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Assessing the impacts of ridesharing services: An agent-based simulation approach

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ABSTRACT

A shift from privately owned vehicles to shared mobility services can affect mobility, energy consumption, and vehicle emissions. Existing literature on ridesharing services has focused on evaluating its traffic and economic impacts. In this study, we propose an integrated framework to analyze the efficiency and environmental benefits of ridesharing on a regional scale. The framework utilizes an agent-based traffic simulation package (i.e., SUMO) to replicate traffic activities for commuting trips in a mid-size city, Chattanooga, Tennessee, based on real-world travel-demand data. We construct scenarios representing different ridesharing strategies and penetrations. The simulation and results analysis show that with a ridesharing ratio of 5%–75% over travel demand in a city scale, many (65%–75%) ridesharing travelers will experience up to a 15-min delay. About 80% of drive-alone travelers will arrive earlier compared with no ridesharing scenario. The average early arrival time would be 5.6 min for all drive-alone travelers. The results also show ridesharing services can achieve a 2%–50% reduction in total city-scale vehicle emissions and energy consumption compared with the no ridesharing scenario. The framework and results of this study can be helpful to transportation practitioners to evaluate environmental benefits when implementing ridesharing services on a city scale.

1. Introduction

Road transportation is a major consumer of energy and contributor to air pollution (Davis and Boundy, 2021; European Union, 2012). Shared mobility is considered an effective way to enhance efficiency in the road transportation system (Shaheen et al., 2016b). Shared mobility is an innovative transportation strategy that provides users with short-term access to transportation on demand. The definition of shared mobility includes various formats, including carsharing, ride-hailing, and ridesharing. These services aim to break traditional car ownership, instead providing users with travel options through a pay-per-use approach. In recent years, there has been rapid development and commercialization of ridesharing services (e.g., Uber, Lyft). Ridesharing is defined as an arrangement where two or more people from different households share the use of a privately owned car for part of a trip and share the driving expenses (Delhomme and Gheorghiu, 2016). Rideshare services has the potential to eliminate traffic congestion and reduce vehicle emissions based on studies in different localities Yu et al. (2017); Jalali et al. (2017); Dai et al. (2022).

Despite progresses in ridesharing services, knowledge gaps still exist, and this prevents transportation practitioners from fully understanding the potential impacts of ridesharing services. As stated by Yu et al. (2017), "most of the existing studies are mainly drawing on the survey data or the small-scale trip data instead of the raw observed order information." In the limited studies based on empirical ridesharing data, their conclusions are retrospective and do not offer insights for future scenarios, which are important for transportation practitioners in evaluating various ridesharing policies. Any tools developed should have the capability to consider individual-level behavior when evaluating ridesharing impacts (Arteaga-Sánchez et al., 2020). Thus, the research questions to address in this study are: (1) how to develop an environmental impact evaluation framework for ridesharing services that considering individual-level (i.e., agent) behavior changes; and (2) how to implement scenario analysis that can be used by transportation practitioners to evaluate the potential impacts of various ridesharing strategies.

In the literature, researchers studied rideshare services in terms of behavior, operation management, and impacts on traffic networks and the environment. Research related to the behavior of rideshare focused on motivations and constraints of people using rideshare services. The

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literature shows that people use rideshare services due to its benefits in cost savings (Correia and Viegas, 2011; Ciasullo et al., 2017) and time savings (Abrahamse and Keall, 2012; Shaheen et al., 2016a). People's sociodemographic characteristics have been shown to influence their choice of ridesharing services (Delhomme and Gheorghiu, 2016; Javid et al., 2017; Molina et al., 2020). Various types of online and offline driver–passenger matching algorithms have been developed to improve operational efficiency in ridesharing services (Guo et al., 2013a, 2013b; Huang et al., 2016; Tamannaei and Irandoost, 2019; Yan et al., 2013).

Recently, studies have focused on impacts of rideshare on congestion, energy consumption, and emission of transportation. The impacts of rideshare on congestion have been well studied (Bahat and Bekhor, 2016; Gurumurthy et al., 2019; Li et al., 2016; Ou and Tang, 2018). But the energy and environmental impacts of ridesharing services are less studied. Some studies employed travel survey data to investigate the environmental and energy impacts of rideshare. Caulfield (2009) explored the environmental benefits of ridesharing in terms of reductions in emissions and vehicle kilometers traveled based on analyzing the 2006 census of Ireland. Minett and Pearce (2011) estimated the energy savings of ridesharing for leisure trips in San Francisco is about 1.7 million to 3.5 million liters of gasoline per year, or 200–400 L for each participant, based on ridesharing opinion data. Other studies used similar approaches with survey data to analyze the energy and emission benefits of ridesharing services in other countries, like China (Yu et al., 2017), Canada (Jalali et al., 2017) and globally (Tikoudis et al., 2021). Although these surveys were rigorously implemented, the data can only represent survey participants' choice under hypothetical conditions. When investigating energy and emission benefits of ridesharing services, it is important to consider a bottom-up approach that can quantify the benefits at individual level and evaluate how changes in driving trajectories can lead to changes in aggregated vehicle emissions.

Agent-based traffic simulation is a technique that can model the transportation system as a collection of autonomous decision-making agents, i.e., travelers, and simulate their movements in the system (Bonabeau, 2002). It has the advantage of modeling a complex transportation system by tuning the interactions among independent decision-making agents. It is possible to evaluate various traffic management policies in traffic simulation and gain insights into the system that would not be possible a priori. Recently, limited studies began to utilize agent-based traffic simulation tools to study impacts of various formats of shared mobility. Becker et al. (2020) established a multimodal traffic simulation application in MATSim to evaluate the economic and travel time impacts of car sharing, bike sharing, and ride hailing. They simulated the road network in Zurich, Switzerland, and implemented scenarios with different shared car or bike fleet sizes. Other studies used similar traffic simulation tools to assess car sharing (Ciari et al., 2015; Balac et al., 2019), shared autonomous taxis (Leich and Bischoff, 2019), and transit first- and last-mile connections (Huang et al., 2021). Thus, agent-based traffic simulation can be a viable method to study the impacts of ridesharing at the transportation system level.

This review of the literature shows that there is a knowledge gap in the literature regarding developing an environmental impact evaluation framework for ridesharing services with consideration of individual-level (i.e., agent) behavior changes. In addition, to be useful for transportation practitioners, the developed framework needs to have scenario analysis capability that can evaluate various ridesharing strategies for comparison purposes. In this study, we propose an integrated framework to analyze the efficiency and environmental benefits of ridesharing on a regional scale. Specifically, the framework utilizes an agent-based traffic simulation package (i.e., SUMO) to replicate traffic activities for commuting trips in a mid-size city, Chattanooga, Tennessee. We utilize real-world travel origin and destination demand data for the city and develop a heuristic matching algorithm for arranging ridesharing trips among travelers. We construct scenarios representing different ridesharing strategies and penetrations. Last, efficiency (delay at system and individual levels) and environmental performance are evaluated and compared among different ridesharing scenarios.

The remainder of this paper is organized as follows. Section 2 presents the traffic simulation methodology, data sources, and construction of simulation scenarios. In Section 3, we discuss simulation results and analyze road network efficiency and environmental impacts due to the implementation of ridesharing services. Section 4 discusses our study and points out some policy implications for transportation practitioners. Section 5 provides the conclusions and future research directions of this study.

2. Methodology

To assess the energy and environmental impacts of ridesharing services, we configure an integrated framework to run scenario-based traffic simulations and analyze traffic outputs for environmental impacts (Fig. 1). The traffic simulation is implemented through Simulation of Urban Mobility (SUMO). SUMO is a highly customizable, open-source microscopic traffic simulator built on agent-based simulation concept (Krajzewicz et al., 2002). Additionally, SUMO provides an interface, TraCI, that allows real-time extracting and passing parameters with a simulation (Wegener et al., 2008). The framework contains three modules: data preparation, shared mobility simulation, and output analysis. In the "Data Preparation" module, road information is prepared to digitally represent traffic network in the traffic simulator SUMO. We obtain travel demand origin and destination (OD) matrix data from the metropolitan planning organization of Chattanooga. The travel demand OD matrix is based on traffic analysis zone (TAZ) and contains hourly vehicle trips between each OD TAZ pair. We assign TAZ-level trips to specific road links according to the land use characteristics of each TAZ. In the "Shared Mobility Simulation" module, a shared mobility toolbox is built using Python. It allows convenient setting of simulation parameters for scenario specifications. In addition, the toolbox enables in-route driver–passenger matching for shared mobility vehicles to maximize matching efficiency. Once scenario-specific simulations are done, the toolbox can process the outputs and generate results at vehicle level (i.e., vehicle trajectory at 1Hz frequency) and road link level (i.e., hourly average speed, density, and volume). The "Output Analysis" module analyzes simulation results and evaluated share mobility impacts on traffic, travelers' schedules, and the environment under various scenarios. For traffic impact analysis, we aggregate 1Hz vehicle trajectory results into 5- or 15-min link-level average speed and volume. We evaluate changes in link-level traffic stream characteristics under different rideshare scenarios. For traveler schedule impact analysis, we track and compare the travel time for each individual under base and various rideshare scenarios. For environmental impact analysis, we obtain 1Hz vehicle emissions of CO_2, PM, and NO_x as provided by SUMO. Vehicle emissions reported by SUMO are based on well-calibrated regulatory vehicle emission model HBEFA and PHEMlight (Lopez et al., 2018) and have been widely used in relevant literature (Erdağı et al., 2019; Validi et al., 2020; Gounni et al., 2019). We aggregate the 1Hz vehicle emission at trip, link, and network levels to evaluate environmental impacts of various shared mobility scenarios.

For the core part of "Shared Mobility Simulation," the process is as follows:

1. Vehicle trip generation. A vehicle trip contains OD road links for vehicle travel. The OD matrix data provide the number of trips between each TAZ pair. We assign each trip to one road link in the origin TAZ and one link in the destination TAZ, based on land use and other link features (e.g., length, traffic volume, etc.). At this step, we divide all vehicle trips into two travel modes, i.e., driving alone and shared rides. The ratio between the two modes can vary under different share mobility scenarios.
2. Route generation. Given OD links for each drive-alone vehicle trip, we find the route of road links for each trip. We employ SUMO's DUAROUTER algorithm to search for the route. This algorithm

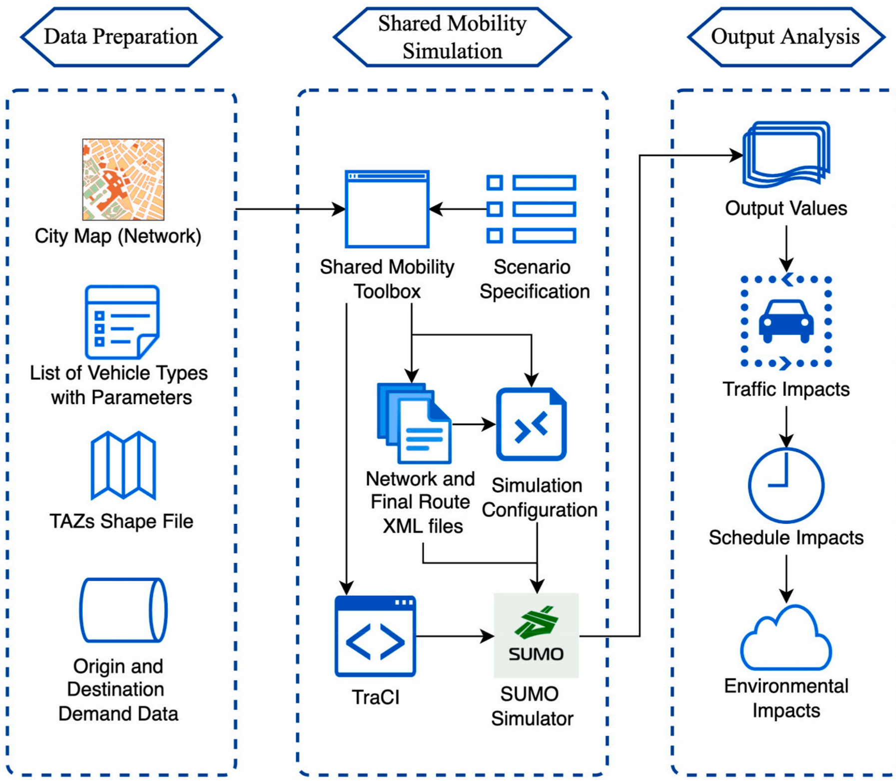

Fig. 1. Framework of the shared mobility simulation.

applies a dynamic user equilibrium method to determine the shortest path for each trip based on time-dependent travel time and costs on road links. The time-dependent individual vehicle routes can be used to calculate the arrival time and schedule delay of each traveler. When aggregating individual vehicle routes, we can obtain link-level traffic volume and speed patterns that can be used to evaluate link-level and network-level traffic and environmental impacts from various shared mobility scenarios.

3. Matching passengers with shared vehicles. For rideshare travel demand, we develop a heuristic vehicle–passenger matching algorithm to match passengers with shared vehicles. The pseudocode of the algorithm is shown in Fig. 2. The main purpose is to ensure every rideshare passenger is served. The algorithm tries to reduce waiting time for riders and minimize routing time for shared vehicles. It first searches for available vehicles that can pick up a rider within 5 min of the desired departure time. If a vehicle is identified, the vehicle's route will be modified to pick up the rider and continue to its destination. A shared vehicle is allowed to pick up as many as 3 passengers. When multiple riders are picked up, the shared vehicle drops off passengers in an order that considers both distance to the destination of each rider and pickup order of riders. If no available vehicles are found in the initial 5-min window, the algorithm extends the window to 10 min and then 20 min. At the 20-min time window, most shared mobility riders can find a matching vehicle.

The experiment scenarios constructed in this paper are based on the real-world data for the city of Chattanooga, Tennessee. This city has a population of 182,803 and is set along the Tennessee River in the foothills of the Appalachian Mountains in the Southeast region of United States. It has a motorization index of 951 vehicles per 1000 people (TN DOT, 2016). According to Tennessee Department of Transportation data, 82% of commuting trips are fulfilled by driving cars and 10% of commuters regularly or sometimes used ridesharing services. Chattanooga was designated as an air quality nonattainment area mainly due to its high vehicle-related emissions. Chattanooga commuters spend an average of 20 min traveling one way (Chattanooga, 2020). Thus, Chattanooga is an ideal testbed for our ridesharing framework given its high vehicle ownership, travelers' openness to rideshare services, and air quality problems due to vehicle-related emissions. In this study, we quantify traffic and environmental impacts of various ridesharing scenarios in Chattanooga.

To make our framework more applicable, we utilize real data from Chattanooga to set up the simulation. We obtain Chattanooga's TAZ-level OD demand for a typical weekday from the Chattanooga transportation planning organization. We use travel demand during morning peak hours (6–9 a.m.) as the OD demand in the traffic simulation. The OD demand shows the number of trips between each TAZ, and each trip is considered to be fulfilled by one agent. Fig. 3 visualizes the travel demand for the 746 TAZs in Chattanooga for the morning peak period. Specifically, we categorize all TAZs into 10 homogenous TAZ clusters based on sociodemographic information. For each TAZ cluster, we split the travel demand into driving alone and sharing rides with different ratios. Specifically, the "Base" scenario assumes all trips are driven alone, which is comparable to the existing situation in Chattanooga. We define five additional scenarios that have share ratio of 5%, 10%, 25%, 50%, and 75%, respectively, of travel demand to be fulfilled by shared mobility services. According to literature, the current ridesharing ratio in Chattanooga is 10% (Chattanooga, 2020) and the national average ridesharing ratio is 9% (U.S. Census Bureau, 2019). Therefore, the 5% and 10% scenarios are realistic scenarios that reflecting current ridesharing status. And our framework can evaluate its environmental impacts. The 25%, 50% and 75% ridesharing scenarios are built in to explore possible impacts of future ridesharing scenarios that could be seen as high at present time. Overall, we are to quantify environmental benefits of ridesharing in current and future scenarios.

We randomly choose 5%, 10%, 25%, 50%, and 75% of the trips in drive-alone scenarios to be fulfilled by ridesharing services for the corresponding scenarios. These travelers will make themselves available to be picked up based on their original departure times in the drive-alone scenario. They are picked up based on the availability of drivers and

Algorithm 1: Ride matching algorithm

Result: Mapping set of rider to car $\boldsymbol{M} = \{\boldsymbol{r} : \boldsymbol{c}\}$;
Initialization:
Available cars $\boldsymbol{AC}_r = \emptyset$ for rider r and a set of cars fully occupied $\boldsymbol{FC} = \emptyset$;
for $r \in \boldsymbol{R}$ **do**
  Statements of depart time (dt_r), depart position (pos_r) for each rider r, and depart time (dt_c), depart position (pos_c) for each candidate shared car c;
  while $length(\boldsymbol{AC}_p) = 0$ **do**
    Search available cars for each rider r within the time widow $TW_r = [dt_p - 2T, dt_p - T]$;
    for $c \in \boldsymbol{C}$ **do**
      if $dt_c \in TW_r$ & $c \notin \boldsymbol{FC}$ **then**
        $\boldsymbol{AC}_r \leftarrow \boldsymbol{AC}_r \cup \{c\}$;
      end
    end
    Update $length(\boldsymbol{AC}_r)$;
    if $length(\boldsymbol{AC}_r = 0)$ **then**
      repeat
        $TW_r \leftarrow TW_r + T$;
        Extend TW with time interval T and continue to search;
      until $TW_r[upperbound] > TW_r + 2T$;
    end
  end
  for $c \in \boldsymbol{AC}_r$ **do**
    Calculate the path length $L(pos_c, pos_r)$ between available car c and rider r;
    Estimate the traveling time $T(c, r) \leftarrow L(pos_c, pos_r)/speed$;
    Get time difference $t(c, r) = T(pos_c, pos_r) + dt_c - dt_r$ between the arrival of c at pos_r and departure of r;
  end
  $c^* \leftarrow argmin_c t(c, r)$;
  $\boldsymbol{M} \leftarrow \boldsymbol{M} \cup \{p : c^*\}$;
  if $count(c \in \boldsymbol{M}) = 4$ **then**
    $\boldsymbol{FC} \leftarrow \boldsymbol{FC} \cup \{c\}$;
  end
end

Fig. 2. Pseudocode for the heuristic matching algorithm.

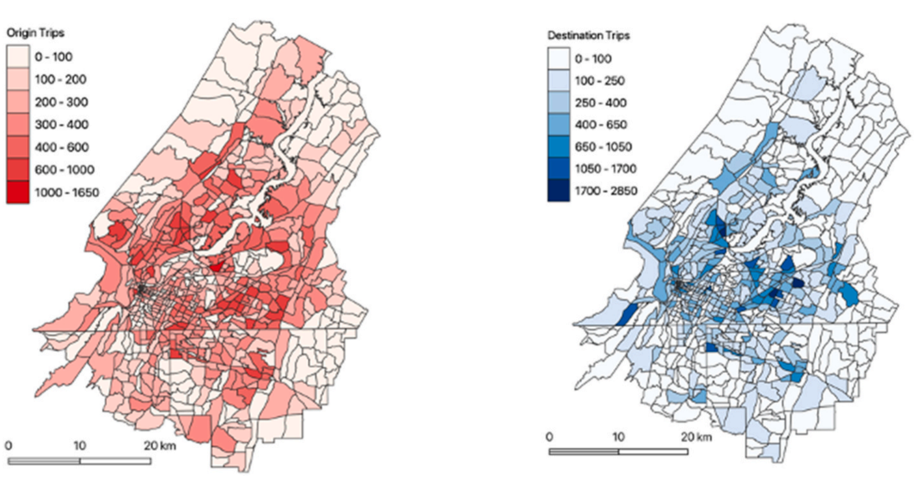

Fig. 3. Spatial distribution of passenger cars departing (left) and arriving (right) in each TAZ of the Chattanooga model area.

traffic conditions in the road network.

3. Results

We construct six scenarios in the shared mobility simulation: (a) no share (all vehicles driving alone); (b) 5% of trips are shared; (c) 10% of trips are shared; (d) 25% of trips are shared; (e) 50% of trips are shared; and (f) 75% of trips are shared. We first split passengers according to the proportions of the scenario based on demand and then assign shared vehicles to each passenger. Table 1 summarizes the volumes of passengers, shared vehicles, and drive-alone vehicles, as well as the average vehicle occupancy for shared vehicles under each scenario. Various outputs are generated by simulating these scenarios, including link-level traffic measurements, trajectories of each vehicle, trip-level

Table 1
Summary of trip volume under different scenarios during peak times (6–9 a.m.).

Trip volume	No rideshare	5% share ratio	10% share ratio	25% share ratio	50% share ratio	75% share ratio
Passengers	0	7250	14501	36,252	72,504	10,8755
Shared vehicles	0	6635	12433	28,421	40,246	33,022
Vehicles driving alone	145,007	131122	118073	80,334	32,257	3230
Average vehicle occupancy	1	1.09	1.17	1.28	1.80	2.94

information, and person-level trip summary. The link-level traffic measurements describe macroscopic values such as the average speed, density, and occupancy of the road link during a specified interval (e.g., 5 or 15 min). Trip-level information contains the departure time, arrival time, and route length of each vehicle and person and the sum of all emissions by the vehicle during its journey.

3.1. Impacts of ridesharing on traffic

Fig. 4 shows the 5-min average speed distributions at the link level of the three scenarios compared with the base scenario during morning peak hours. We observe that all scenarios have a similar spread of link-level speed ranging from 0 to 88 km/h and all density lines have two main peak points at a similar segment-level speed; the primary one lies at around 20 km/h, and the secondary peak is located at about 38 km/h. The pattern of the distribution indicates that many vehicles are driving at a low speed (20 km/h), corresponding to local collector roads. In addition, another group of vehicles is driving around 38 km/h, corresponding to arterial or major arterial roads. This implies that the investigated area encounters traffic congestion during the simulated morning peak hours. As shown in Fig. 4, the densities of shared scenarios (5%, 10%, 25%, 50%, and 75% share ratios) at their primary peak point (20 km/h) are lower than that of the base scenario (no share). Differences between the base scenario and the three shared scenarios at the secondary peak point are also observable, although they are not statistically significant. These differences reveal that the volume of vehicles driving at a relatively low speed is reduced, which means shared mobility significantly contributes to reducing traffic jams. In other words, ridesharing is capable of easing traffic congestion during rush hour. In Fig. 4, we further observe that the reduction of the density at the primary peak point in the high share ratio scenario is the largest, followed by the medium share ratio scenario and the low share ratio scenario. As mentioned, these three scenarios are designed according to the proportions of passengers who would like to share rides with others. Therefore, the comparison among the three scenarios indicates that the remission of traffic congestion is determined by the proportion of passengers in the shared mobility simulation. The higher the proportion of passengers, the fewer vehicles in the traffic jam.

3.2. Impacts of ridesharing on schedule

Besides relieving traffic congestion on the road network, ridesharing has the potential to affect the travel schedule of individual travelers. Fig. 5 reports distributions of changes in arrival time for drive-alone travelers and rideshare travelers. In the simulations, drive-alone travelers will depart at the same time, but arrival times will differ due to different traffic conditions in the road network. Ridesharing travelers' departure (pickup) and arrival (dropoff) times can vary due to driver availability and traffic conditions on roads.

Fig. 5 (left) presents the distribution of changes in arrival time for drive-alone travelers under the three ridesharing scenarios. It shows that most (70%–82%) drive-alone travelers arrive early compared with their original arrival time in the no ridesharing scenario. The early arrival of drive-alone travelers is caused by fewer vehicles on the road due to some travelers choose ridesharing services. In all five ridesharing scenarios, less than 20% of travelers are delayed by more than 5 min and the magnitude decreases as rideshare percentage increases. Some drive-alone travelers experience delays in travel time that are longer than 5 min, but the percentages are minimal. Although traffic volume in the whole network is reduced because of ridesharing services, in certain regions, there could be more traffic due to ridesharing vehicles routing to pick up and drop off passengers. This caused a small fraction of drive-

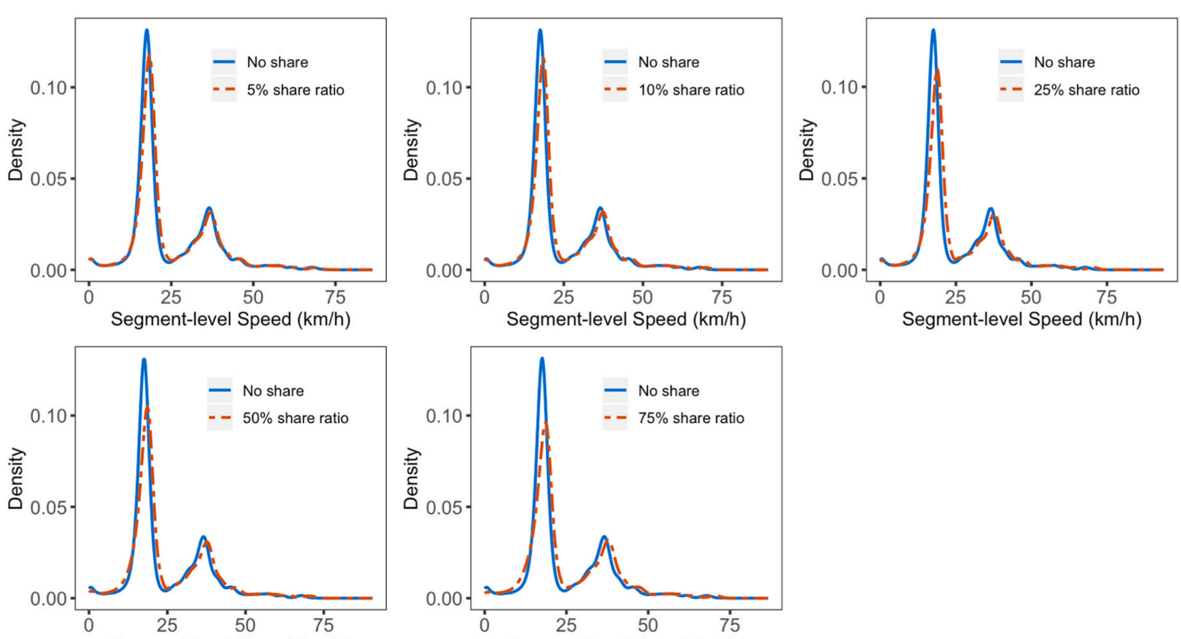

Fig. 4. Distributions of the segment-level speed of three scenarios compared with the base scenario.

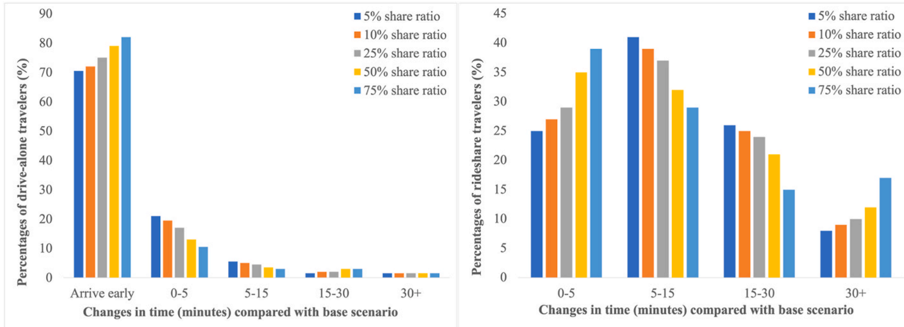

Fig. 5. Distributions of arrival delays of drive-alone travelers (left) and ridesharing travelers (right) under three ridesharing scenarios as compared with the no share scenario.

alone travelers to spend extra time on the road. Our results also indicate an average time savings of 5.6 min per drive-alone travelers, which is a significant benefit in travel time for those travelers. Fig. 5 (right) presents the distribution of arrival delays for travelers using ridesharing services as compared with travel time if they drive alone. We category the arrival delays into four intervals: 0–5 min, 5–15 min, 15–30 min, and more than 30 min. The high share scenario leads to a higher share of travelers with delays less than 5 min. The results also show that 65%–75% of travelers are expected to experience an arrival delay that is less than 15 min under various ridesharing scenarios. The main cause of delay for ridesharing travelers is waiting for vehicle matching and pickup. Particularly, travelers living in remote areas with lower population density are more likely to experience longer delays. The results show that the high share scenario, where more travelers are participating in ridesharing services, has the highest percentage of delays of 30 min or more. This is because in the high share scenario, it is more likely that travelers from isolated areas will need rides.

3.3. Impacts of ridesharing on energy and emission

We investigate the impacts of ridesharing on trip-level vehicle-related emissions. Specifically, we calculate and compare vehicle emissions caused by each traveler in ridesharing scenarios. For the base (no rideshare) case, each traveler drives one car and has a unique vehicle trajectory at 1Hz frequency. We estimate second-level CO_2 emissions based on trajectory-level speed and acceleration and aggregate to trip-level CO_2 emissions of each traveler. For rideshare scenarios, the trip-level CO_2 emissions of each drive-alone travelers are calculated the same way as in the base (no share) scenario. For travelers using ridesharing services, we split the CO_2 emissions among travelers sharing the same vehicle based on their traveling distance. Fig. 6 presents the scatterplot comparing trip-level CO_2 emissions in the no share scenario and each of the three ridesharing scenarios. If emissions of each traveler remain the same in the base and ridesharing scenarios, the scatter points should cluster along the red diagonal line. If the emissions of each traveler in ridesharing scenarios are lower than those in the base (no share) scenario, the scatter plots would be expected to appear above the diagonal line, and vice versa. Fig. 6 shows a larger portion of scatter points above the diagonal line for all three ridesharing scenarios compared with the base (no share) scenario, which means that travelers can generally reduce vehicle emissions with ridesharing options. In addition, the higher the ridesharing ratio, the higher portion of points that appear above the diagonal line. This is expected, because a higher ridesharing ratio can achieve more reductions in vehicle emissions of each traveler. The average trip-level CO_2 emissions are 4.3 kg, 4.2 kg, 4.0 kg, 3.8 kg, 3.2 kg, and 2.9 kg for no rideshare, 5%, 10%, 25%, 50%, and 75% share ratio scenarios, respectively. Clearly, higher ridesharing generally leads to lower average trip-level emissions given the same amount of travel demand. Though the exact reduction in CO_2 emissions is subject to the specific operation of ridesharing services and travel demand, our results are consistent with existing literature on the environmental impacts of ridesharing services, such as Yu et al. (2017) in

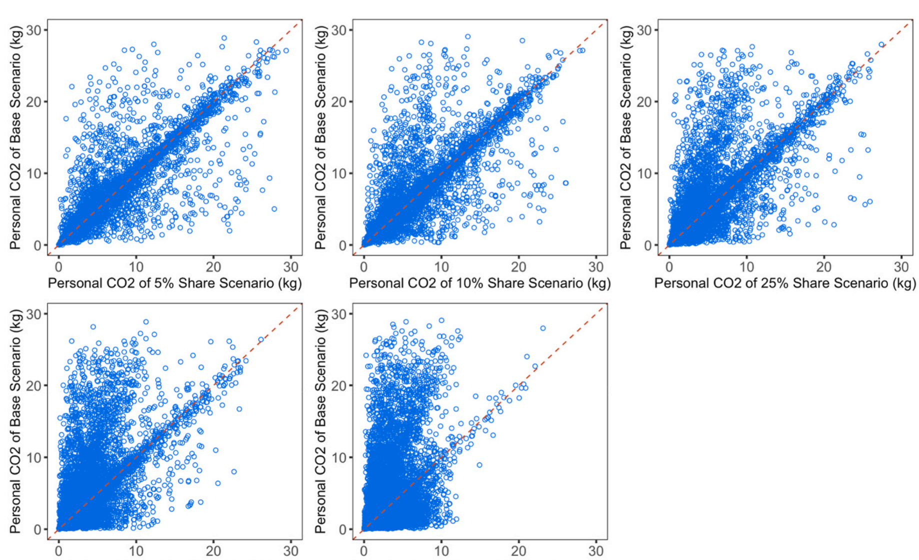

Fig. 6. Scatter plots of CO_2 emissions under five scenarios (5%, 10%, 25%, 50%, and 75% share ratios) versus the CO_2 emissions under the no share scenario for passengers, shared vehicles, and vehicles driving alone.

Beijing, Fagnant and Kockelman (2014) in Austin, and Caulfield (2009) in Dublin.

The system-level impacts of energy consumption, vehicle emissions, and link average speed under different scenarios are presented in Table 2. The exhaust emissions including CO_2, CO, HC, NOx, and PM are significantly reduced from the no share to high share ratio scenarios during the three morning peak hours. CO_2 emissions drop 33% for 75% share ratio, 21% for 50% share ratio, 7% for 25% share ratio, 5% for 10% share ratio, 2% for 5% share ratio, compared with no share. Besides CO2, the CO, HC, NOx, and PM emissions under 75% share ratio drop 46%, 46%, 35%, and 36%, respectively, relative to the base scenario. The energy consumption falls from 67,951 gallons under no share to 45,618 gallons under 75% share ratio, a 33% reduction. These reduction in energy consumption and vehicle emissions are expected because the corresponding average link-level travel speed improves across the scenarios. Average travel speed is considered an indicator of vehicle emission and energy consumption (Barth and Boriboonsomsin, 2009). Previous studies showed vehicle emissions decrease as average speed increases from 5 to 50 mph.

4. Discussions and policy implications

Our analysis demonstrates the potential of ridesharing services in mitigating traffic congestion and reducing vehicle-related emissions. In this section, we discuss our results in the context of previous studies and point out several policy implications for transportation practitioners in implementing or managing ridesharing services. In Table 3, we compare our results on ridesharing services' impacts on traffic and vehicle-related emissions with the relevant literature. It is worth noting that the relevant studies have different scopes and methods; thus, the focus of the comparison is on the general trend of impacts rather than specific numbers. The comparison shows that our results are consistent with existing literature in terms of magnitude and trend of rideshare impacts on travelers' schedule and CO_2 emissions. Most existing studies were based on survey data, and they estimated up to 6% CO_2 emission reductions for up to a 10% ridesharing ratio on a city or national scale. For a study that used simulation data (Fagnant and Kockelman, 2014), the assessed schedule impacts are comparable to our study. Our study simulates scenarios with ridesharing ratios ranging from 5% to 75%, which provides insights into potential impacts of ridesharing on high sharing cases. We found that our studies achieve comparable results to existing studies in assessing environmental impacts of ridesharing services. Most of existing literature studied ridesharing service with up to 10% ratio and found benefits in CO_2 emission reduction up to 6%. We also find 5% reduction in CO_2 emission for 10% rideshare ratio.

Our results and the comparison with relevant studies have several policy implications. First, the literature has consistently demonstrated the environmental benefits of implementing rideshare services at various geographical scales. As indicated by Shaheen et al. (2016b), transportation practitioners in the United States and other countries have started recognizing the environmental and social benefits of ridesharing services. Thus, transportation practitioners should be encouraged to promote transportation ridesharing projects, though it is always recommended to estimate the benefits in a systematic way through either survey or simulation processes as described in this study. Second, vehicle types used in ridesharing services play an important role in estimating the environmental benefits of ridesharing. Many studies, including our study, estimate environmental benefits assuming ridesharing vehicles are regular gasoline-powered cars. Limited studies, e.g., Yu et al. (2017), have investigated potential impacts when electric vehicles are used in ridesharing, and their results show significant environmental benefits. Ridesharing is easier to implement in a centralized operation model (Shi et al., 2019), and there are studies advocating for the use of electric vehicles in ridesharing services (Tu et al., 2019; He et al., 2017; Kang et al., 2017). Our study shows a 35% reduction in CO_2 emissions if up to 75% of trips are shared, and we expect even larger reductions if some or all vehicles are electric cars.

Our results demonstrate benefits of ridesharing in reducing transportation emissions and energy consumption, particularly when ridesharing service ratio is at high range, e.g., 25%–75%. Apparently, it takes efforts to increase ridesharing ratio from the current ~10% in Chattanooga to such a high ratio. Literature shows several transportation policies that can help improve ridesharing ratio. One type of policy is to establish high-occupancy vehicle (HOV) exclusive lane (Di et al., 2017). Studies have shown that the reduction in both travel time (due to traveling on the faster HOV lane) and fuel cost can further encourage riders to adopt ridesharing services. This type of policy works well in regions with high population density and vehicle ownership, such as California Bay area (Shaheen et al., 2016b). However, Chattanooga is a city with relative smaller population size and the road network is not congested for a large portion of day. Thus, adopting HOV lane policy might not be as effective in Chattanooga as in other regions. Another type of policy is to provide monetary incentive to drivers to choose ridesharing service (Ong et al., 2021). Studies have shown by appropriately choosing incentives, this policy can significantly improve ridesharing ratio among drivers (Song et al., 2021). This policy can be considered to implement in Chattanooga. There are various government transportation emission reduction programs, such as the federal's Congestion Mitigation and Air Quality (CMAQ), which provides funding to local transportation authorities to implement policies for emission reduction. As long as the air quality benefits can be quantified, it is justifiable to use government funding to incentivize drivers to choose ridesharing services to achieve lower transportation emission.

5. Conclusions

A shift from privately owned vehicles to shared mobility services can affect mobility, energy consumption, and vehicle emissions. In this study, we investigate efficiency and environmental benefits of ridesharing in a mid-size city (Chattanooga, Tennessee) using an agent-based simulation framework. The purpose of the framework is to help transportation practitioners evaluate the environmental benefits of ridesharing services with a systematic and comprehensive perspective.

The simulation and result analysis demonstrate that ridesharing services have the potential to reduce traffic volume and relieve congestion without significant impacts on travelers' schedules. Specifically, when ridesharing ratios are 5%–75% (trips fulfilled by ridesharing services) in Chattanooga, many (65%–75%) of ridesharing travelers will experience a delay of up to 15 min. Longer delays, 30 min or more, are mainly due to ridesharing travelers in isolated areas because it takes

Table 2
System-level analysis for different scenarios.

Scenarios	CO_2 (ton)	CO (ton)	HC (kg)	NO_x (kg)	PM (kg)	Fuel (gallon)	Average travel speed (kph)
No rideshare	598	24	124	259	14	67,951	22
5% share ratio	585	23	122	257	13	66,024	22
10% share ratio	570	22	118	250	13	64,865	23
25% share ratio	555	21	110	239	12	63,018	24
50% share ratio	475	16	85	202	10	53,994	29
75% share ratio	402	13	67	169	9	45,618	32

Table 3
Comparison of rideshare impacts in the literature.

	Granularity and data source	Ridesharing percentage	Changes in schedule	Changes in CO_2
This study	City scale (Chattanooga) empirical and simulation	5%–75%	25%–35% with 20-min delay or more	2%–35%
Jacobson and King (2009)	U.S. national survey data	1–10%		−1%–5%
Fagnant and Kockelman (2014)	City scale (Austin) simulation data	10%	20% with 20-min delay or more	−4%–6%
Caulfield (2009)	City scale (Dublin) survey data	4%		−2%–4%
Yu et al. (2017)	City scale (Beijing) survey data	1938 sampled travelers		Up to −35% with various levels of electrical vehicle adoption

time to match vehicles to pick them up. Ridesharing services can result in external outcomes that can be beneficial to other travelers and society. This analysis shows 60%–80% of drive-alone travelers will arrive earlier compared with the baseline no ridesharing scenario. The average early arrival time is 5.6 min for all drive-alone travelers. The results show ridesharing services can achieve a 2%–35% reduction in vehicle-related emissions and energy consumption with various ridesharing ratios. This is significant considering most vehicle emissions are generated in urban regions with high population density. The reduction in vehicle emissions has the potential to improve air quality and mitigate adverse impacts on the health of local residents.

We acknowledge there are limitations of the current research that could motivate future research directions. First, the vehicles applied in our simulation model were internal combustion vehicles. Electric vehicles are emerging fast and play an important role in reducing energy consumption and cutting emissions. It would be interesting for future research to consider a diversified vehicle fleet for ridesharing service and associated infrastructure planning. Second, researchers can include other travel modes, such as public transit, shared bike, or micro mobility, with ridesharing to model multimodal travel implementation and estimate associated impacts. This requires more complex planning algorithms to search for optimal mode combinations to reach minimum monetary, time, or environmental impacts. Third, the scenario constructed in our study is for one mid-size city, Chattanooga, where most trips are fulfilled by passenger cars. It would be interesting to look at mega-cities, which normally have diversified travel modes and trip purposes, to identify the most suitable scenarios and locations for implementing ridesharing services.

CRediT authorship contribution statement

Ruixiao Sun: Methodology, Data curation, Writing – original draft, Formal analysis. **Xuanke Wu:** Visualization, Formal analysis. **Yuche Chen:** Conceptualization, Methodology, Writing – original draft.

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.

Data availability

The authors do not have permission to share data.

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References

Abrahamse, W., Keall, M., 2012. Effectiveness of a web-based intervention to encourage carpooling to work: a case study of Wellington, New Zealand. Transport Pol. 21, 45–51. https://doi.org/10.1016/j.tranpol.2012.01.005.

Arteaga-Sánchez, Rocío, Belda-Ruiz, Maria, Ros-Galvez, Alejandro, Rosa-Garcia, Alfonso, 2020. Why continue sharing: Determinants of behavior in ridesharing services. Int. J. Market Res. 62 (6), 725–742. https://doi.org/10.1177/1470785318805300.

Bahat, O., Bekhor, S., 2016. Incorporating ridesharing in the static traffic assignment model. Network. Spatial Econ. 16, 1125–1149. https://doi.org/10.1007/s11067-015-9313-7.

Balac, M., Becker, H., Ciari, F., Axhausen, K.W., 2019. Modeling competing free-floating carsharing operators–A case study for Zurich, Switzerland. Transport. Res. C Emerg. Technol. 98, 101–117.

Barth, M., Boriboonsomsin, K., 2009. Energy and emissions impacts of a freeway-based dynamic eco-driving system. Transport. Res. Part D: Environment 14, 400–410 (Elsevier Press).

Becker, H., Balac, M., Ciari, F., Axhausen, K.W., 2020. Assessing the welfare impacts of shared mobility and mobility as a service (MaaS). Transport. Res. Pol. Pract. 131, 228–243.

Bonabeau, E., 2002. Agent-based modeling: methods and techniques for simulating human systems. Proc. Natl. Acad. Sci. USA 99 (Suppl. 3), 7280–7287.

Caulfield, B., 2009. Estimating the environmental benefits of ride-sharing: a case study of Dublin. Transport. Res. Transport Environ. 14, 527–531. https://doi.org/10.1016/j.trd.2009.07.008.

Ciari, F., Balac, M., Balmer, M., 2015. Modelling the effect of different pricing schemes on free-floating carsharing travel demand: a test case for Zurich, Switzerland. Transportation 42 (3), 413–433.

Ciasullo, M.V., Maione, G., Torre, C., Troisi, O., 2017. The growth of carpooling: insights from a social media investigation. In: Toulon-Verona Conference" Excellence in Services".

Correia, G., Viegas, J.M., 2011. Carpooling and carpool clubs: clarifying concepts and assessing value enhancement possibilities through a Stated Preference web survey in Lisbon, Portugal. Transport. Res. Part A Policy Pract. 45, 81–90.

Dai, Rongjian, Ding, Chuan, Gao, Jian, Wu, Xinkai, Yu, Bin, 2022. Optimization and evaluation for autonomous taxi ride-sharing schedule and depot location from the perspective of energy consumption. Appl. Energy 308, 118388. https://doi.org/10.1016/j.apenergy.2021.118388.

Davis, S.C., Boundy, R.G., 2021. Transportation Energy Data Book: Edition 39.

Delhomme, P., Gheorghiu, A., 2016. Comparing French carpoolers and non-carpoolers: which factors contribute the most to carpooling? Transport. Res. Transport Environ. 42, 1–15. https://doi.org/10.1016/j.trd.2015.10.014.

Di, X., Liu, H.X., Ban, X., Yang, H., 2017. Ridesharing user equilibrium and its implications for high-occupancy toll lane pricing. Transport. Res. Rec. 2667 (1), 39–50.

Erdağı, İ.G., Silgu, M.A., Çelikoğlu, H.B., 2019. Emission effects of cooperative adaptive cruise control: a simulation case using SUMO. EPiC Series in Computing 62, 92–100.

European Union, 2012. European Union Transport in Figures – Statistical Pocketbook.

Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transport. Res. C Emerg. Technol. 40, 1–13.

Gounni, A., Rais, N., Idrissi, M.A., 2019, March. New solutions to reduce the environmental impact of road traffic emissions, using sumo. In: Proceedings of the 2nd International Conference on Networking. Information Systems & Security, pp. 1–7.

Guo, Y., Goncalves, G., Hsu, T., 2013a. A multi-agent based self-adaptive genetic algorithm for the long-term car pooling problem. J. Math. Model. Algorithm. Oper. Res. 12, 45–66.

Guo, Y., Goncalves, G., Hsu, T., 2013b. A multi-destination daily carpooling problem and an ant colony based resolution method. RAIRO-Operations Res. 47, 399–428. https://doi.org/10.1051/ro/2013049.

Gurumurthy, K.M., Kockelman, K.M., Simoni, M.D., 2019. Benefits and costs of ride-sharing in shared automated vehicles across Austin, Texas: opportunities for congestion pricing. Transport. Res. Rec. 2673, 548–556. https://doi.org/10.1177/0361198119850785.

He, L., Mak, H.Y., Rong, Y., Shen, Z.J.M., 2017. Service region design for urban electric vehicle sharing systems. Manuf. Serv. Oper. Manag. 19 (2), 309–327.

Huang, C., Zhang, D., Si, Y.W., Leung, S.C.H., 2016. Tabu search for the real-world carpooling problem. J. Combin. Optim. 32, 492–512. https://doi.org/10.1007/s10878-016-0015-y.

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. Transport. Res. Rec. 2675 (2), 135–149.

Jacobson, S.H., King, D.M., 2009. Fuel saving and ridesharing in the US: motivations, limitations, and opportunities. Transport. Res. Transport Environ. 14, 14–21.

Jalali, R., Koohi-Fayegh, S., El-Khatib, K., Hoornweg, D., Li, H., 2017. Investigating the potential of ridesharing to reduce vehicle emissions. Urban Planning 2 (2), 26–40.

Javid, M.A., Mehmood, T., Asif, H.M., Vaince, A.U., Raza, M., 2017. Travelers' attitudes toward carpooling in Lahore: motives and constraints. J. Mod. Transp. 25, 268–278. https://doi.org/10.1007/s40534-017-0135-9.

Kang, N., Feinberg, F.M., Papalambros, P.Y., 2017. Autonomous electric vehicle sharing system design. J. Mech. Des. 139 (1), 011402.

Krajzewicz, D., Hertkorn, G., Rössel, C., Wagner, P., 2002. Traffic simulation with SUMO – simulation of urban mobility. In: Proceedings of the 4th Middle East Symposium on Simulation and Modelling, pp. 183–187. https://doi.org/10.1007/978-1-4419-6142-6_7.

Leich, G., Bischoff, J., 2019. Should autonomous shared taxis replace buses? A simulation study. Transport. Res. Procedia 41, 450–460.

Li, Z., Hong, Y., Zhang, Z., 2016. Do ride-sharing services affect traffic congestion? An empirical study of uber entry. Soc. Sci. Res. Netw. 2002, 1–29.

Lopez, P.A., Behrisch, M., Bieker-Walz, L., Erdmann, J., Flötteröd, Y.P., Hilbrich, R., Lücken, L., Rummel, J., Wagner, P., Wießner, E., 2018, November. Microscopic traffic simulation using sumo. In: 2018 21st International Conference on Intelligent Transportation Systems (ITSC). IEEE, pp. 2575–2582.

Minett, P., Pearce, J., 2011. Estimating the energy consumption impact of casual carpooling. Energies 4, 126–139. https://doi.org/10.3390/en4010126.

Molina, J.A., Ignacio Giménez-Nadal, J., Velilla, J., 2020. Sustainable commuting: results from a social approach and international evidence on carpooling. Sustain. Times 12, 1–12. https://doi.org/10.3390/su12229587.

Ong, H.Y., Freund, D., Crapis, D., 2021. Driver positioning and incentive budgeting with an escrow mechanism for ride-sharing platforms. Inf. J. Appl. Anal. 51 (5), 373–390.

Ou, H., Tang, T.Q., 2018. Impacts of carpooling on trip costs under car-following model. Phys. A Stat. Mech. its Appl. 505, 136–143. https://doi.org/10.1016/j.physa.2018.03.042.

Shaheen, S., Chan, N.D., Gaynor, T., 2016a. Casual carpooling in the san Francisco Bay area: understanding user characteristics, behaviors, and motivations. Transport Pol. 51, 165–173. https://doi.org/10.1016/j.tranpol.2016.01.003.

Shaheen, S., Cohen, A., Zohdy, I., 2016b. Shared Mobility: Current Practices and Guiding Principles. Federal Highway Administration, United States.

Shi, J., Gao, Y., Wang, W., Yu, N., Ioannou, P.A., 2019. Operating electric vehicle fleet for ride-hailing services with reinforcement learning. IEEE Trans. Intell. Transport. Syst. 21 (11), 4822–4834.

Song, C., Monteil, J., Ygnace, J.L., Rey, D., 2021. Incentives for ridesharing: a case study of welfare and traffic congestion. J. Adv. Transport. 2021.

Tamannaei, M., Irandoost, I., 2019. Carpooling problem: a new mathematical model, branch-and-bound, and heuristic beam search algorithm. J. Intell. Transport. Syst. Technol. Plann. Oper. 23, 203–215. https://doi.org/10.1080/15472450.2018.1484739.

Tikoudis, I., Martinez, L., Farrow, K., Bouyssou, C.G., Petrik, O., Oueslati, W., 2021. Ridesharing services and urban transport CO2 emissions: simulation-based evidence from 247 cities. Transport. Res. Transport Environ. 97, 102923.

TN DOT, 2016. Statewide Transportation Demand Management Plan for Tennessee Nonattanment and Maintenance Areas, Commuter Survey Report. Tennessee Department of Transportation. Available at: https://www.tn.gov/content/dam/tn/tdot/long-range-planning/TDOT%20Employee%20Survey%20Report%202016.pdf. (Accessed May 2022).

Tu, W., Santi, P., Zhao, T., He, X., Li, Q., Dong, L., Wallington, T.J., Ratti, C., 2019. Acceptability, energy consumption, and costs of electric vehicle for ride-hailing drivers in Beijing. Appl. Energy 250, 147–160.

U.S. Census Bureau, 2019. Means of Transportation to Work, 2019 American Community Survey 5-year Estimates. Retrieved from. https://data.census.gov/cedsci/table?q=B08&d=ACS%201-Year%20Estimates%20Detailed%20Tables&tid=ACSDT1Y2019.B08301.

U.S. Census Bureau, 2020. American Community Survey 5-year estimates. Retrieved from Census Reporter Profile page for Chattanooga, TN. https://censusreporter.org/profiles/16000US4714000-chattanooga-tn/.

Validi, A., Polasek, N., Alabi, L., Leitner, M., Olaverri-Monreal, C., 2020, June. Environmental impact of bundling transport deliveries using SUMO: analysis of a cooperative approach in Austria. In: 2020 15th Iberian Conference on Information Systems and Technologies (CISTI). IEEE, pp. 1–5.

Wegener, A., Piórkowski, M., Raya, M., Hellbrück, H., Fischer, S., Hubaux, J.P., 2008. TraCI: an interface for coupling road traffic and network simulators. Proc. 11th Commun. Netw. Simul. Symp. CNS'08 155–163. https://doi.org/10.1145/1400713.1400740.

Yan, S., Chen, C.-Y., Chang, S.-C., 2013. A car pooling model and solution method with stochastic vehicle travel times. IEEE Trans. Intell. Transport. Syst. 15, 47–61.

Yu, B., Ma, Y., Xue, M., Tang, B., Wang, B., Yan, J., Wei, Y.-M., 2017. Environmental benefits from ridesharing: a case of Beijing. Appl. Energy 191, 141–152.