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Optimizing multimodal mobility hub systems with user preference modeling

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Abstract : Ridesharing systems that reflect user preferences are critical for promoting adoption, improving efficiency, and supporting sustainable urban mobility. This paper proposes a multimodal mobility hub system that explicitly incorporates user preferences, including willingness to carpool and tolerance for detours. A case study in Québec evaluates how these behavioral factors influence system performance across four objectives : emissions, user costs, operator costs, and system-wide efficiency. Results show that greater willingness and flexibility substantially increase carpooling shares under emissions and system objectives. To reduce perceived user costs, incentive policies are also analyzed, and their interaction with behavioral factors is assessed. Full driving cost coverage for carpooling reduces user costs by 33.5% and increases ridesharing participation to 97.3% as willingness to carpool shifts from low to high. These findings demonstrate that embedding user preferences within the optimization framework captures realistic behavioral dynamics and supports the design of effective policies for sustainable and efficient multimodal transport systems.

Keywords : Ridesharing ; real-time optimization ; multimodal mobility hub ; user preference ; incentive policies

Résumé : Les systèmes de covoiturage qui tiennent compte des préférences des usagers sont essentiels pour favoriser leur adoption, améliorer l'efficacité et soutenir une mobilité urbaine durable. Cet article propose un système multimodal de pôle de mobilité qui intègre explicitement les préférences des usagers, notamment leur volonté de faire du covoiturage et leur tolérance aux détours. Une étude de cas au Québec évalue l'influence de ces facteurs comportementaux sur la performance du système selon quatre objectifs : les émissions, les coûts pour les usagers, les coûts pour l'opérateur et l'efficacité globale du système. Les résultats montrent qu'une plus grande volonté et une plus grande flexibilité des usagers augmentent considérablement la part du covoiturage lorsque les objectifs portent sur les émissions et la performance globale du système. Afin de réduire les coûts perçus par les usagers, différentes politiques d'incitation sont également analysées, ainsi que leur interaction avec les facteurs comportementaux. La prise en charge intégrale des coûts de conduite liés au covoiturage réduit les coûts pour les usagers de 33,5% et augmente la participation au covoiturage jusqu'à 97,3% lorsque la volonté de covoiturer passe d'un niveau faible à un niveau élevé. Ces résultats montrent que l'intégration des préférences des usagers dans le cadre d'optimisation permet de mieux représenter les dynamiques comportementales réalistes et contribue à la conception de politiques efficaces pour des systèmes de transport multimodaux durables et efficients.

Mots clés : Covoiturage ; optimisation en temps réel ; pôle de mobilité multimodal ; préférences des usagers ; politiques d'incitation

1 Introduction

Urbanization and the rise of shared mobility services are transforming transportation systems worldwide, offering the potential to reduce congestion, lower emissions, and enhance accessibility. Traditional formulations of the vehicle routing problem (VRP) are largely operator-oriented, focusing on minimizing distance, travel time, or operating costs. While these metrics are effective in freight and logistics, other perspectives, including user-oriented objectives and sustainability considerations, are also indispensable (Rodriguez-Valencia et al., 2022; Ning et al., 2021).

To address these perspectives, innovative mobility solutions increasingly emphasize public–private engagement, where personal vehicles play a central role in shared systems (Gu and Liang, 2024). Since personal cars remain the dominant travel mode in many urban areas, their integration into shared mobility is essential to reduce congestion, mitigate externalities, and lower emissions (Vega-Gonzalo et al., 2024). However, widespread adoption faces behavioral barriers : not all users are willing to share their vehicles, and even among those who are, tolerance for detours and additional travel time is often limited (Monchambert, 2020). Disregarding user preferences risks undermining the widespread adoption of shared mobility systems. Aligning system design with user expectations is crucial to ensure sustained engagement, scalability, and long-term viability in urban transport networks (Jie et al., 2021).

Building on our earlier framework (Sadat Asl et al., 2026), which introduced a multimodal mobility hub system optimizing emissions, user costs, operator costs, and system-wide objectives under parking constraints, this paper extends the model by explicitly incorporating user behavioral preferences. Specifically, the optimization process incorporates willingness to carpool and tolerance for detours, enabling the evaluation of behavioral heterogeneity and its impact on system dynamics across distinct objectives. In addition to tolerance for detours, cost savings are recognized as a critical determinant of carpooling decisions (Malodia and Singla, 2016). Monetary incentives serve as a policy instrument to realize these savings, encouraging shifts from single-occupancy vehicles and public transport toward carpooling (Mitropoulos et al., 2021). To capture these behavioral dynamics, the proposed framework introduces incentive policies that subsidize driving costs for personal vehicles engaged in carpooling and examines how these incentives interact with user preferences.

The contributions of this study are as follows. First, multimodal routing formulations are extended by embedding user behavior into the optimization process across emissions, user, operator, and system-wide objectives. Next, the combined effects of behavioral preferences and incentive schemes on system performance are evaluated to offer evidence-based insights for policy design. Finally, the real-world relevance of the proposed framework is demonstrated through a case study in the Québec region, highlighting implications for designing efficient and sustainable multimodal mobility hubs.

The remainder of the paper is structured as follows. Section 2 reviews related studies, and Section 3 formalizes the problem. Section 4 presents the column generation algorithm as the solution method, Section 5 details the computational experiments, and Section 6 summarizes the findings and outlines directions for future research.

2 Related work

The proposed system models user willingness to carpool and tolerance for detours in the optimization process of multimodal mobility hub systems integrating personal vehicles with carpooling options and shuttles. Because the framework is designed for dynamic settings and real-time operations, this section reviews related work in two complementary areas : (i) ridesharing of personal vehicles and (ii) dynamic ridesharing and real-time assignment methods.

2.1 Ridesharing of personal vehicles

Research on ridesharing of personal vehicles can be broadly divided into two categories : (i) behavioral analyses of passenger and driver choices and (ii) optimization of ride-matching mechanisms (Yi et al., 2022). On the behavioral side, mode choice studies have highlighted the role of factors such as travel time, cost, convenience, and incentives in shaping individuals' willingness to carpool across different transportation modes (Le Goff et al., 2022; Salihou et al., 2024). While most of this work emphasizes general attitudes towards these services, fewer studies have examined personal vehicle ridesharing when organized as feeders to public transport (Mitropoulos et al., 2021). On the algorithmic side, Stiglic et al. (2018) introduced a ride-matching algorithm consisting of a match identification phase and an optimization phase that maximizes the number of matched riders while minimizing the total additional driving distance for drivers. Gu and Liang (2024) proposed an integer programming formulation based on hypergraph representations with approximation algorithms to maximize the number of riders assigned to ridesharing routes. Hasan et al. (2020) developed a branch-and-price algorithm for commute trip-sharing that minimizes total travel distance.

2.2 Dynamic ridesharing

A prominent subclass of dynamic vehicle routing problem is dynamic ridesharing, which matches riders with drivers in real time to improve vehicle occupancy and reduce urban congestion (Wang et al., 2018). Dynamic ridesharing has motivated a wide range of optimization approaches. Alonso-Mora et al. (2017) developed a real-time assignment strategy based on pairwise request-vehicle graphs to minimize travel delay and penalize unassigned requests. Simonetto et al. (2019) introduced a federated optimization framework with a linear assignment model to reduce vehicle travel times. Ma et al. (2023) proposed a vector-similarity-based clustering and adaptive large neighborhood searching to minimize vehicle operating costs and penalties for unserved passengers. Riley et al. (2019) applied column generation to large-scale ridesharing dispatch, reducing wait times while maintaining near-direct travel quality. Similarly, Amiri et al. (2024) focused on minimizing waiting times and penalties for unserved ride requests, employing pruning strategies, dynamic pricing, and truncated labeling to improve computational efficiency. Sadat Asl et al. (2026) proposed a multimodal mobility hub framework that independently optimized the objectives of user, operator, emissions, and overall system efficiency under parking constraints at the hub.

While existing literature provides valuable insights into behavioral factors and optimization methods for ridesharing, most studies either analyze user preferences in isolation or develop optimization models without systematically embedding them into multiple objectives. Sadat Asl et al. (2026) assumed that all personal vehicle owners were willing to share their vehicles for carpooling. In practice, however, individuals vary considerably in their willingness to share rides and tolerance for detours, and such heterogeneity can significantly reshape system dynamics and alter cost distributions (Yi et al., 2022).

Designing sustainable transportation systems requires explicitly incorporating user preferences into optimization frameworks to enhance user satisfaction, improve system reliability, and promote greater uptake of shared mobility options. The present study addresses this gap by embedding user behavioral dimensions including willingness to carpool and tolerance for detours directly into the optimization process. This enables evaluation of how behavioral heterogeneity affects system performance across distinct objectives, including emissions, user costs, operator costs, and system-wide objectives. Furthermore, the analysis incorporates incentive policies, assessing how financial support mechanisms can reduce perceived user costs and encourage broader participation in personal vehicle ridesharing.

3 Problem definition

This paper investigates a multimodal mobility hub that serves as the origin and destination of trips. The system manages real-time ride requests for passengers traveling from their origins to the hub (inbound trips) or from the hub to their destinations (outbound trips). It integrates personal vehicles and shuttle services into a unified network, where personal vehicles may participate in carpooling depending on their willingness and detour tolerance. Shuttle vehicles can handle both inbound and outbound requests simultaneously—first serving outbound nodes, then inbound nodes—while personal vehicles are limited to serving either inbound or outbound requests : inbound personal vehicles may serve inbound nodes en route to the hub, whereas outbound personal vehicles may serve outbound nodes departing from the hub.

The problem is defined over a fleet of vehicles $\mathcal{V}$, a set of customers $\mathcal{C}$, and a directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N} = \mathcal{C} \cup \{0, n+1\}$ denotes the set of nodes and $\mathcal{A}$ the set of arcs. Nodes 0 and $n+1$ represent the hub at the start and end of a route, respectively. Let $\mathcal{V}_s$ and $\mathcal{V}_{pv}$ denote the sets of shuttle and personal vehicles, respectively. Then, $\mathcal{V} = \mathcal{V}_s \cup \mathcal{V}_{pv}$. Each customer $i \in \mathcal{C}$ is associated with a demand $m_i > 0$ and a time window $[e_i, l_i]$, where $0 \leq e_i \leq l_i$, indicating the earliest and latest allowable service start times. For hub nodes, let $m_0 = m_{n+1} = 0$ and $e_0 = e_{n+1} = 0$, with $l_0 = l_{n+1} = T$, where T denotes the planning horizon. The travel time associated with each arc $(i, j) \in \mathcal{A}$ is denoted by t_{ij} (Sadat Asl et al., 2026). The objective is defined in four variants, depending on the perspective considered : minimizing (i) emissions, (ii) user costs, (iii) operator costs, or (iv) vehicle underutilization as the system-wide objective. In each case, the goal is to design a set of routes that ensures each customer is visited exactly once and that all time and capacity constraints are respected.

Table 1 summarizes the factors considered under each objective for shuttles and personal vehicles. The emissions objective captures the environmental footprint of vehicles by incorporating life-cycle emissions from production through end-of-life. For personal vehicles, the user cost objective reflects the cost of travel time—computed as travel time multiplied by a value-of-time rate—along with driving expenses including fuel, maintenance, depreciation, and parking fees. Shuttle passengers, by contrast, are only affected by travel time, since operational and ownership expenses are borne by the operator. On the operator side, shuttles incur costs for fuel, maintenance, depreciation, and driver wages, though these can be partly offset by government subsidies. For personal vehicles, operator costs are limited to the upkeep of parking infrastructure, with parking fees contributing as operator revenue. At the system level, both modes are evaluated in terms of capacity underutilization to ensure that available vehicles are used effectively.

Table 1 – Factors considered under each objective for shuttle and personal vehicle modes.

Objective	Shuttle	Personal Vehicle
Emission	Operational and non-operational emissions	Operational and non-operational emissions
User	Travel time costs	Travel time costs ; fuel ; maintenance ; depreciation ; parking fees
Operator	Fuel ; maintenance ; depreciation ; driver wages ; minus government subsidies	Parking maintenance costs ; minus parking revenue
System	Capacity underutilization	Capacity underutilization

In this study, the optimization process incorporates user preferences including willingness to carpool and tolerance for detours, enabling the evaluation of behavioral heterogeneity and its impact on system dynamics across different objectives. Willingness to carpool and detour tolerance are represented as scenario parameters to enable a controlled analysis of their impact on system performance. While these behavioral factors are influenced in practice by incentives, trip characteristics, and user-specific attributes, treating them as fixed across scenarios allows us to isolate their structural effects across different optimization objectives. This approach provides clearer insights into how variations in behavioral flexibility influence routing decisions and overall system outcomes.

To address the described objectives, a column generation framework is employed, decomposing the problem into a restricted master problem, which selects routes from a limited set, and a subproblem, which generates new routes with negative reduced costs. The following section presents the formulation and solution procedure.

4 Methodology

Due to the combinatorial nature of VRPs, they are commonly reformulated as set partitioning problems and solved via column generation, where each column represents a feasible vehicle route (Righini and Salani, 2006). In the designed system, shuttle operations are modeled as a VRP with simultaneous pickup and delivery, while personal vehicle routes are enumerated and include solo and carpooling trips with up to two passengers.

In the column generation algorithm, the precomputed personal vehicle routes are added to the pool of columns. The master problem, formulated as a set partitioning problem, is then solved to obtain dual values, which are used in $|\mathcal{V}_s|$ independent subproblems, each formulated as a shortest path problem with resource constraints, to generate new columns. Any column with negative reduced cost is added to the pool, and the process is repeated iteratively until no improving columns remain. Once column generation converges, a final mixed-integer program (MIP) is solved to enforce integrality on the decision variables.

Let $\mathcal{R} = \bigcup_{v\in\mathcal{V}} \mathcal{R}_v$ denote the set of all feasible routes for the vehicles, where $\mathcal{R}_v$ is the set of feasible routes for vehicle v. For each route $r \in \mathcal{R}$, a binary decision variable y_r is defined, which takes the value 1 if route r is selected, and 0 otherwise. The cost associated with each route, c_r, depends on the objective and is calculated based on the factors summarized in Table 1. Moreover, z_i is a penalty variable indicating if customer $i \in \mathcal{C}$ is unserved, and β_i denotes the corresponding penalty cost. The parameter a_{ir} denotes the number of times customer i is visited on route r. A feasible route $r \in \mathcal{R}_v$ depends on the type of vehicle. For shuttles, a route starts and ends at the hub, serving a sequence of customers while satisfying vehicle capacity and time window constraints. Inbound personal vehicle routes begin at the customer's origin, may carry up to two passengers depending on the owner's willingness to carpool, and terminate at the hub. Outbound personal vehicle routes start at the hub, may likewise carry up to two passengers, and end at the passenger's destination. Feasible personal vehicle routes must respect passenger time windows as well as the detour tolerance of drivers who agree to carpool. The resulting set partitioning formulation is as follows :

$$\min \sum_{r\in\mathcal{R}} c_r y_r + \sum_{i\in\mathcal{C}} \beta_i z_i \tag{1a}$$

$$\text{s.t.} \quad \sum_{r\in\mathcal{R}} a_{ir} y_r + z_i = 1 \quad \forall i \in \mathcal{C}, \qquad (\pi_i) \tag{1b}$$

$$\sum_{r\in\mathcal{R}_v} y_r = 1 \quad \forall v \in \mathcal{V}, \qquad (\sigma_v) \tag{1c}$$

$$z_i \geq 0 \quad \forall i \in \mathcal{C}, \tag{1d}$$

$$y_r \in \{0,1\} \quad \forall r \in \mathcal{R}. \tag{1e}$$

The objective function (1a) minimizes the total cost of the selected routes, along with penalty costs for unserved requests. Constraints (1b) ensure that each customer is either served exactly once or marked as unserved, in which case the corresponding penalty variable is activated in the objective. Constraints (1c) ensure that exactly one route is assigned to each vehicle. Finally, constraints (1d) and (1e) define the domain of the decision variables.

To generate feasible routes, subproblems are solved to minimize the reduced cost associated with each route $r \in \mathcal{R}_v, v \in \mathcal{V}_s$. The reduced cost is given by $\bar{c_r} = c_r - \sum_{i \in C} \pi_i a_{ir} - \sigma_v$, where π_i and σ_v are the dual variables associated with constraints (1b) and (1c), respectively. Each subproblem is defined on a directed graph $\mathcal{G}_v = (\mathcal{N}_v, \mathcal{A}_v)$, where $\mathcal{N}_v$ is the set of nodes and $\mathcal{A}_v$ is the set of arcs for vehicle $v \in \mathcal{V}_s$. Since the shuttle vehicles first serve outbound requests and then inbound requests, $\mathcal{A}_v$ excludes edges from inbound to outbound nodes. The subproblem involves two sets of decision variables. The first, x_{ij}, is a binary variable that equals 1 if the vehicle travels directly from vertex i to vertex j, and 0 otherwise. The second variable, s_i, is associated with each vertex $i \in \mathcal{N}_v$, representing the start time of service at that location. The constraints of pricing problems include capacity constraints, network constraints, time-related constraints, and the permissible values of the decision variables (Desaulniers et al., 2006).

The system provides real-time assignment of requests to available vehicles while ensuring that time and capacity constraints are respected and defined objectives are minimized. Personal vehicles, once assigned, commit to a fixed sequence of stops and are no longer eligible for reassignment, whereas shuttle routes remain flexible and can be updated dynamically as new requests arrive. The re-optimization strategy follows the rolling horizon scheme suggested by Riley et al. (2019). To balance responsiveness with computational efficiency, the planning horizon is divided into 15-minute epochs during which incoming requests are batched for consideration in the subsequent epoch. At each epoch, the system solves a static optimization problem that accounts for the newly accumulated requests and any unserved requests from earlier periods.

5 Computational experiments

5.1 Dataset and settings

The proposed methodology is evaluated through a case study of a dynamic multimodal mobility hub system in the Québec region. The system integrates personal vehicles with carpooling options and shuttle services into a unified network designed to handle real-time inbound and outbound ride requests. The study area includes 3,155 virtual pick-up and drop-off points, with daily demand ranging from 436 to 702 requests over the simulation period of ten weekdays, as shown in Figure 1. The dataset has been made publicly available (Sadat Asl et al., 2025) to support reproducibility and further research.

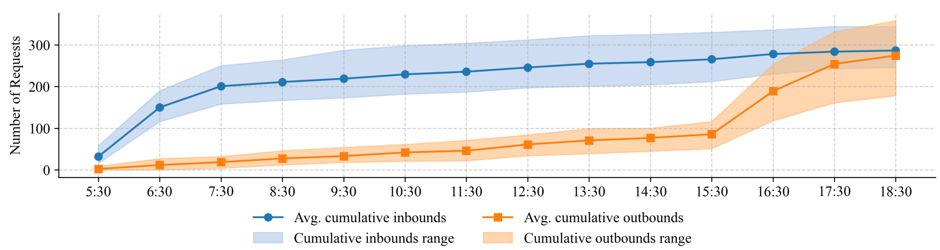

Figure 1 – Average and range of cumulative inbound and outbound requests over ten weekdays.

For outbound requests, the ready time is set to the arrival of alighting passengers, while for inbound requests, it is calculated by subtracting the travel time to the hub and a random preparation time from the boarding time. Each inbound node is assumed to have its own vehicle. For round trips, the system tracks whether an inbound request uses a personal vehicle to ensure availability for the afternoon return. For one-way outbound requests, fewer than 20% of users are assumed to have a vehicle available. Once a request is committed to be served at a specific time, a maximum allowable delay of 5 minutes is enforced during subsequent dynamic reoptimizations to account for minor timing flexibility while limiting deviations from the committed time. In the column generation framework, the master problems are solved with Gurobi 11.0.0, while the pricing subproblems are solved using the cspy package with a bidirectional labeling algorithm (Sanchez, 2020).

5.2 User preferences across objectives

This section examines how tolerance for detours affects the modal share between shuttles and personal vehicles under different levels of carpool willingness across different objectives, with results averaged over ten weekdays to account for daily variability. To evaluate the practical potential of the proposed algorithm within a multimodal mobility hub system, a set of experimental scenarios is designed that reflect variations in user behavior. These scenarios vary the proportion of personal vehicle owners willing to carpool (25%, 50%, and 100%) and the maximum allowable detour ratio (25%, 50%, and 75%), capturing a spectrum of behaviors from reluctant to highly engaged carpoolers. This setup allows assessment of how variations in user preferences impact modal choices and, consequently, the performance of the system across the emissions, user costs, operator costs, and system-wide objectives.

Under low behavioral flexibility (25% willingness to carpool and 25% detour tolerance), the emissions objective assigns 51.8% of passengers to shuttle services, 21.7% to carpooling, and 26.5% to solo vehicle trips. The user objective produces a greater reliance on shuttle services, with shares of 71.9%, 19.9%, and 8.2% for shuttle, carpooling, and solo trips, respectively. Under the system objective, the corresponding shares are 70.9%, 19.9%, and 9.2%, while the operator objective relies predominantly on solo travel, yielding shares of 7.5%, 0.8%, and 91.7%.

Higher flexibility in user behavior leads to an increase in the share of carpooling trips, accompanied by a corresponding reduction in shuttle and solo vehicle use, especially under the system and emissions objectives (see Figure 2). At 25% willingness, carpooling remains limited overall. Under the emissions objective, the share of total passengers traveling by carpooling rises from 21.7% at 25% detour tolerance to 30.2% at 75%. Smaller increases are observed under the user (19.9–22.8%) and system (19.9–25.4%) objectives, while the operator objective produces minimal carpooling shares (0.8–1.2%). At 50% willingness, carpooling becomes a significant portion of trips. The emissions objective shows an increase from 37.1% to 48.4%, while the system objective grows from 34.4% to 45.4%. The user objective produces a modest gain (32.2–35.6%), and the operator objective remains low (1.3–2.3%). At full willingness (100%), carpooling dominates under emissions (58.4–70.9%) and system (54.1–64.7%) objectives, with smaller effects under the user (44.1–45.4%) and operator (2.6–4.0%) perspectives. These shifts in modal share are also reflected in personal vehicle occupancy. The highest personal vehicle occupancy is observed under the system objective, increasing from 1.8 passengers at 25% willingness and 25% detour tolerance to 2.7 passengers at 100% willingness and 75% detour tolerance, reflecting its direct penalty on underutilized capacity and strong promotion of carpooling. Under the emissions objective, occupancy increases from 1.4 to 2.3 passengers across the same scenarios, as consolidating passengers into fewer vehicles reduces total travel distance and consequently lowers environmental impacts. The user objective exhibits more moderate changes, with occupancy ranging from 1.7 to 2.1 passengers, since lower shared travel expenses are partially offset by additional travel time caused by detours. By contrast, the operator objective maintains an average personal vehicle occupancy close to one passenger across all scenarios, as its emphasis on parking revenue creates a disincentive for ridesharing.

Figure 3 illustrates how cost savings evolve with increasing flexibility in user preferences under each objective, relative to a baseline scenario without carpooling. At the system level, savings are the most significant, starting from about 50.5% at 25% detour and 25% willingness, and reaching over 77% at 75% detour with full willingness. Savings under the emissions objective roughly triple, increasing from around 6–9% at low willingness to nearly 28% under full willingness. Operator savings exhibit a similar trend, although at a smaller scale, increasing from less than 1% at low flexibility levels to more than 8% at the highest flexibility level. User savings also increase with willingness, rising from about 15–17% at low willingness to over 32% under full willingness, although they are less sensitive to detour levels compared to the other objectives.

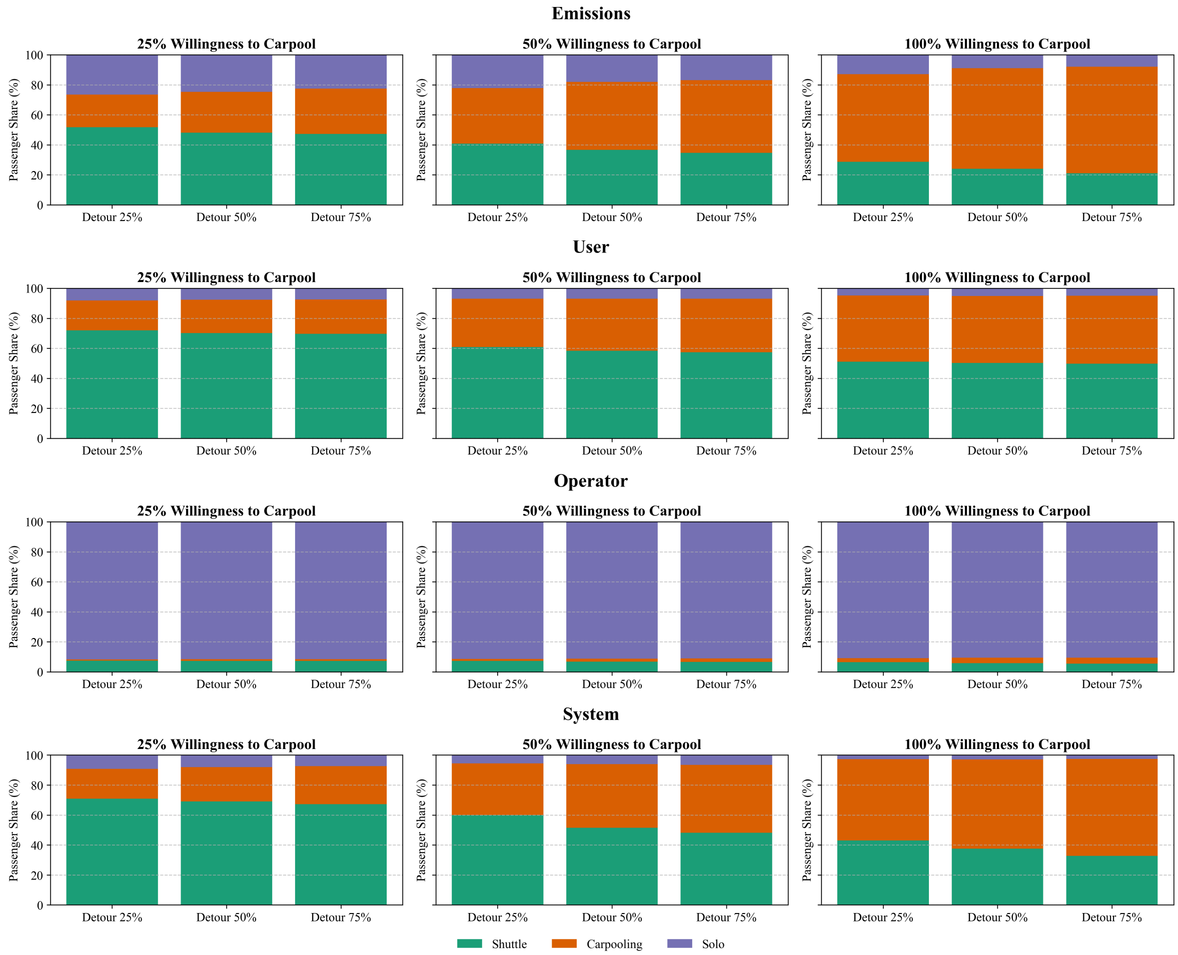

Figure 2 – Impact of detour tolerance on average modal share across carpooling willingness levels under different objectives.

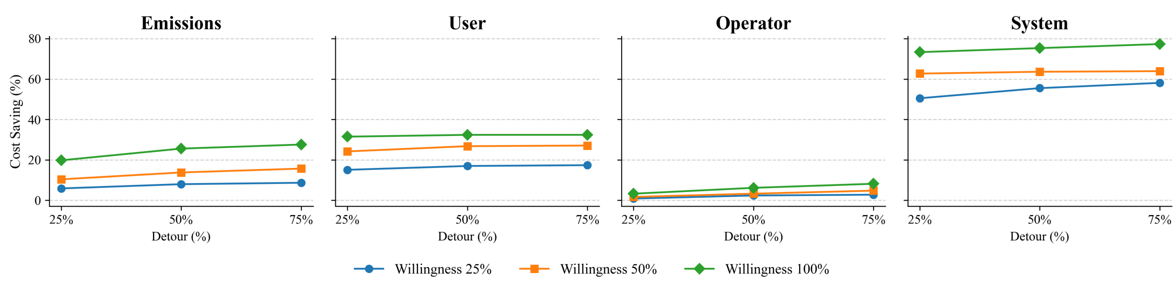

Figure 3 – Cost savings across objectives under varying detour tolerances and user willingness to carpool, relative to a no-carpooling baseline.

Beyond cost savings, behavioral flexibility also affects operational performance indicators such as total vehicle distance traveled and passenger delays. Under the emissions objective, total vehicle distance decreases from 1428.2 km at the lowest flexibility setting to 1240.4 km at the highest flexibility setting, while average passenger delay is reduced from 7.2 to 4.3 min. For the system objective, greater levels of ride matching and detours lead to comparatively larger passenger delays ; however, increasing behavioral flexibility still reduces average delay from 13.6 to 9.2 min, while total travel distance increases slightly from 1635.1 to 1672.5 km. Similarly, under the user objective, reducing average passenger delay from 3.5 to 0.9 min requires additional travel distance, which rises from 1979.5 to 2074.7

km. The operator objective, due to its strong reliance on solo travel, results in minimal passenger delays, decreasing only marginally from 0.5 to 0.4 min as flexibility increases. However, this objective also produces the largest travel distances among all objectives, with only a slight reduction from 2262.4 to 2238.4 km because of the limited use of ridesharing. The results highlight that while a user-oriented perspective can support meaningful levels of shared mobility, there remains substantial potential to further encourage users to act as transportation providers. One limiting factor is the relatively high driving costs of personal vehicles, which may discourage ridesharing. In user-centric transportation systems, targeted measures such as incentive policies could help overcome these barriers and increase shared mobility adoption. Accordingly, the subsequent analysis shifts to the user objective, where incentives are modeled as direct reductions in user costs.

5.3 Incentive analysis

The previous subsection examined modal share shifts under varying willingness and detour tolerance without monetary incentives. Here, the analysis is extended by incorporating incentive rates IR_r of 25%, 50%, and 100% for carpooling routes, and by examining their combined effect with detour tolerance under the user cost objective. These incentives are modeled as proportional discounts on driving costs, including fuel consumption, maintenance, and depreciation of personal vehicles. Let FC_r, MA_r, DE_r, PC_r, and TT_r denote, respectively, the fuel consumption, maintenance, depreciation, parking, and travel time costs for route r, all expressed in monetary units, and let IR_r represent the incentive rate. The total cost of route r is given by :

$$c_r = \begin{cases} TT_r, & r \in \mathcal{R}_v,\ v \in \mathcal{V}_s, \\ (FC_r + MA_r + DE_r) \cdot (1 - IR_r) + PC_r + TT_r, & r \in \mathcal{R}_v,\ v \in \mathcal{V}_{pv}. \end{cases} \tag{2}$$

Because incentives are introduced to promote ridesharing in personal vehicles, the incentive rate applied to carpooling routes is henceforth denoted by IR. Figure 4 presents the change in passenger share (percentage points, pp) for carpool and shuttle modes, relative to a base scenario for each willingness level defined by 25% detour tolerance and zero IR. This approach allows us to isolate the compounded impact of incentives and detour tolerance at each willingness level.

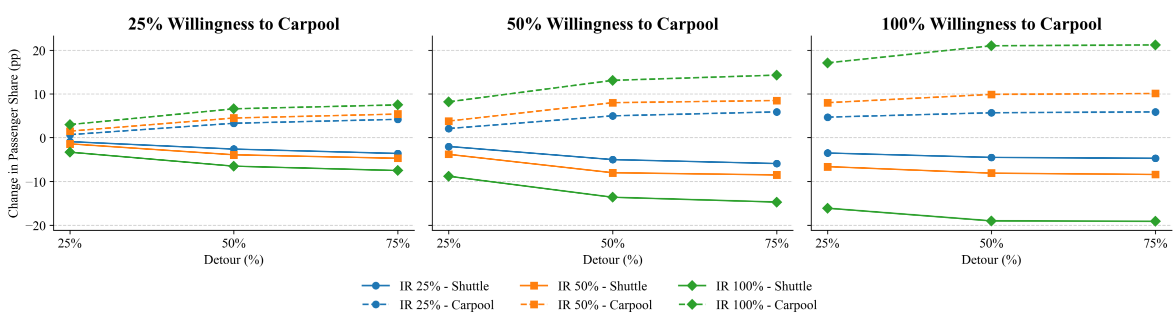

Figure 4 – Combined effects of detour tolerance and incentives on average carpool and shuttle shares across carpooling willingness levels.

Across all willingness levels, higher incentive rates consistently increase the share of carpool trips while reducing shuttle use. The magnitude of these shifts grows markedly with user willingness, suggesting that monetary incentives are most effective when the willingness to carpool is high. In all cases, shuttle share reductions closely mirror carpool share gains, implying that the primary mode shift under these policies occurs from shuttle to personal vehicle ridesharing, with limited changes to solo travel.

At 25% willingness, the results show that without incentives (Figure 2), raising detour tolerance from 25% to 75% increased carpool share of total passengers by 2.9 pp (from 19.9% to 22.8%) under the user objective. With a 25% IR, carpooling share increases by up to 4.2 pp, indicating an additional 1.3 pp attributable to the incentive. Under a 50% IR, carpool gains range from 1.5–5.4 pp (up to 2.5 pp due to the incentive), and with a 100% IR, they range from 3.0–7.5 pp (up to 4.6 pp due to the incentive). At 50% willingness, without incentives, increasing detour tolerance from 25% to 75% raises carpool share by 3.4 pp (from 32.2% to 35.6%). Adding a 25% IR increases carpool share by 2.1 pp at 25% detour and 5.9 pp at 75% detour. With a 50% IR, gains range from 3.8–8.5 pp, and under a 100% IR, carpool share increases by up to 14.3 pp—over four times the increase achieved without incentives. At 100% willingness, detour tolerance alone produces minimal change (1.3 pp) without incentives. Thus, the increases observed here primarily stem from policy interventions. With a 25% IR, carpool share rises by 4.7–5.9 pp ; with a 50% IR, the increase is 8.0–10.1 pp. Under a 100% IR, carpool share grows by 17.1–21.2 pp, corresponding to an additional gain of nearly 20.0 pp when combined with a 75% detour tolerance.

These findings demonstrate that incentives and detour tolerance act as complementary levers. Incentives provide a direct monetary motivation to shift from shuttle to carpool, while greater detour tolerance expands the feasible match set, amplifying the policy effect. From a policy perspective, substantial gains in ridesharing can be achieved by combining financial incentives with measures that promote flexibility in travel routes, particularly when targeting populations with medium-to-high willingness to carpool. Such interventions can meaningfully reduce the passenger load on public transport systems while increasing the utilization efficiency of private vehicle fleets.

5.4 Policy implications

Building on the earlier analysis of detour tolerance and incentives, a third dimension is now incorporated to quantify gains in carpool share and passenger cost savings resulting from shifts in willingness to carpool. Using a base scenario of 25% willingness, 25% detour tolerance, and zero incentive, Figure 5 illustrates the combined effects of increased willingness (50% and 100%) across different detour tolerances and incentive rates on carpool share (pp) and passenger cost savings (%), relative to the base scenario. This framing allows us to assess not only the interaction between incentives and detour tolerance, but also the additional benefits from shifts in willingness.

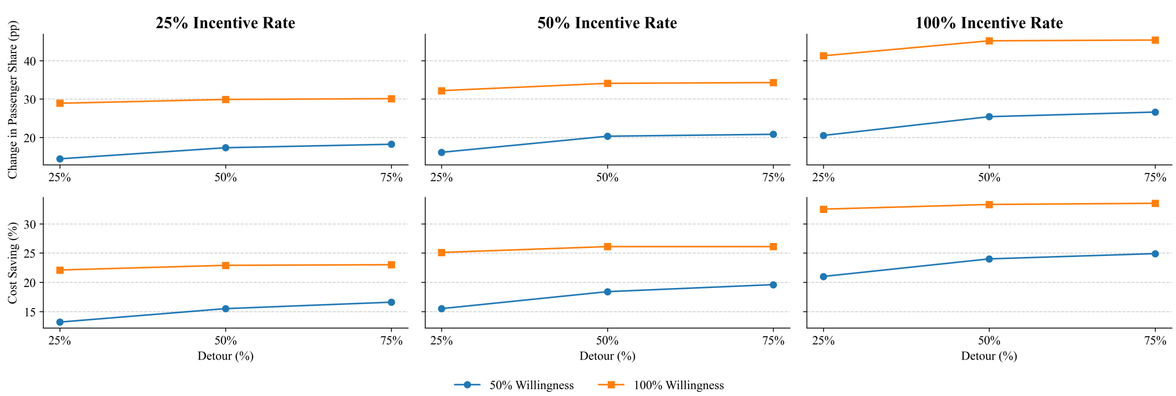

Figure 5 – Combined effects of detour tolerance, incentive rates, and willingness to carpool on carpool share and passenger cost savings.

At a 25% IR, increasing willingness from 25% to 50% increases the carpool share by 14.4 pp (25% detour tolerance) and by 18.2 pp (75% detour tolerance), while 100% willingness yields 28.9–30.1 pp. By comparison, under a 25% IR, the combined effect of detour tolerance and incentives alone (Figure 4) produced gains of up to 5.9 pp. With a 50% IR, the carpool share increase ranges from 16.1 to 20.8 pp under 50% willingness and from 32.2 to 34.3 pp under 100% willingness, compared to a maximum increase of 10.1 pp in Figure 4. At 100% IR, carpool share rises by 20.5–26.6 pp under 50% willingness and by 41.3–45.4 pp under 100% willingness—nearly doubling the 21.2 pp maximum gain seen when only detour and incentives varied.

Cost savings follow a similar pattern. At 25% IR, the reductions reach 16.6% for 50% willingness and 23.0% for 100% willingness. At 50% IR, these values increase to 19.6% and 26.1%, respectively. The largest gains occur with a 100% IR, yielding up to 24.9% savings for 50% willingness and 33.5% for 100% willingness.

While full cost coverage (100% IR) consistently yields the highest carpool shares and cost savings across all scenarios, its implementation requires authorities to absorb the complete driving costs of all carpooling participants. At high willingness levels where ridesharing participation exceeds 97%, this represents a large-scale fiscal commitment. In practice, a 50% IR may represent a more balanced policy instrument ; it achieves substantial carpool share gains (up to 20.8 pp at 50% willingness and 34.3 pp at 100% willingness) and meaningful cost savings (up to 19.6% and 26.1%, respectively) while limiting public expenditure to half of driving costs. Policymakers may therefore consider a staged approach : beginning with moderate incentives (25–50% IR) and gradually scaling subsidies as ridesharing adoption grows and fiscal returns from reduced shuttle operations and infrastructure savings become measurable.

Overall, the findings highlight that shifts in individuals' willingness to share personal vehicles can generate substantial advantages for the mobility system. By aligning economic rewards with greater flexibility in routing, policymakers can lower the perceived costs of carpooling and enhance its competitiveness and attractiveness relative to solo driving. While ridesharing decisions are also shaped by broader factors, including government policies, technological platforms, and socioeconomic and user characteristics, well-designed incentive schemes can gradually reshape commuter habits, embedding carpooling as a routine mobility choice rather than an exception. Beyond reducing congestion and passenger loads on public transport, such behavioral shifts improve the utilization efficiency of private vehicle fleets and contribute to broader sustainability objectives. Over time, repeated participation in incentivized carpooling can reinforce these habits, fostering a long-term cultural shift toward more sustainable and efficient travel patterns.

6 Conclusion

This study examines behavioral factors and user preferences in a multimodal mobility hub system across emissions, user, operator, and system-wide objectives. A column generation algorithm was used to optimize the routes of shuttles and personal vehicles under different willingness levels and detour tolerances. The case study in Québec illustrates that increasing flexibility in personal vehicle drivers' ridesharing decisions can significantly boost the share of carpooling under emissions and system objectives. To lower perceived user costs, incentive policies were considered, and the results indicate how behavioral factors interact with financial incentives to reshape modal shares, reduce passenger costs, and alleviate pressure on public shuttles. Notably, fully subsidizing the driving costs of carpool participants reduces user costs by 33.5% as willingness shifts from low to high, increases the share of passengers carpooling to 65.3%, and raises overall ridesharing participation to 97.3%, leaving solo vehicle use at a minimum. These results underscore the pivotal role of targeted incentives in accelerating shared mobility adoption. Beyond policy implications, the findings highlight broader opportunities for embedding user-centric optimization into mobility planning. Aligning economic incentives with traveler preferences can shift demand toward shared modes, yielding efficiency gains while improving user satisfaction. A promising direction for future research is to integrate behavioral choice models, such as logit-based formulations, into the proposed framework. This would allow willingness to carpool and detour tolerance to vary with incentives, travel conditions, and user-specific characteristics, such as discomfort and time perception, providing a more realistic representation of traveler decision-making. Furthermore, the framework could be extended to account for uncertainty in demand and coordination among multiple mobility hubs.

Références

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., & Rus, D. (2017). On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proceedings of the National Academy of Sciences, 114(3), 462–467. https://doi.org/10.1073/pnas.1611675114

Amiri, E., Legrain, A., & El Hallaoui, I. (2024). Accelerated column generation : Application in real-time dial-a-ride problem. Les Cahiers du GERAD ISSN, 711, 2440.

Desaulniers, G., Desrosiers, J., & Solomon, M. M. (Eds.). (2006). Column Generation (Vol. 5). Springer Science & Business Media. https://doi.org/10.1007/b135457

Gu, Q.P. and Liang, J.L. (2024). Algorithms and computational study on a transportation system integrating public transit and ridesharing of personal vehicles. Computers & Operations Research, 164, p.106529. https://doi.org/10.1016/j.cor.2024.106529

Hasan, M. H., Van Hentenryck, P., & Legrain, A. (2020). The commute trip-sharing problem. Transportation Science, 54(6), 1640–1675. https://doi.org/10.1287/trsc.2019.0969

Jie, F., Standing, C., Biermann, S., Standing, S., & Le, T. (2021). Factors affecting the adoption of shared mobility systems : Evidence from Australia. Research in Transportation Business & Management, 41, 100651. https://doi.org/10.1016/j.rtbm.2021.100651

Le Goff, A., Monchambert, G., & Raux, C. (2022). Are solo driving commuters ready to switch to carpool ? Heterogeneity of preferences in Lyon's urban area. Transport Policy, 115, 27–39. https://doi.org/10.1016/j.tranpol.2021.10.001

Ma, W., Zeng, L., & An, K. (2023). Dynamic vehicle routing problem for flexible buses considering stochastic requests. Transportation Research Part C : Emerging Technologies, 148, 104030. https://doi.org/10.1016/j.trc.2023.104030

Malodia, S., & Singla, H. (2016). A study of carpooling behaviour using a stated preference web survey in selected cities of India. Transportation Planning and Technology, 39(5), 538–550. https://doi.org/10.1080/03081060.2016.1174368

Mitropoulos, L., Kortsari, A., & Ayfantopoulou, G. (2021). Factors affecting drivers to participate in a carpooling to public transport service. Sustainability, 13(16), 9129. https://doi.org/10.3390/su13169129

Monchambert, G. (2020). Why do (or don't) people carpool for long distance trips ? A discrete choice experiment in France. Transportation Research Part A : Policy and Practice, 132, 911–931. https://doi.org/10.1016/j.tra.2019.12.033

Ning, F., Jiang, G., Lam, S. K., Ou, C., He, P., & Sun, Y. (2021). Passenger-centric vehicle routing for first-mile transportation considering request uncertainty. Information Sciences, 570, 241–261. https://doi.org/10.1016/j.ins.2021.04.054

Righini, G., & Salani, M. (2006). Symmetry helps : Bounded bi-directional dynamic programming for the elementary shortest path problem with resource constraints. Discrete Optimization, 3(3), 255–273. https://doi.org/10.1016/j.disopt.2006.05.007

Riley, C., Legrain, A., & Van Hentenryck, P. (2019, April). Column generation for real-time ride-sharing operations. In International Conference on Integration of Constraint Programming, Artificial Intelligence, and Operations Research (pp. 472–487). Cham : Springer International Publishing. https://doi.org/10.1007/978-3-030-19212-9_31

Rodriguez-Valencia, A., Ortiz-Ramirez, H. A., Simancas, W., & Vallejo-Borda, J. A. (2022). Understanding transit user satisfaction with an integrated bus system. Journal of Public Transportation, 24, 100037. https://doi.org/10.1016/j.jpubtr.2022.100037

Sadat Asl, A. A., Delmaire, H., Legrain, A., & Soumis, F. (2026). Optimizing diverse stakeholders' objectives in a real-time multimodal mobility hub system. Journal of Public Transportation, 28, 100147. https://doi.org/10.1016/j.jpubtr.2026.100147

Sadat Asl, A. A., Delmaire, H., Legrain, A., & Soumis, F. (2025). Dataset : Real-Time Multimodal Mobility Hub System [Data set]. Zenodo. https://doi.org/10.5281/zenodo.15122591

Salihou, F., Bulteau, J., Le Boennec, R., Berrada, J., & Da Costa, P. (2024). The impacts of combining incentives on carpooling for commuting in the Paris region. Journal of Environmental Planning and Management, 1–27. https://doi.org/10.1080/09640568.2024.2392645

Sanchez, D. T. (2020). cspy : A Python package with a collection of algorithms for the (resource) constrained shortest path problem. Journal of Open Source Software, 5(49), p.1655. https://doi.org/10.21105/joss.01655

Simonetto, A., Monteil, J., & Gambella, C. (2019). Real-time city-scale ridesharing via linear assignment problems. Transportation Research Part C : Emerging Technologies, 101, 208–232. https://doi.org/10.1016/j.trc.2019.01.019

Stiglic, M., Agatz, N., Savelsbergh, M. and Gradisar, M. (2018). Enhancing urban mobility : Integrating ride-sharing and public transit. Computers & Operations Research, 90, pp.12–21. https://doi.org/10.1016/j.cor.2017.08.016

Vega-Gonzalo, M., Gomez, J., Christidis, P., & Vassallo, J. M. (2024). The role of shared mobility in reducing perceived private car dependency. Transportation Research Part D : Transport and Environment, 126, 104023. https://doi.org/10.1016/j.trd.2023.104023

Wang, X., Agatz, N., & Erera, A. (2018). Stable matching for dynamic ride-sharing systems. Transportation Science, 52(4), 850–867. https://doi.org/10.1287/trsc.2017.0768

Yi, X., Lian, F., & Yang, Z. (2022). Research on commuters' carpooling behavior in the mobile internet context. Transport Policy, 126, 14–25. https://doi.org/10.1016/j.tranpol.2022.06.016