational cost under accessibility constraint.

Once the Stage 1 model has established the maximum achievable level of accessibility across all income groups, this benchmark is used as a reference point for cost-oriented optimization. In Stage 2, the objective shifts toward minimizing the total operational cost of delivering the bus service plan while preserving accessibility at an acceptable level. This is achieved by embedding the Stage 1 optimal accessibility value into the Stage 2 formulation as a soft constraint, allowing for a controlled trade-off between service quality and cost efficiency.

$$\min \sum_{b\in B} \sum_{k_0 \in \bar{K}\setminus\{k_1\}} \sum_{k_1 \in \bar{K}\setminus\{k_1\}} p_{k_0 k_1} \cdot g^b_{k_0 k_1} + \sum_{b \in B} o_b \cdot w_b + \mu_1 \cdot \epsilon_1 \tag{21}$$

Subject to:

$$\epsilon_1 \geq L(u) - \sum_{q \in Q} \lambda_q \cdot \log\left(\sum_{k \in K_l} \sum_{l \in L} y_{lk} \cdot e^{U_{lkq}} \right) \tag{22}$$

$$x_k, y_{lk}, z_{kb}, w_b, g^b_{k_0 k_1}, f_{ln} \in \{0,1\}, \forall l \in L,\ \forall b \in B,\ \forall k, k_0, k_1 \in K,\ k_0 \neq k_1,\ n \in N_l \tag{23}$$

Remaining constraints are identical to Stage 1 (7)–(18).

The first term of the objective (21) accounts for the cost of assigning feasible trip sequences to buses, as captured by the pre-computed pairing cost $p_{k_0k_1}$ and assignment decision $g^b_{k_0k_1}$. The second term reflects the fixed costs of using bus b. This component not only captures the expense of operating individual vehicles but also provides a basis for capacity planning, as it enables transit agencies to anticipate the minimum number of buses required under different service and fairness scenarios. Therefore, the model can inform strategic decisions regarding fleet procurement and resource allocation in addition to daily operational scheduling. The third term introduces a flexibility cost based on deviations from accessibility optimality.

In Stage 2, the model focuses on minimizing the total operational cost while preserving the level of accessibility previously optimized in Stage 1. The value $L(u)$, representing the optimal accessibility obtained in Stage 1, is treated as an upper benchmark. A deviation term ϵ_1 is introduced in Constraint (22) to measure the loss in accessibility resulting from cost-oriented optimization decisions. This deviation is then softly penalized in the objective function through a tunable parameter μ_1, which balances the trade-off between operational efficiency and fairness.

By embedding the accessibility metric directly into the second-stage constraints and objective, the model ensures that cost minimization does not come at the expense of unacceptable accessibility loss. This bi-level integration allows the model to simultaneously account for social fairness and financial sustainability, resulting in a scheduling plan that is both inclusive and operationally viable.

2) Transit operator-led cost-first model

Following the government-led approach, which emphasizes fairness in accessibility, we now introduce the transit operator-led model that structured from the perspective of operational efficiency. While both frameworks share the same underlying system architecture and constraints, they differ fundamentally in optimization priorities and planning rationale.

Stage 1: Minimize total operational cost.

The first stage of the transit operator-led model prioritizes cost minimization, aiming to identify the most economically efficient scheduling plan. This formulation does not include an explicit accessibility constraint. Instead, a lower bound on accessibility is implicitly maintained through the existing capacity constraints, which ensure that a minimum level of service is provided to meet passenger demand. In other words, while accessibility is not directly optimized in this stage, it is not entirely ignored, as the system must still accommodate a baseline number of passengers through feasible bus-trip-flight assignments.

$$L(c) = \min \sum_{b\in B} \sum_{k_0\in \bar{K}\setminus\{k_1\}} \sum_{k_1\in \bar{K}\setminus\{k_1\}} p_{k_0k_1} \cdot g^b_{k_0k_1} + \sum_{b\in B} o_b \cdot w_b + \mu_1 \cdot \epsilon_1 \tag{24}$$

subject to: Constraints (7)–(18)

All operational and scheduling constraints from Stage 1 of the government-led model (Constraints (7)–(18)) remain in effect to ensure service coverage, fleet continuity, and routing feasibility.

Here, the objective function (24) minimizes the total operational cost, composed of two main components: the cumulative cost of assigning feasible sequences of bus trips ($p_{k_0k_1}$) and the fixed operating cost associated with deploying each bus (o_b).

Stage 2: Maximize accessibility under cost constraints.

In the second stage of the operator-led model, the objective shifts from purely minimizing cost to improving accessibility within the financial limits established in Stage 1. The model maximizes aggregate accessibility across all census tracts while explicitly penalizing operational cost increases beyond the previously optimized baseline.

$$\max \sum_{q\in Q} \lambda_q \cdot \log\left(\sum_{k\in K_l} \sum_{l\in L} y_{lk} \cdot e^{U_{lkq}}\right) - \mu_2\epsilon_2 \tag{25}$$

The first term in the objective function (25) represents the total logsum-based accessibility. The second term introduces a penalty for cost deviations, where ϵ_2 measures the increase in operational cost relative to the minimum cost benchmark $L(c)$. The trade-off is moderated by the parameter μ_2, which reflects the operator's tolerance for cost increases in pursuit of improved accessibility.

Subject to:

$$\epsilon_2 \geq \sum_{b\in B} \sum_{k_0\in \bar{K}\setminus\{k_1\}} \sum_{k_1\in \bar{K}\setminus\{k_1\}} p_{k_0k_1} \cdot g^b_{k_0k_1} + \sum_{b\in B} o_b \cdot w_b + \mu_1 \cdot \epsilon_1 - L(c) \tag{26}$$

Constraints (7)–(18)

$$x_k, y_{lk}, z_{kb}, w_b, g^b_{k_0k_1}, f_{ln} \in \{0,1\}, \quad \forall l \in L, \forall b \in B, \forall k, k_0, k_1 \in K, k_0 \neq k_1, n \in N_l \tag{25}$$

All other constraints remain consistent with the government-led model (Constraints (7)–(18)).

Constraint (26) ensures that any improvements in accessibility do not lead to excessive increases in operational cost compared to the baseline obtained in Stage 1. By embedding this deviation into the objective function, the model balances access gains with budget discipline, guiding service enhancements toward routes and stops where they yield the highest marginal benefit per cost.

3.3. Two-stage solution framework

To reflect the differing priorities of public agencies and transit operators, the proposed scheduling model is solved through a two-stage procedure under two decision paradigms: a Government-led Accessibility-First approach and an Operator-led Cost-First approach. Both paradigms use the same underlying MILP structure but apply it in a sequential manner that anchors one objective in Stage 1 and refines the complementary objective in Stage 2. This design enables transparent trade-off evaluation and ensures that each stakeholder's primary goal is satisfied before optimizing the secondary goal.

Government-led accessibility-first procedure

The government-led approach prioritizes maximizing accessibility while ensuring that costs remain within an administratively acceptable range. The procedure consists of the following steps:

1. Initialization

Load all model inputs, including candidate bus trips, vehicle availability, flight schedules, demand by income group and zone, and a loose upper bound on operating cost $C_{\max}^{\text{loose}}$. A scaling parameter μ_1 is set to control accessibility loss in Stage 2.

2. Stage 1: Maximize Accessibility under Loose Cost Bound

A MILP model G_1 is constructed with the objective

$$\max A(x),$$

subject to service coverage, demand-satisfaction, bus capacity, headway, and fleet-assignment constraints.

The cost constraint

$$C(x) \le C_{\max}^{\text{loose}}$$

is imposed but intentionally kept non-binding to avoid restricting feasible schedules.

3. Solve Stage 1 If G_1 is infeasible, model inputs such as candidate trips or allowable cost bounds are adjusted and Stage 1 is rebuilt. If feasible, the optimal solution yields

$$x_A^*, \quad A_A^*, \quad C_A^*.$$

4.Stage 2: Minimize Cost while Preserving Maximum Accessibility

A second MILP model G_2 is formulated with objective

$$\min C(x) + \mu_1 \varepsilon_1,$$

where ε_1 represents the allowed accessibility shortfall.

The constraint

$$\varepsilon_1 \ge A_A^* - A(x)$$

ensures that accessibility in Stage 2 does not decrease by more than ε_1.

All operational constraints from Stage 1 are retained.

5. Solve Stage 2

The resulting solution

$$x_G^*, \quad A_G^*, \quad C_G^*$$

represents the optimized government-led schedule that achieves nearly maximal accessibility at minimized cost.

Operator-led cost-first procedure

Transit operators typically focus on minimizing operating cost while still providing a basic level of service. The operator-led approach reverses the priority structure of the government-led model:

1. Initialization Load candidate trips, vehicles, demand, and a loose lower bound on service requirements. Define a weighting parameter μ_2 for controlling cost increases in Stage 2.

2. Stage 1: Minimize Cost under Loose Accessibility Requirement

A MILP model O_1 is constructed with the objective

$$\min C(x),$$

subject to operational constraints and a minimal service requirement.

3. Solve Stage 1 If O_1 is infeasible, candidate trips or feasibility settings are adjusted. If feasible, the solution provides a cost-anchored baseline:

$$x_C^*, \quad C_C^*, \quad A_C^*.$$

4. Stage 2: Maximize Accessibility with Cost Anchored

A second model O_2 is formulated with the objective

$$\max A(x) - \mu_2 \varepsilon_2,$$

where ε_2 captures allowable cost increases beyond the baseline.

The constraint

$$\varepsilon_2 \geq C(x) - C_C^*$$

ensures that cost deviation is explicitly penalized. All operational constraints remain identical to Stage 1.

5. Solve Stage 2

The optimal operator-oriented schedule

$$x_O^*, \quad A_O^*, \quad C_O^*$$

achieves the best possible accessibility improvement without substantially increasing cost relative to the operator's baseline plan.

4. Case study

4.1. Background: Airport access in Hong Kong

As of 2025, Hong Kong International Airport (HKIA) ranks 6th globally in Skytrax's World's Top 100 Airports and has returned to the list of the world's 10 busiest airports (Hub, 2025), handling over 5 million passengers per month. It connects to more than 220 global destinations via 120 airlines (HKIA, 2025a), reinforcing its role as a major international hub. Hong Kong is geographically isolated as a peninsula surrounded by islands. Air travel is the dominant and often only feasible option for long-distance trips beyond Mainland China, particularly to Southeast Asia, Europe, and North America. Unlike continental systems such as the European or Mainland China high-speed rail network, Hong Kong lacks comparable long-distance rail or ferry alternatives.

HKIA's strategic importance is not only infrastructural but also socioeconomic. As a global business center, Hong Kong generates considerable demand for international air travel, both for business and personal purposes. Its airport has earned international praise for its efficiency, connectivity, and service quality, often outperforming peer cities in terms of processing speed and traveler experience.

Despite these strengths, ground access to the airport remains a critical equity issue. While high-speed options like the Airport Express (HKD $115 one-way) and taxis (often exceeding HKD $300–400 from distant districts) provide rapid but expensive access, bus services remain the only affordable mode for many residents. In total, there are approximately 80 airport-bound bus routes in operation (HKIA, 2025b). These buses offer lower fares (typically HKD $20–40), making them particularly important for low- income and middle-income travelers. However, bus access varies substantially across districts in terms of coverage, frequency, and travel time (Chang et al., 2019).

Hong Kong is a city marked by deep socioeconomic disparities. As shown in official 2024 census data, median monthly household income across the 18 District Council districts ranges from HKD $24,200 (Kwun Tong) to HKD $42,400 (Central and Western), with the city-wide average at HKD $30,000 (HKSAR, 2025). These income differences shape people's travel behavior and access to long-distance mobility. Residents of districts such as Sham Shui Po, Kwun Tong, and Wong Tai Sin, all with relatively low-income levels, often face longer travel times, fewer direct bus routes, and higher access costs to reach HKIA.

Moreover, systemic inequities in long-distance air travel are further highlighted when considering specific groups. One prominent example is the community of foreign domestic helpers (FDHs). In 2024, Hong Kong is home to over 368,000 FDHs, primarily from the Philippines (55%) and Indonesia (42%), comprising 9.6% of the local workforce (LegCo, 2025). These individuals are typically required by contract to return to their home countries every two years. Yet, the cost of round-trip airfare (HKD $1,500–3,300) represents a significant financial burden against their monthly wage of around HKD $5,000. Many FDHs fall into debt to finance travel and recruitment expenses. Although contributing more than HKD $100 billion (Time, 2019) to the Hong Kong economy annually, FDHs often face barriers to accessing affordable, frequent, and well-timed transport to the airport, especially when living in remote low-income neighborhoods poorly served by bus routes.

Similarly, public housing residents, many of whom reside in the New Territories, encounter multiple transfers, long walking distances, and time-consuming detours when accessing airport bus stops. Compared to higher-income areas with dense bus connectivity and direct services (e.g., Central, Wan Chai), these residents are disproportionately impacted by the current spatial configuration of airport access.

In this context, our study introduces the Fairness Airport Accessibility Metric (FAAM) to empirically assess how different socioeconomic and geographic groups in Hong Kong experience varying levels of accessibility to HKIA via bus. This case study focuses on quantifying such disparities and identifying regions of potential policy intervention.

4.1.1. Data sources and parameterization

To operationalize the FAAM metric in the context of HKIA, we collected multi-source empirical data reflecting airfare, flight schedules, service frequency, and ground transportation accessibility. Our approach integrates aviation and ground transport data through public and proprietary APIs to construct an individualized, zone-based accessibility analysis across Hong Kong's 18 administrative districts.

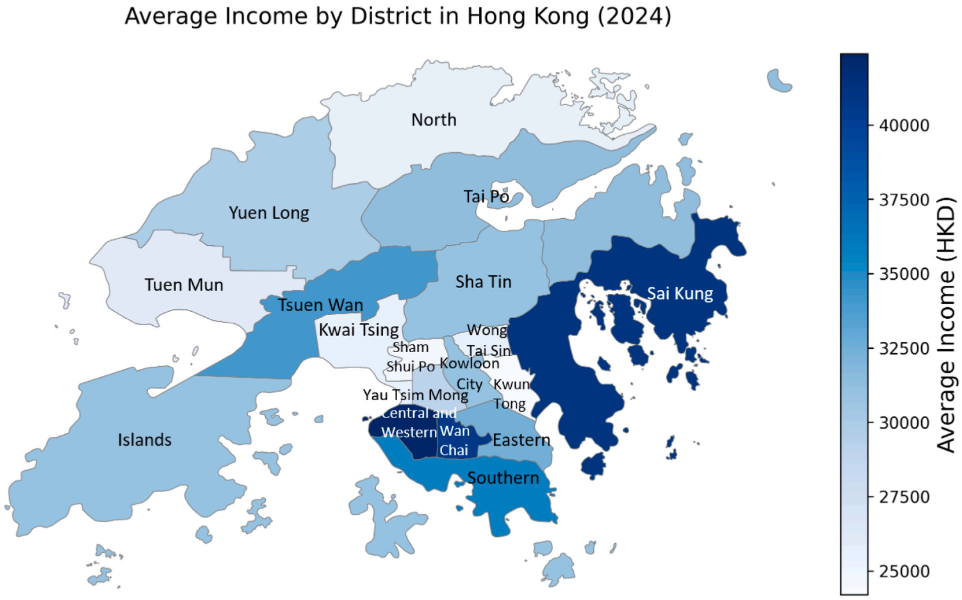

Fig. 5. Average household income in 18 districts of Hong Kong (2024).

4.1.2. *Air travel variables*

Each flight l is characterized by the following components:

- Airfare (r_l): For each arrival and departure flight serving HKIA, we first identified all active flights via the FlightRadar24 platform (Flightradar24, 2025). These flight numbers were then queried using the Google Flights API (API, 2025), retrieving average round-trip fares across a rolling two-week window. This approach approximates the dynamic pricing landscape faced by travelers booking short- to mid-term itineraries.
- In-Air Travel Time (t_l): Retrieved through the Google Flights API, in-air flight time for each flight l was recorded as the scheduled airborne duration between Hong Kong and its respective destination or origin airport.
- Departure and Arrival Times (d_l, b_l): Scheduled takeoff time (d_l) and landing time (b_l) were sourced directly from HKIA's official flight data (HKIA, 2025c), ensuring time-specific consistency for daily service scheduling.
- Flight Frequency (f_l): Using a web scraper on the Google Flights API, we tracked each flight number's presence over a 14-day interval to determine its operational frequency. This method reflects seasonal patterns and weekly service variability while smoothing out short-term disruptions.

4.1.3. *Ground transportation accessibility variables*

For each zone q representing one of Hong Kong's 18 districts, we define access to HKIA via bus or car using the following:

- Automobile Travel Time (a_q): Google Maps was used to estimate average vehicle travel time from the representative centroid of each district to HKIA, assuming regular daytime traffic conditions.
- Public Bus Routes and Schedules (t_{kq}): Bus departure times and route structures were collected from Citybus. We accessed route-level data via Citybus's official website (Citybus, 2025), which includes route maps and scheduled departure intervals.
- Ground Access Fare (c_q): For each zone q, we computed the average bus fare from the district centroid to HKIA, based on the fare tables available on the Citybus route interface. This forms a critical component of the cost impedance in our utility formulation.

4.1.4. *Fairness parameterization*

To account for income-based variation in accessibility, we classify Hong Kong's 18 districts into two socioeconomic categories:

- High-income districts: Defined as those with a median monthly household income above the city-wide average (HKD $30,000).
- Low-income districts: All remaining districts below this threshold.

We apply district-based coefficients that differ across these two categories. A complete list of coefficients and their source references is summarized in Table 2. The coefficients in the utility function (Table 2) are based on discrete choice modeling studies conducted by Hess et al. (2007) and Hess and Polak (2006). These studies use stated and revealed preference data to model airport, airline, and access mode choices. The coefficients reflect key trade-offs made by travelers. Airfare (α_q) reflects income-group-specific sensitivity to ticket prices of each group q; Travel Time (β) captures the negative impact of extended travel durations; Waiting Time (θ) quantifies the disutility caused by longer waiting periods; Flight Frequency (δ) represents the positive utility derived from higher flight availability;

Table 2
Estimated coefficient values for airport accessibility model (Hess and Polak, 2006).

Coefficient	Value
$\alpha_{\text{low-income}}$ · (airfare for low-income)	-0.0501
$\alpha_{\text{high-income}}$ · (airfare for high-income)	-0.0267
β · (travel time)	-0.0293
θ · (waiting time)	-0.2507
δ · (flight frequency)	1.3066
$\gamma_{\text{low-income}}$ · (access time for low-income)	-0.0496
$\gamma_{\text{high-income}}$ · (access time for high-income)	-0.0820
$\zeta_{\text{low-income}}$ · (access cost for low-income)	-0.0286
$\zeta_{\text{high-income}}$ · (access cost for high-income)	-0.0219

Access Time (γ_q) indicates the inconvenience of longer travel times to the airport, with differences across income groups; Access Cost (ζ_q) reflects the financial burden of access costs, particularly significant for low-income travelers. Consistent with multinomial logit theory, this error term is assumed to be independently and identically distributed with an extreme-value (Type I) distribution across observations, choice events, and alternatives. This assumption is widely used in airport-access modeling and leads to a closed-form logsum expression for expected maximum utility, which forms the foundation of our FAAM metric.

The estimated coefficient values are as follows:

These coefficients provide a comprehensive framework for evaluating airport accessibility, reflecting the diverse preferences and constraints across different income groups. It is important to note that the values used in this study are illustrative and drawn from prior literature. The proposed model is flexible and readily accommodates context-specific parameter adjustments. In practical applications, coefficients can be recalibrated using local travel survey data or updated preference studies to better reflect regional behavior patterns and policy environments. While the current study adopts a two-group (high vs. low income) classification for simplicity, this structure is extensible. Future research could incorporate three or more income bands (e.g., low, middle, high) or further stratify travelers based on occupation, age, or travel purpose. This would enable more granular modeling of air travel constraints and accessibility barriers.

4.2. Calibrating and validating utility coefficients for the Hong Kong case

4.2.1. Macro-level justification for parameter transfer

The discrete-choice coefficients obtained from Hess and Polak (2006) were originally estimated for the San Francisco Bay Area, yet several macro-level similarities between the Bay Area and Hong Kong justify their transfer to the HKIA context. Both regions are polycentric coastal megaregions anchored by major international hubs (SFO and HKIA) with comparable pre-pandemic passenger volumes (57.5 million vs. 71.5 million) and strongly international, long-haul traffic mixes (SFO, 2019; HKIA, 2019). Both airports serve as major international hubs with high frequencies of medium/long-haul flights and a strong regional feeder role. High commuting and business-travel intensity in both metropolitan areas. Hong Kong's Gini coefficient is among the highest in developed economies, reflecting deep income inequality. San Francisco's Gini coefficient is also elevated, driven by tech wealth and housing costs. In the Hong Kong context, high inequality coexists with a well-developed public transit system (MTR and buses) that limits private car dependence. However, lower-income residents still face long commutes and limited housing near transit hubs (C&SD, 2021). Although San Francisco has higher car ownership, both regions show clear income-segmented modal patterns. Wealthier travelers increasingly use private cars or ride-hailing, while lower-income groups depend on buses, BART, or the MTR (SFMTA, 2019). For airport access specifically, both metropolitan areas operate within planning frameworks that highlight fair and sustainable mobility. This reinforces the importance of understanding income-differentiated accessibility outcomes.

These structural parallels in airport role, demand intensity, multimodal access environment, and income-segmented behavior provide a credible behavioral foundation. They support treating the Hess–Polak coefficients as portable predictors of access-mode sensitivity in the Hong Kong setting.

4.2.2. Empirical validation using the A21 airport bus corridor

To provide localized grounding beyond macro-level arguments, we implemented a corridor-level validation using Hong Kong's A21 airport bus line, which spans four socioeconomically distinct districts: Kowloon City, Yau Tsim Mong, Sham Shui Po, and Kwai Tsing. Income group assignment followed census median income (Kowloon City = high-income; others = low-income). For each district, we used the actual A21 timetable and observed HKIA flight schedules to construct all feasible bus–flight connections based on a behaviorally realistic service window of 65–80 min prior to flight departure. Flights not serviceable within this window (e.g., early-morning departures before A21 service begins) were excluded. District-level weights λ_q were derived from population shares to reflect the distribution of potential travelers (C&SD, 2025).

Using the unadjusted Hess–Polak coefficients, the resulting FAAM values were (see Table 3):

Population-weighted aggregation yields a corridor FAAM of 25.8. The spatial pattern follows the expected accessibility hierarchy observed in real HKIA access patterns, namely Kowloon City, followed by Kwai Tsing, and Sham Shui Po, and then Yau Tsim Mong. This consistency provides initial empirical evidence that the transferred coefficients reproduce plausible spatial accessibility differences in Hong Kong.

Table 3
Unadjusted baseline coefficient set.

Tract	FAAM
Kowloon City	43.7
Yau Tsim Mong	18.2
Sham Shui Po	20.1
Kwai Tsing	20.5

Table 4
Scenario-based behavioral perturbation set.

Scenario	FAAM
Base (SFO coefficients)	25.8
High time sensitivity	24.9
Low access cost sensitivity	26.2
Low cost sensitivity	33.5
Mixed heterogeneity	23.2

4.2.3. Robustness of coefficient transfer: Behavioral scenario analysis

To address reviewer concerns regarding parameter sensitivity, we conducted a scenario-based robustness test in which major behavioral dimensions were systematically perturbed while holding the transportation supply fixed. The scenarios include:

- High time sensitivity: β, γ increased by 30%
- Low access cost sensitivity: ζ decreased by 30%
- Low cost sensitivity: α, ζ decreased by 30%
- Mixed heterogeneity: random $\pm 20\%$ variation applied to all coefficients

The resulting corridor-level FAAM values are see Table 4):

After conducting a series of parameter adjustments, we find that the results remain broadly stable across all scenarios. This indicates that the parameters calibrated with SFO Airport data can, to a certain extent, be transferred to the context of HKIA, and that the model is resilient to moderate variations in inputs. First, the relative ranking of the four districts does not change under any scenario. This shows that the spatial fairness pattern is structurally robust and not driven by any specific parameter setting. Second, the changes in FAAM values are intuitive and align with known travel behavior in Hong Kong. For example, when cost sensitivity decreases, districts with more price-sensitive travelers show higher accessibility levels, which is consistent with established evidence on fare elasticity among low-income groups. The scenario with low cost sensitivity (-30% α, ζ) generates the largest increase in FAAM because the cost coefficients influence not only ground-access fares but also airfare. As a result, reducing α and ζ effectively lowers the perceived disutility of the entire end-to-end journey (origin → airport → destination). This amplifies the improvement in generalized utility across all feasible alternatives, thereby producing a more pronounced accessibility gain compared with adjustments made to time-related parameters alone. Aside from this expected amplification effect, the FAAM values across all remaining scenarios remain close to the baseline, and the qualitative insights, such as spatial ordering, fairness implications, and relative policy effects, remain intact. Third, even with coefficient perturbations of ± 20 percent, the FAAM values remain close to the baseline, and all key qualitative insights persist. These results together demonstrate that the model tolerates reasonable levels of misspecification and that its main conclusions are robust.

4.2.4. Evidence for transferability and extensibility

Taken together, the macro-level similarity, corridor-level empirical validation, and scenario-based robustness analysis demonstrate that the SFO-estimated coefficients are:

- Transferable: They reproduce realistic, interpretable accessibility patterns when applied to Hong Kong's actual schedule and population data.
- Stable: After conducting a series of coefficient-perturbation experiments, the key results remain stable under wide perturbations. District rankings, fairness gaps, and the direction of policy effects all stay consistent.
- Extensible: The specification supports more granular segmentation (e.g., high–middle–low income, elderly travelers, occupational groups) and can accommodate Hong Kong-specific stated preference or revealed preference data if available in future work.

4.3. Accessibility results and fairness analysis

To evaluate the accessibility of Hong Kong Airport across income groups, we computed FAAM-based accessibility scores for each of the city's 18 districts. Each district is represented by a single, central reference point, and the availability component ($\text{availability}_{lkq}$) is defined as the total number of direct bus routes and their daily departures connecting that district to HKIA. These routes were derived from official Citybus airport bus service schedules.

Fig. 6. FAAM-based accessibility scores to HKIA.

The resulting accessibility scores vary substantially across districts (Fig. 6). High-density, inner-city districts such as Central and Western (97.2), Wan Chai (94.9), and Eastern (94.1) achieve the highest accessibility values. These areas benefit from dense public transport coverage, multiple overlapping airport bus routes, and short travel distances to HKIA. In contrast, districts in the New Territories such as North (14.2), Tuen Mun (14.5), Tai Po (15.5), and Yuen Long (15.9) exhibit the lowest accessibility. While their population densities are significant, these districts have fewer direct airport bus connections, and longer travel times, factors that sharply reduce their availability scores.

The core source of disparity lies in the number of available trips and the alignment between bus schedules and flight departures. This mismatch becomes especially critical during late-night and early-morning hours, when service frequencies often decline to one departure per hour. These time windows, while associated with lower airfares, are disproportionately inaccessible to residents in remote areas, further widening the gap between affordability and availability.

From a fairness perspective, the accessibility map reveals deep structural imbalances. Some high-income districts, such as Kowloon City (70.4), have relatively fewer airport routes due to their low-density residential character (e.g., Kadoorie Hill or Deep Water Bay). However, their close proximity to HKIA allows them to maintain moderate-to-high accessibility scores, despite limited service coverage. In contrast, low-income districts such as Sham Shui Po (36.3), Kwun Tong (38.1), and Wong Tai Sin (39.6) are located at similar distances from the airport but exhibit significantly lower accessibility. This is largely due to fewer direct bus routes and weaker transit integration, which collectively constrain their ability to affordably and reliably access air travel. In the outer New Territories, the physical distance is compounded by poor bus connectivity, making air travel particularly difficult for low-income residents who rely on public transport. Although airport bus fares remain relatively affordable (HKD $20–40), the availability and time costs borne by low-income travelers represent a form of hidden exclusion, limiting access to economic opportunities, family visits, or emergency travel.

These disparities underscore the importance of targeted transit interventions. While the FAAM metric effectively identifies regions with limited accessibility, this study also proposes a bus scheduling optimization model to address these gaps. By incorporating real flight schedules, income-based demand segmentation, and operational constraints, the model enables a more equitable distribution of limited transit resources. Specifically, it supports dynamic allocation of buses to underserved time windows and low-accessibility districts, especially during red-eye hours when commercial service is limited but demand remains high.

This dual approach, combining diagnostic and prescriptive tools, demonstrates the value of embedding income group differentiation into accessibility planning. High-income areas, while already well served, leave limited room for marginal improvement. However, for low-income districts, even modest scheduling enhancements can yield disproportionately large fairness gains. Therefore, considering income-sensitive travel needs is essential not only for transport fairness but also for regional development and inclusive service design.

From a policy perspective, these results point to several key recommendations:

- Fairness-weighted planning metrics (like FAAM) should be incorporated into transit investment strategies to ensure that accessibility improvements benefit vulnerable populations.
- The expansion of late-night and early-morning service, even on a targeted basis, could dramatically improve access for residents with limited alternatives.

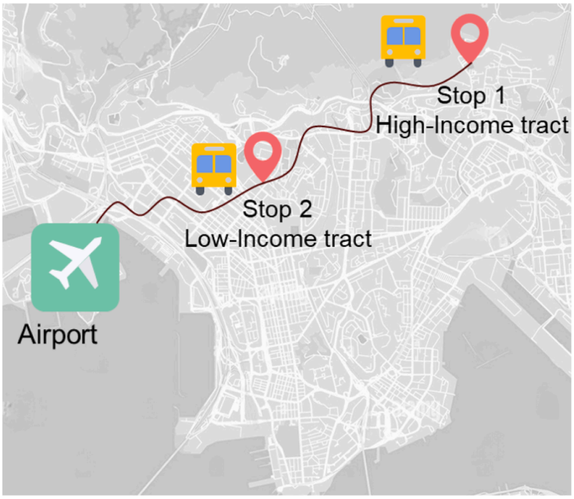

Fig. 7. Synthetic bus routes and stops.

- Rather than relying solely on system-wide improvements, targeted subsidies should be implemented in areas with poor transportation, such as increasing bus frequency, reducing fares, or launching dedicated shuttle services to narrow service gaps and ensure fair access across regions.

Ultimately, the integration of FAAM and the bus scheduling model provides a scalable and policy-relevant framework for improving airport access in Hong Kong. It reinforces the idea that fairness is not a byproduct of efficiency, but a necessary design objective in public transport planning.

5. Numerical experiments

To validate the proposed accessibility metric and bus scheduling optimization model, we constructed a realistic synthetic setting that integrates real-world flight data from Hong Kong International Airport (HKIA) with synthetically generated public transit network inputs. In this setting, virtual bus stops and service routes were designed to reflect typical urban-airport connectivity patterns, while the flight data ensures empirical grounding. This hybrid experimental setup enables systematic testing of the model's performance under varying transit configurations and socioeconomic conditions, balancing realism with control and flexibility for analysis.

5.1. Data setup

5.1.1. Synthetic public transit network configuration

Bus routes and stops:. To simulate airport ground access, we developed a synthetic public transit network consisting of two virtual bus stops, each representing a distinct urban area. These stops are geospatially mapped to representative census tracts, which act as proxies for residential origins. Based on the socioeconomic attributes of these tracts, passengers are classified into high-income and low-income groups. This setup allows the model to capture spatial and income-based disparities in airport accessibility (see Fig. 7).

This classification is consistent with the income group segmentation used in Section 4.1.1, ensuring coherence between the empirical case setup and the subsequent numerical experiments. While this binary segmentation represents an extreme simplification, it facilitates a clear contrast between income groups, thereby highlighting the distributional effects of accessibility policies. Importantly, the proposed model is readily extensible to more granular income stratifications, allowing for finer representation of real-world socioeconomic diversity when more detailed data is available.

Bus capacity and frequency:. Each bus is assumed to have a maximum capacity of 50 passengers and operates under a high-frequency schedule, with departures every 10 min, resulting in a total of 144 candidate trips per day. This setup reflects the design of a typical airport shuttle service offering consistent and frequent connections. The average travel time between the two virtual stops is assumed to be 20 min, representing typical intra-urban transit conditions.

5.1.2. Operational cost and revenue parameters

The operational cost structure consists of both fixed and variable components. A daily fixed cost of \$100 per bus is assumed, reflecting overhead expenses such as driver wages and routine maintenance (Fisher, 2022). Additionally, a departure-based fixed cost of \$2.52 per trip is applied to capture preparatory costs, including vehicle turnover and dispatching activities. For active bus operation, a variable cost of \$28.85 per hour is included, encompassing fuel, maintenance, and labor during service hours (salaryexpert, 2025; AAA Fuel Prices, 2024). A flat ticket price of \$3 per passenger is assumed.

Table 5
Example of inputting arrival airport flight data.

Flight ID	Departure ID	Departure Time (min)	Arrival ID	Arrival Time (min)	Duration (hour)	Price (USD)	Frequency	First Class Seats (Business + Premium Economy)	Economy Class Seats
3U 3959	TFU	885	HKIA	1045	2.7	123	3	23	185
5J 110	MNL	435	HKIA	585	2.5	113.6	12	62	220
5J 112	MNL	930	HKIA	1090	2.7	115.9	7	62	220
5J 114	MNL	1070	HKIA	1220	2.5	136.1	10	18	140
5J 120	CRK	1150	HKIA	1290	2.3	115.5	14	23	185

5.1.3. *Flight data*

Flight schedules for Hong Kong International Airport (HKIA) were collected from Flightradar24 (2025) and API (2025) for the period of May 1–14, 2025. The dataset includes key information such as departure and arrival times, flight durations, average ticket prices, and flight frequencies across a mix of domestic and international routes. This real-world dataset provides the empirical foundation for modeling airport access demand.

Each flight is uniquely defined based on its direction: for arrival flights, it is identified by a combination of departure airport, departure time, and flight ID; for departure flights, by arrival airport, arrival time, and flight ID. While individual flights are uniquely identified by these attributes, their bus service windows may overlap, enabling passengers from different flights to be grouped into the same bus trip if their scheduled times fall within the valid transfer interval.

In order to cater to socioeconomic demand segmentation, the dataset encompasses seat configuration details. Specifically, “First Class Seats” is a term that combines the total count of Business Class and Premium Economy seats, and this figure serves as a basis for estimating the demand from high-income travelers. “Economy Class Seats” indicate the number of seats that are accessible to low-income travelers. This assumption reflects a simplified, mirroring of the network design where two representative bus stops are mapped to high-income and low-income districts, respectively. While this binary segmentation facilitates clear analysis of distributional impacts, the modeling framework remains extensible. In practical applications, the model can be readily adapted to accommodate a broader range of income brackets or more nuanced socioeconomic profiles, supporting richer demand representation and greater operational realism.

Average ticket prices were calculated by aggregating fares from the same Flight ID, at the same origin–destination pair and scheduled time, over the two-week period. Flight frequency refers to how many times the same flight operated at the same scheduled time during this window. Table 5 provides an example of the structured flight input data used in the model.

5.2. *Data processing*

Estimating bus demand:. Flight-specific passenger demand was estimated using (IATA, 2023) average load factor of 0.8. To model the subset of air travelers who are likely to use airport buses, we applied a scaling coefficient $\phi_{\min} = 0.05$, i.e., 5% of total flight load is assumed to require bus transit access.

Income-based segmentation:. The estimated passenger demand was further split into high-income and low-income groups based on seating class. High-income passengers include those in business class or premium economy, while low-income passengers include those in standard economy class. These proportions are derived from typical cabin configurations and airline fare structures, allowing realistic socioeconomic segmentation.

Flight–bus trip matching:. Each flight is linked to feasible bus trips based on the [65, 80]-min service window. Only bus trips that satisfy this timing constraint are considered valid connections. This ensures logical and convenient transfers, preserving service feasibility in practice.

Final input construction:. The model uses a predefined pool of 144 candidate bus trips per day, matched against real flight schedules and population-weighted census tract data. This hybrid structure allows the simulation to capture spatiotemporal accessibility variations and evaluate how different income groups are served under constrained transit resources.

5.3. *Computational setup*

All optimization models are implemented in Python using Gurobi 11.0. The computational experiments were executed on a workstation equipped with an Intel® Core™ i7–14700KF CPU @ 3.40 GHz, 32 GB RAM, running a 64-bit Windows operating system.

The typical runtime for a full two-stage experiment is under 1200 s. The problem size for the main numerical experiments includes 1116 flights and 288 candidate bus trips, along with all induced assignment, sequencing, and capacity variables. The model solves reliably across all sensitivity scenarios, demonstrating the robustness of the proposed formulation.

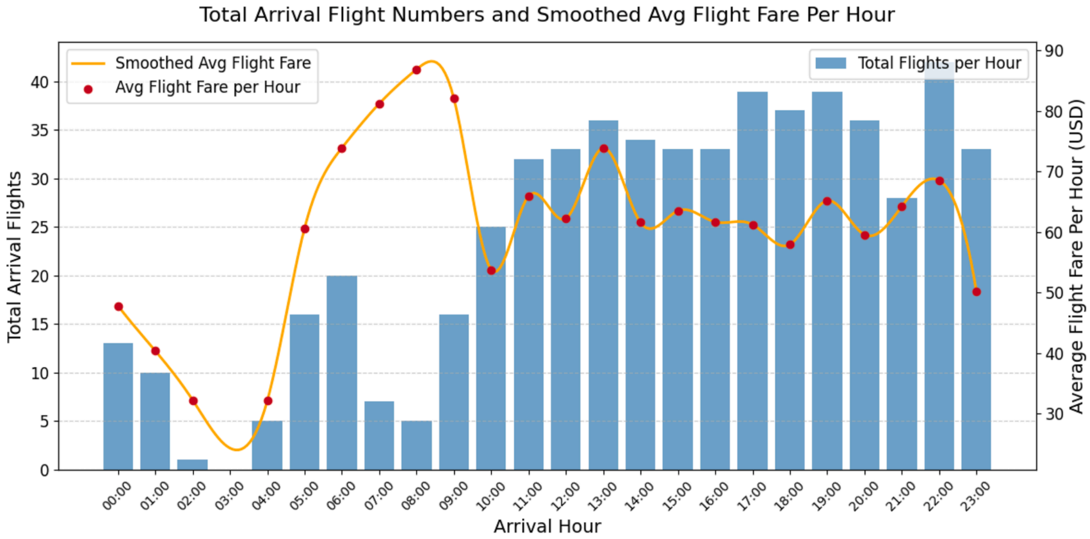

Fig. 8. Hourly arrival flight volume and corresponding average flight fare.

5.4. *Rationale for using a synthetic transit network*

A synthetic network is used in the numerical study for three main reasons.

1. Ensuring tractable and interpretable sensitivity analysis: Applying the full Hong Kong airport–bus network within the MILP would introduce hundreds of stops, dozens of routes, and thousands of feasible service combinations. This complexity masks the structural behavior of the FAAM metric and the two-stage model, making it difficult to isolate the causal effect of parameter changes. The synthetic network enables clean, replicable experiments across broad parameter ranges.
2. Isolating model mechanisms from local network idiosyncrasies: The simplified network ensures that results reflect generalizable scheduling and accessibility mechanisms, rather than the particulars of Hong Kong's bus topology. This separation enhances the policy relevance of the findings and enables transfer to other airports and regions.
3. Alignment with real-world values and case-study design: Although simplified, the synthetic network's calibration draws directly from real-world values. 10-min headways reflect realistic minimum headways for Hong Kong airport buses. The 20–40 min travel-time assumptions fall within typical bus travel times observed in A- and E-series airport buses. The income-based tract representation mirrors Hong Kong's district-level socioeconomic structure as introduced in Section 4.

Thus, the synthetic model is not arbitrary; it is an abstraction grounded in empirical characteristics of Hong Kong's transport system.

In Section 5.5.2, we further validate our findings by applying the Pareto-efficient schedules produced by the model to a real Hong Kong airport corridor (A21). This demonstrates that insights generated in the synthetic environment also improve accessibility under real-world conditions, reinforcing both transferability and policy applicability.

5.5. *Analysis and discussion*

5.5.1. *Flight schedule analysis*

The combined analysis of arrival and departure flight patterns at Hong Kong Airport (Figs. 8 and 9) reveals clear temporal and socioeconomic travel distinctions. As shown in the figures, early morning (00:00–06:00) hours exhibit both low fares and limited flight activity, indicating usage primarily by budget-conscious, lower-income travelers who prioritize affordability over convenience. In contrast, the morning peak (06:00–09:00) demonstrates sharp increases in both fares and flight volume, reflecting demand from high-income or business travelers seeking time-efficient departures and arrivals. From midday to early evening, flight volumes and fares remain moderate, attracting a broad mix of travelers. Late evening hours again show lower fares, as depicted in the charts, appealing to more flexible or cost-sensitive passengers. These patterns underscore the need to align airport ground transport services, especially bus schedules, not only with high-demand periods but also with the travel needs of underserved groups. A fair and efficient airport bus system should ensure service availability during off-peak, low-cost travel windows to support fair access for all socioeconomic segments.

5.5.2. *Impact of scaling coefficient μ on accessibility and operational cost*

To evaluate the trade-off between accessibility and operational cost, we conducted a sensitivity analysis by varying the scaling coefficient μ, which governs the relative weight of accessibility deviation in the Stage 2 objective function. A higher value of μ_1 places

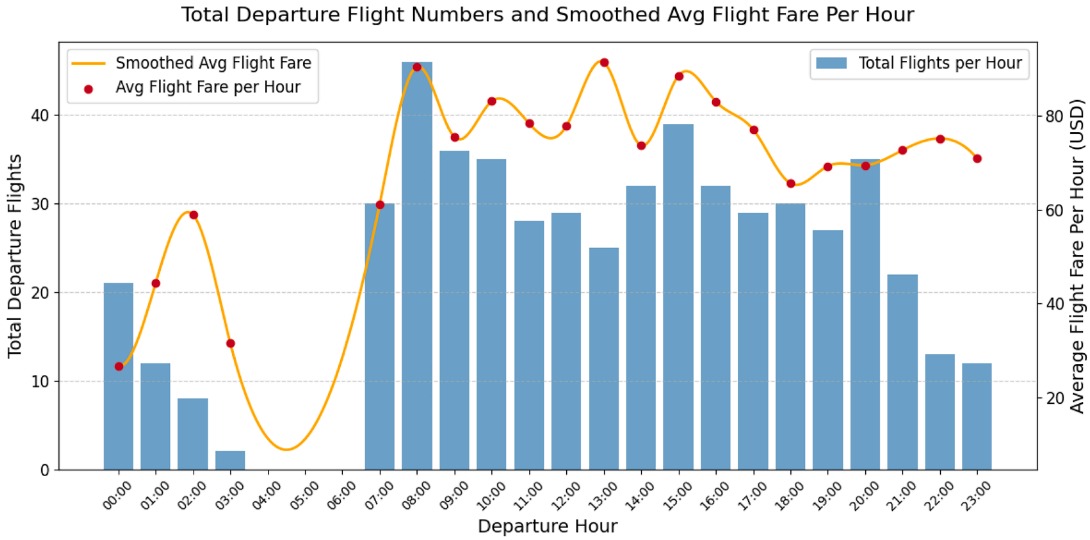

Fig. 9. Hourly departure flight volume and corresponding average flight fare.

Table 6
Sensitivity analysis of scaling parameter μ_1: Government-led model.

μ_1	Total accessibility	Total operational Cost	Accessibility Gap (%)	Cost Gap (%)	Total Gap (%)	Operational Cost Reduction (%) -Stage 1
1	97.8	3255.5	18.7	0.0	18.7	36.9
2	97.8	3255.7	18.6	0.0	18.6	36.9
3	99.7	3260.7	17.0	0.2	17.2	36.8
5	101.0	3265.8	15.9	0.3	16.2	36.7
8	103.0	3276.0	14.2	0.6	14.9	36.5
10	109.9	3338.9	8.4	2.6	11.0	35.3
15	112.4	3368.7	6.4	3.5	9.9	34.7
20	113.3	3384.0	5.7	4.0	9.6	34.4
30	117.3	3467.1	2.3	6.5	8.9	32.8
40	119.1	3520.8	0.8	8.2	9.0	31.8
45	119.2	3525.9	0.7	8.3	9.1	31.7
50	119.3	3531.0	0.6	8.5	9.1	31.6
55	119.6	3536.1	0.6	8.6	9.2	31.5
70	119.5	3541.2	0.5	8.8	9.3	31.4
100	119.6	3565.5	0.3	9.5	9.8	30.9

greater emphasis on preserving accessibility. Both models were tested under a fairness assumption using equal income group weights $\lambda = [0.5, 0.5]$, ensuring an unbiased assessment of socioeconomic accessibility.

Tables 6 and 7 present the results of the two-stage optimization model under varying values of the scaling coefficient μ, for the government-led and operator-led perspectives, respectively. For each setting of μ, the model outputs two primary performance metrics: Total Accessibility and Total Operational Cost, both computed based on the second-stage objective that balances accessibility with cost efficiency.

To facilitate comparative analysis, additional columns are derived by benchmarking these results against the Stage 1 baseline solutions, which represent the two extremes of the trade-off space:

1. The accessibility-maximizing solution (Stage 1-Government) yields the highest possible accessibility score: 120.84, but with a high operational cost.
2. The cost-minimizing solution (Stage 1-Operator) delivers the lowest possible cost: 325.18, but with minimal accessibility.

Using these benchmarks, we define the following metrics:

1. Accessibility Gap (%): The percentage difference between the current accessibility value and the maximum value from Stage 1-Government (120.84), reflecting how close the solution is to the accessibility ideal.
2. Cost Gap (%): The percentage difference between the current operational cost and the minimum cost from Stage 1-Operator (3255.18), showing how much additional cost is incurred relative to the lowest-cost baseline.
3. Total Gap (%): The sum of Accessibility Gap and Cost Gap, used to identify Pareto-optimal configurations where both goals are reasonably met.

Table 7
Sensitivity analysis of scaling parameter μ_2: Transit operator-led model.

μ_2	Total accessibility	Total operational Cost	Accessibility Gap (%)	Cost Gap (%)	Total Gap (%)	Accessibility Improvement (%) -Stage 1
0.7	97.7	3255.5	18.7	0.0	18.7	36.9
0.5	97.8	3255.7	18.6	0.0	18.6	36.9
0.3	99.7	3260.7	17.0	0.2	17.2	36.8
0.2	101.0	3265.8	15.9	0.3	16.2	36.7
0.09	109.9	3338.9	8.4	2.6	11.0	35.3
0.08	112.0	3363.6	6.7	3.3	10.1	34.9
0.07	112.4	3368.7	6.4	3.5	9.9	34.7
0.06	112.7	3373.8	6.1	3.7	9.8	34.6
0.04	117.3	3467.1	2.3	6.5	8.9	32.8
0.03	118.9	3515.7	1.0	8.0	9.0	31.9
0.02	119.3	3531.0	0.6	8.5	9.1	31.6
0.01	119.8	3565.5	0.3	9.5	9.8	30.9
0.001	120.1	3615.6	0.0	11.1	11.1	30.2

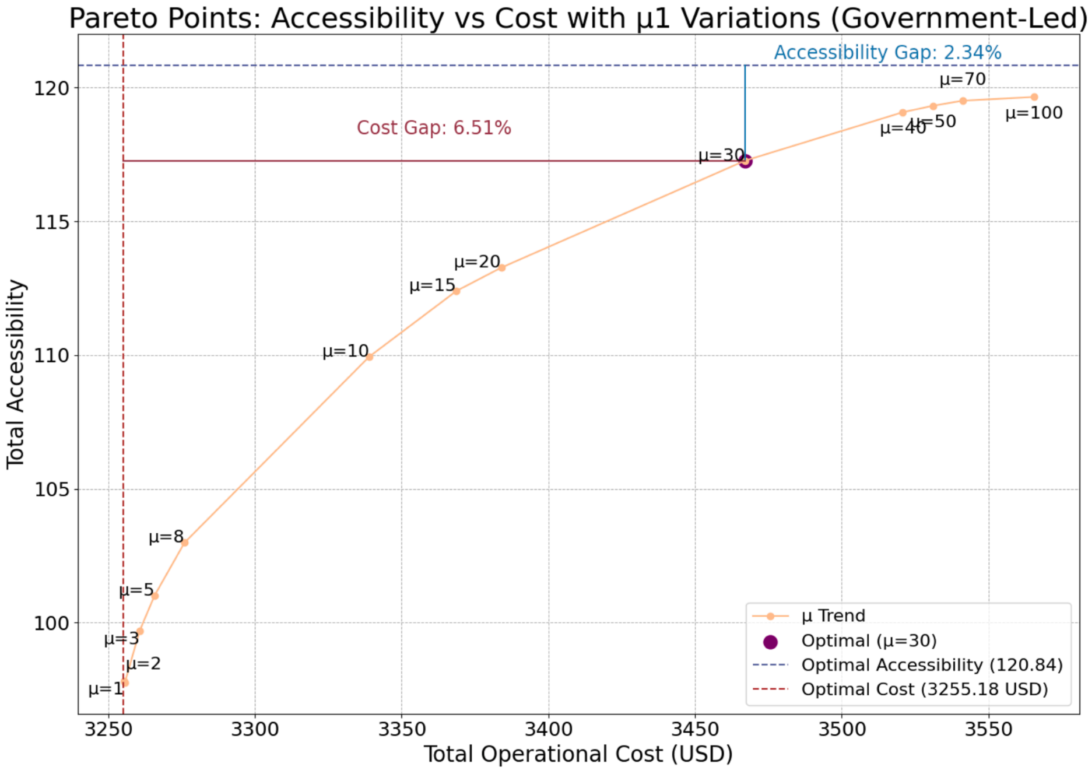

Fig. 10. Pareto points: Accessibility vs. Cost with μ_1 Variants: Government-led model.

For the government-led model (Table 6), an additional column–Operational Cost Reduction (%) – Stage 1–is included. This metric quantifies the percentage reduction in cost relative to the accessibility-maximizing solution from Stage 1-Government, highlighting the cost savings achieved by introducing cost constraints in Stage 2.

For the operator-led model (Table 7), the final column–Accessibility Improvement (%)–indicates the percentage increase in accessibility compared to the cost-minimizing baseline (Stage 1-Operator). This value demonstrates how much accessibility can be improved over the minimal-access benchmark while still managing operational cost growth. These metrics provide a structured way to assess how adjustments to the scaling coefficient μ influence the efficiency–fairness trade-off.

In the government-led model, increasing the scaling parameter μ_1 progressively shifts the optimization objective toward maximizing accessibility, placing greater emphasis on ensuring that underserved communities are adequately connected to airport services. As shown in Table 6 and Fig. 10, this shift produces a non-linear trade-off between accessibility gains and operational costs.

Accessibility improves steadily with increasing μ_1, particularly between $\mu_1 = 1$ and $\mu_1 = 30$, where significant gains are achieved with relatively moderate increases in operational expenditure. For instance, increasing μ_1 from 1 to 8 improves accessibility by over

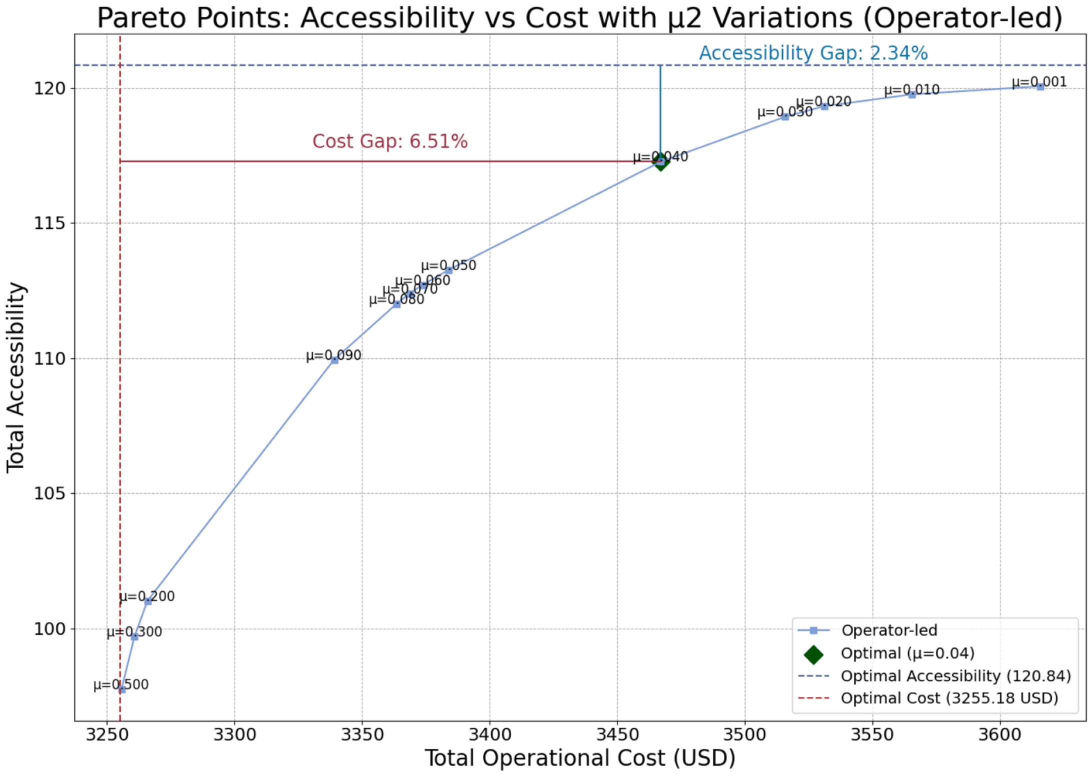

Fig. 11. Pareto points: Accessibility vs. Cost with μ_2 Variants: Transit operator-led model.

4%, while the associated cost rises by less than 1%, suggesting a high return on investment in the early range. Beyond $\mu_1 = 30$, however, the rate of accessibility improvement begins to diminish, while operational costs accelerate more sharply. This reflects the typical diminishing returns pattern observed in resource allocation problems. For example, moving from $\mu_1 = 30$ to $\mu_1 = 70$ increases accessibility by only 1.8%, but incurs a 2.3% increase in cost. The marginal cost per unit of accessibility gain becomes progressively higher.

The Pareto-optimal trade-off point is observed at $\mu_1 = 30$, where the combined percentage gap, defined as the sum of relative accessibility shortfall and cost increase compared to their respective optimal, is minimized at 8.9%. This balance point is particularly valuable for policymakers, as it captures substantial accessibility benefits with only a moderate cost impact. This suggests that $\mu_1 = 30$ is a pragmatic policy threshold where fairness-focused objectives can be meaningfully advanced without imposing excessive budgetary burden.

Additionally, compared to the Stage 1 solution, which focuses solely on maximizing accessibility with loose cost constraints, all values of μ_1 in Stage 2 result in substantially reduced operational costs. This highlights the effectiveness of the two-stage framework in achieving more balanced outcomes. While the Stage 1 solution may deliver the highest possible accessibility, it does so at an unsustainable cost. In contrast, the Stage 2 government-led model demonstrates that strategically adjusting μ_1 allows for significant cost savings with only marginal compromises in accessibility. This underscores the value of optimization-guided policy design, where moderate reductions in accessibility can lead to disproportionately large efficiency gains, making socially inclusive transit systems more financially viable.

Ultimately, the government-led model illustrates how policy-driven prioritization of accessibility can reshape bus schedules to better serve all socioeconomic groups. The results provide a decision-support tool for governments seeking to embed fairness into transit policy while maintaining fiscal accountability. By tuning μ_1, decision-makers can calibrate their level of investment in social accessibility according to budget capacity, public demand, and political priorities.

In the transit operator-led model, the optimization begins from a cost-minimizing baseline and incrementally introduces accessibility considerations by adjusting the scaling parameter μ_2. Higher values of μ_2 prioritize strict cost control, while lower values progressively relax budget constraints to allow for greater accessibility coverage. This structure reflects a pragmatic approach to bus planning, where accessibility improvements are pursued within the bounds of financial sustainability.

As shown in Table 7 and Fig. 11, decreasing μ_2 yields steady improvements in accessibility, accompanied by a gradual increase in operational costs. This trend mirrors the behavior observed in the government-led model, albeit from an inverse starting point. At $\mu_2 = 0.04$, the model achieves a particularly efficient balance, matching the performance of the government-led model at $\mu_1 = 30$.

This point represents a Pareto-optimal configuration, capturing substantial accessibility gains while keeping cost growth within manageable limits.

Importantly, the results show that across all tested values of μ_2, accessibility improves significantly over the Stage 1 baseline, where cost was the sole optimization focus. This underscores the model's flexibility in reallocating service resources to enhance fairness outcomes without compromising financial viability. Even more aggressive accessibility prioritization (e.g., $\mu_2 = 0.01$) continues to deliver incremental improvements, although with diminishing cost-efficiency, as the model approaches upper bounds of total accessibility.

Together, the government-led and operator-led models reflect complementary planning philosophies. The government-led approach elevates social accessibility as a public good, ensuring that underserved populations receive transit coverage regardless of operational cost pressures. In contrast, the operator-led model begins from a foundation of cost efficiency, allowing for gradual and controlled improvements in accessibility based on budgetary flexibility.

Despite these differing starting points, both models converge toward similar optimal operating zones, where accessibility is maximized without unsustainable cost burdens. This convergence suggests that fairness and efficiency are not mutually exclusive, but rather can be harmonized through strategic policy tuning. The use of scaling parameters μ_1 and μ_2 offers planners a practical mechanism to navigate this trade-off, enabling tailored strategies based on policy priorities, resource availability, and service fairness goals.

To further validate the portability of the FAAM framework, we apply the Pareto-efficient schedules obtained from the synthetic experiments to two real airport bus routes in Hong Kong: A21 and A25. These routes serve districts with different socioeconomic compositions. A25 passes primarily through Kowloon City and Yau Tsim Mong, which can be mapped to the high-income and low-income groups respectively. In this context, λ_q is directly determined by the population size of each census tract.

Using the optimized departure frequencies derived from the two-stage model, we observe that A21 and A25 would experience increases in effective service frequency of approximately 8% and 30% respectively. These improvements arise mainly from reallocating services to better match temporal demand profiles, particularly during off-peak periods. Both routes currently operate with reduced evening frequencies and no departures between midnight and 5:20 AM, which creates substantial accessibility gaps for passengers on red-eye flights. Such travelers often face prolonged overnight waiting times at the airport. This inconvenience disproportionately affects low-income groups, who rely on public transport rather than taxis.

While existing schedules primarily reflect the operational cost considerations of bus operators, the FAAM-based framework provides a mechanism to explore more flexible and demand-responsive adjustments. While absolute accessibility levels depend on the synthetic parameterization, the structural relationships, relative rankings, and fairness–efficiency patterns remain stable. By tuning the scaling coefficient μ, policymakers can explicitly balance operational cost against fair accessibility, enabling the identification of intermediate, near-optimal schedules that improve service provision for underserved time windows without imposing excessive operating burdens. This distinction ensures that the FAAM framework is interpreted as a policy-exploration tool for structural insights, rather than a predictor of absolute service levels.

The results from A21 and A25 illustrate that the proposed approach not only supports synthetic scenario exploration but also produces meaningful recommendations when applied to real routes. Incorporating flight departure patterns into departure planning further enhances the match between ground access supply and air travel demand. These findings demonstrate the practical relevance of the FAAM framework and highlight its potential to inform dynamic, fairness-oriented airport bus scheduling strategies.

5.5.3. Fairness–efficiency trade-off under varying income prioritization

To further explore the fairness implications of airport bus scheduling, we conduct a sensitivity analysis on the income-group weighting parameter λ at the previously identified trade-off points, $\mu_1 = 30$ for the government-led model and $\mu_2 = 0.04$ for the operator-led model. The parameter $\lambda = [\lambda_H, \lambda_L]$ governs the relative priority assigned to high-income (λ_H) and low-income (λ_L) groups in the utility function. We evaluate nine scenarios, ranging from full prioritization of low-income travelers ($[0.1, 0.9]$) to full prioritization of high-income travelers ($[0.9, 0.1]$), including two extreme baseline cases: $\lambda = [0, 1]$ and $\lambda = [1, 0]$.

In this analysis, we assess how changes in λ affect total accessibility as well as the accessibility gap for each income group. The accessibility gap for low-income and high-income travelers is computed by comparing the group-specific accessibility under each λ setting to the corresponding group's maximum achievable accessibility observed across all scenarios. This normalization allows us to evaluate fairness outcomes in relative terms, highlighting disparities that emerge as prioritization shifts between groups.

The results are visualized in two figures, illustrating group-level accessibility gaps under both government-led (Fig. 12) and operator-led (Fig. 13) strategies.

(a) Prioritizing low-income groups does not maximize total accessibility.

Total accessibility increases nearly linearly with greater prioritization of high-income users. This pattern holds across both the government-led and operator-led models. However, this trend reveals a critical insight: total accessibility maximization does not equate to inclusion. In fact, the lowest total accessibility is observed when low-income users are prioritized ($\lambda = [0.1, 0.9]$): 29.7 in the government-led model and 33.5 in the operator-led model.

This counterintuitive result is explained by behavioral patterns. Low-income travelers tend to avoid peak hours and price-sensitive periods, leading to lower utilization of system capacity, even when services are tailored toward them. In contrast, deprioritizing high-income users reduces overall system efficiency, as they typically travel more frequently and across a wider temporal range. This finding highlights the importance of demand-responsive, behaviorally aware interventions. Merely assigning higher utility weights to underserved groups is insufficient. Policymakers should instead combine prioritization with structural supports, such as off-peak

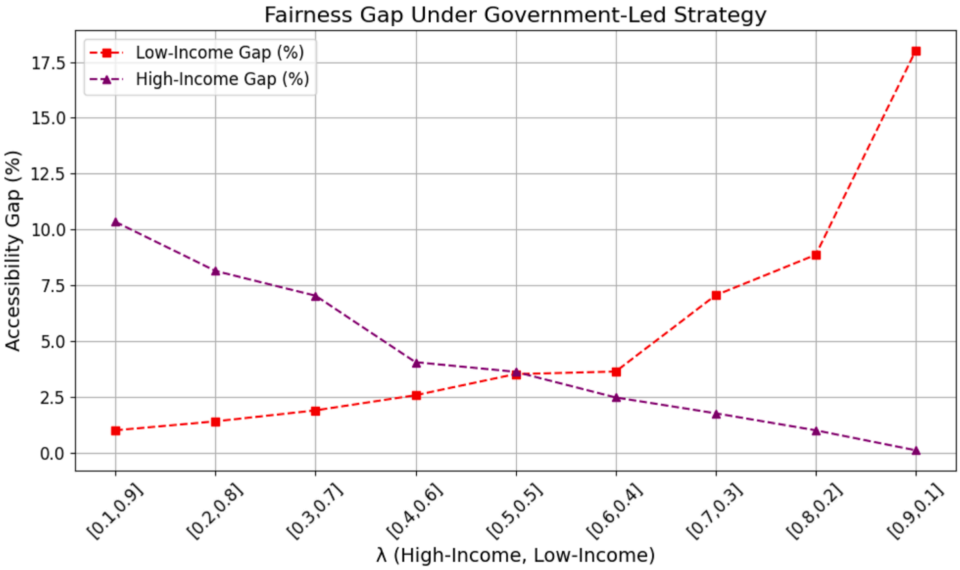

Fig. 12. Fairness gaps across different λ Weightings: Government-led model.

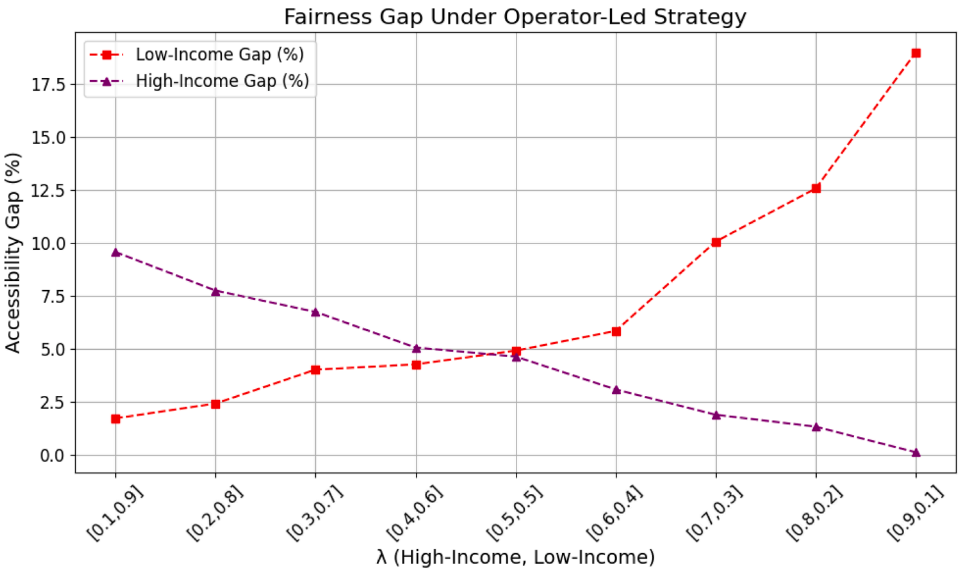

Fig. 13. Fairness gaps across different λ Weightings: Transit operator-led model.

service incentives, targeted fare subsidies, and behavioral nudges, to unlock latent demand in a way that improves both inclusion and system performance.

(b) High-income weighting increases accessibility at the cost of fairness.

At the other end of the spectrum, total accessibility peaks under $\lambda = [0.9, 0.1]$, reaching 199.4 and 201.2 in the government-led and operator-led models, respectively. This outcome is largely driven by high-income users' greater travel frequency, flexibility, and price tolerant, traits that contribute to better utilization of peak and off-peak services alike. However, this improvement in system-wide performance comes at the expense of fairness. Under this configuration, the accessibility gap for low-income travelers exceeds 18%, indicating a high level of marginalization. This illustrates a familiar trade-off in public transit systems: optimizing for aggregate performance often leads to the exclusion of vulnerable groups.

To avoid this pitfall, total accessibility metrics must be complemented by fairness safeguards. Without such checks, optimization processes may unintentionally favor already advantaged users. Policy tools like minimum service thresholds for low-income areas or gap-based fairness constraints can mitigate this risk.

(c) Fairness gaps reveal tensions between inclusion and system efficiency.

Figs. 12 and 13 show that the accessibility gaps for low- and high-income groups move in opposite directions as λ shifts. When low-income users are prioritized, their accessibility gap narrows, but at the cost of increasing exclusion for high-income travelers. Conversely, prioritizing high-income users leads to marginalization of the low-income group. The minimum total group gap occurs near $\lambda = [0.5, 0.5]$, supporting the rationale for balanced weighting as a baseline policy default. At this point, both groups achieve near-optimal accessibility without severe exclusion of the other, reinforcing the role of equal-weighted fairness as a middle-ground approach when explicit targeting is not feasible. From a policy standpoint, systems designed solely to maximize total accessibility risk magnifying transport inequalities. Without safeguards, such strategies may disproportionately favor already advantaged groups.

(d) Fairness-blind optimization risks structural favoritism.

Importantly, optimizing total accessibility without accounting for income disparities results in outcomes that disproportionately benefit high-income travelers, simply because they travel more frequently and across more time slots. This highlights a critical policy risk: accessibility-maximizing objectives, if unqualified by fairness constraints, may exacerbate transport inequality. The findings emphasize the necessity of incorporating income-weighted utility or fairness constraints into transit optimization models to avoid unintentionally privileging already advantaged populations.

This underscore that fairness should be explicitly embedded in both the objective function and constraint design of transit optimization models. Policymakers must recognize that performance-only approaches risk institutionalizing privilege. Incorporating income-weighted utility, fairness gaps, or distributional fairness metrics is essential for building inclusive systems that serve diverse populations equitably. As transportation systems become increasingly data-driven, the ethical imperative is to ensure that algorithmic decision-making enhances, rather than erodes, public equity.

(e) Alternative weighting schemes.

In practice, λ_q can be calibrated through multiple approaches depending on policymaking priorities and available data. For example, transportation agencies may use (1) census-based population shares when prioritizing geographic equity, (2) observed traveler compositions at airport terminals when focusing on user-centered service planning, or (3) elasticity-adjusted weights that reflect heterogeneous travel behavior across income groups. These alternative schemes enable policymakers to emphasize different fairness objectives, such as redistributive fairness, opportunity-based accessibility, or demand-driven efficiency.

Furthermore, λ_q may be endogenously optimized within the FAAM framework when planners wish to formalize explicit fairness targets (e.g., minimizing inter-group accessibility gaps). The flexibility of the FAAM structure ensures that the selection of λ_q is not tied to a single socioeconomic interpretation; rather, it can be adapted to local demographic conditions, mobility habits, trip purposes, or long-term planning goals. This adaptability enhances the metric's policy relevance and allows decision-makers to adopt weighting schemes that best reflect their regional priorities and equity mandates.

5.5.4. Fare policy experiments for enhancing accessibility

Building on the behavioral insights and demand elasticity patterns identified in Section 5.5.3, this section evaluates the effectiveness of targeted fare policies in improving airport accessibility for income-differentiated populations. Recognizing that low-income travelers tend to avoid peak-period services due to cost sensitivity, we simulate the impact of three fare policy interventions: a income-based ticket subsidies, b) zero-fare shuttles during late-night hours, and c) tiered pricing with off-peak discounts. Each policy is designed to align with the temporal and financial constraints of different user groups and to assess the extent to which pricing adjustments can enhance transit fairness.

The Income-Based Subsidy policy introduces a HKD $8 fare reduction exclusively for low-income travelers, lowering their ticket price from HKD $24 to HKD $16. This seemingly modest subsidy produces a 4.6% increase in accessibility for low-income users, highlighting the high price elasticity of this group and reinforcing the notion that even minor reductions in financial barriers can significantly expand mobility options for disadvantaged populations.

The Zero-Fare Late-Hour Shuttle, which provides free hourly service between 10:30 p.m. and 6:30 a.m. from a low-income tract to the airport, results in a 2.7% increase in low-income accessibility. Although the absolute gain is smaller than the flat subsidy, the policy offers an important complement to the daily service by addressing mobility gaps during late-night periods when both flight prices and service frequencies are lower.

The third strategy, Tiered Pricing for Off-Peak Travel, applies a 50% fare discount during the off-peak period from 10:00 p.m. to 6:00 a.m., reducing the fare from HKD $24 to HKD $12. This policy leads to a 3.15% increase in overall accessibility, benefiting both low- and high-income travelers who are flexible enough to travel during lower-cost windows. The result demonstrates that time-based pricing incentives can redistribute demand, improving network efficiency while simultaneously expanding access in a socially inclusive manner.

Beyond these empirical experiments, the FAAM–utility framework provides a broader foundation for fare design by incorporating fare elasticity of demand. In the MNL formulation, the elasticity of choosing bus trip k with respect to fare c for income group q is:

$$E_c^q = \zeta_q (1 - P_{kq})\, c, \tag{27}$$

where ζ_q is the access-cost coefficient and P_{kq} is the probability of selecting trip k. This relationship enables policymakers to anticipate how marginal fare adjustments influence accessibility outcomes:

$$\Delta \mathrm{FAAM}_q \approx \frac{\partial \mathrm{FAAM}_q}{\partial c}\, \Delta c, \tag{28}$$

allowing fare instruments to be used proactively to manage demand, mitigate peak congestion, and enhance fairness.

The framework naturally extends to time-varying and demand-responsive pricing. The fare in time interval τ is defined as

$$c(\tau) = c_0 - \rho D(\tau), \tag{29}$$

where $D(\tau)$ denotes observed or predicted demand, the following optimization problem supports principled fare planning:

$$\max_{c(\tau)} \ \text{FAAM}_{\text{total}}. \tag{30}$$

This provides a structured way to balance accessibility gains with operational feasibility.

Although this study distinguishes only between high- and low-income travelers, the approach extends seamlessly to richer demographic sets, including middle-income residents, elderly travelers, business travelers, and tourists. Differences in sensitivity to cost, waiting time, schedule reliability, or comfort can be accommodated by assigning group-specific parameters and weights, enabling more nuanced and socially inclusive policy evaluations.

Taken together, these findings emphasize that fare policy is a powerful and flexible lever for fair airport access. Elasticity-informed pricing allows agencies to design targeted, cost-effective interventions that improve accessibility without major infrastructure expansion. Policymakers can therefore employ fare strategies not only to reduce financial barriers for vulnerable groups but also to shape system-wide demand patterns, making fare design an integral component of inclusive and efficient airport transit planning.

6. Conclusion

This study presents a comprehensive, fairness-aware optimization framework for airport shuttle scheduling that integrates socioeconomic diversity, real-world constraints, and system efficiency. By introducing the Fairness Airport Accessibility Metric (FAAM), we capture income-specific variations in transit preferences and constraints, and embed them into a dual-perspective, two-stage scheduling model that reflects the operational tension between fairness and cost-effectiveness.

Our numerical experiments yield several key insights. First, while increasing the accessibility weight μ generally enhances service levels, balanced trade-off points emerge at government-led and operator-led, where accessibility improvements are achieved without disproportionate cost increases. Second, income prioritization alone does not guarantee fairness. Prioritizing low-income users reduces accessibility gaps but leads to lower system efficiency due to behavioral patterns such as peak-hour avoidance. Conversely, prioritizing high-income users increases total accessibility but exacerbates inclusion disparities. These findings validate the use of balanced income weighting in fairness-oriented transit design.

Our policy simulations further demonstrate that targeted, low-cost fare strategies, such as income-based subsidies and off-peak pricing, can significantly improve accessibility for cost-sensitive groups without requiring major infrastructure expansion. These strategies offer actionable levers for enhancing distributional fairness while preserving system efficiency.

While the current framework provides a robust foundation for fairness-aware scheduling, it assumes deterministic inputs. In reality, flight delays, demand fluctuations, and operational disruptions introduce uncertainty. Future research could extend this work by integrating stochastic or adaptive optimization, real-time data streams, and dynamic reallocation policies to improve resilience and responsiveness in real-world transit operations.

By bridging public policy goals with operational imperatives, the proposed framework equips planners with a scalable, data-driven approach to design inclusive, cost-efficient, and behaviorally informed airport ground access systems. It highlights the importance of explicitly embedding fairness into optimization models, not only to improve access but to ensure that transportation systems evolve fairness as they become increasingly automated and data-driven.

Data availability

The data used in this study was collected from publicly available sources, with links cited in the reference section.

CRediT authorship contribution statement

Tinghe Zhang: Writing – original draft, Methodology, Formal analysis; **Ang Li:** Writing – review & editing, Supervision, Methodology; **Lingxiao Wu:** Writing – review & editing, Methodology; **Changmin Jiang:** Writing – review & editing.

References

AAA Fuel Prices, 2024. State gas price averages. https://gasprices.aaa.com/state-gas-price-averages/.

Abdelaziz, F.B., Masri, H., Alaya, H., 2017. A recourse goal programming approach for airport bus routing problem. Ann. Oper. Res. 251, 383–396. https://doi.org/10.1007/s10479-015-1851-3

API, G.F., 2025. Google flights API (via serpAPI). https://serpapi.com/google-flights-api.

Avogadro, N., Cattaneo, M., Paleari, S., et al., 2021. Replacing short-medium haul intra-european flights with high-speed rail: impact on CO2 emissions and regional accessibility. Transp. Policy 114, 25–39. https://doi.org/10.1016/j.tranpol.2021.08.014

Bergantino, A.S., Capurso, M., Hess, S., 2020. Modelling regional accessibility to airports using discrete choice models: an application to a system of regional airports. Trans. Res. Part A Policy Pract. 132, 855–871. https://doi.org/10.1016/j.tra.2019.12.012

Bhadra, D., 2004. Air travel in small communities: an econometric framework and results. J. Trans. Res. Forum 43 (1). https://doi.org/10.5399/osu/jtrf.43.1.711

BTS, 2017. National household travel survey long distance travel quick facts. https://www.bts.gov/statistical-products/surveys/national-household-travel-survey-long-distance-travel-quick-facts.

Burghouwt, G., Redondi, R., 2013. Connectivity in air transport networks: an assessment of models and applications. J. Transport Econ. Policy 47 (1), 35–53.
Chang, Z., Chen, J., Li, W., Li, X., 2019. Public transportation and the spatial inequality of urban park accessibility: new evidence from Hong Kong. Trans. Res. Part D Transport Environ. 76, 111–122. https://doi.org/10.1016/j.trd.2019.09.012
Chen, J., Wang, S., Liu, Z., et al., 2017. Design of suburban bus route for airport access. Trans. A Transport Sci. 13 (6), 568–589. https://doi.org/10.1080/23249935.2017.1306896
Choi, J.H., Wang, K., Xia, W., et al., 2019. Determining factors of air passengers' transfer airport choice in the Southeast Asia–North America market: managerial and policy implications. Trans. Res. Part A Policy Pract. 124, 203–216. https://doi.org/10.1016/j.tra.2019.03.008
Citybus, 2025. Citybus route information portal. https://mobile.citybus.com.hk/nwp3/?f=1&ds=All&l=1.
Coppola, P., Silvestri, F., 2018. Estimating and visualizing perceived accessibility to transportation and urban facilities. Transp. Res. Procedia 31, 136–145. https://doi.org/10.1016/j.trpro.2018.09.051
C&SD, 2021. Public transport patronage of Hong Kong, 2010 to 2020. https://www.censtatd.gov.hk/en/data/stat_report/product/FA100065/att/B72104FB2021XXXXB0100.pdf.
C&SD, 2025. Table 110–02001: Land area, land population and population density by district council district. https://www.censtatd.gov.hk/en/web_table.html?id=110-02001.
El-Geneidy, A., Levinson, D., Diab, E., et al., 2016. The cost of equity: assessing transit accessibility and social disparity using total travel cost. Trans. Res. Part A Policy Pract. 91, 302–316. https://doi.org/10.1016/j.tra.2016.07.003
Fisher, M., 2022. How much does a bus cost to purchase and operate? https://www.liveabout.com/bus-cost-to-purchase-and-operate-2798845.
Flightradar24, 2025. Hong Kong international airport (HKG) arrivals and departures. https://www.flightradar24.com/data/airports/hkg.
Fuellhart, K., 2007. Airport catchment and leakage in a multi-airport region: the case of harrisburg international. J. Transp. Geogr. 15 (4), 231–244. https://doi.org/10.1016/j.jtrangeo.2006.08.001
Grubesic, T.H., Wei, F., 2012. Evaluating the efficiency of the essential air service program in the united states. Trans. Res. Part A Policy Pract. 46 (10), 1562–1573. https://doi.org/10.1016/j.tra.2012.08.004
Handy, S.L., Niemeier, D.A., 1997. Measuring accessibility: an exploration of issues and alternatives. Environ. Plann. A 29 (7), 1175–1194. https://doi.org/10.1068/a291175
He, P., Jin, J.G., Schulte, F., 2024. The flexible airport bus and last-mile ride-sharing problem: math-heuristic and metaheuristic approaches. Transp. Res. Part E Logist. Transp. Rev. 184, 103489. https://doi.org/10.1016/j.tre.2024.103489
Hess, S., Adler, T., Polak, J.W., 2007. Modelling airport and airline choice behaviour with the use of stated preference survey data. Transp. Res. Part E Logist. Transp. Rev. 43 (3), 221–233. https://doi.org/10.1016/j.tre.2006.10.002
Hess, S., Polak, J.W., 2006. Airport, airline and access mode choice in the san francisco bay area. Papers Reg. Sci. 85 (4), 543–567. https://doi.org/10.1111/j.1435-5957.2006.00097.x
HKIA, 2019. Finalized civil international air traffic statistics at HKIA year 2019. https://www.hongkongairport.com/iwov-resources/file/the-airport/hkia-at-a-glance/facts-figures/2019e.pdf. Total passengers: 71,543,000 (Calendar Year 2019).
HKIA, 2025a. HKIA at a glance. https://www.hongkongairport.com/en/the-airport/hkia-at-a-glance/fact-figures.page.
HKIA, 2025b. Public buses – to/from airport. https://www.hongkongairport.com/en/transport/to-from-airport/public-buses.page.
HKIA, 2025c. Passenger arrivals – flight information. https://www.hongkongairport.com/en/flights/arrivals/passenger.page.
HKIA, 2025d. Special needs access. https://www.hongkongairport.com/en/passenger-guide/airport-facilities-services/special-needs-access.
HKSAR, 2025. Average household size and median monthly household income of households by district council district. https://data.gov.hk/en-data/dataset/hk-censtatd-tablechart-130-06806/resource/533c0513-6aa1-4338-9b58-ce2c775dc090.
Hub, T. H.K., 2025. Hong Kong airport back in world's 10 best airports, ranked 6th in 2025. https://thehkhub.com/hong-kong-airport-back-in-worlds-10-best-airports-ranked-6th-in-2025/.
IATA, 2023. Air passenger market analysis - december 2023. https://www.iata.org/en/iata-repository/publications/economic-reports/air-passenger-market-analysis-december-2023/.
Kalakou, S., Moura, F., 2021. Analyzing passenger behavior in airport terminals based on activity preferences. J. Air Transport Manage. 96, 102110. https://doi.org/10.1016/j.jairtraman.2021.102110
Karam, S., Nam, S.J., Ryerson, M.S., 2022. Aiming for equity in aviation accessibility: development of the aviation-accessibility integrated mobility (aim) metric. Transp. Res. Rec. 2676 (8), 398–411. https://doi.org/10.1177/03611981221083923
Kompil, M., Jacobs-Crisioni, C., Dijkstra, L., et al., 2019. Mapping accessibility to generic services in Europe: a market-potential based approach. Sustainable Cities Soc. 47, 101372. https://doi.org/10.1016/j.scs.2018.11.047
LegCo, 2025. Foreign domestic helpers in Hong Kong. https://app7.legco.gov.hk/rpdb/en/uploads/2025/ISSH/ISSH02_2025_20250224_en.pdf.
Lenaerts, B., et al., 2021. Measuring the quality of air transport networks: a topology of connectivity and accessibility metrics. In: Air Transport and Regional Development Policies. Routledge, 1st edition. p. 6–30. https://doi.org/10.4324/9781003092070-2
Lu, J., Yang, Z., Timmermans, H., et al., 2016. Optimization of airport bus timetable in cultivation period considering passenger dynamic airport choice under conditions of uncertainty. Transp. Res. Part C Emerging Technol. 67, 15–30. https://doi.org/10.1016/j.trc.2016.01.012
Mutiganda, J.C., Skoog, M., Igudia, E., 2023. Understanding the process of improving accessibility and affordability of inter-municipal bus transport system. Eur. Transport Res. Rev. 15 (1). https://doi.org/10.1186/s12544-023-00598-x
OAG, 2024. Low-cost carriers in the aviation industry: where next? https://www.oag.com/blog/what-next-low-cost-carriers-aviation.
Öner, N., Gultekin, H., Koç, c., 2020. The airport shuttle bus scheduling problem. Int. J. Prod. Res. 59 (24), 7400–7422. https://doi.org/10.1080/00207543.2020.1841317
Pan, A.Q., Deakin, E., Shaheen, S.A., 2023. Crabgrass confinement: housing and transportation challenges of low-and moderate-income suburban residents in the san francisco bay area. Case Stud. Transport Policy . https://doi.org/10.1016/j.cstp.2023.101059
Prentice, C., Kadan, M., 2019. The role of airport service quality in airport and destination choice. J. Retailing Consum. Serv. 47, 40–48. https://doi.org/10.1016/j.jretconser.2018.10.006
Rahardja, F.A., Chen, S.C., Rahardja, U., 2022. Review of behavioral psychology in transition to solar photovoltaics for low-income individuals. Sustainability 14 (3), 1537. https://doi.org/10.3390/su14031537
Rossolov, A., Naumov, V., Popova, N., et al., 2021. Estimation of transport accessibility in case of rational transport hub location. Transport 36 (1), 1–12. https://doi.org/10.3846/transport.2021.14299
Ryerson, M.S., Kim, A.M., 2018. A drive for better air service: how air service imbalances across neighboring regions integrate air and highway demands. Transp. Res. Part A Policy Pract. 114, 237–255. https://doi.org/10.1016/j.tra.2017.10.005
salaryexpert, 2025. Bus driver salary Hong Kong SAR. https://www.salaryexpert.com/salary/job/bus-driver/hong-kong-sar.
SFMTA, 2019. San Francisco mobility trends report 2018. https://www.sfmta.com/sites/default/files/reports-and-documents/2019/01/sfmta_mobility_trends_report_2018.pdf.
SFO, 2019. Fy 2018–2019 facts & figures. https://www.flysfo.com/fy-2018-2019-facts-figures. Total passengers: 57,573,124 (FY 2018–2019).
Stacherl, B., Sauzet, O., 2023. Gravity models for potential spatial healthcare access measurement: a systematic methodological review. Int. J. Health Geogr. 22 (1), 34. https://doi.org/10.1186/s12942-023-00358-z
Time, 2019. Here's how much migrant domestic workers contribute to Hong Kong's economy. https://time.com/5543633/migrant-domestic-workers-hong-kong-economy/.
Wikipedia, 2025a. HKeToll. https://en.wikipedia.org/wiki/HKeToll.
Wikipedia, 2025b. Hong Kong international airport automated people mover. https://en.wikipedia.org/wiki/Hong_Kong_International_Airport_Automated_People_Mover.

Wikipedia, 2025c. Hong Kong international airport master plan 2030. https://en.wikipedia.org/wiki/Hong_Kong_International_Airport_Master_Plan_2030.
Yoo, S., Beumer, R., van Wee, B., et al., 2025. Perceived accessibility by air transportation: a focus group study of potential air travelers in the netherlands. Transp. Res. Part A Policy Pract. 193, 104394. https://doi.org/10.1016/j.tra.2025.104394
Yoo, S., van Wee, B., Molin, E., 2024. Long distance accessibility by air transportation: a literature review. Transport Rev. 44 (4), 811–833. https://doi.org/10.1080/01441647.2024.2322430