Transportation Research Part D 159 (2026) 105514

Contents lists available at ScienceDirect

Transportation Research Part D

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

Redefining empty trips through occupancy and transferability of cross-modal strategies: A review☆

Pedram Akbari [a], Gonçalo Homem de Almeida Correia [b], Merkebe Getachew Demissie [a,*]

[a] The University of Calgary, Department of Civil Engineering, 2500 University Drive N.W., Calgary, Alberta T2N lN4, Canada
[b] Department of Transport & Planning, Delft University of Technology, Building 23, Stevinweg 1, 2628 CN Delft, the Netherlands

ARTICLE INFO

Keywords:
Empty trips
Travel efficiency
Cross-modal strategies
Sustainable transportation
Shared mobility

ABSTRACT

Empty trips, vehicle movements without payload, generate unsustainable externalities. This study addresses these challenges by identifying shortcomings in the literature on empty trip generation across all modes through a combined narrative and systematic review. The review revealed that the conventional definition of empty trips adopts a binary empty/non-empty perspective, which fails to capture the extent of the problem. In response, we propose a continuous measure based on the proportion of unused vehicle capacity. Our review also reveals that mitigation strategies are often case-specific, which limits their impact and transferability across modes. To address this limitation, we introduce a framework that facilitates the transferability of strategies by highlighting cross-modal similarities in generating empty trips. Finally, we reviewed these strategies, their methodologies, and the associated problems related to empty trips using the systematic review in driver-provided mobility, which includes public transportation, carpooling, taxi, and ride-hailing to support sustainable mobility through strategy generalization.

1. Introduction

A major obstacle to achieving sustainability in transportation is the inefficient use of resources driven by unsustainable travel behavior and mobility patterns. A persistent yet underexplored outcome of this inefficiency is the occurrence of empty trips. Although not explicitly defined in the literature, empty trips are movements of a vehicle without transporting any freight or passengers. However, as will be discussed in this paper, the concept is more complex than this simple definition suggests.

Investigating empty trips is crucial because they contribute to road congestion, accidents, emissions, and fuel consumption (Nasibov et al., 2013; Farren et al., 2024). These trips make up a considerable share of traffic, accounting for approximately 20%-40% of freight movements (Gonzalez-Calderon et al., 2012; Gonzalez-Calderon et al., 2018) and 35%-40% of total travel time in taxi and ride-hailing services (O'Keeffe et al., 2022; Guo et al., 2022). Mitigating empty trips not only reduces passenger costs and enhances perceived safety in shared services (He et al., 2018; Ouali et al., 2020) but also improves operational profitability by optimizing fleet size and reducing overhead (Farren et al., 2024).

Despite these environmental and operational implications, the literature remains limited in fully explaining both the environmental

☆ This article is part of a special issue entitled: '30 anniversary of TRD' published in Transportation Research Part D.

* Corresponding author.
E-mail address: merkebe.demissie@ucalgary.ca (M.G. Demissie).

https://doi.org/10.1016/j.trd.2026.105514
Received 31 October 2025; Received in revised form 2 July 2026; Accepted 3 July 2026
Available online 13 July 2026

impacts and operational inefficiencies associated with empty movements. This limitation partly stems from how empty trips have been defined in the literature. Erhardt et al. (2019) defined empty trips in passenger transportation as vehicle movements without passengers, whereas in freight transportation, they are primarily defined by comparison with loaded trips (Barla et al., 2010; Gonzalez-Calderon et al., 2021; Holguín-Veras et al., 2010; Holguín-Veras and Thorson, 2003). Recently, Farren et al. (2024) framed emptiness as the absence of cargo in return trips. Together, these perspectives imply a binary conceptualization, categorizing trips as either empty or non-empty. While this conclusion requires further verification across transport modes, such a binary view may limit the ability to capture potential efficiency improvements, which is the central motivation for studying empty trips. For instance, a bus operating with only a single passenger, though categorized as non-empty under this definition, is far closer in operational inefficiency to an empty vehicle than to a fully occupied one. Therefore, the full extent of efficiency improvement cannot be captured under the current binary approach. In addition to definitional limitations, most studies in this field have been case-specific, that is, they focused on one or a limited set of examples within a single mode. For example, Willoughby (2002) examined empty public transportation trips as movements between depots and terminal stops at the beginning or end of service (commonly referred to as pull-in and pull-out). Sevim et al. (2022) extended this scope to include repositioning between terminal stops for scheduling purposes. Likewise, Hsu et al. (2021) included trips to recharging stations, alongside pull-in and pull-out, as empty trips in their analysis. While such case-specific approaches provide valuable context for developing tailored strategies, a broader review across transport modes is needed to systematically capture all forms of empty trips. Such a review would not only verify whether the binary framing is consistent across the literature but also reveal the full range of empty trip examples within and across modes. This, in turn, can facilitate cross-temporal and cross-regional comparisons, enhance our understanding of the operational characteristics that generate empty trips, and highlight similarities across modes. Identifying these patterns allows strategies effective in one mode to be generalized to others, thereby addressing empty trips more efficiently.

Beyond the basic understanding of empty trips, there is a lack of systematic knowledge about mitigation strategies. Although numerous approaches have been proposed, ranging from policies such as pricing schemes to operational solutions such as driver-passenger matching, they remain dispersed across studies and contexts. This absence of a consolidated synthesis hinders the identification of best practices and applied methodologies and obscures research gaps. Therefore, a comprehensive synthesis of strategies and their methodologies is required to inform more effective future planning and operational efforts. Consequently, this study aims to address the following research questions:

1- How consistently is the binary definition of empty versus non-empty trips applied across modes, and what refinements are needed to better capture their environmental impacts and operational inefficiencies?
2- What operational characteristics of transportation systems contribute to the generation of empty trips, and how can they be organized within a framework that facilitates the transferability of strategies across modes?
3- What insights from existing strategies aimed at reducing empty trips can be taken to support the development of more efficient and sustainable transport operations?

While the first two research questions require consideration of all transportation modes, the scope of the third question is limited to public transportation, carpooling, taxi, and ride-hailing, for which more detailed information, such as the mitigation strategies applied

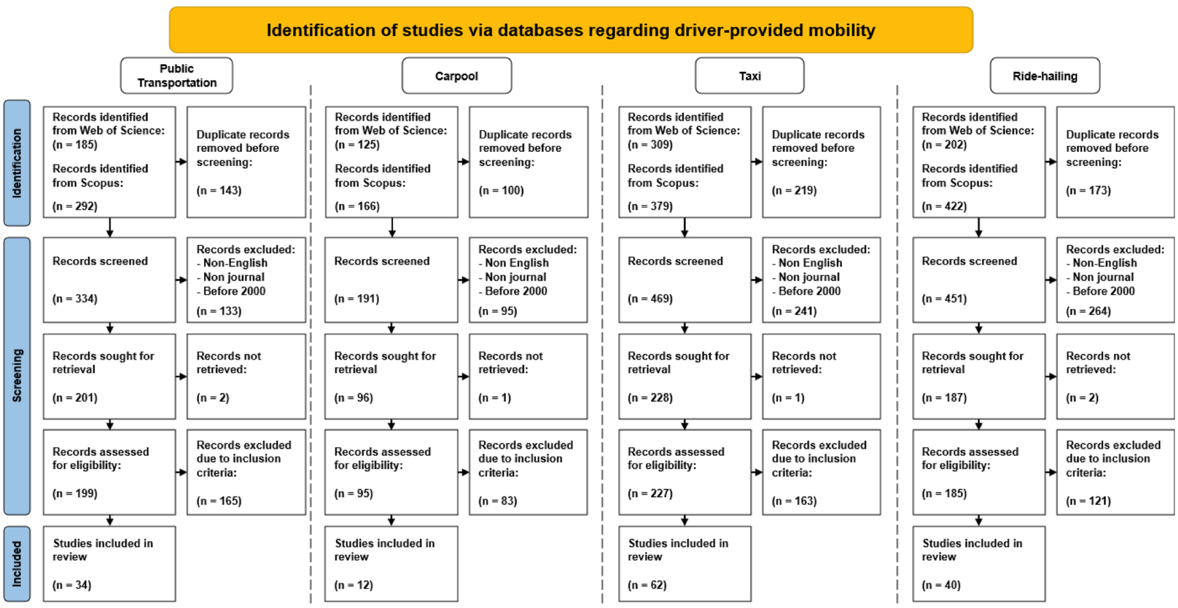

Fig. 1. PRISMA methodology details for the review of driver-provided mobility.

and their corresponding methodologies, needs to be examined. These four modes were selected for their similar operational patterns, such as repositioning, deadheading, and passenger searching, which inherently generate empty trips. Narrowing the focus to these four modes enables a more coherent, in-depth, and methodologically consistent synthesis of mitigation strategies, while enhancing their applicability across passenger transportation systems. Because they share the common characteristic of relying on drivers to provide services to passengers, this paper classifies them as “driver-provided mobility,” distinguishing them from “shared user-operated mobility,” such as micromobility and carsharing, where users operate the vehicles themselves.

Given the broad scope of the first two research questions and the more specific focus of the third, we adopted a mixed-method review approach. Specifically, research question three, along with relevant aspects of research questions one and two concerning driver-provided mobility, were addressed through a systematic literature review, while the remaining modes under the first two questions, from freight transportation to shared user-operated mobility, were analyzed using a narrative review. This methodology aligns with established practices that utilize narrative reviews as a complementary approach to explore broad research topics (De-Toledo et al., 2024).

The remainder of this literature review is organized as follows: Section 2 outlines the methodology for identifying relevant studies. Section 3 examines examples of empty trips in depth, paving the way for a discussion of the binary approach to empty trips and providing context for the transferability of strategies. Section 4 synthesizes current mitigation strategies and their methodologies, offering insights for designing more effective approaches. Section 5 highlights the implications of this study for theory, policy, and practice. Finally, Section 6 presents a conclusion and discusses future research opportunities.

2. Review methodology

The systematic review followed PRISMA guidelines (Page et al., 2021) (Fig. 1) using Scopus and Web of Science to identify English-language journal articles published after 2000. Keywords were selected after extensive testing of combinations and applied to titles, abstracts, and author keywords. The search string followed a core structure of ‘mode of study’ + ‘empty and its synonyms,’ as detailed in Table 1. In this study, synonyms for “empty” included vacant, unoccupied, and deadhead* (where ‘*’ denotes a truncation operator). The less common terms “idle” and “nonrevenue” were excluded. Studies were selected based on the following eligibility criteria: (1) empty trips must be a primary focus, to ensure an explicit analysis of causes, impacts, or mitigation; (2) the term “empty” or its synonyms had to align with the definition adopted in this paper; studies using these terms in unrelated contexts (e.g., deadheading policies discussed in Section 3.4.1) were excluded; (3) the research must specifically address public transport, carpooling, taxi, or ride-hailing; and (4) studies addressing emerging forms of driver-provided mobility (e.g., automation, modularity, or consolidation technologies) were excluded to maintain conceptual consistency.

The narrative literature review used a methodology consistent with the systematic review, employing targeted keyword searches in Scopus. The search strategy combined transportation modes with the term “empty” and its synonyms, and was restricted to English-language journal articles published after 2000. Papers were selected based on the following criteria: (1) empty trips had to be a primary focus to ensure a direct investigation of causes, impacts, and mitigation; (2) inclusion was limited to Q1 or Q2 journals; and (3) highly cited studies were prioritized to reflect their influence within the field.

3. How are empty trips generated across different modes?

3.1. Freight transportation

The empty-trip problem in freight transportation primarily arises because vehicles must return to their depots after completing deliveries. This challenge is exacerbated by regional freight demand imbalances, where some areas are primarily exporters and others are importers, as well as by commodity-specific equipment requirements that limit opportunities for matching return loads.

These logistical constraints lead to a lack of return shipments, commonly referred to as the “backhaul problem” in the literature, which forces carriers to reposition empty vehicles to maintain their operational capacity (Boumahdaf et al., 2023). Empty trips may also occur at the start of a journey if the vehicle’s depot does not coincide with the shipment’s origin (Barla et al., 2010). Despite these varying circumstances, the underlying cause across all cases remains an imbalance between supply and demand, necessitating the repositioning of empty vehicles.

Empty trips account for a significant share of freight vehicle mileage, representing approximately 56% for straight trucks without trailers, 58% for straight trucks with trailers, and about 33% for truck-tractors (power units) pulling one or more trailers. Furthermore,

Table 1
The details of search method for driver-provided mobility.

Mode	Seach phrase
Public Transportation	(“public transport*” OR “public transit*”) AND (“empty” OR “deadhead*” OR “vacant” OR “unoccupied”)
Carpool	(“carpool*” OR “carshar*” OR “car-shar*” OR “car pool*” OR “car-pool*” OR “rideshar*” OR “ride-shar*”) AND (“empty” OR “deadhead*” OR “vacant” OR “unoccupied”)
Taxi	(taxi) AND (“empty” OR “deadhead*” OR “vacant” OR “unoccupied”)
Ride-sourcing	(“ridesourc*” OR “ride sourc*” OR “rideshar*” OR “ride-shar*” OR “ridehail*” OR “ride hail*” OR “Uber” OR “lyft” OR “TNC”) AND (“empty” OR “deadhead*” OR “vacant” OR “unoccupied”)

empty travel accounts for about 20% of urban truck traffic and 30%–40% of intercity freight operations (Gonzalez-Calderon et al., 2012; Gonzalez-Calderon et al., 2018).

The analysis of empty trips in freight transportation varies by the unit of flow: vehicle trips or commodity flows. Vehicle trip-based models focus on predicting traffic and can capture both loaded and empty movements, though they often overlook specific load attributes. Conversely, commodity flow models typically represent only loaded flows but can incorporate attributes that influence empty trip generation, such as commodity type (Gonzalez-Calderon et al., 2021). To estimate empty vehicle movements within commodity flow modeling, complementary approaches such as the Noortman and Van Es (NVE) and the Generalized NVE and Hautzinger are commonly employed (Holguín-Veras et al., 2014). Holguín-Veras and Thorson (2003) introduced a methodology that formulated empty vehicle flow as a function of the commodity matrix, grounded in trip chaining, probability principles, and spatial interaction. This formulation was further refined in subsequent studies (Holguín-Veras et al., 2010). Other methods use optimization techniques, such as the linear programming approach applied by Mesa-Arango et al. (2013) to model empty trips over time-expanded networks. These frameworks provide essential insights for managing empty trips in freight transportation. Research on freight empty trips includes incorporating empty trips into the planning process, such as Origin-Destination planning and four-step modeling (Holguín-Veras and Patil, 2007; Cantillo et al., 2014; Holguín-Veras et al., 2011), and modeling the flow of empty vehicles (Farren et al., 2024; Gonzalez-Calderon et al., 2021).

3.2. Autonomous vehicles

While automation exists across various modes, this analysis focuses on its application in private vehicles. Autonomous vehicles (AVs) have been shown to increase road capacity, improve accessibility for elderly and disabled individuals, reduce emissions, lower the incidence of crashes, and save fuel (Fagnant and Kockelman, 2015). A distinctive feature of AVs is their ability to self-reposition without a driver, which results in the generation of empty vehicles. For example, an AV may drop off passengers and autonomously navigate to a parking location, known as AVs' self-parking capability, to avoid expensive or congested areas (Shafiei et al., 2023a). This movement, and the subsequent return to retrieve passengers, both constitute empty trips. In other instances, the vehicle may return home rather than park elsewhere (Millard-Ball, 2019). Regardless of the specific destination, the common factor is the vehicle traveling to a pick-up point with no passengers on board. These operations can increase empty vehicle miles traveled by nearly 20%, which, in specific urban contexts, accounts for an additional 22 million vehicle miles (Mondal et al., 2023; Tajaddini and Vu, 2023). One study area in AVs' empty repositioning is AV adoption, which can involve planning processes, such as the impact of empty vehicles in four-step travel models (Tajaddini and Vu, 2023; Levin and Boyles, 2015; Levin et al., 2019), facility location problems like locating parking for empty vehicles (Levin et al., 2020), or empty trips in the context of interactions of AVs with other modes (Shafiei et al., 2023b; Saleh and Hatzopoulou, 2020; Zhang et al., 2018a; Schlenther et al., 2020).

Some of the literature on empty trips in AVs concerns shared AVs. A distinctive feature of empty trips in shared AVs is repositioning to a location to pick up the first passenger. One research area that has received particular attention is quantifying empty trips generated by this technology across different applications (Abkarian et al., 2022; Khayati et al., 2021; Yan et al., 2020; Huang et al., 2021). Given the exclusion of automation from the driver-provided mobility section, and noting that empty trips in both shared and private AVs share a similar repositioning mechanism, subsequent discussions will primarily focus on the private application of AVs.

3.3. Shared user-operated mobility

In this type of service, users rent vehicles from a company for short-term use via mobile applications and other advanced technologies. This category includes micromobility (bike- and scooter-sharing) and carsharing systems. Empty trips in these systems occur when operators collect vehicles for maintenance. For micromobility, this typically involves van fleets retrieving scooters for overnight charging (Turan and Wakolbinger, 2023), while carsharing often relies on staff relocating vehicles to refueling or charging stations (Folkestad et al., 2020). Another form of empty trips involves relocating vehicles between stations to address surplus or deficit inventories caused by spatiotemporal imbalances in supply and demand (Zhang et al., 2023a). Because these relocation operations are costly and generate significant greenhouse gas (GHG) emissions, they warrant detailed examination (Silva et al., 2024). The following section reviews empty trips in shared user-operated mobility.

3.3.1. Micromobility

Shared scooters and bikes are designed to address first- and last-mile connectivity, reduce air pollution, and alleviate traffic congestion (Zhu et al., 2020; Chu et al., 2023). Empty repositioning in these services is typically managed by operators using transport vehicles, with the specific approach determined by the system type and operational design. Micromobility systems can be categorized as either free-floating (dockless) or station-based (docked) (Orozco-Fontalvo et al., 2023). In free-floating systems, vehicles can be secured to any ordinary rack, solid frame, or standalone fixture without requiring specific stations, unlike station-based systems (Pal and Zhang, 2017). Repositioning operations are further classified as static or dynamic. Static operations occur primarily at night, when network conditions change slowly, whereas dynamic operations take place during the day when system utilization is high (Raviv et al., 2013). Although static repositioning does not contribute to traffic congestion or parking problems (Raviv et al., 2013), it is insufficient to accommodate the tidal variations in demand during daytime hours. In such cases, dynamic repositioning is required to maintain system balance (Li et al., 2024). Rebalancing can also be distinguished as either complete or partial, depending on whether the entire network or only a specific subset of stations is included in the operation (Pal and Zhang, 2017). A more recent advancement in the field is self-repositioning micromobility, in which vehicles autonomously reposition themselves without operator intervention (Kondor et al., 2021).

For the aforementioned operations, Pal and Zhang (2017) investigated static rebalancing of free-floating bikes, while Raviv et al. (2013) analyzed the same process in a station-based system. Studies on scooter-sharing systems include Saum et al. (2024) for free-floating configurations and Osorio et al. (2021) for station-based systems. Examples of dynamic repositioning appear in Chen et al. (2024) for free-floating services and in Li et al. (2024) for station-based systems. While most literature focuses on operator-based repositioning using transport vehicles, Kondor et al. (2021) examined self-repositioning scooters by estimating their potential to improve operational efficiency.

3.3.2. Carsharing

Carsharing offers a viable alternative for daily commutes and first- or last-mile trips by eliminating ownership costs, such as insurance, maintenance, and fuel (Folkestad et al., 2020). Carsharing systems are generally categorized as round-trip or one-way. In round-trip systems, users return the vehicle to its original rental station, resulting in minimal empty rebalancing trips. Conversely, one-way systems provide more flexibility but require more management and can be divided into free-floating and station-based operations. In free-floating systems, users can park vehicles anywhere within a defined service area, whereas in station-based systems, vehicles must be returned to designated stations. The operational model, especially parking constraints, directly influences the frequency of empty rebalancing trips and the overall need for vehicle repositioning. Research in carsharing optimization focuses on reducing costs across various operational models. For example, Zhao et al. (2018) developed a mixed-integer linear programming model to minimize the combined costs of vehicle and staff investments and relocation in a station-based carsharing system. Similar frameworks were proposed to optimize free-floating (Folkestad et al., 2020) and round-trip (Changaival et al., 2021) operations. Additionally, Nourinejad and Roorda (2015) conducted a comparative analysis of round-trip and one-way systems, revealing that one-way systems require smaller fleets but entail higher relocation times.

The relocation process may be carried out either by operators or by users. In operator-based rebalancing, staff are deployed based on the trade-off between relocation volume and labor costs. In contrast, user-based rebalancing relies on incentivizing customers to assist in repositioning by adjusting their pickup/drop-off locations or travel times. In this case, operators must determine optimal values for decision variables such as delivery locations, incentive levels, and the scale of user participation (Eliyan and Kerbache, 2024). For example, Samie and Rezaee (2022) examined the optimal contributions of operators and users to relocation processes under varying levels of freelance driver involvement.

3.4. Driver-provided mobility

In this group, which includes public transportation, carpooling, taxi services, and ride-hailing, an empty trip is any movement of a vehicle without passengers on board. These trips are generally categorized into three types:

1. Refueling/recharging trips: when a vehicle in service travels to a gas station or a charging station.
2. Access trips: when a vehicle travels between an origin point (e.g., the driver's home or a bus depot) and the designated service area.
3. Repositioning trips: when an empty vehicle is moved within the service area to improve performance metrics, such as revenue or service quality.

Depending on the mode, some of these types may not occur, while others may appear as well. The following sections provide detailed examples of empty trips for each of the four modes.

3.4.1. Public transportation

Our review has identified 4 types of empty trips in this transportation mode. First, in electric fleets, vehicles generate empty trips when they deviate from their regular routes to reach charging stations without passengers (Hsu et al., 2021; Olsen and Kliewer, 2022). Second, empty trips arise from travel between depots (garages) and terminal route stops at the beginning (pull-out) or end of service (pull-in), during which vehicles operate without passengers (Nasibov et al., 2013; Al Ali and Hassan, 2018). Third, some studies have examined the repositioning of empty vehicles between the termini or stops of different lines, typically to maintain schedule adherence (Sevim et al., 2022; Xu et al., 2023). Finally, routine travel along a designated route is considered an empty trip if the vehicle is operating without any passengers on board (Hsu et al., 2021; Olsen and Kliewer, 2022). Beyond fixed-route services (FRS), other public transportation systems, such as personal rapid transit (PRT) and demand-responsive transit (DRT), exhibit similar empty trip patterns. PRT systems consist of small, computer-guided vehicles operating on dedicated guideways for direct station-to-station travel (Lees-Miller et al., 2010). In these systems, empty trips primarily result from repositioning vehicles between stations to balance supply with fluctuating demand. In contrast, DRT services adjust their paths based on specific passenger pick-up and drop-off requests (Mehran et al., 2020). These vehicles can experience all four types of empty trips found in conventional public transportation.

Our evaluation of available data from the United States and Canada suggests that at least 12% and 14% of vehicle miles traveled by roadway-based public transportation (APTA, 2023) were empty in 2019 and 2020, respectively. This is particularly important because even slight reductions in empty mileage can improve operational efficiency, lowering fuel costs for diesel fleets and improving scheduling performance for electric vehicles. These benefits become increasingly critical as service areas and fleets expand. Beyond operational gains, minimizing empty trips also supports environmental sustainability, particularly in diesel-dependent systems (Nasibov et al., 2013; Hsu et al., 2021). Given their higher passenger capacity, addressing empty trips in public transportation is crucial (Tang et al., 2021).

In the literature, “deadheading” is the primary term for empty trips in public transportation. However, this term encompasses two related yet distinct meanings. The first refers to trips without passengers (i.e., empty trips), while the second denotes a strategy in which buses bypass certain stops in low-demand directions to return more quickly to high-demand areas (Cortés et al., 2011). To maintain a consistent focus on vehicle movement, this review concentrates exclusively on the former concept, including studies that examine the effect of deadheading policies on empty mileage.

3.4.2. Carpool

Carpooling matches individuals without access to a vehicle with drivers who have available seats, provided that their itineraries align (Aydin and Gökaşar, 2021). While it offers environmental and economic benefits, it remains less popular than services such as ride-hailing due to longer waiting times, detours, and the inconvenience of sharing a vehicle with a stranger (Jiao and Ramezani, 2022). In carpooling, an empty trip typically refers to the distance a driver travels from their origin to the first passenger’s pickup location, before any passengers are on board (Yao and Bekhor, 2021).

A major research area in carpooling focuses on empty trips, particularly on matching passengers with drivers. This research area can be categorized into three groups. The first involves assigning a single passenger to a single driver who is willing to transport only one passenger. The second group considers multiple passengers traveling with one driver, while the final group involves matching several drivers with one passenger, where passengers may transfer between services to reach their destination (Huang et al., 2014).

3.4.3. Taxi

In this study, the term “taxi” refers specifically to conventional services, in which drivers pick up passengers by cruising or waiting at designated locations, such as taxi stands. Empty trips in this mode can be categorized into three main types of driver-provided mobility. First, vehicles may operate without passengers when traveling to fueling or charging stations to replenish their energy supply, a situation increasingly relevant with the adoption of electric taxi fleets (Jamshidi et al., 2021). Second, empty trips occur when vehicles travel to or from designated service areas without carrying passengers. Third, taxis may reposition themselves (cruise) within the service area while searching for passengers, a phenomenon that has received the most attention in the literature (Seow et al., 2009).

Taxis are a significant component of daily passenger transport. For instance, they account for approximately 10% of the modal share in New York City (Ramezani and Nourinejad, 2018) and nearly 25% of total traffic in Hong Kong (Zong et al., 2018). Despite their widespread use, a considerable share of taxi operations consists of empty trips. Reported vacancy rates range from 35 to 50% in New York and around 40% in Beijing (Lee and Sohn, 2017). Similarly, O’Keeffe et al. (2022) noted that nearly 60% of taxi travel time is spent unoccupied, while in Shanghai, empty travel constitutes about 35% of total fleet mileage (Feng et al., 2021). The implications of these inefficiencies are substantial: according to a survey, a 1% reduction in empty taxi mileage has been associated with a decrease of approximately 266 vehicles in the fleet (Lee and Sohn, 2017).

3.4.4. Ride-hailing

Ride-hailing services, also known as ride-sourcing, provide on-demand mobility by connecting passengers with nearby drivers in real time via smartphone applications (Tengilimoglu and Wadud, 2022). Although both ride-hailing and traditional taxi services offer door-to-door urban mobility, ride-hailing offers greater flexibility through several distinctive features (Zhang and Xu, 2021) that can influence the generation of empty trips:

- Attracting more part-time drivers by letting them start and end their shifts anywhere and anytime.

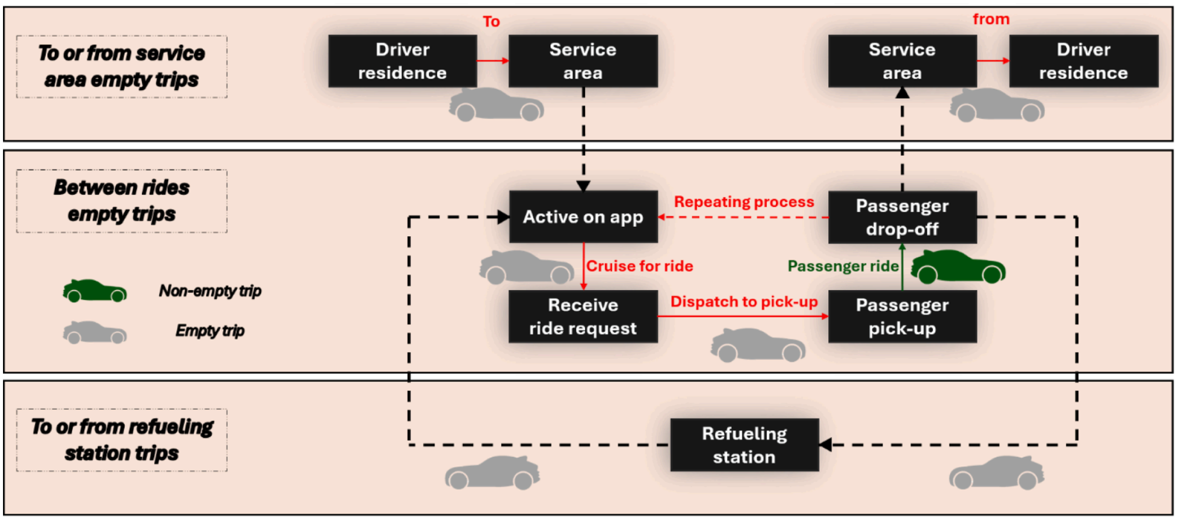

Fig. 2. Different types of empty trips in ride-hailing services.

- Applying dynamic (surge) pricing based on local supply and demand conditions.
- Addressing diverse passenger preferences, such as economic or luxury trips, in a single application.
- Providing passengers with enhanced trip information, such as driver availability, estimated wait times, and trip costs.

The following examples are common types of empty trips observed in ride-hailing services. First, the discussion of energy supply (i.e., traveling to or from fueling or charging stations) in Section 3.4.3 also applies to this mode. Second, empty trips may occur when a driver travels to a preferred service area before logging in to the platform or when returning from the work area to their home. Third, some drivers may cruise streets to increase matching opportunities rather than waiting at a fixed location. Alternatively, after completing a trip, a driver may accept a new ride request and travel to the next passenger's pickup location (McKane and Hess, 2023). These latter two cases are commonly referred to in the literature as between-ride empty trips (Wenzel et al., 2019). Previous studies suggest that the lower bound of empty trip mileage in ride-hailing is around 40% (Tengilimoglu and Wadud, 2022; Henao and Marshall, 2019b). Using the RideAustin dataset, Wenzel et al. (2019) estimated that between-ride empty trips and to- or from-service-area empty trips accounted for 26% and 19% of total ride-hailing vehicle-miles traveled, respectively. Fig. 2 illustrates the various types of empty trips in ride-hailing, expanding upon earlier representations in the literature, such as the figure presented by Wenzel et al. (2019).

3.5. *Private transportation*

Empty private vehicles, often referred to as single-occupant vehicles, are trips with only the driver on board. Previous studies suggest that increasing occupancy beyond the driver improves both transportation efficiency and safety. For example, injury severity has been reported to be lower when multiple occupants are present with an intoxicated driver compared to single-occupant vehicles (Lidbe et al., 2020). Some aspects of empty private transportation in the literature examine the impact of various measures on the number of single-occupant vehicles (Watts and Battista, 2014; Burris and Xu, 2006; Goodall and Smith, 2010; Pessaro and Buddenbrock, 2015) and investigate this issue in the context of mode choice (Washbrook et al., 2006).

3.6. *Reframing empty trips: Insights from a critical synthesis*

The review established a foundation for identifying the conventional definition of empty trips and for examining its binary nature. Building on this, the present section further investigates the underlying causes of empty trips and the operational characteristics that support generalizing effective mitigation strategies across modes.

3.6.1. *Empty trips: From a binary to a continuous approach*

We examined examples of empty trips across various transportation modes. Although these modes differ in how empty trips are generated, a common concept consistently emerges in the literature: the absence of payload, passengers, or freight in a vehicle. Therefore, "empty trips" are defined in the literature as the movement of a vehicle without any onboard payload. In conventional vehicles, the presence of a driver does not contradict this definition, as the driver is an essential operator rather than a payload. In contrast, in AVs, the presence of even a single occupant violates this definition, as the vehicle's operation is independent of human control.

The literature predominantly defines empty trips through a binary lens, in which the presence/absence of passengers or freight on board determines whether a trip is categorized as empty or non-empty. However, a traditional binary definition may lead to biased assessments in studies focused on environmental impact, operational efficiency, and capacity utilization. It treats a vehicle with minimal occupancy the same as one that is fully occupied, which may underestimate the environmental burden per passenger or per unit of payload. This issue is particularly relevant when evaluating environmental sustainability, such as GHG emissions (Wei and Frey, 2020), as well as social sustainability, including whether services are socially inclusive or only marginally utilized due to poor accessibility. In addition, binary classification obscures important differences in operational efficiency by failing to reflect how effectively a system uses its resources. For example, Hassold and Ceder (2014) show that although total energy use increases with more passengers, energy use per passenger decreases nonlinearly as occupancy rises. Finally, binary definitions fail to capture variations in capacity utilization, limiting insights into demand–supply matching and system optimization. Therefore, we propose defining empty trips as a continuous spectrum of occupancy to better reflect service efficiency. This perspective has also been partially recognized in the literature. For example, Henao and Marshall (2019a) proposed per-mile ride-hailing fees that start at zero occupancy and decline as vehicle occupancy increases. Building upon these insights, we recommend that the term empty be accompanied by quantitative measures (e.g., percentages) or relative descriptors (e.g., hardly, semi, or almost empty) based on vehicle occupancy. For instance, a car carrying one passenger in a four-seat capacity could be described as "75% empty" or "almost empty." An analogous concept to occupancy in freight transportation is load factor (or load ratio), defined as the ratio of the vehicle's load to its total capacity (Ni and Wang, 2021; Rivera-Royero et al., 2021), which can similarly be expressed through quantitative or descriptive terms.

3.6.2. *Underlying reasons behind empty trips*

Identifying the underlying causes of empty trips is essential for aligning policies with the operational dynamics of each mode. The literature identifies a supply–demand imbalance between the available fleet and passenger or freight demand as the primary cause (Caminha et al., 2018; Panichpapiboon, 2025). For example, rebalancing in shared user-operated mobility and repositioning in other modes, both central themes in the empty trips literature, seek to enhance system accessibility by mitigating these supply–demand imbalances.

Another form of imbalance, which has received little attention in the literature, arises from energy constraints. Unlike conventional empty trips caused by a lack of passengers, these trips occur when vehicles temporarily withdraw from service to replenish their energy supply. In such cases, vehicles (e.g., taxis or buses) travel empty to fueling or charging stations, thereby generating an empty trip despite existing demand. This imbalance is particularly evident in shared transportation systems (i.e., driver-provided mobility and shared user-operated mobility). In driver-provided mobility, it occurs when drivers travel to refuel or recharge their vehicles, whereas in shared user-operated mobility, it arises when operators collect vehicles from the streets and transport them to charging facilities.

3.6.3. A mode-based classification to inform cross-modal transferability of mitigation strategy

As our review revealed, most studies on empty trips are case-specific, focusing on one or a few examples within a given mode. While this provides valuable context-dependent insights, it limits understanding of cross-modal transferability. To generalize effective strategies across modes, we propose a mode-based categorization (Fig. 3), based on stakeholders involved, shared operational characteristics, and underlying reasons associated with the generation of empty trips. As the categorization progresses, the similarity between modes increases, enhancing the potential for strategy transfer within each category.

Strategy generalization is feasible when the stakeholders for a strategy are similar across modes. Building on this, we first distinguish between entity-based and privately owned mobility. Entity-based modes involve three stakeholders, operators, users (passengers or freight customers), and society, whereas privately owned mobility involves only operators and society. In entity-based systems, reducing empty trips benefits all stakeholders by increasing operator revenue, reducing user waiting time, and lowering negative externalities for society through vehicle sharing. In contrast, in privately owned mobility, reducing empty trips may conflict with operator interests (e.g., preserving privacy), even though it still benefits society. In addition, empty trips in entity-based mobility are mainly linked to repositioning (or rebalancing), whereas in privately owned mobility they often result from low utilization. These differences in stakeholder alignment and operational characteristics limit the transferability of strategies between the two groups.

While stakeholders and their interests are similar within entity-based mobility, several operational characteristics distinguish freight transportation from shared-passenger mobility. Freight transportation generally follows more predictable and stable demand patterns than the more dynamic nature of shared-passenger systems, reducing the need to focus on demand scenarios in the freight sector. Furthermore, freight often requires specialized vehicles tailored to specific commodity types, volumes, or perishability requirements. This specialization reduces operational flexibility and increases the likelihood of empty trips. Additionally, empty mileage in the freight sector is primarily driven by bidirectional constraints, known as the backhaul problem. In contrast, non-directional travel patterns in passenger transportation, such as mode rebalancing, also contribute to empty trip generation. A final factor complicating the generalization of strategies is the underlying cause of empty trips. While shared-passenger mobility must account for both supply–demand imbalances and energy imbalances, freight transportation is affected only by supply–demand imbalances.

At a finer level, shared transportation can be categorized as either user-operated or driver-provided mobility. These two groups share similar stakeholders and underlying causes of empty trips, with repositioning as the main mechanism. However, driver-provided mobility includes additional types of empty trips, such as travel to and from service areas, and allows vehicles to remain available while relocating, reflecting a more flexible and decentralized structure. In contrast, in user-operated mobility, empty trips are mostly limited to repositioning, during which vehicles are typically unavailable, and rebalancing is centrally managed through scheduled operations rather than driver-initiated movements.

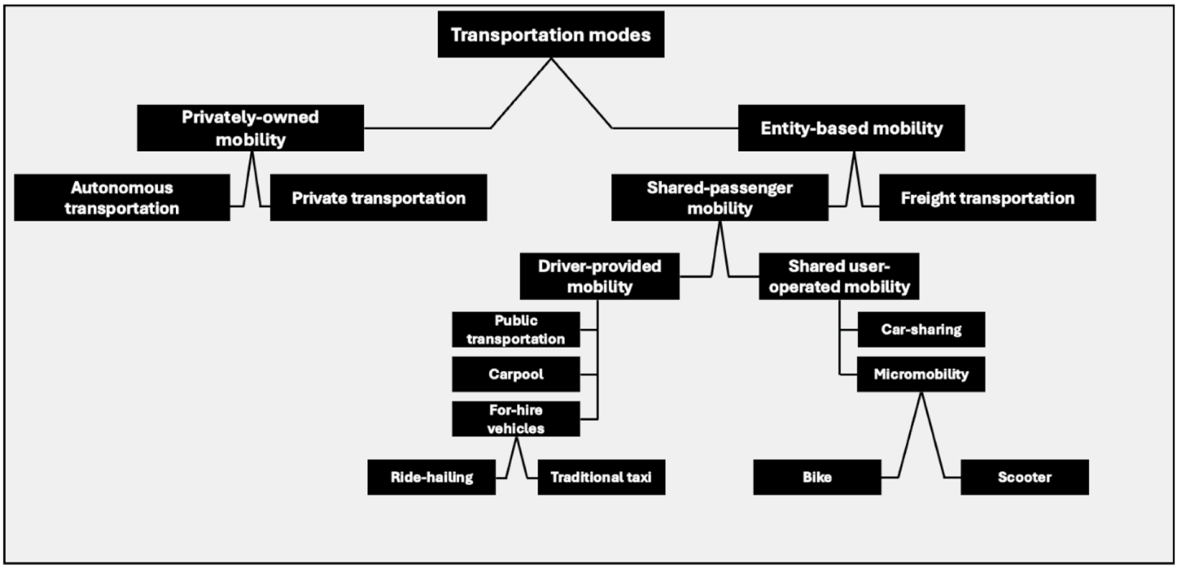

Fig. 3. Categorization of transportation modes based on empty trip generation.

The transferability of mitigation strategies lies not in applying identical solutions across modes, but in targeting shared underlying mechanisms. Despite differences in service context, management structures, and user behavior, mitigation strategies can be generalized if they align with similar operational characteristics, underlying causes, and stakeholder structures. For example, locating charging stations to reduce empty trips can be transferred from driver-provided mobility to shared user-operated mobility due to these shared mechanisms. However, this strategy is not directly applicable to freight transportation because of differences in underlying causes and operational characteristics. Table 2 presents examples of strategies that can be generalized across driver-provided mobility.

3.6.4. Limitations and unavoidable empty trips

A mode-grouped strategy framework, while efficient, has inherent limitations. Some strategies are transferable across modes due to shared mechanisms of empty trip generation; however, their applicability depends on similarities in underlying causes of these trips, operational characteristics, and targeted stakeholders, while others remain mode-specific due to differences in these factors. Furthermore, operational similarities may obscure critical differences among transportation modes that affect a strategy's success; thus, transferability does not ensure comparable outcomes. For instance, a facility location strategy for siting electric charging stations may be adapted from taxi systems to bus networks, but its configuration may not yield equivalent benefits. Additionally, some empty trips are structurally unavoidable, arising from operational necessities such as refueling in taxi fleets. As these trips are essential to operation and cannot be eliminated, strategies focus on optimizing their frequency and impact. Avoidable empty trips, like their unavoidable counterparts, also cause inefficiencies but can often be reduced or eliminated without disrupting core operations. However, full elimination may not always be desirable. For example, maintaining DRT service levels in low-demand areas may require intentional empty trips to achieve broader equity objectives. Therefore, while grouping modes by operational similarity enables cross-modal strategy transfer, effective implementation requires sensitivity to context-specific constraints and adaptive, data-informed management.

4. Empty trip in driver-provided mobility: an analysis of mitigation strategies

In this study, mitigation strategies refer to operational, technological, planning, and policy measures or scenarios designed to reduce the frequency, duration, or distance of empty vehicle movements, or to mitigate their associated impacts. Strategies are included only if they directly or indirectly affect the generation, reduction, or impacts of empty trips. The following discussion first groups studies by strategy themes within each mode, then presents details on methodologies, problem configurations, and, where available, strategy effectiveness in each theme. This information improves understanding of both the generation and mitigation of empty trips and enhances overall comprehension of the strategies. Finally, a multi-dimensional analysis is conducted to synthesize the presented material.

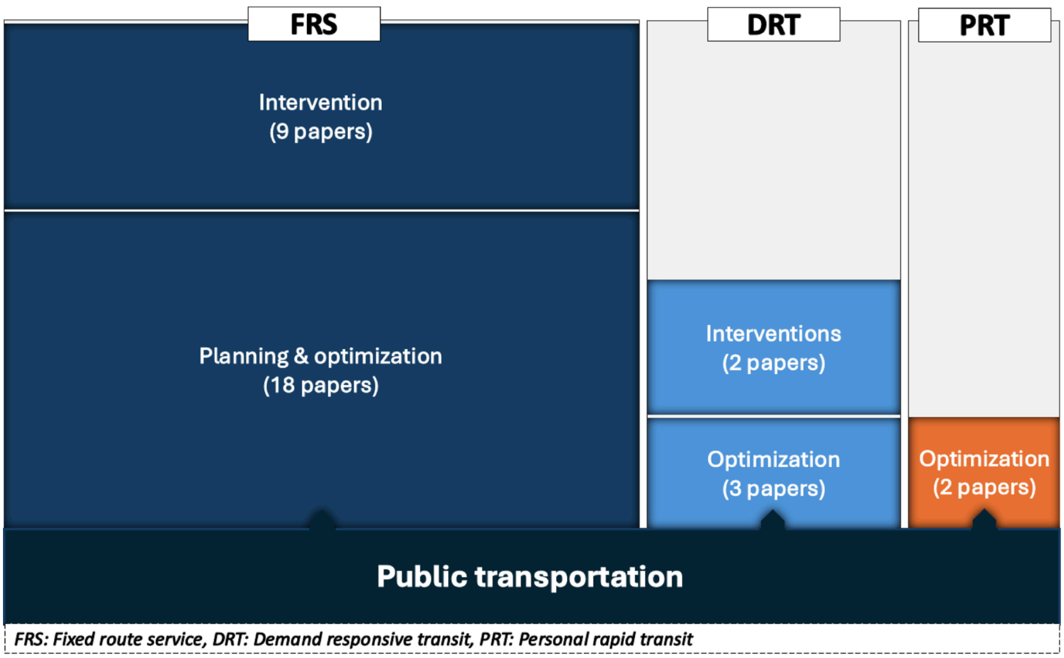

Fig. 4. Categories and sub-categories for the literature of empty trips in public transportation.

4.1. Analyzing empty trip strategies in public transportation

The literature addressing empty trips in public transportation is examined across three types of services: FRS, PRT, and DRT. Fig. 4 illustrates the number of studies in each category and subcategory.

4.1.1. Addressing empty trips in FRS: operation and planning

The first group of studies in FRS evaluates the impact of interventions on public transportation performance in relation to empty trips. The interventions aim not only to minimize empty seats but also to enhance overall system efficiency and potentially reduce the required fleet size (Shang et al., 2019). Interventions in this context can be classified into operational and managerial categories.

Operational interventions include short turns (i.e., serving short cycles on a route), limited-stop service (i.e., visiting only a subset of stops), and deadheading. Some studies examined all three jointly (Tang et al., 2018b; Tang et al., 2020a), while others considered subsets, such as limited-stop and short-turn (Tang et al., 2018a; Tang et al., 2021) or short-turn and deadheading (Cortés et al., 2011). Among these, short-turn and limited-stop strategies have shown substantial benefits, reducing empty seat time by up to 50% (Tang et al., 2021) and 18% (Tang et al., 2018a), respectively. In contrast, deadheading yields smaller gains because of the cost of operating empty buses (Cortés et al., 2011). Combining interventions generally outperforms single measures (Tang et al., 2020a; Tang et al., 2021), though selection depends on trade-offs between passenger and operator costs (Tang et al., 2018a; Tang et al., 2018b) and is primarily influenced by demand profiles and operational characteristics such as payment methods (Tang et al., 2020a). Another operationally effective intervention involves maintaining even headways and balanced passenger loads at maximum-loading points, which was found to reduce empty seat hours by 47% (Ceder et al., 2013). Managerial interventions, on the other hand, relate to the management of the transit network, depots, and facilities rather than individual route operations. Studies show that control structure (centralized vs. decentralized) and depot capacity (capacitated vs. uncapacitated) affect empty mileage, with centralized and uncapacitated systems yielding the greatest long-term improvements (Nasibov et al., 2013). Similarly, Marra and Oswald (2024) reported a potential 14% reduction in empty trips through centralized depot management in London.

The second line of research in FRS addresses transit planning for empty trips, typically treating empty operations as a secondary objective in facility location or vehicle scheduling problems. Facility location determines optimal sites for transit facilities, while vehicle scheduling assigns vehicles to daily service trips. A summary of relevant studies is provided in Table A1 (Appendix A). These studies have considered internal combustion engine (ICE) fleets, electric fleets (Rizopoulos and Gkiotsalitis, 2025; Gkiotsalitis et al., 2025), or a mixed system with regular service (Baldoquin and Rengifo-Campo, 2018) or specialized services such as Bus Rapid Transit (Sevim et al., 2022). Empty trips tend to be slightly higher in electric fleets due to deadheading to charging stations. Problem formulations vary with factors such as vehicle characteristics (capacity and size), the number and capacity of depots, and the involvement of multiple operators. Most studies use optimization programming to address these problems, although alternative approaches exist; for instance, Herbon and Hadas (2015) applied the newsvendor model, an analytical method, to incorporate empty trips into public transportation planning.

4.1.2. PRT main theme: vehicle redistribution

In PRT systems, strategies to address empty trips primarily focus on efficiently redistributing vehicles to ensure system viability. For example, Schweizer et al. (2012) developed a linear programming model to assess the operational feasibility of a PRT system and estimate flows of both empty and occupied vehicles. Their findings identified network bottlenecks and helped determine the initial fleet size required for a specific network. Similarly, Gotzler et al. (2022) used the Simulation of Urban Mobility (SUMO) software to evaluate PRT operations in a city. Their results indicated that targeted operational strategies could reduce the required fleet size and

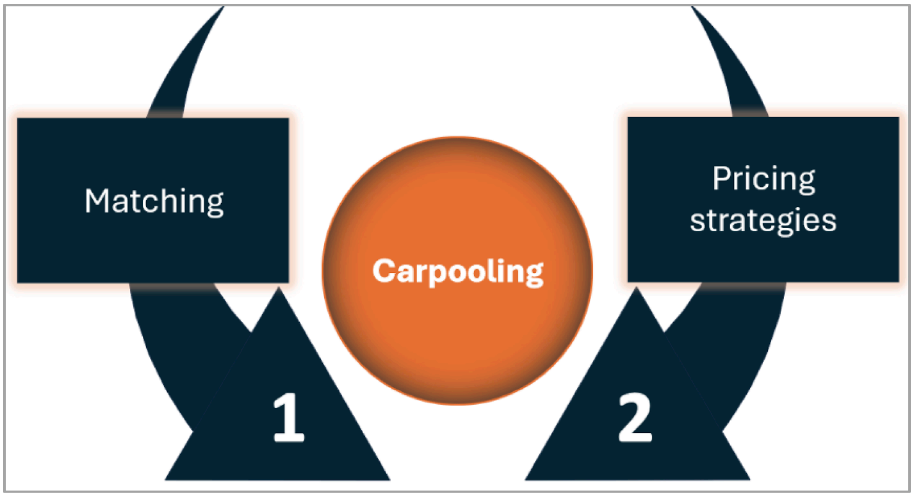

Fig. 5. Categories for the literature of empty trips in carpooling.

improve system efficiency.

4.1.3. Empty trips in DRT: From matching to planning strategies

Mitigating empty trips in DRT services is addressed primarily through two interconnected issues. The first concerns the impact of operational interventions on system performance. For instance, Quadrifoglio et al. (2008) and Shen and Quadrifoglio (2013) compared zoning and non-zoning configurations and found that lower zoning levels improve efficiency, as reflected in smaller fleet sizes and reduced empty mileage.

The second issue concerns planning strategies that optimize matching and operations. Problem formulations vary by planning horizon (short- vs. long-term), passenger characteristics, and methodology. For example, Lai et al. (2020) enhanced short-term matching between appointment-based and real-time passengers, whereas Hartleb et al. (2022) addressed long-term strategic vehicle scheduling in DRT systems.

4.2. Analyzing empty trip strategies in carpooling services

Fig. 5 summarizes strategies related to empty trips in carpooling. Studies in this domain can be categorized into two groups: matching methodologies and pricing strategies with economic implications.

A considerable number of studies have focused on improving passenger–driver matching to increase vehicle occupancy. These efforts target either matching quality, aimed at enhancing passenger satisfaction (Aydin and Gökaşar, 2021; Bravo-Torres et al., 2016), or matching quantity, measured by the number of successful matches (Lin et al., 2018; Yao and Bekhor, 2021; Rahimi et al., 2025). Improving quantity is achieved through methodological advances, such as more efficient algorithms that reduce computational time (Huang et al., 2014) or memory requirements (Jiau and Huang, 2015), as well as operational strategies such as vehicle rebalancing (Ye et al., 2024). While these approaches enhance efficiency by maximizing completed matches, overemphasis on quantity may reduce passenger satisfaction and equity. In contrast, quality-oriented approaches can improve user experience but may reduce match rates (Aydin and Gökaşar, 2021) and raise privacy concerns (Hartenstein and Laberteaux, 2008) due to the need for detailed personal data. Therefore, achieving an optimal balance between matching quantity and quality is crucial for enhancing both service efficiency and user experience.

Another central aspect of the carpooling literature is pricing strategies. Numerous studies have examined how pricing mechanisms

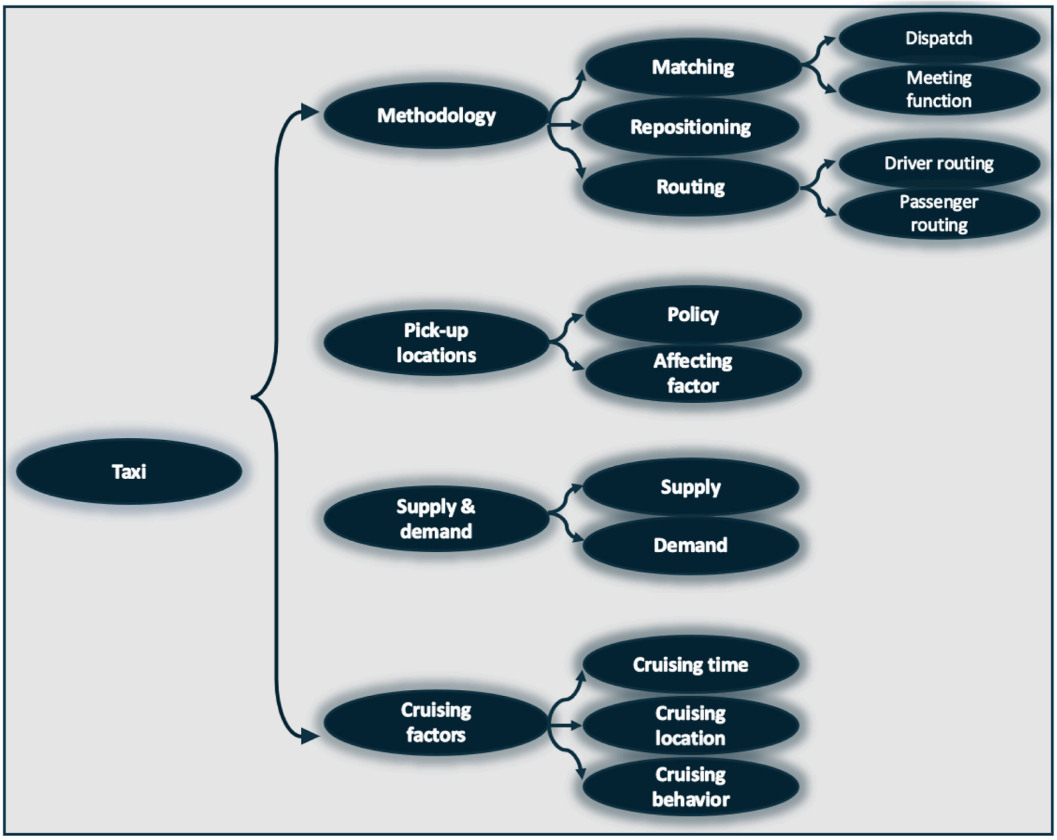

Fig. 6. Categories and sub-categories for the literature of empty trips in taxi services.

affect matching outcomes and broader market dynamics. For instance, Farajallah et al. (2019) analyzed how pricing influences matching rates and overall market performance. Conversely, Tafreshian and Masoud (2020) and Jiao and Ramezani (2022) proposed pricing strategies to increase the attractiveness of ridesharing. A common approach in this literature is to use mathematical programming to develop dynamic pricing models that balance stakeholder interests.

4.3. Analyzing empty trip strategies in taxi systems

Fig. 6 illustrates the four main categories of strategies in the taxi literature. The first focuses on methodological approaches for connecting drivers and passengers to minimize empty movements, addressing three main problem types: matching, vehicle repositioning, and routing. Matching has been studied using meeting functions (Yang and Yang, 2011; Ramezani and Nourinejad, 2018) and dispatch systems (Seow et al., 2009; Zhan et al., 2016). Meeting functions model interaction dynamics in which agents expend resources to achieve successful matches (Ramezani and Nourinejad, 2018), whereas dispatch systems assign requests to available vehicles to reduce passenger waiting times or increase driver earnings (Qian et al., 2022). In electric taxi systems, matching problems include an additional charging stage (Jamshidi et al., 2021).

Some studies have also focused on repositioning empty taxis to balance supply and demand, thereby improving service quality and increasing match rates. Vehicle repositioning involves proactively dispatching empty vehicles to high-demand areas, increasing the likelihood of serving future requests (Qian et al., 2022). For example, Liu et al. (2021) proposed a reinforcement learning model for large-scale repositioning of empty taxis, while Jamshidi et al. (2021) and Yan and Tang (2025) developed integrated dispatching–repositioning frameworks for electric and conventional taxis, respectively.

The final methodological theme is route recommendation, which involves guiding drivers or passengers to one or more pickup locations, typically using GPS data. For passengers, pickup points are discrete locations, such as intersections (Rong et al., 2020), whereas drivers may operate along routes or multiple road segments. Some studies recommended pickup locations for passengers (Rong et al., 2020; Wong et al., 2015), while others guided drivers (Rong et al., 2021; Yu et al., 2019; Liu et al., 2024; O'Keeffe et al., 2022; Gao et al., 2018; Liu et al., 2023a; Tang et al., 2020b), and one considered both simultaneously (Yuan et al., 2012). A common analytical framework for route recommendation is the Markov Decision Process, typically solved via dynamic programming or reinforcement learning (Yu and Gao, 2022). Some approaches also offer unique advantages, such as real-time (or online) route recommendations (Ye et al., 2018; Ji et al., 2020; Liu et al., 2023b) or computational efficiency (Yu and Gao, 2022).

The second category focuses on analyzing pick-up locations and the factors influencing pick-up behavior, using both visual analytics (Gu et al., 2024) and econometric modeling (Liu et al., 2020; Demissie et al., 2020; Zhang et al., 2018b). Some studies focused on street hailing (Demissie et al., 2020; Gu et al., 2024), while others examined station-based services, including taxi stands (Qu et al., 2019) and airports (Ji et al., 2017). Another theme concerns pick-up policies that affect empty trip frequency. For example, zonal pick-up restrictions, which prevent taxis from operating outside their jurisdiction, can substantially increase empty trips in both intercity (Seymour, 2018; Flores-Guri, 2005) and urban contexts (King and Saldarriaga, 2017). Additional studies analyzed constraints such as a fixed number of taxis permitted to operate, fixed time- and location-based tariffs, and passenger-type restrictions, showing that more flexible policies can improve match rates (Buchholz, 2022).

The third category examines how taxi supply and demand affect empty trips. Accurate forecasting of these patterns enables

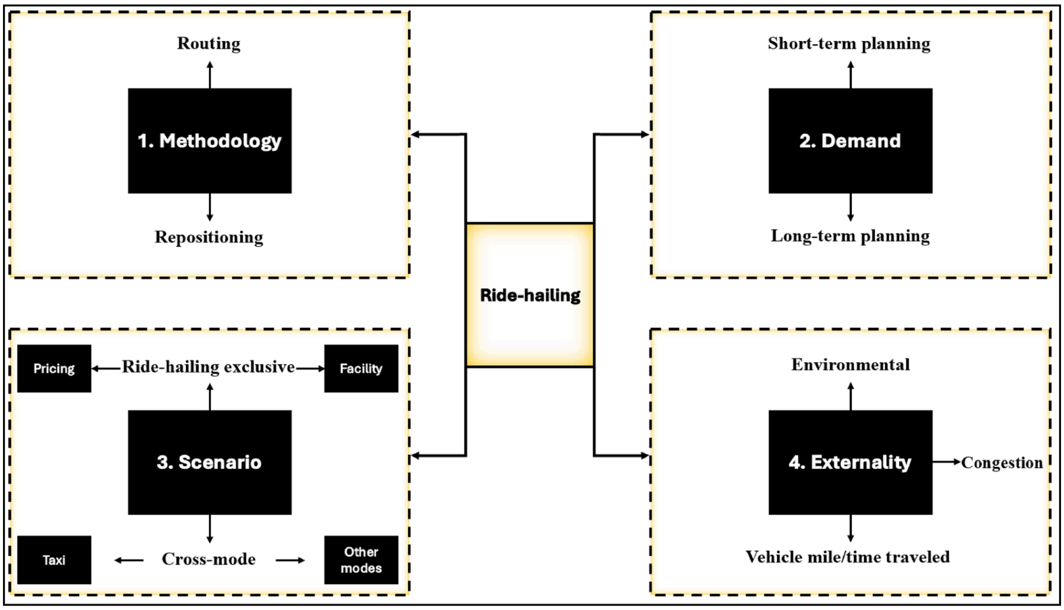

Fig. 7. Categories and sub-categories for the literature of empty trips in ride-hailing services.

proactive repositioning of vacant taxis from oversupplied to high-demand areas. Some studies focus on demand forecasting (Naji et al., 2024; Guo et al., 2024; Chen et al., 2021; Luo et al., 2021), while others predict supply levels, i.e., the number of vacant vehicles (Zhou et al., 2020; Hu and Thill, 2019). These studies commonly apply machine learning and deep learning models. Another line of research explores supply–demand dynamics, including determining the optimal fleet size under specific conditions. For example, Król and Król (2019) examined the optimal number of taxis for special demand scenarios. While most studies consider normal operating conditions, Wong et al. (2021) analyzed supply–demand relationships during extreme weather events.

Finally, the fourth category investigates factors influencing taxi cruising. This literature examines determinants of cruising time, including the built environment (Nian et al., 2022; Zhang et al., 2017), external and internal factors (Liang et al., 2024), and contextual variables such as weather, demographics, and socioeconomic conditions (Lee and Sohn, 2017). The built environment refers to urban design and artificial structures that shape mobility patterns (Nian et al., 2022). External factors are beyond a driver's control, whereas internal factors are driver-specific (Liang et al., 2024). Additional studies analyzed cruising locations (Zong et al., 2018) and broader cruising behaviors (Yu et al., 2025; Lv et al., 2025; Wong et al., 2014b; Szeto et al., 2019). Cruising behavior varies by time of day (Szeto et al., 2013; Wong et al., 2014a), though findings on the influence of specific factors are sometimes contradictory. For instance, Nian et al. (2022) reported that proximity to subway stations increases cruising time, whereas Zhang et al. (2017) found the opposite effect.

4.4. *Analyzing empty trip strategies in ride-hailing*

Fig. 7 summarizes the key research areas on empty trips in ride-hailing services. In this mode, passenger-seeking and direct matching between drivers and passengers do not occur; instead, the e-hailing platform assigns idle drivers to requests. Nevertheless, vehicles still need to reposition to increase their likelihood of future matches. Consequently, the three methodological components in taxi services, matching, repositioning, and routing, are consolidated into two primary areas in ride-hailing: routing (Shi et al., 2019; Guo et al., 2020; Braverman et al., 2019; Liu and Jiang, 2022; Zhang et al., 2023a) and repositioning (Guo et al., 2022; Beojone and Geroliminis, 2023; Ackermann and Rieck, 2023; Qian et al., 2022; Shou et al., 2020; Liu et al., 2022; Deng et al., 2022; Beojone et al., 2024). Most studies emphasize repositioning rather than routing, because supply and demand locations are predetermined, making routing a subset of repositioning. This contrasts with taxi systems, where locating passengers is the primary challenge. However, as in taxi studies, Markov Decision Processes are widely applied in ride-hailing research (Shi et al., 2019; Guo et al., 2020; Braverman et al., 2019; Liu and Jiang, 2022; Zhang et al., 2023b; Guo et al., 2022; Beojone and Geroliminis, 2023; Ackermann and Rieck, 2023; Qian et al., 2022; Shou et al., 2020; Liu et al., 2022; Deng et al., 2022).

The second research area examines how demand affects the reduction of empty trips from both short-term and long-term perspectives. Short-term planning focuses on demand forecasting to optimize fleet management and reduce empty cruising (Jiang, 2023; Kontou et al., 2020; Li et al., 2022). Deep neural networks are widely used and have been shown to outperform traditional statistical methods (Li et al., 2022). Long-term planning, by contrast, examines demand over extended time horizons to reshape overall travel demand patterns. For instance, Mondal et al. (2023) incorporated empty ride-hailing trips into a four-step travel demand model to evaluate their future impact in Texas, while Nair et al. (2020) analyzed empty ride-hailing trips within a regional demand model to inform policy and pricing interventions.

Another line of research evaluates strategies through scenarios designed to assess their effectiveness in mitigating empty trips. These scenarios are typically categorized as ride-hailing-exclusive or cross-mode. In the first category, studies examine vehicle assignment to specific facilities, such as charging stations (Anastasiadis et al., 2020) or parking infrastructure, including garages (Gao et al., 2022) and on-street parking (Xu et al., 2017), to address cruising and curbside management. Pricing-based scenarios are another key focus, including strategies to maximize revenue through route recommendations (Guo et al., 2020) or by incorporating empty miles into revenue estimation and modeling driver behavior (Henao and Marshall, 2019a). Other studies explore the effects of dynamic pricing on supply and demand (Nourinejad and Ramezani, 2020; Chen et al., 2020). Additionally, multi-homing, where drivers operate across multiple platforms, adds complexity to supply-side dynamics (Gao et al., 2025).

Studies of cross-modal scenarios examine interactions between ride-hailing services and other modes, particularly empty cruising, often compared with traditional taxis. These studies compare performance measures across the two systems (Sui et al., 2019) or analyze their interactions (Zhang and Zhang, 2021; Agarwal et al., 2022). Although differences among ride-hailing platforms are relatively limited, traditional taxis generally have longer empty periods than ride-hailing services (Jiang et al., 2018). Additional research examines substitution and competition between ride-hailing and other modes, including public transit and private vehicles (Karamanis et al., 2021; Ruch et al., 2021; Ward et al., 2021).

Finally, a substantial body of research examined ride-hailing externalities, noting that empty trips significantly increase GHG emissions compared to carpooling or private vehicles (Sun and Ertz, 2021), though electrification could cut emissions by up to 90% (Saleh et al., 2024). Another externality is congestion, which worsens due to mode shifts from transit (Di and Ban, 2019), inefficient vehicle assignment and competition among platforms (Hryhoryeva and Leclercq, 2024), and additional vehicle miles traveled from empty pick-ups (Schaller, 2021). Empirical evidence supports these effects; for example, removing ride-hailing services significantly reduced travel times in three Indian cities (Agarwal et al., 2023). Further evidence highlights the scale of empty travel. Using 1.5 million rides in Austin, Wenzel et al. (2019) found that travel to and from service areas and between-ride deadheading accounted for 19% and 26% of total mileage, respectively, while Komanduri et al. (2018) reported that empty travel constituted 37% of total mileage. Similar externalities are observed in taxi operations, including environmental and congestion impacts (Feng et al., 2021; Mo et al., 2020; Gao et al., 2023).

4.5. Mitigation strategies in driver-provided mobility: a synthesis

While the preceding sections presented a theme-based categorization of strategies in driver-provided mobility, this section synthesizes key insights to inform the design of effective strategies for future research and practice.

4.5.1. Methodology and open dataset

Methodological approaches in the empty trip literature vary considerably across transportation modes. In public transportation, optimization and mathematical programming models dominate, whereas platform-based mobility and taxi studies employ a broader range of methods tailored to study objectives. For example, Markov Decision Processes and reinforcement learning are commonly used for optimization tasks such as routing and passenger–driver matching, while deep neural networks and statistical models are frequently applied to demand–supply prediction and to analyzing influencing factors, respectively.

A wide range of datasets supports research on empty services across modes. In public transportation, the General Transit Feed

Table 2
Summary of mitigation strategies addressing empty trips in driver-provided mobility (public transportation, carpooling, taxi, and ride-hailing).

Strategy theme	Example of cross-modal applicability	Popular methodology	Avoidable/ unavoidable	Underlying cause
Public Transportation				
Managerial and operational interventions in FRS	– Centralized/decentralized fleet/depot management (PRT and DRT) – Centralized carpool hubs to coordinate shared pick-up points (carpool) – Dynamic zone-based dispatch (taxi and ride-hailing)	Programming optimization	– Avoidable (e.g., deadheading policy) – Unavoidable (e.g., pull-in and pull-out)	– Supply-demand imbalance (e.g., deadheading, short-turn strategies)
Strategic Transit Network Planning	– Strategic electric charging station/ stop placement (PRT, DRT, carpooling, taxi and ride-hailing)	Programming optimization	– Avoidable (e.g., on-route empty operation) – Unavoidable (e.g., Refueling/recharging trips)	– Supply-demand imbalance (e.g., depot location, vehicle schedule) – Energy imbalance (e.g., locating charging station)
Redistribution and matching strategies in PRT	– Redistribution of idle vehicles to busy routes (FRS) – Dynamic vehicle reallocation based on real-time demand (DRT, carpooling, taxi, and ride-hailing)	Simulation-based evaluation	– Avoidable (e.g., between-stop empty operation)	– Supply-demand imbalance (e.g., redistributing empty vehicles between stations)
Interventions in DRT	– Centralized/decentralized fleet/depot management (FRS, PRT and carpooling) – Dynamic zoning to reduce empty movements (taxi and ride-hailing)	Simulation-based evaluation	– Avoidable (e.g., on-route empty operation) – Unavoidable (e.g., pull-in and pull-out)	– Supply-demand imbalance (e.g., zoning strategies to adjust supply)
Matching strategies in DRT	– Matching service frequency and vehicle schedules to passenger demand (FRS) – Real-time passenger-vehicle matching algorithms (PRT, DRT, carpooling, taxi and ride-hailing)	Programming optimization	– Avoidable (e.g., on-route empty operation)	– Supply-demand imbalance (e.g., vehicle scheduling to meet demand)
Carpooling				
Passenger–vehicle matching	– Matching service frequency and vehicle schedules to passenger demand (FRS) – Real-time passenger-vehicle matching algorithms (PRT, carpooling, taxi and ride-hailing)	Programming optimization	– Avoidable (e.g., on-route empty operation) – Unavoidable (e.g., Refueling/recharging trips)	– Supply-demand imbalance (e.g., maximizing matches in number or quality)
Pricing and marketing strategies	– Dynamic pricing to balance supply and demand (all modes)	Programming optimization	– Avoidable (e.g., on-route empty operation)	– Supply-demand imbalance (e.g., pricing's impact on matches)
Taxi				
Matching, repositioning, and routing strategies	– Matching service frequency and vehicle schedules to passenger demand (FRS) – Real-time passenger-vehicle matching algorithms (PRT, carpooling, taxi and ride-hailing)	Markov decision process	– Avoidable (e.g., empty cruising) – Unavoidable (e.g., Refueling/recharging trips)	– Supply-demand imbalance (e.g., dispatching to high-demand areas) – Energy imbalance (e.g., charging schedules while matching)
Pick-up location analysis	– Station location, access control policies, influencing access design (e.g., stop/terminal access) affecting passenger boarding (FRS and PRT) – Pick-up/drop-off zoning and stop assignment policies affecting matching efficiency (DRT, carpooling, and ride-hailing)	Statistical and econometric modeling	– Avoidable (e.g., empty cruising)	– Supply-demand imbalance (e.g., impact of zonal policy on empty trips

Specification (GTFS), available for many cities including Toronto, New York, and Calgary, is widely used for evaluating strategies (Rizopoulos and Gkiotsalitis, 2025; Todd et al., 2022). For taxi and ride-hailing services, three commonly used open datasets include RideAustin, Didi (Chengdu), and the New York Taxi datasets.

4.5.2. Ancillary problems

Several ancillary challenges can be addressed alongside efforts to reduce empty trips. Although reducing empty trips is the primary objective, it can also alleviate other operational and strategic issues. For instance, in fleet-based organizations such as taxi companies and transit agencies, fleet size management is closely tied to the prevalence of empty trips and can be optimized accordingly (Shang et al., 2019). Similarly, in driver-provided mobility services, issues such as depot location (Todd et al., 2022), passenger waiting time (Seow et al., 2009), and operator income (Liu et al., 2023) are, to varying degrees, influenced by reductions in empty trips.

Furthermore, mitigating empty trips yields broader sustainability benefits. Research shows that reducing empty trips is associated with lower energy consumption and emissions (Feng et al., 2021), reduced total vehicle mileage (Wenzel et al., 2019), and less traffic congestion (Agarwal et al., 2023). Therefore, reducing empty trips is an important step toward more sustainable and efficient urban mobility systems.

4.5.3. Mitigation strategies

Repositioning is a common corrective strategy across transportation modes, including driver-provided mobility. It addresses supply–demand imbalances and improves service accessibility. Despite its potential benefits, repositioning is often costly and increases emissions (Silva et al., 2024), creating a trade-off between operational efficiency and environmental impact. While repositioning is a universal concept, its application varies by mode. It is a central theme in ride-hailing and taxi services, where it appears not only as a standalone strategy but also indirectly through related themes, such as demand prediction, which ultimately serve repositioning objectives. In contrast, the focus on this strategy is comparatively limited in carpooling. Given its broad applicability and potential impact, repositioning warrants consistent attention in future policy and system design.

Some strategies involve a single mode, while others may engage multiple modes. Parking management is a cross-modal approach in which both off-street (e.g., garages) (Gao et al., 2022) and on-street parking spaces (Xu et al., 2017) can serve as staging areas for taxis, ride-hailing vehicles, and other shared modes during periods of low demand, reducing unnecessary cruising. However, increasing competition for curbside space from deliveries, micromobility, pedestrians, and public transit requires careful planning to avoid conflicts. Accordingly, parking strategies should adopt flexible, demand-responsive designs that integrate parking supply with real-time fleet operations.

The effectiveness of strategies varies not only across modes but also with local conditions, such as land-use patterns, travel demand, traveler behavior, and socio-economic characteristics. For example, limited-stop and short-turn operations in public transport reduce empty trips, but their effectiveness across cases depends on contextual factors, including demand distribution, network configuration, and operational costs (Tang et al., 2020a).

Finally, future planning should systematically account for empty trips to better anticipate operational challenges and long-term impacts. Studies such as Mondal et al. (2023) and Tajaddini and Vu (2023) integrate empty trips into four-step travel demand models and show that they increase network-wide delays and reduce travel speeds. Therefore, incorporating empty trips into transportation planning frameworks is essential for evaluating system-wide performance.

In summary, Table 2 synthesizes the key themes of mitigation strategies reviewed in Section 4, including their cross-modal applicability, commonly used methodologies, whether the associated empty trips are avoidable or unavoidable, and underlying causes. The examples presented in the cross-modal applicability column are intended to illustrate potential adaptations of mitigation strategies across different mobility modes. These examples are suggestive rather than prescriptive, and their applicability may vary depending on the operational, regulatory, and service characteristics of each mode.

5. Implications for sustainable transportation

The paper has several implications, particularly from a sustainability perspective. First, shifting from a binary definition of empty trips to a continuous spectrum enables a more comprehensive representation of system inefficiency. This refinement captures unused capacity more accurately, which is often overlooked in conventional analyses. From an environmental sustainability standpoint, the proposed representation provides a more sensitive measure of mobility inefficiency and their associated environmental burdens across transport modes. For example, Wei and Frey (2020) and Hassold and Ceder (2014) discussed that GHG emissions and energy use per passenger, respectively, decrease nonlinearly as occupancy rises. This, in turn, improves the comparability of different systems and supports the identification of targeted interventions to reduce unnecessary vehicle kilometers traveled, ultimately contributing to more effective emission and energy reduction strategies.

From a social sustainability perspective, improved visibility into system underutilization enables operators to optimize resource allocation and support more equitable service provision. Identifying spatial and temporal inefficiencies facilitates the redistribution of services to underserved areas, enhancing accessibility and quality of life for transit-dependent populations. For instance, research conducted by Hartleb et al. (2022) aligns with this perspective by adjusting DRT vehicle schedules based on demand, thereby minimizing empty trips. However, the results of the present study indicate that substituting this binary concept of empty trips with a comprehensive occupancy framework offers a more precise evaluation metric.

From an economic sustainability perspective, this approach enhances cost-effectiveness by revealing hidden inefficiencies. This allows providers to maximize vehicle utilization and minimize costs associated with empty or underutilized trips, such as fleet sizing and overhead, ultimately driving higher operational profitability (Farren et al., 2024). Additionally, the proposed framework for generalizing strategies lowers implementation costs by enabling the transfer of proven methods across modes, reducing reliance on case-specific research and development.

This study also reviewed mitigation strategies and extracted central themes that can be generalized across various modes using a mode-based categorization. While the strategies discussed may seem operational or planning-oriented, they also carry notable sustainability impacts. For example, beyond reducing emissions and fuel consumption, they can influence travel behavior by encouraging shifts toward low-carbon, shared mobility. At the same time, the framework acknowledges that certain empty trips, such as those required to maintain service in low-demand area, are essential for fostering equitable access. These strategies also enhance resilience against future disruptions by improving system adaptability, ensuring that transport networks remain both functional and resource-efficient under changing conditions. Therefore, the impact of these contributions spans a wide range of dimensions, from immediate emission mitigation to long-term adaptive applications.

6. Conclusion

This study synthesizes the literature on empty trips in driver-provided mobility systems and highlights a key limitation of the conventional binary definition, which fails to capture variations in unused capacity. By reframing empty trips in terms of occupancy, the paper provides a more accurate basis for assessing inefficiencies and informing sustainable mobility planning. The findings indicate that empty trips are a systemic issue driven by spatial–temporal and energy imbalances and operational characteristics across modes. While strategies such as vehicle repositioning and demand prediction are widely applied, their integration into planning frameworks remains limited, and opportunities for cross-modal transfer are underexplored. Overall, the findings show that addressing empty trips can contribute not only to greater operational efficiency and financial benefits, but also to sustainability goals by reducing energy use and emissions, supporting more efficient use of transport resources (Nasibov et al., 2013; Farren et al., 2024), and enabling more equitable and resilient mobility systems.

Looking ahead, future research should address several gaps in mitigating empty trips. First, integrating multiple transportation modes, particularly sustainable ones, within a single trip chain could improve occupancy, with Mobility as a Service representing a promising yet underexplored alternative to driver-provided mobility. Second, collaboration between ride-hailing and taxi services warrants attention, as existing studies focus on comparison rather than cooperation. Insights into mode choice could inform spatial and temporal integration strategies. Third, the joint optimization of parking and charging infrastructure remains largely unexplored and requires models that capture interactions among facility types, spatiotemporal demand, land use, and urban systems. Finally, future research should examine the performance of matching algorithms under abnormal conditions, such as large-scale events or extreme weather, when conventional supply–demand dynamics are disrupted, to improve their adaptability and robustness.

CRediT authorship contribution statement

Pedram Akbari: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gonçalo Homem de Almeida Correia:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Merkebe Getachew Demissie:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

.

Table A1
Summary of studies in public transportation planning in the context of empty trips.

Reference	Objective	Case study	Vehicle	Depots	Method	Empty trips
(Baldoquin and Rengifo-Campo, 2018)	Vehicle schedule planning	Cali, Colombia	Multiple vehicle type (ICE) and multiple operator	Multi depot – capacitated – can finish and start at different depot	MILP, minimization of deadheading and maximum deviation from the ideal amount of kms	Pull in and pull out
(Sevim et al., 2022)	Vehicle schedule planning	Istanbul, Turkey	Single vehicle type (ICE) and single operator	Multi depot – capacitated – finish and start at the same depot	IP, minimization of deadheading and fleet size	Pull in and pull out, trip between two terminals

(continued on next page)

Table A1 (*continued*)

Reference	Objective	Case study	Vehicle	Depots	Method	Empty trips
(Moreno et al., 2019)	Vehicle schedule planning	Colombia	Single vehicle type (ICE) and single operator	Multi depot – capacitated – finish and start at the same depot	MIP, minimization of deadheading and fleet size	Pull in and pull out, trip between two terminals
(Gintner et al., 2005)	Vehicle schedule planning	Several cities in Germany	Multiple vehicle type (ICE) and single operator	Multi depot – capacitated – finish and start at the same depot	MIP, minimization of fleet size, distance and time dependent travel costs outside of depot	Pull in and pull out, trip between two terminals
(Hassold and Ceder, 2014)	Vehicle schedule planning	Auckland, New Zealand	Multiple vehicle types and single operator	–	Pareto-optimal timetables	Pull in and pull out, empty seats during a trip
(Gong et al., 2025)	Vehicle schedule planning	Tin Shui Wai, Hong Kong	Multiple vehicle type (ICE) and single operator	Single depot – capacitated – finish and start at the same depot	MINLP maximizing profit and social welfare	Pull in and pull out and trip between two terminals
(Todd et al., 2022)	Facility location problem (depot)	Fulton County, Georgia.	Single vehicle type (ICE) and single operator	Multi depot – uncapacitated – finish and start at the same depot	Network analysis using GIS and shortest path algorithms	Pull in and pull out
(Willoughby, 2002)	Mixed facility location problem (depot)	Vancouver, Canada	Multiple vehicle type (ICE and wired-electric) and single operator	Multi depot – capacitated – finish and start at the same depot	MIP, minimizing vehicle deadhead cost, the capital cost of constructing new garages and salvage value	Pull in and pull out
(Al Ali and Hassan, 2018)	Mixed facility location problem (depot and maintenance center)	Vancouver, Canada	Multiple vehicle type, (ICE and wired-electric) and single operator	Multi depot – capacitated – finish and start at the same depot	MILP, minimizing deadheading distance, the capital cost of constructing new depots, adding maintenance center to depots and salvage value	Pull in and pull out
(Wen et al., 2016)	Electric Vehicle schedule planning	–	Single vehicle type (electric charging vehicles) and single operator	Multi depot – uncapacitated – finish and start at the same depot	MILP, minimizing fleet size, total traveling distance, which is equivalent to minimizing the total deadheading	Pull in and pull out, recharging and travel between any two terminals
(Yao et al., 2020)	Electric Vehicle schedule planning	Beijing, China	Multiple vehicle type (electric charging vehicles) and single operator	Multi depot – capacitated – finish and start at the same depot	MILP, minimizing fleet size, the purchase and installation costs of chargers, recharging cost determined by recharging trips, operating cost of deadheading trips and timetabled trips	Pull in and pull out, recharging and trip between two terminals
(Hsu et al., 2021)	Mixed facility location problem (depot, maintenance center and charging station)	Taoyuan, Taiwan	Multiple vehicle type (ICE and electric charging vehicles) and single operator	Multi depot – capacitated – can finish and start at different depot	IP, minimizing deadhead distance, establishing new depots, maintenance and charging stations, and the cost of renting external buses, minus value obtained from selling the land with existing depot	Pull in and pull out and recharging
(Olsen and Kliewer, 2022)	Electric facility location and vehicle scheduling	–	Multiple vehicle type (electric charging vehicles) and single operator	Multiple depot-uncapacitated-finish and start at the same depot	MILP minimizing fixed costs for electric vehicles as well as charging stations and operational costs for the buses	Pull in and pull out and recharging
(Xu et al., 2023)	Electric Vehicle schedule planning	Hefei, China	Single vehicle type (electric charging vehicles) and single operator	Multiple depot-uncapacitated-finish and start at the same depot	IP maximizing profit, defined as the difference between the operational profit and operational cost of buses	Pull in and pull out and trip between two terminals
(Kisielewski et al., 2024)	Mixed Vehicle schedule planning	Two cities in Poland	Multiple vehicle type (ICE and electric charging vehicles) and single operator	Multiple depot – uncapacitated – can finish and start at different depot	MILP minimizing costs of trips, charging, variable costs of using vehicles, fleet size, environmental impact, deadhead distance, total time of standstills between trips	Pull in and pull out and trip between two terminals

Data availability

No data was used for the research described in the article.

References

Abkarian, H., Mahmassani, H.S., Hyland, M., 2022. Modeling the mixed-service fleet problem of shared-use autonomous mobility systems for on-demand ridesourcing and carsharing with reservations. Transp. Res. Rec. 2676 (8), 363–375. https://doi.org/10.1177/03611981221083617.

Ackermann, C., Rieck, J., 2023. A novel repositioning approach and analysis for dynamic ride-hailing problems. EURO J. Trans. Logist. 12, 100109. https://doi.org/10.1016/j.ejtl.2023.100109.

Agarwal, S., Charoenwong, B., Cheng, S.F., Keppo, J., 2022. The impact of ride-hail surge factors on taxi bookings. Transp. Res. Part C Emerging Technol. 136, 103508. https://doi.org/10.1016/j.trc.2021.103508.

Agarwal, S., Mani, D., Telang, R., 2023. The impact of ride-hailing services on congestion: evidence from Indian cities. Manuf. Serv. Oper. Manag. 25 (3), 862–883. https://doi.org/10.1287/msom.2022.1158.

Al Ali, F., Hassan, N.M., 2018. Optimization of bus depot location with consideration of maintenance center availability. J. Trans/ Eng. Part A: Syst. 144 (2), 05017011. https://doi.org/10.1061/JTEPBS.0000114.

Anastasiadis, E., Angeloudis, P., Ainalis, D., Ye, Q., Hsu, P.Y., Karamanis, R., Escribano Macias, J., Stettler, M., 2020. On the selection of charging facility locations for EV-based ride-hailing services: a computational case study. Sustainability 13 (1), 168. https://doi.org/10.3390/su13010168.

APTA (2023) 2022 Public Transportation Fact Book Appendix A: Historical Tables. Washington D.C.

Aydin, O.F., Gökaşar, İ., 2021. The effects of including social factors in ride-matching algorithms on the performance and the quality of matches. Turkish J. Eng. 5 (1), 41–47. https://doi.org/10.31127/tuje.657867.

Baldoquin, M.G., Rengifo-Campo, A.J., 2018. A model for solving vehicle scheduling problems: a case study. Revista Facultad De Ingeniería Universidad De Antioquia 88, 16–25. https://doi.org/10.17533/udea.redin.n88a03.

Barla, P., Bolduc, D., Boucher, N., Watters, J., 2010. Information technology and efficiency in trucking. Canadian J. Economics/revue Canadienne D'économique 43 (1), 254–279. https://doi.org/10.1111/j.1540-5982.2009.01571.x.

Beojone, C.V., Geroliminis, N., 2023. Relocation incentives for ride-sourcing drivers with path-oriented revenue forecasting based on a Markov Chain model. Transp. Res. Part C Emerging Technol. 157, 104375. https://doi.org/10.1016/j.trc.2023.104375.

Beojone, C.V., Zhu, P., Sirmatel, I.I., Geroliminis, N., 2024. A hierarchical control framework for vehicle repositioning in ride-hailing systems. Transp. Res. Part C Emerging Technol., 104717 https://doi.org/10.1016/j.trc.2024.104717.

Boumahdaf, A., Broniatowski, M., Miranda, E., Le Squeren, A., 2023. A behavioral probabilistic model of carrier spatial repositioning decision-making. Transp. Res. Part C Emerging Technol. 153, 104194. https://doi.org/10.1016/j.trc.2023.104194.

Braverman, A., Dai, J.G., Liu, X., Ying, L., 2019. Empty-car routing in ridesharing systems. Oper. Res. 67 (5), 1437–1452. https://doi.org/10.1287/opre.2018.1822.

Bravo-Torres, J.F., Blanco-Fernández, Y., López-Nores, M., Pazos-Arias, J.J., Ramos-Cabrer, M., Gil-Solla, A., 2016. Proactive discovery and management of ride-sharing opportunities in smart vehicular Ad-Hoc networks. Inform. Technol. Control 45 (2), 121–135. https://doi.org/10.5755/j01.itc.45.2.8464.

Buchholz, N., 2022. Spatial equilibrium, search frictions, and dynamic efficiency in the taxi industry. Rev. Econ. Stud. 89 (2), 556–591. https://doi.org/10.1093/restud/rdab050.

Burris, M.W., Xu, L., 1960. (2006) 'potential single-occupancy vehicle demand for high-occupancy vehicle lanes: results from stated-preference survey of travelers in high-occupancy toll corridors'. Transp. Res. Rec. 1, 108–118. https://doi.org/10.1177/0361198106196000114.

Caminha, C., Furtado, V., Pinheiro, V., Ponte, C., 2018. Graph mining for the detection of overcrowding and waste of resources in public transport. J. Internet Services Appl. 9, 1–11. https://doi.org/10.1186/s13174-018-0094-3.

Cantillo, V., Jaller, M., Holguín-Veras, J., 2014. The Colombian strategic freight transport model based on product analysis. Promet-Traffic & Transportation 26 (6), 487–496. https://doi.org/10.7307/ptt.v26i6.1460.

Ceder, A., Hassold, S., Dunlop, C., Chen, I., 2013. Improving urban public transport service using new timetabling strategies with different vehicle sizes. Int. J. Urban Sci. 17 (2), 239–258. https://doi.org/10.1080/12265934.2013.776287.

Changaival, B., Lavangnananda, K., Danoy, G., Kliazovich, D., Guinand, F., Brust, M., Musial, J., Bouvry, P., 2021. Optimization of carsharing fleet placement in round-trip carsharing service. Appl. Sci. 11 (23), 11393. https://doi.org/10.3390/app112311393.

Chen, D., Wang, J., Xiong, C., 2021. Research on origin-destination travel demand prediction method of inter-regional online taxi based on SpatialOD-BiConvLSTM. IET Intel. Transport Syst. 15 (12), 1533–1547. https://doi.org/10.1049/itr2.12119.

Chen, Q., Ma, S., Li, H., Zhu, N., He, Q.C., 2024. Optimizing bike rebalancing strategies in free-floating bike-sharing systems: an enhanced distributionally robust approach. Transp. Res. Part E: Logist. Transp. Rev. 184, 103477. https://doi.org/10.1016/j.tre.2024.103477.

Chen, X.M., Zheng, H., Ke, J., Yang, H., 2020. Dynamic optimization strategies for on-demand ride services platform: Surge pricing, commission rate, and incentives. Transp. Res. B Methodol. 138, 23–45. https://doi.org/10.1016/j.trb.2020.05.005.

Chu, J.C., Lin, H.C., Liao, F.Y., Yu, Y.H., 2023. Dynamic repositioning problem of dockless electric scooter sharing systems. Transp. Lett. 15 (9), 1066–1082. https://doi.org/10.1080/19427867.2022.2129209.

Cortés, C.E., Jara-Díaz, S., Tirachini, A., 2011. Integrating short turning and deadheading in the optimization of transit services. Transp. Res. A Policy Pract. 45 (5), 419–434. https://doi.org/10.1016/j.tra.2011.02.002.

Demissie, M.G., Kattan, L., Phithakkitnukoon, S., de Almeida Correia, G.H., Veloso, M., Bento, C., 2020. Modeling location choice of taxi drivers for passenger pickup using GPS data. IEEE Intell. Transp. Syst. Mag. 13 (1), 70–90. https://doi.org/10.1109/MITS.2020.3014099.

Deng, Y., Chen, H., Shao, S., Tang, J., Pi, J., Gupta, A., 2022. Multi-objective vehicle rebalancing for ridehailing system using a reinforcement learning approach. J. Manag. Sci. Eng. 7 (2), 346–364. https://doi.org/10.1016/j.jmse.2021.12.004.

De-Toledo, K.P., O'Hern, S., Koppel, S., 2024. I saw a fox in Melbourne CBD: Urban travel behavior changes during COVID-19 and beyond. Trans. Res. Part F: Traffic Psychol. Behav. 100, 115–132. https://doi.org/10.1016/j.trf.2023.11.01.

Di, X., Ban, X.J., 2019. A unified equilibrium framework of new shared mobility systems. Transp. Res. B Methodol. 129, 50–78. https://doi.org/10.1016/j.trb.2019.09.002.

Eliyan, A.F., Kerbache, L., 2024. Vehicle relocation in one-way carsharing: a review. Sustainability 16 (3), 1014. https://doi.org/10.3390/su16031014.

Erhardt, G.D., Roy, S., Cooper, D., Sana, B., Chen, M., Castiglione, J., 2019. Do transportation network companies decrease or increase congestion? Sci. Adv. 5 (5), p. eaau2670. https://doi.org/10.1126/sciadv.aau2670.

Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp. Res. A Policy Pract. 77, 167–181. https://doi.org/10.1016/j.tra.2015.04.003.

Farajallah, M., Hammond, R.G., Pénard, T., 2019. 'What drives pricing behavior in peer-to-peer markets? Evidence from the Carsharing Platform BlaBlaCar'. Inform. Econ. Policy 48, 15–31. https://doi.org/10.1016/j.infoecopol.2019.01.002.

Farren, D., Giesen, R., Rizzi, L., 2024. The economics of empty trips. Econ. Transp. 39, 100361. https://doi.org/10.1016/j.ecotra.2024.100361.

Feng, R., Yao, B., Gu, X., Zhang, M., Yu, B., 2021. Environmental benefits mining based on data-driven taxi cruising recommendation strategy. J. Clean. Prod. 326, 129376. https://doi.org/10.1016/j.jclepro.2021.129376.

Flores-Guri, D., 2005. Local exclusive cruising regulation and efficiency in taxicab markets. Journal of Transport Economics and Policy (JTEP) 39 (2), 155–166.

Folkestad, C.A., Hansen, N., Fagerholt, K., Andersson, H., Pantuso, G., 2020. Optimal charging and repositioning of electric vehicles in a free-floating carsharing system. Comput. Oper. Res. 113, 104771. https://doi.org/10.1016/j.cor.2019.104771.

Gao, C., Wang, Y., He, F., Lin, X., 2025. Modeling and analyzing ride-hailing market equilibrium considering drivers' multi-homing choice behavior. Transp. Res. Part E: Logist. Transp. Rev. 197, 104055. https://doi.org/10.1016/j.tre.2025.104055.

Gao, F., Liu, K., Ding, D., 2023. A Framework to determine the utilization of vacant taxis on HOV lanes with the optimal deployment. Appl. Sci. 13 (2), 913. https://doi.org/10.3390/app13020913.

Gao, J., Li, S., Yang, H., 2022. Shared parking for ride-sourcing platforms to reduce cruising traffic. Transp. Res. Part C Emerging Technol. 137, 103562. https://doi.org/10.1016/j.trc.2022.103562.

Gao, Y., Jiang, D., Xu, Y., 2018. Optimize taxi driving strategies based on reinforcement learning. Int. J. Geogr. Inf. Sci. 32 (8), 1677–1696. https://doi.org/10.1080/13658816.2018.1458984.

Gintner, V., Kliewer, N., Suhl, L., 2005. Solving large multiple-depot multiple-vehicle-type bus scheduling problems in practice. OR Spectr. 27, 507–523. https://doi.org/10.1007/s00291-005-0207-9.

Gkiotsalitis, K., Rizopoulos, D., Merakou, M., Iliopoulou, C., Liu, T., Cats, O., 2025. Electric bus charging station location selection problem with slow and fast charging. Appl. Energy 382, 125242. https://doi.org/10.1016/j.apenergy.2024.125242.

Gong, J., Szeto, W.Y., Sun, S., 2025. A multi-period asymmetric transit frequency design problem. Trans. Res. Part E: Logist. Transp. Rev. 195, 103886. https://doi.org/10.1016/j.tre.2024.103886.

Gonzalez-Calderon, C.A., Sánchez Díaz, I., Holguín Veras, J., 2012. An empirical investigation on the impacts of spatial and temporal aggregation on empty trips models. Revista Facultad De Ingeniería Universidad De Antioquia 64, 150–162.

Gonzalez-Calderon, C.A., Sánchez-Díaz, I., Sarmiento-Ordosgoitia, I., Holguín-Veras, J., 2018. 'Characterization and analysis of metropolitan freight patterns in Medellin Colombia'. Eur. Trans. Res. Rev. 10, 1–11. https://doi.org/10.1186/s12544-018-0290-z.

Gonzalez-Calderon, C.A., Holguín-Veras, J., Amaya, J., Sánchez-Díaz, I., Sarmiento, I., 2021. Generalized noortman and van es' empty trips model. Transp. Res. A Policy Pract. 145, 260–268. https://doi.org/10.1016/j.tra.2021.01.005.

Goodall, N., Smith, B.L., 2010. What drives decisions of single-occupant travelers in high-occupancy vehicle lanes? Investigation using archived traffic and tolling data from MnPASS express lanes. Transp. Res. Rec. 2178 (1), 156–161. https://doi.org/10.3141/2178-17.

Gotzler, F., Neumann, F., Adenaw, L., 2022. Assessment of personal rapid transit system configurations regarding efficiency and service quality. Future Transportation 2 (3), 734–752. https://doi.org/10.3390/futuretransp2030041.

Gu, S., Dai, Y., Feng, Z., Wang, Y., Zeng, H., 2024. T-PickSeer: visual analysis of taxi pick-up point selection behavior. J. Vis. 1–18. https://doi.org/10.1007/s12650-024-00968-0.

Guo, D., Sun, M., Wang, Q., Zhang, J., 2024. Taxi demand method based on SCSSA-CNN-BiLSTM. Sustainability 16 (18), 7879. https://doi.org/10.3390/su16187879.

Guo, S., Chen, C., Wang, J., Ding, Y., Liu, Y., Xu, K., Yu, Z., Zhang, D., 2020. A force-directed approach to seeking route recommendation in ride-on-demand service using multi-source urban data. IEEE Trans. Mob. Comput. 21 (6), 1909–1926. https://doi.org/10.1109/TMC.2020.3033274.

Guo, X., Wang, Q., Zhao, J., 2022. Data-driven vehicle rebalancing with predictive prescriptions in the ride-hailing system. IEEE Open J. Intell. Transp. Syst. 3, 251–266. https://doi.org/10.1109/OJITS.2022.3163180.

Hartenstein, H., Laberteaux, L.P., 2008. A tutorial survey on vehicular ad hoc networks. IEEE Commun. Magaz. 46, 164–171. https://doi.org/10.1109/MCOM.2008.4539481.

Hartleb, J., Friedrich, M., Richter, E., 2022. Vehicle scheduling for on-demand vehicle fleets in macroscopic travel demand models. Transportation 49, 1133–1155. https://doi.org/10.1007/s11116-021-10205-4.

Hassold, S., Ceder, A., 2014. Improving energy efficiency of public transport bus services by using multiple vehicle types. Transp. Res. Rec. 2415 (1), 65–71. https://doi.org/10.3141/2415-07.

He, Y., Ni, J., Wang, X., Niu, B., Li, F., Shen, X., 2018. Privacy-preserving partner selection for ride-sharing services. IEEE Trans. Veh. Technol. 67 (7), 5994–6005. https://doi.org/10.1109/TVT.2018.2809039.

Henao, A., Marshall, W.E., 2019a. An analysis of the individual economics of ride-hailing drivers. Transp. Res. A Policy Pract. 130, 440–451. https://doi.org/10.1016/j.tra.2019.09.056.

Henao, A., Marshall, W.E., 2019b. The impact of ride-hailing on vehicle miles traveled. Transportation 46 (6), 2173–2194. https://doi.org/10.1007/s11116-018-9923-2.

Herbon, A., Hadas, Y., 2015. Determining optimal frequency and vehicle capacity for public transit routes: a generalized newsvendor model. Transp. Res. B Methodol. 71, 85–99. https://doi.org/10.1016/j.trb.2014.10.007.

Holguín-Veras, J., Sánchez, I., González-Calderón, C., Sarmiento, I., Thorson, E., 2011. Time-dependent effects on parameters of freight demand models: empirical investigation. Transp. Res. Rec. 2224 (1), 42–50. https://doi.org/10.3141/2224-06.

Holguín-Veras, J., González-Calderón, C., Sánchez-Díaz, I., Jaller, M., Campbell, S., 2014. Vehicle-trip estimation models. In: Modelling Freight Transport. Elsevier, London, UK, pp. 143–162. https://doi.org/10.1016/B978-0-12-410400-6.00007-0.

Holguín-Veras, J., Patil, G.R., 2008. Integrated origin–destination synthesis model for freight with commodity-based and empty trip models. Transp. Res. Rec. 1, 60–66. https://doi.org/10.3141/2008-08.

Holguín-Veras, J., Thorson, E., Zorrilla, J.C., 2010. Commercial vehicle empty trip models with variable zero order empty trip probabilities. Netw. Spat. Econ. 10, 241–259. https://doi.org/10.1007/s11067-008-9066-7.

Holguín-Veras, J., Thorson, E., 2003. Modeling commercial vehicle empty trips with a first order trip chain model. Transp. Res. B Methodol. 37 (2), 129–148. https://doi.org/10.1016/S0191-2615(01)00048-0.

Hryhoryeva, M., Leclercq, L., 2024. Competition in ride-hailing service operations: impacts on travel distances and service performance. Transp. Res. Rec. 2678 (1), 439–459. https://doi.org/10.1177/03611981231171155.

Hsu, Y.-T., Yan, S., Huang, P., 2021. The depot and charging facility location problem for electrifying urban bus services. Transp. Res. Part D: Transp. Environ. 100, 103053. https://doi.org/10.1016/j.trd.2021.103053.

Hu, C., Thill, J.-C., 2019. Predicting the upcoming services of vacant taxis near fixed locations using taxi trajectories. ISPRS Int. J. Geo Inf. 8 (7), 295. https://doi.org/10.3390/ijgi8070295.

Huang, S.-C., Jiau, M.-K., Lin, C.-H., 2014. A genetic-algorithm-based approach to solve carpool service problems in cloud computing. IEEE Trans. Intell. Transp. Syst. 16 (1), 352–364. https://doi.org/10.1109/TITS.2014.2334597.

Huang, Y., Kockelman, K.M., Garikapati, V., Zhu, L., Young, S., 2021. Use of shared automated vehicles for first-mile last-mile service: Micro-simulation of rail-transit connections in Austin, Texas. Transp. Res. Rec. 2675 (2), 135–149. https://doi.org/10.1177/0361198120962491.

Jamshidi, H., Correia, G.H., van Essen, J.T., Nökel, K., 2021. Dynamic planning for simultaneous recharging and relocation of shared electric taxies: a sequential MILP approach. Transp. Res. Part C Emerging Technol. 125, 102933. https://doi.org/10.1016/j.trc.2020.102933.

Ji, S., Wang, Z., Li, T., Zheng, Y., 2020. Spatio-temporal feature fusion for dynamic taxi route recommendation via deep reinforcement learning. Knowl.-Based Syst. 205, 106302. https://doi.org/10.1016/j.knosys.2020.106302.

Ji, Y., Du, Y., Liu, Y., Zhang, H.M., 2017. Empirical behavioral study of airport-serving taxi drivers using automatic vehicle location data. J. Urban Plann. Dev. 143 (1), 04016026. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000353.

Jiang, W., 2023. Travel demand prediction model and applications. In: Handbook of Mobility Data Mining. Elsevier, pp. 89–112. https://doi.org/10.1016/B978-0-323-95892-9.00003-6.

Jiang, S., Chen, L., Mislove, A., Wilson, C., 2018. April. on ridesharing competition and accessibility: evidence from Uber, Lyft, and taxi. In: Proceedings of the 2018 World Wide Web Conference, pp. 863–872. https://doi.org/10.1145/3178876.3186134.

Jiao, G., Ramezani, M., 2022. Incentivizing shared rides in e-hailing markets: dynamic discounting. Transp. Res. Part C Emerging Technol. 144, 103879. https://doi.org/10.1016/j.trc.2022.103879.

Jiau, M.-K., Huang, S.-C., 2015. Services-oriented computing using the compact genetic algorithm for solving the carpool services problem. IEEE Trans. Intell. Transp. Syst. 16 (5), 2711–2722. https://doi.org/10.1109/TITS.2015.2421557.

Karamanis, R., Anastasiadis, E., Stettler, M., Angeloudis, P., 2021. Vehicle redistribution in ride-sourcing markets using convex minimum cost flows. IEEE Trans. Intell. Transp. Syst. 23 (8), 10287–10298. https://doi.org/10.1109/TITS.2021.3089777.

Khayati, Y., Kang, J.E., Karwan, M., Murray, C., 2021. Household use of autonomous vehicles with ride sourcing. Transp. Res. Part C Emerging Technol. 125, 102998. https://doi.org/10.1016/j.trc.2021.102998.

Kisielewski, P., Duda, J., Karkula, M., Skalna, I., Redmer, A., Fierek, S., 2024. Optimization of urban transport vehicle tasks for large, mixed fleet of vehicles and real-world constraints. Arch. Trans. 70 (2), 65–78. https://doi.org/10.61089/aot2024.qnwb3h25.

King, D.A., Saldarriaga, J.F., 2017. Spatial regulation of taxicab services: measuring excess travel from New York City. J. Trans. Land Use 11 (1), 181–194. https://doi.org/10.5198/jtlu.2018.1063.

Komanduri, A., Wafa, Z., Proussaloglou, K., Jacobs, S., 2018. Assessing the impact of app-based ride share systems in an urban context: Findings from Austin. Transp. Res. Rec. 2672 (7), 34–46. https://doi.org/10.1177/0361198118796025.

Kondor, D., Zhang, X., Meghjani, M., Santi, P., Zhao, J., Ratti, C., 2021. Estimating the potential for shared autonomous scooters. IEEE Trans. Intell. Transp. Syst. 23 (5), 4651–4662. https://doi.org/10.1109/TITS.2020.304714.

Kontou, E., Garikapati, V., Hou, Y., 2020. Reducing ridesourcing empty vehicle travel with future travel demand prediction. Transp. Res. Part C Emerging Technol. 121, 102826. https://doi.org/10.1016/j.trc.2020.102826.

Król, A., Król, M., 2019. A stochastic simulation model for the optimization of the taxi management system. Sustainability 11 (14), 3838. https://doi.org/10.3390/su11143838.

Lai, Y., Yang, S., Xiong, A., Yang, F., Li, L., Zhou, X., 2020. Utility-based matching of vehicles and hybrid requests on rider demand responsive systems. IEEE Trans. Intell. Transp. Syst. 23 (2), 1058–1072. https://doi.org/10.1109/TITS.2020.3019791.

Lee, W.K., Sohn, S.Y., 2017. Taxi vacancy duration: a regression analysis. Transp. Plan. Technol. 40 (7), 771–795. https://doi.org/10.1080/03081060.2017.1340025.

Lees-Miller, J.D., Hammersley, J.C., Wilson, R.E., 2010. Theoretical maximum capacity as benchmark for empty vehicle redistribution in personal rapid transit. Transp. Res. Rec. 2146 (1), 76–83. https://doi.org/10.3141/2146-10.

Levin, M.W., Wong, E., Nault-Maurer, B., Khani, A., 2020. Parking infrastructure design for repositioning autonomous vehicles. Transp. Res. Part C Emerging Technol. 120, 102838. https://doi.org/10.1016/j.trc.2020.102838.

Levin, M.W., Boyles, S.D., 2015. Effects of autonomous vehicle ownership on trip, mode, and route choice. Transp. Res. Rec. 2493 (1), 29–38. https://doi.org/10.3141/2493-04.

Levin, M.W., Smith, H., Boyles, S.D., 2019. Dynamic four-step planning model of empty repositioning trips for personal autonomous vehicles. J. Transp. Eng., Part A: Syst. 145 (5), 04019015. https://doi.org/10.1061/JTEPBS.0000235.

Li, C., Zhang, H., Wang, Z., Wu, Y., Yang, F., 2022. Multigraph aggregation spatiotemporal graph convolution network for ride-hailing pick-up region prediction. Wirel. Commun. Mob. Comput. 1, 9815133. https://doi.org/10.1155/2022/9815133.

Li, X., Wang, X., Feng, Z., 2024. Dynamic repositioning in bike-sharing systems with uncertain demand: an improved rolling horizon framework. Omega, 103047. https://doi.org/10.1016/j.omega.2024.103047.

Liang, Y., Zhao, Z., Zhang, X., 2024. Modeling taxi cruising time based on multi-source data: a case study in Shanghai. Transportation 51 (3), 761–790. https://doi.org/10.1007/s11116-022-10348-y.

Lidbe, A., Adanu, E.K., Tedla, E., Jones, S., 2020. Role of passengers in single-vehicle drunk-driving crashes: an injury-severity analysis. Safety 6 (2), 30. https://doi.org/10.3390/safety6020030.

Lin, J.-J., Huang, S.-C., Jiau, M.-K., 2018. An evolutionary multiobjective carpool algorithm using set-based operator based on simulated binary crossover. IEEE Trans. Cybern. 49 (9), 3432–3442. https://doi.org/10.1109/TCYB.2018.2844324.

Liu, C., Chen, C.-X., Chen, C., 2021. Meta: a city-wide taxi repositioning framework based on multi-agent reinforcement learning. IEEE Trans. Intell. Transp. Syst. 23 (8), 13890–13895. https://doi.org/10.1109/TITS.2021.3096226.

Liu, J., Teng, M., Chen, W., Xiong, H., 2023a. A cost-effective sequential route recommender system for taxi drivers. INFORMS J. Comput. 35 (5), 1098–1119. https://doi.org/10.1287/ijoc.2021.0112.

Liu, L., Yan, J., Xu, J., 2024. On exploring the carrying-charging demand balance in cruising route recommendation for vacant electric taxis. IEEE Trans. Mob. Comput. 23 (10), 9567–9581. https://doi.org/10.1109/TMC.2024.3364654.

Liu, L., Zhou, Y., Xu, J., 2023b. A cloud-edge-end collaboration framework for cruising route recommendation of vacant taxis. IEEE Trans. Mob. Comput. 23 (5), 4678–4693. https://doi.org/10.1109/TMC.2023.3294898.

Liu, Q., Ding, C., Chen, P., 2020. A panel analysis of the effect of the urban environment on the spatiotemporal pattern of taxi demand. Travel Behavior and Society 18, 29–36. https://doi.org/10.1016/j.tbs.2019.09.003.

Liu, S., Jiang, H., 2022. Personalized route recommendation for ride-hailing with deep inverse reinforcement learning and real-time traffic conditions. Trans. Res. Part E: Logist. Transp. Rev. 164, 102780. https://doi.org/10.1016/j.tre.2022.102780.

Liu, Y., Wu, F., Lyu, C., Li, S., Ye, J., Qu, X., 2022. Deep dispatching: a deep reinforcement learning approach for vehicle dispatching on online ride-hailing platform. Transp. Res. Part E: Logist. Transp. Rev. 161, 102694. https://doi.org/10.1016/j.tre.2022.102694.

Luo, H., Cai, J., Zhang, K., Xie, R., Zheng, L., 2021. A multi-task deep learning model for short-term taxi demand forecasting considering spatiotemporal dependences. J. Traffic Transp. Eng. (English Edition) 8 (1), 83–94. https://doi.org/10.1016/j.jtte.2019.07.002.

Lv, B., Meng, X., Chen, Q., 2025. Decision model of taxi drivers at high-speed railway stations based on profit priority. Transp. Plan. Technol. 48 (1), 90–110. https://doi.org/10.1080/03081060.2024.2360138.

Marra, M., Oswald, F., 2024. Ownership frictions in a procurement market: evidence from London buses. Int. J. Ind Organiz 96, 103080. https://doi.org/10.1016/j.ijindorg.2024.103080.

McKane, R.G., Hess, D., 2023. The impact of ridesourcing on equity and sustainability in North American cities: a systematic review of the literature. Cities 133, 104122. https://doi.org/10.1016/j.cities.2022.104122.

Mehran, B., Yang, Y., Mishra, S., 2020. Analytical models for comparing operational costs of regular bus and semi-flexible transit services. Public Transp. 12 (1), 147–169. https://doi.org/10.1007/s12469-019-00222-z.

Mesa-Arango, R., Ukkusuri, S., Sarmiento, I., 2013. Network flow methodology for estimating empty trips in freight transportation models. Transp. Res. Rec. 2378 (1), 110–119. https://doi.org/10.3141/2378-12.

Millard-Ball, A., 2019. The autonomous vehicle parking problem. Transp. Policy 75, 99–108. https://doi.org/10.1016/j.tranpol.2019.01.003.

Mo, M.M., Lwin, K.K., Sekimoto, Y., 2020. Measuring traffic congestion based on the taxi operations of traditional and on-demand taxis in Yangon. J. Disaster Res. 15 (3), 451–460. https://doi.org/10.20965/jdr.2020.p0451.

Mondal, A., Juri, N.R., Bhat, C.R., Mirzaei, A., 2023. Accounting for ride-hailing and connected and autonomous vehicle empty trips in a four-step travel demand model. Transp. Res. Rec. 2677 (3), 217–228. https://doi.org/10.1177/03611981221115072.

Moreno, C., Falcón, L., Bolaños, R., Subramanian, A., Zuluaga, A., Echeverri, M., 2019. A hybrid algorithm for the multi-depot vehicle scheduling problem arising in public transportation. Int. J. Ind. Eng. Comput. 10 (3), 361–374. https://doi.org/10.5267/j.ijiec.2019.2.002.

Nair, G.S., Bhat, C.R., Batur, I., Pendyala, R.M., Lam, W.H., 2020. A model of deadheading trips and pick-up locations for ride-hailing service vehicles. Transp. Res. A Policy Pract. 135, 289–308. https://doi.org/10.1016/j.tra.2020.03.015.

Naji, H.A., Xue, Q., Li, T., 2024. A distributed VMD-BiLSTM model for taxi demand forecasting with GPS sensor data. Sensors 24 (20), 6683. https://doi.org/10.3390/s24206683.

Nasibov, E., Eliiyi, U., Ertaç, M.Ö., Kuvvetli, Ü., 2013. Deadhead trip minimization in city bus transportation: a real life application. Promet-Traffic Transp. 25 (2), 137–145. https://doi.org/10.7307/ptt.v25i2.1289.

Ni, L., Wang, X., 2021. Load factors of less-than-truckload delivery tours: an analysis with operation data. Transp. Res. Part E: Logist. Transp. Rev. 150, 102296. https://doi.org/10.1016/j.tre.2021.102296.

Nian, G., Huang, J., Sun, D., 2022. Exploring built environment influence on taxi vacant time in megacities: a case study of Chongqing China. J. Adv. Trans. 1, 3096901. https://doi.org/10.1155/2022/3096901.

Nourinejad, M., Ramezani, M., 2020. Ride-sourcing modeling and pricing in non-equilibrium two-sided markets. Transp. Res. B Methodol. 132, 340–357. https://doi.org/10.1016/j.trb.2019.05.019.

Nourinejad, M., Roorda, M.J., 2015. Carsharing operations policies: a comparison between one-way and two-way systems. Transportation 42 (3), 497–518. https://doi.org/10.1007/s11116-015-9604-3.

O'Keeffe, K., Anklesaria, S., Santi, P., Ratti, C., 2022. Using reinforcement learning to minimize taxi idle times. J. Intell. Transp. Syst. 26 (4), 498–509. https://doi.org/10.1080/15472450.2021.1897803.

Olsen, N., Kliewer, N., 2022. Location planning of charging stations for electric buses in public transport considering vehicle scheduling: a variable neighborhood search based approach. Appl. Sci. 12 (8), 3855. https://doi.org/10.3390/app12083855.

Orozco-Fontalvo, M., Llerena, L., Cantillo, V., 2023. Dockless electric scooters: a review of a growing micromobility mode. Int. J. Sustain. Transp. 17 (4), 406–422. https://doi.org/10.1080/15568318.2022.2044097.

Osorio, J., Lei, C., Ouyang, Y., 2021. Optimal rebalancing and on-board charging of shared electric scooters. Transp. Res. B Methodol. 147, 197–219. https://doi.org/10.1016/j.trb.2021.03.009.

Ouali, L.A.B., Graham, D.J., Barron, A., Trompet, M., 2020. Gender differences in the perception of safety in public transport. J. R. Stat. Soc. Ser. A Stat. Soc. 183 (3), 737–769. https://doi.org/10.1111/rssa.12558.

Panichpapiboon, S., 2025. Modeling the distributions of taxi supply: a case study in Bangkok. Int. J. Intell. Transp. Syst. Res. 23, 558–567. https://doi.org/10.1007/s13177-025-00469-w.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. The British Med. J. 372, n71. https://doi.org/10.1136/bmj.n71.

Pal, A., Zhang, Y., 2017. Free-floating bike sharing: solving real-life large-scale static rebalancing problems. Transp. Res. Part C Emerging Technol. 80, 92–116. https://doi.org/10.1016/j.trc.2017.03.016.

Pessaro, B., Buddenbrock, P., 2015. Managed lane toll prices: impact of transportation demand management activities and toll exemptions. Transp. Res. Rec. 2484 (1), 159–164. https://doi.org/10.3141/2484-17.

Qian, X., Guo, S., Aggarwal, V., 2022. DROP: deep relocating option policy for optimal ride-hailing vehicle repositioning. Transp. Res. Part C Emerging Technol. 145, 103923. https://doi.org/10.1016/j.trc.2022.103923.

Qu, Z., Wang, X., Song, X., Pan, Z., Li, H., 2019. Location optimization for urban taxi stands based on taxi GPS trajectory big data. IEEE Access 7, 62273–62283. https://doi.org/10.1109/ACCESS.2019.2916342.

Quadrifoglio, L., Dessouky, M.M., Ordóñez, F., 2008. A simulation study of demand responsive transit system design. Transp. Res. A Policy Pract. 42 (4), 718–737. https://doi.org/10.1016/j.tra.2008.01.018.

Rahimi, S.S.G.C., Behzadi, S., Zanjirabad, H.A., Sharifi, A., Vafaeinejad, A., 2025. Ridesharing optimization using GIS & TS algorithm based on spatial methods. GeoJournal 90 (3), 133. https://doi.org/10.1007/s10708-025-11381-x.

Ramezani, M., Nourinejad, M., 2018. Dynamic modeling and control of taxi services in large-scale urban networks: a macroscopic approach. Transp. Res. Part C Emerging Technol. 94, 203–219. https://doi.org/10.1016/j.trc.2017.08.011.

Raviv, T., Tzur, M., Forma, I.A., 2013. Static repositioning in a bike-sharing system: models and solution approaches. EURO J. Transp. Logist. 2 (3), 187–229. https://doi.org/10.1007/s13676-012-0017-6.

Rizopoulos, D., Gkiotsalitis, K., 2025. Extending electric bus charging infrastructure considering charging scheduling and energy pricing. Transp. Res. Part C Emerging Technol. 176, 105141. https://doi.org/10.1016/j.trc.2025.105141.

Rivera-Royero, D., Jaller, M., Kim, C.M., 2021. Spatio-temporal analysis of freight flows in Southern California. Transp. Res. Rec. 2675 (9), 740–755. https://doi.org/10.1177/03611981211004130.

Rong, H., Zhang, X., Li, Z., Ai, Z., 2020. Waiting or moving? A crossroad network-based markov decision process approach to catch vacant taxis. IEEE Access 8, 10528–10542. https://doi.org/10.1109/ACCESS.2020.2965171.

Rong, H., Huo, S., Zhang, Q., Zheng, H., Yang, C., 2021. GREEN: a global optimization scheme for transportation efficiency by mining taxi mobility. IEEE Trans. Intell. Transp. Syst. 23 (2), 1596–1606. https://doi.org/10.1109/TITS.2021.3089487.

Ruch, C., Hörl, S., Gächter, J., Hakenberg, J., 2021. The impact of fleet coordination on taxi operations. J. Adv. Transp. 1, 2145716. https://doi.org/10.1155/2021/2145716.

Saleh, M., Hatzopoulou, M., 2020. Greenhouse gas emissions attributed to empty kilometers in automated vehicles. Transp. Res. Part D: Transp. Environ. 88, 102567. https://doi.org/10.1016/j.trd.2020.102567.

Saleh, M., Yamanouchi, S., Hatzopoulou, M., 2024. Greenhouse gas emissions and potential for electrifying transportation network companies in Toronto. Transp. Res. Rec., 03611981241236480 https://doi.org/10.1177/03611981241236480.

Samie, S., Rezaee, B., 2022. Dynamic discrimination pricing and freelance drivers to rebalance mixed-fleet carsharing systems. IEEE Trans. Intell. Transp. Syst. 23 (12), 24738–24752. https://doi.org/10.1109/TITS.2022.3206413.

Saum, N., Sugiura, S., Piantanakulchai, M., 2024. Optimizing shared e-scooter operations under demand uncertainty: a framework integrating machine learning and optimization techniques. IEEE Access 12, 26957–26977. https://doi.org/10.1109/ACCESS.2024.3365947.

Schaller, B., 2021. Can sharing a ride make for less traffic? evidence from uber and lyft and implications for cities. Transport Policy 102, 1–10. https://doi.org/10.1016/j.tranpol.2020.12.015.

Schlenther, T., Martins-Turner, K., Bischoff, J.F., Nagel, K., 2020. Potential of private autonomous vehicles for parcel delivery. Transp. Res. Rec. 2674 (11), 520–531. https://doi.org/10.1177/0361198120949878.

Schweizer, J., Danesi, A., Rupi, F., Traversi, E., 2012. Comparison of static vehicle flow assignment methods and microsimulations for a personal rapid transit network. J. Adv. Transp. 46 (4), 340–350. https://doi.org/10.1002/atr.1196.

Seow, K.T., Dang, N.H., Lee, D.-H., 2009. A collaborative multiagent taxi-dispatch system. IEEE Trans. Autom. Sci. Eng. 7 (3), 607–616. https://doi.org/10.1109/TASE.2009.2028577.

Sevim, I., Tekiner-Moğulkoç, H., Güler, M.G., 2022. Scheduling the vehicles of bus rapid transit systems: a case study. Int. Trans. Oper. Res. 29 (1), 347–371. https://doi.org/10.1111/itor.12763.

Seymour, D.T., 2018. Free to cruise: designing a market for tradable taxicab rights. Econ. Transp. 16, 1–20. https://doi.org/10.1016/j.ecotra.2018.09.001.

Shafiei, S., Dia, H., Wu, W., Grzybowska, H., Qin, A.K., 2023a. An agent-based simulation approach for urban road pricing considering the integration of autonomous vehicles with public transport. IEEE Trans. Intell. Transp. Syst. https://doi.org/10.1109/TITS.2023.3315338.

Shafiei, S., Gu, Z., Grzybowska, H., Cai, C., 2023b. Impact of self-parking autonomous vehicles on urban traffic congestion. Transportation 50 (1), 183–203. https://doi.org/10.1007/s11116-021-10241-0.

Shang, H., Liu, Y., Huang, H., Guo, R., 2019. (2019) 'Vehicle scheduling optimization considering the passenger waiting cost'. J. Adv. Transp. 1, 4212631. https://doi.org/10.1155/2019/4212631.

Shen, C.-W., Quadrifoglio, L., 2013. Evaluating centralized versus decentralized zoning strategies for metropolitan ADA paratransit services. J. Transp. Eng. 139 (5), 524–532. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000529.

Shi, D., Ding, J., Errapotu, S.M., Yue, H., Xu, W., Zhou, X., Pan, M., 2019. Deep Q-Network-Based Route Scheduling for TNC Vehicles with Passengers Location Differential Privacy. IEEE Internet of Things J. 6 (5), 7681–7692. https://doi.org/10.1109/JIOT.2019.2902815.

Shou, Z., Di, X., Ye, J., Zhu, H., Zhang, H., Hampshire, R., 2020. Optimal passenger-seeking policies on E-hailing platforms using Markov decision process and imitation learning. Transp. Res. Part C Emerging Technol. 111, 91–113. https://doi.org/10.1016/j.trc.2019.12.005.

Silva, M.C.M., Aloise, D., Jena, S.D., 2024. On the simultaneous computation of target inventories and intervals for bimodal bike-sharing systems. Transp. Eng. 16, 100226. https://doi.org/10.1016/j.treng.2024.100226.

Sui, Y., Zhang, H., Song, X., Shao, F., Yu, X., Shibasaki, R., Sun, R., Yuan, M., Wang, C., Li, S., Li, Y., 2019. GPS data in urban online ride-hailing: a comparative analysis on fuel consumption and emissions. J. Clean. Prod. 227, 495–505. https://doi.org/10.1016/j.jclepro.2019.04.159.

Sun, S., Ertz, M., 2021. Environmental impact of mutualized mobility: evidence from a life cycle perspective. Sci. Total Environ. 772, 145014. https://doi.org/10.1016/j.scitotenv.2021.145014.

Szeto, W.Y., Wong, R.C.P., Wong, S.C., Yang, H., 2013. A time-dependent logit-based taxi customer-search model. Int. J. Urban Sci. 17 (2), 184–198. https://doi.org/10.1080/12265934.2013.776292.

Szeto, W.Y., Wong, R.C.P., Yang, W.H., 2019. Guiding vacant taxi drivers to demand locations by taxi-calling signals: a sequential binary logistic regression modeling approach and policy implications. Transp. Policy 76, 100–110. https://doi.org/10.1016/j.tranpol.2018.06.009.

Tafreshian, A., Masoud, N., 2020. Using subsidies to stabilize peer-to-peer ridesharing markets with role assignment. Transp. Res. Part C Emerging Technol. 120, 102770. https://doi.org/10.1016/j.trc.2020.102770.

Tajaddini, A., Vu, H.L., 2023. Modeling the long-term regional impacts of autonomous vehicles: a case study of Victoria, Australia. J. Intell. Transp. Syst. 27 (4), 459–470. https://doi.org/10.1080/15472450.2022.2053528.

Tang, C., Ceder, A., Ge, Y.E., Liu, T., 2021. Optimal operational strategies for single bus lines using network-based method. Int. J. Sustain. Transp. 15 (5), 325–337. https://doi.org/10.1080/15568318.2020.1765053.

Tang, C., Ceder, A., Ge, Y.E., Wu, N., 2020a. Optimal operational strategies for multiple bus lines considering passengers' preferences. Transp. Res. Rec. 2674 (5), 572–586. https://doi.org/10.1177/0361198120917159.

Tang, C., Ceder, A.A., Zhao, S., 2018a. Minimizing user and operator costs of single line bus service using operational strategies. Transport 33 (4), 993–1004. https://doi.org/10.3846/transport.2018.6595.

Tang, C., Ceder, A., Zhao, S., Ge, Y.E., 2018b. Vehicle scheduling of single-line bus service using operational strategies. IEEE Trans. Intell. Transp. Syst. 20 (3), 1149–1159. https://doi.org/10.1109/TITS.2018.2841061.

Tang, Q., Hu, X., Qi, H., 2020b. Modeling routing behavior learning process for vacant taxis in a congested urban traffic network. J. Transp. Eng. Part A: Syst. 146 (6), 04020043. https://doi.org/10.1061/JTEPBS.0000352.

Tengilimoglu, O., Wadud, Z., 2022. Evaluating the mileage and time efficiency of ridesourcing services: Austin, Texas case. Transp. Lett. 14 (5), 478–491. https://doi.org/10.1080/19427867.2021.1892936.

Todd, K., Brandel-Tanis, F., Arias, D., Edison Watkins, K., 2022. Deadhead minimization with a flexible facility locator tool. Transp. Res. Rec. 2676 (2), 504–515. https://doi.org/10.1177/03611981211044455.

Turan, B., Wakolbinger, T., 2023. The electric scooter collection problem: a case study in the city of Vienna. Sustainability 15 (13), 10058. https://doi.org/10.3390/su151310058.

Ward, J.W., Michalek, J.J., Samaras, C., 2021. Air pollution, greenhouse gas, and traffic externality benefits and costs of shifting private vehicle travel to ridesourcing services. Environ. Sci. Technol. 55 (19), 13174–13185. https://doi.org/10.1021/acs.est.1c01641.

Washbrook, K., Haider, W., Jaccard, M., 2006. Estimating commuter mode choice: a discrete choice analysis of the impact of road pricing and parking charges. Transportation 33, 621–639. https://doi.org/10.1007/s11116-005-5711-x.

Watts, R., Battista, G., 2014. Reducing Single-Occupancy Vehicle Use in Northern New England; Unlimited Access, Employee Incentives and Ridesharing. University of Vermont Transportation Research Center, Burlington.

Wei, T., Frey, H.C., 2020. Factors affecting variability in fossil-fueled transit bus emission rates. Atmos. Environ. 233, 117613. https://doi.org/10.1016/j.atmosenv.2020.117613.

Wen, M., Linde, E., Ropke, S., Mirchandani, P., Larsen, A., 2016. An adaptive large neighborhood search heuristic for the electric vehicle scheduling problem. Comput. Oper. Res. 76, 73–83. https://doi.org/10.1016/j.cor.2016.06.013.

Wenzel, T., Rames, C., Kontou, E., Henao, A., 2019. 'Travel and energy implications of ridesourcing service in Austin Texas. Transp. Res. Part D: Trans. Environ. 70, 18–34. https://doi.org/10.1016/j.trd.2019.03.005.

Willoughby, K.A., 2002. A mathematical programming analysis of public transit systems. Omega 30 (3), 137–142. https://doi.org/10.1016/S0305-0483(02)00022-1.

Wong, R.C.P., Szeto, W.Y., Wong, S.C., Yang, H., 2014a. Modelling multi-period customer-searching behavior of taxi drivers. Transportmetrica b: Transport Dynamics 2 (1), 40–59. https://doi.org/10.1080/21680566.2013.869187.

Wong, R.C.P., Mak, P.L., Szeto, W.Y., Yang, W.H., 2021. Spatio-temporal influence of extreme weather on a taxi market. Transp. Res. Rec. 2675 (9), 639–651. https://doi.org/10.1177/03611981211003894.

Wong, R.C.P., Szeto, W.Y., Wong, S.C., 2014b. Bi-level decisions of vacant taxi drivers traveling towards taxi stands in customer-search: Modeling methodology and policy implications. Transp. Policy 33, 73–81. https://doi.org/10.1016/j.tranpol.2014.02.011.

Wong, R.C.P., Szeto, W.Y., Wong, S.C., 2015. Behavior of taxi customers in hailing vacant taxis: a nested logit model for policy analysis. J. Adv. Transp. 49 (8), 867–883. https://doi.org/10.1002/atr.1307.

Xu, X., Yu, Y., Long, J., 2023. Integrated electric bus timetabling and scheduling problem. Transp. Res. Part C Emerging Technol. 149, 104057. https://doi.org/10.1016/j.trc.2023.104057.

Xu, Z., Yin, Y., Zha, L., 2017. Optimal parking provision for ride-sourcing services. Transp. Res. B Methodol. 105, 559–578. https://doi.org/10.1016/j.trb.2017.10.003.

Yan, H., Kockelman, K.M., Gurumurthy, K.M., 2020. Shared autonomous vehicle fleet performance: Impacts of trip densities and parking limitations. Transp. Res. Part D: Transp. Environ. 89, 102577. https://doi.org/10.1016/j.trd.2020.102577.

Yan, L., Tang, R., 2025. Dual-layer optimization for supply–demand balance in urban taxi systems: multi-agent reinforcement learning with dual-attention mechanisms. Electronics 14 (13), 2562. https://doi.org/10.3390/electronics14132562.

Yang, H., Yang, T., 2011. Equilibrium properties of taxi markets with search frictions. Transp. Res. B Methodol. 45 (4), 696–713. https://doi.org/10.1016/j.trb.2011.01.002.

Yao, E., Liu, T., Lu, T., Yang, Y., 2020. Optimization of electric vehicle scheduling with multiple vehicle types in public transport. Sustain. Cities Soc. 52, 101862. https://doi.org/10.1016/j.scs.2019.101862.

Yao, R., Bekhor, S., 2021. A dynamic tree algorithm for peer-to-peer ridesharing matching. Netw. Spat. Econ. 21 (4), 801–837. https://doi.org/10.1007/s11067-021-09523-y.

Ye, J., Pantuso, G., Pisinger, D., 2024. Order dispatching and vacant vehicles rebalancing for the first-mile ride-sharing problem. EURO J. Trans. Logist. 13, 100132. https://doi.org/10.1016/j.ejtl.2024.100132.

Ye, Z., Xiao, K., Ge, Y., Deng, Y., 2018. Applying simulated annealing and parallel computing to the mobile sequential recommendation. IEEE Trans. Knowl. Data Eng. 31 (2), 243–256. https://doi.org/10.1109/TKDE.2018.2827047.

Yu, X., Gao, S., Hu, X., Park, H., 2019. A Markov decision process approach to vacant taxi routing with e-hailing. Transp. Res. B Methodol. 121, 114–134. https://doi.org/10.1016/j.trb.2018.12.013.

Yu, X., Gao, S., 2022. A batch reinforcement learning approach to vacant taxi routing. Transp. Res. Part C Emerging Technol. 139, 103640. https://doi.org/10.1016/j.trc.2022.103640.

Yu, X., Hua, M., Chen, J., Peng, J., Mao, H., 2025. Uncovering passenger-seeking behavior of vacant taxis from trajectory data via self-supervised deep spectral clustering. IEEE Trans. Intell. Transp. Syst. 26 (4), 5307–5321. https://doi.org/10.1109/TITS.2025.3546293.

Yuan, N.J., Zheng, Y., Zhang, L., Xie, X., 2012. T-finder: a recommender system for finding passengers and vacant taxis. IEEE Trans. Knowl. Data Eng. 25 (10), 2390–2403. https://doi.org/10.1109/TKDE.2012.153.

Zhan, X., Qian, X., Ukkusuri, S.V., 2016. A graph-based approach to measuring the efficiency of an urban taxi service system. IEEE Trans. Intell. Transp. Syst. 17 (9), 2479–2489. https://doi.org/10.1109/TITS.2016.2521862.

Zhang, K., Mittal, A., Djavadian, S., Twumasi-Boakye, R., Nie, Y.M., 2023a. RIde-hail vehicle routing (RIVER) as a congestion game. Transp. Res. B Methodol. 177, 102819. https://doi.org/10.1016/j.trb.2023.102819.

Zhang, R., Kan, H., Wang, Z., Liu, Z., 2023b. Relocation-related problems in vehicle sharing systems: a literature review. Comput. Ind. Eng., 109504 https://doi.org/10.1016/j.cie.2023.109504.

Zhang, W., Guhathakurta, S., Khalil, E.B., 2018a. The impact of private autonomous vehicles on vehicle ownership and unoccupied VMT generation. Transp. Res. Part C Emerging Technol. 90, 156–165. https://doi.org/10.1016/j.trc.2018.03.005.

Zhang, W., Ukkusuri, S.V., Lu, J.J., 2017. Impacts of urban built environment on empty taxi trips using limited geolocation data. Transportation 44, 1445–1473. https://doi.org/10.1007/s11116-016-9709-3.

Zhang, W., Ukkusuri, S.V., Yang, C., 2018b. Modeling the taxi drivers' customer-searching behaviors outside downtown areas. Sustainability 10 (9), 3003. https://doi.org/10.3390/su10093003.

Zhang, W., Xu, C., 2021. Exploring app-based taxi movement patterns from large-scale geolocation data. ISPRS Int. J. Geo Inf. 10 (11), 751. https://doi.org/10.3390/ijgi10110751.

Zhang, Z., Zhang, N., 2021. Re-recognition of ride-sourcing service: from the perspective of operational efficiency and social welfare. Sustainability 13 (15), 8198. https://doi.org/10.3390/su13158198.

Zhao, M., Li, X., Yin, J., Cui, J., Yang, L., An, S., 2018. An integrated framework for electric vehicle rebalancing and staff relocation in one-way carsharing systems: Model formulation and Lagrangian relaxation-based solution approach. Transp. Res. B Methodol. 117, 542–572. https://doi.org/10.1016/j.trb.2018.09.014.

Zhou, W., Yang, Y., Zhang, Y., Wang, D., Zhang, X., 2020. Deep flexible structured spatial–temporal model for taxi capacity prediction. Knowl.-Based Syst. 205, 106286. https://doi.org/10.1016/j.knosys.2020.106286.

Zhu, R., Zhang, X., Kondor, D., Santi, P., Ratti, C., 2020. Understanding spatio-temporal heterogeneity of bike-sharing and scooter-sharing mobility. Comput. Environ. Urban Syst. 81, 101483.

Zong, F., Wu, T., Jia, H., 2018. Taxi drivers' cruising patterns—Insights from taxi GPS traces. IEEE Trans. Intell. Transp. Syst. 20 (2), 571–582. https://doi.org/10.1016/j.compenvurbsys.2020.101483.