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Ridesourcing systems: A framework and review

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A B S T R A C T

With the rapid development and popularization of mobile and wireless communication technologies, ridesourcing companies have been able to leverage internet-based platforms to operate e-hailing services in many cities around the world. These companies connect passengers and drivers in real time and are disruptively changing the transportation industry. As pioneers in a general sharing economy context, ridesourcing shared transportation platforms consist of a typical two-sided market. On the demand side, passengers are sensitive to the price and quality of the service. On the supply side, drivers, as freelancers, make working decisions flexibly based on their income from the platform and many other factors. Diverse variables and factors in the system are strongly endogenous and interactively dependent. How to design and operate ridesourcing systems is vital—and challenging—for all stakeholders: passengers/users, drivers/service providers, platforms, policy makers, and the general public. In this paper, we propose a general framework to describe ridesourcing systems. This framework can aid understanding of the interactions between endogenous and exogenous variables, their changes in response to platforms' operational strategies and decisions, multiple system objectives, and market equilibria in a dynamic manner. Under the proposed general framework, we summarize important research problems and the corresponding methodologies that have been and are being developed and implemented to address these problems. We conduct a comprehensive review of the literature on these problems in different areas from diverse perspectives, including (1) demand and pricing, (2) supply and incentives, (3) platform operations, and (4) competition, impacts, and regulations. The proposed framework and the review also suggest many avenues requiring future research.

1. Introduction

With the rapid development and popularization of mobile and wireless communication technologies, ridesourcing companies have been able to leverage internet-based platforms to operate e-hailing services in many cities around the world. These companies—including Uber, Lyft, Didi, Grab, Careem, and Ola—connect passengers and drivers in real time and are disruptively changing the transportation industry, and especially the conventional taxi industry. The sharing economy, as defined by Hu (2019), refers to an online platform that enables individuals or small entities as buyers and sellers to interact effectively and efficiently or a market model that allows the sharing of access to goods and services. Although the exact

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definition of the sharing economy is still a matter of debate (e.g., Belk, 2014; Frenken, 2017; and Frenken and Schor, 2017), these shared transportation companies, as providers of on-demand transportation services on online platforms, are often viewed as pioneers in a general sharing economy.

The recent penetration of mobile internet technologies in our daily lives has enabled the rapid expansion of these ridesourcing services. Uber, for instance, has grown from a ridesourcing service provider to a one-stop mobile transportation platform, offering a variety of services in more than 700 metropolitan areas in 65 countries. It offers a menu of services, including UberX (the least expensive service), Uber Black (executive luxury service), Uber Pool (ridesplitting service), Taxi (taxi service on platform), SUV (luxury service with extra seats), etc., to more than 91 million users with 15 million daily trips as of mid-2019, according to data collected by a third-party (see DMR, 2019a). Didi, the largest shared mobility platform in China, offers services including Taxi (taxi service on platform), Express (the least expensive service), Premier (mid-price upgraded service), Luxe (executive luxury service), Pool (ridesplitting service), Hitch (ridesharing service), Minibus (minibus shared-ride service), Designated Driving (designated driver for passenger's own vehicle), Bike-sharing (bicycle-sharing service), etc., to more than 550 million users in 400 cities in China, with 30 million daily trips as of mid-2019 (see DMR, 2019b). These companies are emerging as a disruptive force for the conventional transportation industry. They are also deploying electric vehicles and developing self-driving technologies to address the transportation needs of citizens in a sustainable urban ecology.

Ridesourcing companies provide a platform for and/or intermediary means of connecting demand (i.e., passengers) and supply (i.e., drivers) (see, for example, Shaheen et al., 2017, Mobility on Demand Operational Concept Report). Passengers enter their travel request details on an e-hailing mobile app, including trip origin, destination, departure time, and service type; idle drivers affiliated with the platform may cruise around the city or wait at specific locations. The online platform then enables a convenient match between passengers and drivers using matching and order dispatching algorithms. The platform charges a fare to passengers and pays a wage and/or bonus to drivers. The difference between the fare and the wage is the commission withheld by the platform, which is normally between 15% and 30%, depending on the time, region, and company. After each trip, passengers can rate the drivers who provided the transportation service, which helps to quantify the quality of service provided by the affiliated drivers.

The ridesourcing platforms consist of a typical two-sided market, which is a meeting place for two groups of agents (passengers and drivers, in this case) who interact and provide each other with network benefits. Rochet and Tirole (2003, 2006) demonstrate the commonality across seemingly different businesses and markets with a clear characterization of the two-sided market. A two-sided market provides a platform that enables interactions between end-users and works to align the two sides by charging each side appropriately. Mathematically, consider a platform charging a^b and a^s per-interaction to the buyer and seller sides. The market for interactions between the two sides is one-sided if the volume V of transactions realized on the platform depends only on the aggregate price level $a = a^b + a^s$, i.e., is insensitive to reallocations of the total price a between the buyer and the seller. If by contrast V varies with a^b and a^s while a is kept constant, the market is said to be two-sided. Specifically, in the context of ridesourcing, passengers and drivers are sensitive to the prices and wages of the service, which are the critical decisions the platform makes to coordinate and balance demand and supply. The volume of transactions (i.e., the number of served orders) depends on both the price charged to the passengers (i.e., a^b) and the wage paid to the drivers (i.e., $-a^s$) when $a^b + a^s$ is a constant. These features motivate various operational strategies, such as "dynamic or surge pricing/wage," by which the platform adjusts both the prices and wages dynamically depending on real-time supply and demand information, taking both platform performance (such as revenue, number of served orders, market share, and profit) and social welfare (including passenger utility and driver income) into consideration.

In conventional taxi businesses, drivers, who are often employees of taxi companies, are usually required to obtain an occupational license, or "medallion," to provide transportation services to passengers. In practice, there is great variety in taxi regulations, which vary widely between countries or even regions or cities. In some cases, the regions in which drivers can pick up passengers are restricted to the jurisdiction that issued the medallion, and fares are often set by regulatory bodies. In some places, taxi drivers are required to work full-time, and in others, taxi drivers may schedule their work flexibly as private business owners.

By comparison with conventional taxi businesses, ridesourcing systems provide private car owners with opportunities for more flexible working, providing an additional source of service providers to satisfy on-demand travel requests. In ridesourcing systems, drivers, often freelancers, can use their own or leased cars to offer transportation services whenever and wherever they choose, subject to fewer regulations than taxi drivers. They design their working schedules more flexibly and decide whether, when and how long to work on the platform on a day-to-day basis in response to many factors, such as wage and income fluctuations. Another key difference is that drivers in ridesourcing systems cannot be hailed in the street, in contrast to conventional taxi drivers for whom hailing is the main source of passengers. The emergence of ridesourcing systems and the ways in which they differ from conventional taxi systems raises controversial issues and regulatory problems, such as unclear regulation of labor relations between platforms and drivers, the debatable effects of surge pricing, "gray" tax enforcement on driver income, inconsistency between platform interests and social welfare, and other societal and environmental impacts.

Designing and operating ridesourcing systems is vital—and challenging—for all stakeholders: passengers/users, drivers/service providers, platforms, policy makers, and the general public. In this paper, we propose a general framework to describe ridesourcing systems. The framework can aid understanding of interactions between endogenous and exogenous variables, their changes in response to platforms' operational strategies and decisions, multiple system objectives, and market equilibria in a dynamic manner. We summarize important research problems concerning ridesourcing systems and the corresponding methodologies that have been and are being developed and implemented to address these problems. We conduct a comprehensive review of the literature about these problems in different areas from diverse perspectives, including (1) demand and pricing, (2) supply and incentives, (3) platform operations, and (4) competition, impacts and regulations. We also discuss directions for future research.

There are several different but similar terminologies in shared transportation services, such as ridesourcing, ridehailing, ridesharing, ridesplitting, and transportation network companies (TNC). In this paper, we focus on ridesourcing systems (i.e., a fleet of freelance drivers providing on-demand transportation service using their own or leased vehicles in flexible self-determined working shifts) that are conducted through e-hailing (i.e., the operation of shared transportation services to connect passengers and drivers using mobile devices with internet-based real-time information). Ridesourcing systems are also often called ridehailing systems or TNC, where the former term emphasizes the fact that drivers use their own or leased vehicles slightly. As for the term ridesplitting, it refers to a ridesourcing service in which passengers can opt to split both a ride and the fare (i.e., like dynamic carpooling). The service allows dynamic matching and route variation in real time to combine passenger requests with close itineraries in multi-rider trips. The price for a ridesplitting service is normally lower than that of regular ridesourcing services. Another term, ridesharing, refers to a service that connects drivers and passengers who share similar origins, destinations, and departure times. Drivers in a ridesharing system have their own travel needs which they modify to accommodate one or more passengers to conserve resources and save money. Unlike ridesharing, ridesourcing drivers operate for profit and typically provide rides not incidental to their own trips.

The structure of the paper is as follows. In Section 2, we present a general framework to describe ridesourcing systems and summarize important research problems and relevant methodologies. In Section 3, we conduct a review of research problems and studies of the demand and pricing of ridesourcing systems. In Section 4, we review the research and literature on supply and incentives. In Section 5, we review the research and literature on various platform operational strategies. In Section 6, we review the research and literature on platform competition, their impacts, and government regulations. Relevant future research directions are also discussed in Sections 3–6. Finally, in Section 7, we provide concluding remarks.

2. A general framework

2.1. Framework

A general framework for ridesourcing systems is depicted in Fig. 1, which illustrates the intrinsic relations between variables and factors for the relevant stakeholders, agents and attributes.

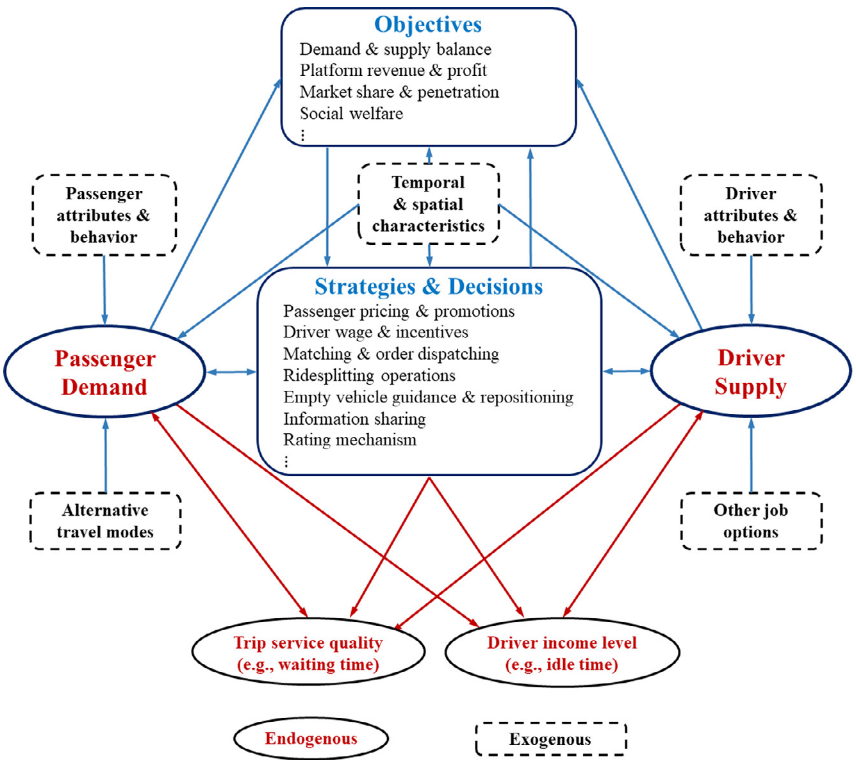

Fig. 1. General framework for ridesourcing systems.

The objectives of ridesourcing systems exist in multiple dimensions and may change according to the specific developmental stage, market conditions, platform competition, and government regulations. Some common objectives include balancing passenger demand and driver (vehicle) supply over time and space, maximizing long-term and/or short-term platform revenue and profit, maximizing long-term and/or short-term market share and penetration, and maximizing social welfare. To operate the transportation service and achieve these objectives, platforms must employ various operational strategies and make decisions from diverse perspectives. Specifically, some of the critical strategies used and decisions made by platform operators include static, dynamic or surge pricing and promotions for passengers; static, dynamic or surge wages and incentives for drivers; order dispatching and matching between drivers and passengers; ridesplitting operations related to assignment and fare splitting; guidance and repositioning of empty vehicles (i.e., idle drivers awaiting new passengers); information sharing and disclosure; rating mechanism, etc.

Passenger demand and driver supply are the two major components of the ridesourcing market. On the demand side, depending on passengers' attributes and behavior (e.g., value of time, willingness to pay) with temporal and spatial characteristics, potential passengers evaluate ridesourcing services by the service quality (e.g., waiting time until pick-up) and fare charged by the platform, and weigh these against alternative travel modes, such as conventional taxis and other public transportation services to make their travel decisions. On the supply side, depending on drivers' attributes, qualifications, and behavior (e.g., vehicle operation and fuel as the cost of working on the platform, reservation wage as an opportunity cost to work), potential drivers make working decisions regarding whether to work on the platform—and if so, when and how long to work—in response to many variables and factors particular to each platform; these are compared with other job options, including income level, working environment, job security, comfort level, pressure of work, exposure to risk, etc. The income level is a critical factor, which depends on the hourly wage, working cost, incentives and bonuses, as well as the fraction of idle time for drivers. In order to capture the temporal and spatial characteristics of the market, the platforms usually divide an entire region served (e.g., a city) into small cells using a grid (e.g., a hexagonal lattice is used in Didi's modeling platform in China) and discretize time into short intervals (e.g., 15 min per interval), and then make general predictions on the demand and supply for each gird cell and time interval for their operational strategies.

In ridesourcing systems, the interface between passengers and drivers is still rife with meeting friction caused by many spatial and temporal factors (e.g., Yang et al., 2002). Although this friction is much effectively reduced by comparison with conventional taxi services, it cannot be eliminated completely. As shown in Fig. 1, the ridesourcing market has two important characteristics: trip service quality (e.g., passenger's waiting time, ridesplitting detours) and driver income level (which is affected, for example, by the driver idle time on the platform, working costs, incentives and bonuses). On one hand, the equilibrium demand is realized at a certain level of average passenger waiting time, which is generally considered to be an important measure of the service quality. Higher passenger demand and lower driver supply usually decrease the service quality (e.g., by increasing passenger waiting time), while decreased trip service quality will in turn reduce passenger demand. On the other hand, the equilibrium quantity of services supplied is greater than the actual quantity of services consumed with a certain amount of slack (e.g., average vacant vehicle-hours like the taxi idle time of Arnott, 1996), which is an important factor that affects the actual income received by drivers. Higher passenger demand and lower driver supply usually increase drivers' income level (e.g., by reducing driver idle time), while an increased driver income level in turn attracts more drivers. Therefore, trip service quality, driver income level, passenger demand, and driver supply are strongly endogenous and interactively dependent, while the endogenous influences and interactions are highly dynamic. These variables are thus crucial factors influencing operational strategies and decisions (e.g., pricing and promotions for passengers, wage and incentives for drivers, matching and order dispatching, ridesplitting assignment and fare splitting, guidance and repositioning of empty vehicles, information sharing, and ratings) and the resulting efficiency of the ridesourcing market.

2.2. Summary of research problems and methodologies

As described in Section 2.1, ridesourcing systems are complex, with many endogenous variables and interactive decisions. The design and operation of ridesourcing systems is challenging, encompassing numerous research problems from diverse perspectives.

On the demand side, important research problems include (1) spatio-temporal demand estimation for ridesourcing systems, (2) passenger mode choice with other travel alternatives, (3) mechanisms and algorithms for static and dynamic pricing, and (4) other passenger promotions.

On the supply side, important research problems include (1) driver supply models to describe short- and long-term platform service capacity, (2) driver supply elasticity with respect to wage and incentives, (3) other driver behavior, and (4) mechanisms and algorithms for static and dynamic wages and incentives.

To operate platform services better and improve system performance and efficiency, research problems for operators include (1) estimated time of arrival (ETA) for both pick-up and ride trips; efficient operational strategies and algorithms for (2) order dispatching and matching between passengers and drivers, (3) ridesplitting operations related to assignment and fare splitting, and (4) guidance and repositioning of empty vehicles awaiting new passengers; and (5) information sharing and disclosure and (6) rating mechanism.

Considering ridesourcing services as a part of a larger urban transportation system, research problems arise from (1) platform competition, (2) impacts on other transportation services, (3) societal and environmental impacts, and (4) relevant governmental regulations and policies.

To address these research problems, many models and algorithms using advanced methodologies, both classic and novel, have been and are being developed and implemented. These methodologies include statistics and econometrics, labor economics, microeconomics, queueing theory and stochastic process, integer and combinatorial optimization, stochastic and dynamic programming, game theory and mechanism design, and machine learning techniques (especially deep learning and reinforcement learning). We summarize the research problems and methodologies in Table 1. The first two columns list the areas and subareas of research problems; the first row lists methodology fields. A ticked cell in the table indicates that the corresponding methodology has been and is being developed and implemented to address the corresponding research problem. Note that the methodology terms listed are not necessarily mutually exclusive; some terms have vague boundaries and overlap. We use these terms for ease in creating a general classification and summary.

3. Demand and pricing

Understanding the patterns of demand and designing corresponding pricing schemes are prevalent research topics in many industries, including ridesourcing systems. Several studies examine the general factors that affect ridesourcing passenger demand. For example, Dias et al. (2017) show that users of ridesourcing platforms tend to be young, well-educated, higher-income working individuals who reside in higher-density areas. Gilibert et al. (2017) find a greater intended use of ridesourcing services in a young population (age 18–29) using survey data from Barcelona. Alemi et al. (2018) find a greater likelihood of using on-demand ride services by (i) highly educated, older millennials, (ii) travelers with a greater number of long-distance business trips and a higher share of long-distance trips made by air, (iii) frequent users of transportation-related smartphone apps, and (iv) users with stronger pro-environmental, technology-embracing, and variety-seeking attitudes, as well as (v) in areas with greater land-use mix and regional accessibility by car. Zhen (2019) finds that (i) social and recreational trips are the predominant type of ridesourcing trips followed by work trips, and (ii) trip lengths are shorter and vehicle occupancy rates are greater than typical trip makers. These studies give us a general picture of passenger demand for ridesourcing markets. In this section, we review research into demand and pricing for ridesourcing systems in four areas: spatio-temporal demand estimation in Section 3.1, passenger mode choice in Section 3.2, pricing schemes in Section 3.3, and other passenger promotions in Section 3.4.

3.1. Spatio-temporal demand estimation

Spatio-temporal demand estimation is important for all transportation systems, and a large body of literature has emerged over the last few decades. An accurate description and prediction of demand is critical in the design and operational strategies of ridesourcing systems, including system capacity plans, fleet recruitment and management, pricing and incentives design, etc.

Long before the arrival of smartphone ridesourcing systems, many researchers proposed various methods for origin-destination (OD) flow estimation in terms of vehicle traffic in the context of different transportation systems. For example, four methods based on a systems dynamics approach (Cremer and Keller, 1987); OD estimation with geometric distributed travel time (Bell, 1991); two state-space models with state-vector (Ashok and Ben-Akiva, 2000); a parametric optimization approach with a least squares model and column generation (Sherali and Park, 2001); equilibrium-based estimation with congestion effects (Yang et al., 1992, 2001); and a relaxation strategy with variational inequality and column generation (Nie and Zhang, 2008). Recent work includes quasi-dynamic estimation (Cascetta et al., 2013); linear assignment matrix approximation (Toledo and Kolechkina, 2013); extended quasi-dynamic estimation (Bauer et al., 2018); simultaneous perturbation stochastic approximation (Tympakianaki et al., 2018); propagation algorithm on a layered computational graph (Wu et al., 2018); and simulation-based optimization (Osorio, 2019). Such vehicle flow OD estimation can provide information to estimate passenger-level ridesourcing request OD demand, but it cannot be applied to ridesourcing demand estimation directly. Recent work has studied direct passenger demand estimation, mainly in the context of the taxi industry. For example, Moreira-Matias et al. (2016) propose an incremental framework to maintain statistics on urban mobility dynamics over a time-evolving OD matrix using high-speed GPS data streams, which the authors tested in a taxi network in Portugal. Held et al. (2018) provide a model order reduction approach to cluster mobility demand according to characteristic population groups that share similar travel behavior. Using Swiss household travel survey data and machine learning algorithms, they can extrapolate future mobility demand based on sociodemographic information. Other relevant work includes Moreira-Matias et al. (2012, 2013), Zhao et al. (2016), Zhang et al. (2017a), etc.

Identifying the spatio-temporal demand pattern is critical for the design and operation of ridesourcing systems. Space-dependent patterns provide information on hot and cold areas, and time-dependent patterns of peak and off-peak hours. Recent studies have examined the prediction of spatio-temporal demand for ridesourcing services using machine learning techniques, given macro-level data such as land use and urban configuration, in addition to micro-level data such as passenger demographic information and real-time weather and traffic conditions. For example, Saadi et al. (2017) propose a spatio-temporal estimation of short-term demand that is a function of variables related to traffic, pricing, and weather conditions for a ridesourcing system. They adapt and compare several machine learning methods, including a single decision tree, bootstrap-aggregated decision trees, random forest, boosted decision trees, and artificial neural network. Ke et al. (2017) propose a deep learning approach—the fusion convolutional long short-term memory network (FCL-Net)—to

Table 1
Research problems and methodologies for ridesourcing systems.

Research problem		Methodology							
		Statistics and econometrics	Labor economics	Micro-economics	Queueing theory and stochastic process	Integer and combinatorial optimization	Stochastic and dynamic programming	Game theory and mechanism design	Machine learning
Demand and pricing	Spatio-temporal demand estimation	√							√
	Passenger mode choice	√		√				√	√
	Pricing			√	√		√	√	√
	Passenger promotions			√			√		
Supply and incentives	Driver supply model	√	√	√	√		√		
	Supply elasticity	√	√	√					
	Driver behavior		√	√				√	√
	Wage and incentives		√	√	√		√	√	
Platform operations	Estimated time of arrival (ETA)	√							√
	Matching and order dispatching				√	√	√		√
	Ridesplitting operations				√	√	√		√
	Empty vehicle guidance and repositioning				√	√	√	√	√
	Information sharing and disclosure		√		√		√	√	
	Rating mechanism	√	√	√				√	
Competition, impacts & regulations	Competition		√	√	√	√	√	√	
	Impacts on other transportation services	√						√	
	Societal and environmental impacts	√							
	Regulations		√	√				√	

forecast short-term demand. The model is stacked and fused by multiple convolutional long short-term memory (LSTM) layers, standard LSTM layers, and convolutional layers. The fusion of convolutional techniques and the LSTM network enables the proposed deep learning approach to capture the spatio-temporal characteristics and correlations of explanatory variables better. Yao et al. (2018) propose a deep multi-view spatio-temporal network (DMVST-Net) framework to model both spatial and temporal demand relations. The model consists of three views: a temporal view of modeling correlations between future demand values and near time points using LSTM, a spatial view of modeling local spatial correlation using local CNN, and a semantic view modeling correlations between regions sharing similar temporal patterns. In addition, combining estimates of both demand and supply, Wang et al. (2017a) present an end-to-end framework called deep supply-demand (DeepSD) using a deep neural network structure to predict the gap between supply and demand in a particular area over the next few minutes. Ke et al. (2018) partition a city into regular hexagonal lattices and propose a hexagon-based convolutional neural network (H-CNN) to predict the short-term supply-demand gap in ridesourcing services.

As a future direction, we expect more advanced methods to combine emerging machine learning techniques with structural models of ridesourcing systems for the spatio-temporal demand estimation. The different characteristics between short-term demand and long-term demand must be well studied for different purposes, such as short-term spatio-temporal pricing/promotions and long-term pricing strategies. Demand with uncertainty and extreme events also attracts great attention from industry players (e.g., uncertainty estimation in Zhu and Laptev, 2017), which is another future research topic.

3.2. Passenger mode choice

Ridesourcing platforms normally provide a set of service options differentiated by price and quality. As described previously, Uber provides service options such as Express, Black, Carpool, SUV, and Taxi; Didi provides service options such as Express, Premier, Luxe, Carpool, Hitch, Minibus, and Taxi. Therefore, passengers must not only decide whether to use the ridesourcing platforms rather than conventional transportation modes, but also choose a specific service option. The choice may depend on the characteristics of the service options (e.g., price, waiting time, travel time, vehicle type), of the passenger (e.g., number of people requesting a trip, budget, price elasticity, value of time, other preferences), and some other conditions (e.g., weather, congestion).

The travel mode choice problem has been studied for a long time and is used to estimate the ridership share for existing and/or proposed transportation services. Influential work on general models of travel mode choice include Ben-Akiva et al. (1985), Bhat (1995), Swait (2001), Wen and Koppelman (2001), Bhat (2003), and Train (2009). Extensive work has also been conducted on travel mode choice in diverse specific contexts, such as built environments (Cervero, 2002); travel mode with a theory of planned behavior (Bamberg et al., 2003); children's travel modes to school (McMillan, 2007); urban forms of mode choice (Kockelman, 1997; Schwanen and Mokhtarian, 2005; Frank et al., 2008); the choice between a taxi and a bike (Faghih-Imani et al., 2017); and the importance of social dependency effects on shared mobility service usage (Vinayak et al., 2018).

The choice between a ridesourcing platform and conventional modes—e.g., taxi, bus, and metro—has been studied recently. For example, Agarwal et al. (2019) investigate whether passengers switching between taxis and ridesourcing are influenced by relative prices using the market in Singapore. They find that a 10% increase in the ridesourcing surge factor raises taxi bookings by 4% in the same area of origin and half-hour interval. This substitution between ridesourcing services and taxi bookings in response to the surge factor comprises around 10% of taxi booking revenues. Other work includes the factors that influence passengers' choice to use Uber or a taxi service in Taiwan (Hwang et al., 2018), and the choice between, and comparison of, Uber and taxi services in US cities such as New York (NYC) and Chicago (Salnikov et al., 2015; Wallsten, 2015).

The choice between diverse service options on ridesourcing platforms has also attracted much attention recently, especially the choice between a solo ride and a shared ride (i.e., ridesplitting service such as Uber Pool, Lyft Line, Didi Pool, and Grab Share). For example, Lavieri and Bhat (2019) study two essential elements in the adoption of ridesplitting shared rides: the individual's acceptance of the increased travel time associated with other passengers' pick-up/drop-off and the individual's approval to share a vehicle with strangers. Using a multivariate integrated choice and latent variable approach, they examine current choices and future intentions regarding the use of shared rides and estimate individuals' willingness to share, as well as the value of travel time, for distinct trip purposes. Sarriera et al. (2017) focus on the social and behavioral considerations of shared rides using survey of ridesourcing users through Mechanical Turk and identify the role of social interactions in passenger mode choice. Stocker and Shaheen (2018) review possible future shared automated vehicle business models and their potential impacts on shared mobility services and user behavior. They point out that shared rides could become more common if automation renders deviation more efficient, more cost effective, and less onerous to users. Chen et al. (2017c) present an ensemble learning approach to understand the ridesplitting behavior of passengers better, and employ a boosting ensemble by growing individual decision trees sequentially, then assembling the trees to produce a powerful classification model to predict whether an individual will share a ride. They rank and select a variety of features using the ReliefF algorithm, such as trip travel time, trip costs, trip length, waiting time fee, travel time reliability of origins/destinations, and so on.

The behavior and impact of passenger choice between diverse service options on a platform is an important area for future research. As demonstrated by Ke et al. (2019), a key concern is that passenger choice will in turn affect the utility of each service option. For example, if more passengers choose ridesplitting and the platform has a high density of ridesplitting passengers, the actual detour pick-up time and travel distance for the ridesplitting service will decrease, which will in turn increase the utility of the ridesplitting option. Such endogeneity between the decision maker's choice and the service option's utility must be considered carefully. For the platform operator, considering substitutions between diverse service options, providing good service segmentation, and managing a limited fleet to provide multiple substituted service options are important issues. Another area that is important but has not been well examined is passenger behavior in the ridesourcing market. Examples of such behavior include passenger cancellation because of a long wait before being assigned to a vehicle (e.g., Wang et al., 2019), passenger cancellation because of a long pick-up time after being assigned a vehicle, passenger reorder and rebooking after cancellation, passenger attitude towards and choice of a bundled service option (e.g., a passenger may be neutral regarding services by taxi or private car, or neutral regarding ridesplitting or non-splitting services. The platforms provide a bundled service option and assign the passengers opting for a bundle option to either service), and passenger perceptions of and reaction to driver ratings.

3.3. Pricing

Ridesourcing platforms consist of a typical two-sided market. In the most influential work on two-sided markets, Rochet and Tirole (2003) consider a general model of competition between two platforms with the transaction volume in a multiplicative function of demand and supply. Other influential work on the economics of two-sided markets include Armstrong (2006), Rochet and Tirole (2006), Rysman (2009), and Weyl (2010). In a two-sided market, price affects both demand (i.e., passengers in the ridesourcing market) and supply (i.e., drivers in the ridesourcing market). Specifically, if we call the fare charged to passengers the price, the remuneration paid to drivers the wage, and the difference between price and wage withheld by the platform the commission, the necessity of determining the price, wage, and commission for ridesourcing platforms is central to their operation. Therefore, in this subsection, we refer to the interactive and integrated optimization of price, wage and commission as pricing problems.

Pricing in the two-sided market, especially in the context of a ridesourcing two-sided market, has attracted considerable attention recently. Many researchers focus on the interactions and endogeneity between various factors involved in pricing. For example, Bai et al. (2018) propose a queueing model that considers earnings-sensitive independent drivers with heterogeneous reservation prices, and price-sensitive passengers with heterogeneous valuations of the service. They propose a pricing framework and examine how various factors affect the optimal price, wage, and commission with an objective of maximizing the platform's profit or social welfare. They find that the optimal price is not necessarily monotonic when the driver's service capacity or passenger waiting cost increases. The platform should use a lower commission ratio as demand increases, capacity decreases, or passengers become more sensitive to waiting time. Conversely, it should increase its commission ratio when the number of drivers and passenger demand increase at about the same rate. Taylor (2018) also uses a queueing formulation with a two-point distribution for passenger and driver valuation, derives the demand rate and number of drivers in equilibrium for a given price and wage, and finds that uncertainty in passenger delay sensitivity and driver independence may change the intuitive price and wage prescriptions. Hu and Zhou (2019) study the performance of a flat commission contract. For a given realized market condition, they show that the joint price and wage optimization can be reduced to the one-dimensional problem of solving for the optimal matching quantity, and that the optimal price has a U-shaped relationship with the wage. They assume the total transaction volume is a function of aggregated supply and potential demand. When the aggregated supply function is concave in the wage rate, they show that a constant commission ratio can achieve 75% of the optimal profit. Wang et al. (2016) use an aggregate and static approach and show the existence and stability of equilibria in the two-sided market. Fang et al. (2017) provide insight into the trade-off between revenue maximizing prices and the social welfare maximizing process. They bound the efficiency loss under profit maximizing prices and show a strong alignment between profit and efficiency in practical settings.

Both demand and supply on ridesourcing platforms have strong temporal patterns. Dynamic pricing, sometimes referred to as surge pricing—i.e., pricing which reacts to instantaneous imbalances between real-time demand and supply—is a powerful tool commonly used by industry practitioners. However, dynamic or surge pricing is controversial, and has been questioned by passengers, drivers, scholars, and policy makers. Some studies, such as Hall et al. (2015), Cohen et al. (2016), Guo et al. (2018), and Jiao (2018), have examined the practices of surge pricing and/or the reactions of different stakeholders using real data. Many scholars study the modeling and optimization of dynamic pricing and debate the advantages and disadvantages of dynamic pricing with surge against static pricing. In favor of dynamic or surge pricing, Cachon et al. (2017) study several pricing schemes and find that the optimal dynamic contract substantially increases the platform's profit by comparison with contracts that have a fixed price or fixed wage, although surge pricing is not optimal, it generally achieves nearly the optimal profit. Castillo et al. (2017) argue that surge pricing can help to prevent a type of system inefficiency, the "wild goose chase," in which matching failure occurs when idle drivers are matched with distant customers and must waste substantial pickup time. They show that such a matching failure will cause the trip supply curve bend backwards, while surge pricing can suppress demand, allowing the system to avoid this regime. Nourinejad and Ramezani (2019) argue that by relaxing a common constraint that price is higher than wage at all times which is needed in equilibrium formulation, the long-term daily profit of the platform using dynamic pricing can be further improved.

By contrast, Banerjee et al. (2015) study the pricing problem as a queueing-theoretic economic model. They show that dynamic pricing does not provide more profit than optimal static pricing with a large market limit. The benefit of dynamic pricing, as compared to static pricing, is its robustness to fluctuations in system parameters. Chen and Hu (2019) study the behavior of passengers and drivers when they wait strategically for better prices, and show that in the presence of some forward-looking behavior, surge pricing underperforms static pricing in terms of platform profit when the market environment is stable and the market size is large. Zhong et al. (2019) compare surge pricing and static price queueing from multiple perspectives. They argue that (i) surge pricing dominates queueing in terms of consumer surplus, (ii) queueing dominates surge pricing in terms of gross merchandise volume, and (iii) when considering response rate and demand satisfaction rate, surge pricing should be followed by queueing as demand goes up, and the critical value depends on the characteristics of the market.

Another important feature of ridesourcing pricing is spatial price segmentation, i.e., setting different prices in different regions to balance demand and supply in the spatial dimension. Some recent work focuses on such spatial pricing. For example, Bimpikis et al. (2019) consider a spatial pricing problem in a network of locations and show that platform profits are higher when the demand pattern is more balanced between locations. They also show that there is no need for the platform to discriminate by price when the demand pattern is balanced; by contrast, it is beneficial to set different prices for passengers according to their origin when there are demand imbalances. Guda and Subramanian (2019) analyze spatial surge pricing and consider that drivers can move between adjacent zones, explicitly accounting for the strategic interaction in their decisions to move. They show that spatial surge pricing can be useful even in regions in which supply exceeds demand. Interestingly, more drivers can be encouraged to move from a zone with excess drivers by strategically using a surge price to throttle demand in that zone. Such strategic surge pricing can increase the total platform profit across zones and even be more profitable than offering drivers bonuses to move. Besbes et al. (2018) propose a two-dimensional framework for the spatial pricing problem, assuming that drivers choose where to relocate in response to an equilibrium between prices, travel costs, and driver congestion levels. Interestingly, when considering a surge in demand in a city center, they discuss the possibility of creating "damaged regions" through both prices and congestion steering the flow of drivers toward the area of high demand. Zha et al. (2018) propose a discrete time geometric matching model and investigate market equilibria under spatial pricing assuming a revenue-maximizing objective. They find that the platform may resort to a relatively higher price to avoid inefficient supply if spatial price differentiation is not allowed. They propose a commission ratio cap on spatial pricing to achieve the second-best outcome making some assumptions of homogeneity. Ma et al. (2018) design incentive-aligned pricing mechanisms in the presence of strategic driver behavior with a multi-location, multi-period setting. They provide a dynamic price that is appropriately smooth in space and time, so that drivers will choose to accept their dispatched trips, rather than moving to another area or waiting for higher prices or a better trip.

An important aspect of the pricing problem is demand elasticity with respect to price, which is a critical input for pricing problems and is examined in several industry reports. For instance, in the context of conventional taxis, Booz Allen Hamilton (2003) reports that the majority of international results for taxi demand elasticity range between -0.2 and -1.0; the NSW Independent Pricing & Regulatory Tribunal in Australia (see IPART, 2015) assumes an elasticity of -0.8 in the Sydney taxi market. The Center for International Economics in Australia (CIE, 2015) reports elasticity of around -1 for Melbourne, according to a study by the Victorian Taxi Inquiry. The CIE report finds that the price elasticity of taxi services without ridesourcing is -0.8, but where ridesourcing exists, the elasticity is -1.2. It also assumes that the price elasticity for ridesourcing services is -2.0. Deloitte Access Economics (2016) argues that it is likely that the demand for a single ridesourcing company would be more elastic than that for the entire market; that is, consumers would be more responsive to a change in price, as they can easily change to another company. We expect more empirical findings of spatio-temporal demand elasticity with respect to price (e.g., Litman, 2017) using real data from ridesourcing companies across countries and markets, which will provide more reliable inputs and assumptions for pricing models and mechanisms.

There is much relevant research into the pricing problem in shared transportation systems from different perspectives under diverse settings, such as pricing for dial-a-ride problem (Sayarshad and Chow, 2015); pricing for last-mile shared rides (Chen and Wang, 2018a, 2018b); auction pricing for ridesourcing (Asghari et al., 2016; Asghari and Shahabi, 2017); dynamic pricing with dispatching (Chen et al., 2017b); pricing with reservation cancellation (He et al., 2018); and surge pricing with strategic timing and information asymmetry (Abhishek et al., 2018). We expect more research into pricing problems for ridesourcing systems with diverse settings to, for example, capture big or subtle differences between different service options, changing market conditions, short-term and long-term demand behavior, and multiple objectives. The interdependence and interaction of prices between ridesourcing platforms and taxis are also worth investigating.

3.4. Other passenger promotions

In addition to spatial-temporal dynamic/surge pricing, ridesourcing platforms often use diverse passenger promotions to boost both short- and long-term demand. One commonly used promotion is *reward* and *loyalty programs*, in which the platform provides diverse benefits to passengers based on their usage. Passengers who use ridesourcing services frequently may enjoy special discounted prices during specified times, redeem free trips using their accumulated mileage, and offset a portion of the trip fare using rewards. Another commonly used promotion is the *referrals bonus*: A current passenger can recommend the ridesourcing service to a friend who has never used it by sending a message or sharing a referral code. If the friend accepts the referral and uses the service, both parties receive a bonus. There are many other promotions adopted by platforms. For example, *compensation* and *apology* for passengers after a bad experience; *philanthropic donations* where a charitable donation is made based on passenger usage; and *bundled trip packages* with a discounted fare for a certain number of trips within specified regions during specified times.

Reward schemes and loyalty programs are popular practices across a broad spectrum of industries, including airlines, hotels, supermarkets, telecommunication, and recently, e-commerce online shopping; see Kim et al. (2001, 2004); Singh et al. (2008); Caminal (2012); and Gandomi and Zolfaghari (2013). In the context of a ridesourcing market, Yang et al. (2018) propose a reward scheme integrated with surge pricing: In addition to a certain predetermined allowable range of surge pricing, passengers may opt to pay an additional amount on top of the regular surge price to a dedicated reward account during peak hours with over-demand, then use the balance in the reward account to compensate for trips during off-peak hours with over-supply. This mechanism provides another useful tool to balance demand and supply. They compare scenarios with and without such reward schemes from three perspectives: passenger utility, driver income, and platform revenue and profit, and find that the reward scheme will benefit all three stakeholders under some market conditions. From a markedly different perspective, Singh et al. (2017) compare the uptake of discount-based promotions and philanthropic promotions (which they call "charity-linked promotions") for online taxi booking platforms using field experiments in Singapore. They find that take-up rates for charity-linked promotions are not only much smaller than for discount-based promotions but also less sensitive to the exact amount involved. This is consistent with the view that the decision to take up a charity-linked promotion is driven in part by experiencing a "warm glow" from mere association with giving—i.e., an individual derives significant utility from the mere act of helping others, independent of the benefit achieved for society. They also find that charity-linked promotions are taken up disproportionately by people who are already more active customers.

Other recent work has modeled and compared various passenger promotions. For example, Cohen et al. (2019) use econometric models to conduct an empirical analysis of referral programs using real data from a ridesourcing platform. They show that the probability of making a referral in a given week decreases with the experience level (captured by the number of past rides), increases with the current usage intensity (number of rides in the same week), and decreases with the length of the inactive period. They also find that referral quality, as measured by the number of rides completed by the referred passenger, increases with experience but is affected by neither current usage nor recency. Cohen et al. (2018) study the effect of a passenger's bad experience or frustration, which may cause the person to stop using the service. They consider long waiting times and long travel times as frustrations and examine whether the platform should proactively send compensation to users who have experienced a frustration, which they call "frustration-based promotions." They find that sending proactive compensation to frustrated passengers is indeed profitable and boosts passengers' engagement, and works well for long waiting times but not for long travel times. Such compensation seems to be more effective than sending the same offer to non-frustrated riders, and more effective with frequent users. They also find that it is better to send credit for future usage rather than waiving the charge or sending an apologetic message. Using a nationwide field experiment involving 1.5 million Uber passengers who experienced late rides, Halperin et al. (2019) find that the efficacy of an apology and whether it is effective depends on the nature of the apology. Money speaks louder than words; i.e., the best form of apology is to include a coupon for a future trip, and in some cases sending an apology is worse than sending nothing at all, particularly in the case of repeated apologies.

Passenger promotion practices by ridesourcing companies are both innovative and down-to-earth across countries and markets. We expect more investigation of these diverse types of industry initiatives, regardless of their success or failure. Identifying which type of promotion should be sent to which groups of passengers with particular features and characteristics warrants further examination. We also expect more empirical findings concerning the response of passenger behavior to different promotions, as well as corresponding economic and decision-making models.

4. Supply and incentives

Understanding the patterns of supply and designing appropriate wage and incentive schemes/programs are also prevalent research topics in many industries, including ridesourcing systems. In a two-sided market, the supply side of the ridesourcing platform affects transaction volume, service level and quality, and service price. In this section, we review research concerning the supply and incentives for ridesourcing systems in four areas: driver supply models in Section 4.1, empirical analysis of supply elasticity in Section 4.2, other driver behavior in Section 4.3, and wage and incentive designs in Section 4.4.

4.1. Driver supply model

Several studies discuss the general reasons why drivers work in ridesourcing systems, and in particular, the flexibility such systems offer. For example, Hall and Krueger et al. (2018) argue that drivers work on the ridesourcing platform largely because of the flexibility, the level of compensation, and the fact that earnings per hour do not vary much with the number of hours worked. They find that Uber's drivers are more similar in age and education to the general workforce than to taxi drivers and chauffeurs. Most of Uber's drivers had full- or part-time employment before joining Uber, and many continue in those positions after starting to drive for Uber, rendering flexibility to set their own hours especially valuable. Drivers often cite the desire to smooth fluctuations in their income as one of their reasons for partnering with Uber. Using data on hourly earnings for Uber drivers, Chen et al. (2017a) argue that drivers benefit from real-time flexibility in terms of driver surplus, which is defined as the excess wage paid by the platform over the driver's reservation wage. Such flexibility for service providers is a key feature of on-demand ridesourcing platforms. However, this flexibility may also cause problems.

For example, based on data and interviews in Norway, Leiren and Aarhaug (2016) find that online ridesourcing platforms may contribute to a loss of service supply in rural areas.

As freelancers, drivers on ridesourcing platforms make daily decisions regarding whether to work, and if so, when and how many hours to work. The participation decision corresponds to service supply at the *extensive margin*, and the working-hours decision corresponds to service supply at the *intensive margin*. Long before the emergence of smartphone ridesourcing platforms, extensive work in the literature of labor economics examined general labor supply models considering both extensive and intensive margins, and the design of corresponding wage contracts, incentive schemes, tax policies, and welfare design while considering the distinctions between the two margins. Influential work includes Barzel (1973); Cogan (1981); Heckman (1993); Meyer (2002); Saez (2002); Rogerson and Wallenius (2009); Blundell et al. (2011); Chang et al. (2011); and Cesarini et al. (2017).

In the context of on-demand service platforms, a growing literature addresses driver service supply behavior. Specifically, most of the work on the ridesourcing pricing problems (i.e., fare, wage, and commission) discussed in Section 3.3 base their assumptions on certain driver behaviors and propose service supply models. Some studies use an aggregated service supply that does not differentiate between extensive and intensive margins. For example, Hu and Zhou (2019) assume a continuous aggregated supply function that increases with wage rate, and the total transaction volume is a function of the continuous aggregated supply and the potential demand. Some work has focused on the intensive margin, i.e., drivers' decisions concerning working-hours. For example, Farber (2005) analyzes the probability of a driver stopping work after a particular service trip, which essentially examines the working duration at the intensive margin. Zha et al. (2017) assume that drivers differ in their preferred start period and work duration. They measure drivers' disutility when choosing a particular start hour and also from cumulative working hours, which is assumed to increase more than linearly with the cumulative working hours at the intensive margin.

Much work in the literature has focused on the extensive margin, i.e., drivers' decision to participate on a platform. These studies examine the total number of active drivers at the extensive margin of on-demand service platforms by modeling the decisions of drivers to participate. For example, based on a queue-theoretical model, Banerjee et al. (2015), Bai et al. (2018), and Taylor (2018) assume that a potential service provider participates if and only if his anticipated average earning rate from working on the platform is at least equal to his reservation earning rate. Using an augmented newsvendor model, Gurvich et al. (2019) assume that each driver's participation at each period depends on a random threshold, and the distribution of the threshold is independent between periods. Cachon et al. (2017) assumes a two-period decision for drivers: a long-term decision on whether or not to join a platform in the first period (which gives a total number of joined drivers, N), and then a short-term decision on whether or not to participate in work at a particular time in the second period (which gives a proportion of participating drivers under a realized market condition, G); then the number of participating drivers at a particular time unit is assumed to be $N \cdot G$.

Some work considers both the extensive and intensive margins. For example, Baron (2018) provides micro-foundations for strategy analysis by modeling individual drivers at both the intensive and extensive margins, assuming driver's utility from working is a quadratic function of working hours, and the optimal working hours at the intensive margin are determined by maximizing net compensation. They show that the elasticity of working hours at the intensive margin increases strictly with opportunity cost, so part-time drivers with potentially higher opportunity costs are more elastic to compensation than full-time drivers. The elasticity of the number of drivers at the extensive margin is equal to 1. Bimpikis et al. (2019) assume that a driver enters an on-demand service platform if the expected lifetime earnings from the platform are greater than a positive threshold and chooses a location to maximize the expected lifetime earnings. They assume a simple constant exit probability after the completion of each trip to capture the intensive margin. Sun et al. (2019a) propose a service supply model that considers drivers' daily decisions about participation and working hours. They assume that drivers' participation on ridesourcing platforms incurs operating costs, reduces idle time, and brings income; therefore, drivers are making a trade-off between the utility from income and leisure time. They analyze drivers' optimal working decisions and the effect of heterogeneity on service supply behavior and supply elasticity. Benjaafar et al. (2018) study labor welfare in an on-demand service platform that relies on agents who decide whether and how much to work. Using an equilibrium model that accounts for the interaction among price, wage, labor supply, customer delay and demand, they argue that labor pool size may have nonmonotonic effects on labor welfare and both customers and workers may benefit by the imposition of an effective wage floor.

Drivers' service supply on ridesourcing platforms differs according to both their short- and long-term behavior, which may cause a fundamental difference between the design of short-term incentive programs and long-term wage contracts. This is an important area for future research. Other research directions include models to capture drivers' working decisions on time-within-day and space-within-city, as well as corresponding spatio-temporal service supply patterns. Models of and theories for integrated decisions and the scheduling of full-time job and part-time service supply on ridesourcing platforms are also interesting topics for research.

4.2. Supply elasticity

Factors such as hourly income rates (i.e., wage rates) affect both drivers' decisions to participate and their decisions about working-hours, so evaluation of the impact of the hourly income rate on service supply is critical. In standard labor economics theory, as introduced by Cahuc et al. (2014), income rates have two distinct effects on labor supply by influencing two margins: one is intensive, and relates to the number of hours worked; the other is extensive, and relates to the decision to participate or not in the labor market. The study of a driver's service supply elasticity at both the extensive and intensive margins with respect to hourly income rate is critical to the design and operation of driver incentive mechanisms in ridesourcing systems. As Scheiber (2016) points out, labor economists have been debating how drivers make working decisions and the corresponding supply elasticity for decades.

The first mainstream research into supply elasticity is by behavioral economists, using reference-dependent theory. The most representative work is Camerer et al. (1997), who use hours worked as the measure of labor supply and all drivers' average hourly income as an instrumental variable to individual driver's income rate. From NYC taxi driver data, they find that some drivers are irrational and come into the market with an income target, which implies that drivers will work longer hours when driving pays less than usual and shorter hours when it pays more. The corresponding elasticity is negative ($-0.355 \sim -0.618$) in such a case. Chou (2002) uses a similar method and finds a negative elasticity ($-0.3 \sim -0.9$) for taxi drivers using Singapore survey data. Fehr and Goette (2007) study bicycle messengers' working hours and effort and find a negative effort elasticity (-0.24) and a positive working-hours elasticity ($1.34 \sim 1.50$) using a randomized controlled trial. Income-target behavior, if it exists, tends to generate a negative elasticity in a range of hourly income rate and undermines the benefits of dynamic pricing/wage and/or other bonus incentives for drivers.

Another strand of mainstream research into supply elasticity is based on neoclassical and/or intertemporal labor supply models. The most influential and representative work is by Farber (2005, 2015), who also uses hours worked as the measure of labor supply and all drivers' average hourly income as an instrumental variable to individual driver's income rate. From NYC taxi driver data, Farber finds that drivers are rational decision makers and typically work longer hours when income rates are higher, which provides a positive elasticity ($0.32 \sim 0.62$) and is opposite to the results of Camerer et al. (1997). Using real driver working data from Uber, Chen and Sheldon (2016) and Sheldon (2016) employ a similar method and find that drivers have a positive elasticity ($0.13 \sim 0.25$) and adjust flexibly to drive more at high surge times.

Considering both participation and working-hours decisions, Sun et al. (2019b) model the sample self-selection bias of driver participation and the endogeneity of income rate using a Heckman two-step method with an exogenous income multiplier as the instrumental variable. Using real driver working data from Didi for a city in China, they find a positive participation elasticity at the extensive margin ($0.11 \sim 0.52$) and a positive working-hours elasticity at the intensive margin ($0.02 \sim 1.04$). Angrist et al. (2017) find almost zero participation elasticity and positive working hour elasticity (1.2) using randomized controlled trial data from Uber. There is also a rich literature concerning labor supply elasticity in other industries, such as positive participation and working-hours elasticity for trans-Alaska pipeline workers (Carrington, 1996); positive participation elasticity for baseball stadium vendors (Oettinger, 1999); positive participation and working-hours elasticity for lobstermen in Florida (Stafford, 2015); and positive participation elasticity for boat owners in southern India (Giné et al., 2017).

In general, income-target behavior may undermine the benefits of an emerging sharing economy or on-demand economy markets in which tasks are usually dynamically priced. Econometric models, analysis, and estimation of short-term and long-term supply elasticity under diverse contexts in ridesourcing systems are important; mitigating endogeneity bias in a service supply elasticity model still requires study; and more randomized control trials are needed. In addition, the impacts of the time horizon—e.g., hourly vs. daily vs. monthly driver decisions—on the income target and supply elasticity will be interesting and challenging topics for future research.

4.3. Other driver behavior

Understanding driver behavior is important to improve the planning and operation of the supply/service side of ridesourcing systems. Active drivers show a common behavior when deciding when and where to drive on the platform. Chaudhari et al. (2018) show that strategic behavior regarding when and where to drive can substantially increase driver income. Assuming an earnings-maximization strategy for a driver, they describe a series of dynamic programming algorithms for different sets of modeled actions available to drivers and exemplify the models and methods in a large-scale simulation of driving for Uber in NYC. They find that repositioning throughout the day is the key to maximizing driver earnings, but that chasing a surge is typically a misguided, and sometimes costly, move.

Where to drive to seek passengers when idle (e.g., empty vehicle cruise) is important, but varies substantially between drivers. In the context of conventional taxis, various methods are assumed to model bilateral taxi driver and passenger searching and meeting behavior on networks. Yang and Wong (1998) and Yang et al. (2002, 2010) assume that idle drivers will either cruise streets or areas or wait at specific locations, such as airports, and that their decisions take into account the expected searching/waiting time for passengers and the expected revenue per ride from a zone or location. Szeto et al. (2019) study the factors that influence vacant drivers' customer-search decisions on whether to enter or bypass recommended areas while cruising along a road with a series of taxi-calling signals. Observational survey data are collected and analyzed to understand the travel behavior of vacant taxi drivers, and a sequential binary logistic regression model is proposed to examine their dynamic decision-making process. The status of taxi-calling signals, which reveal passenger demand at locations away from the roadside to cruising vacant taxis, is found to be the most influential factor encouraging vacant taxi drivers to enter sites to pick up passengers. Rong et al. (2017) find that top-performing taxi drivers can earn 25% more in a given period than those with mediocre seeking strategies. To investigate independent worker's behavioral biases in the context of on-demand service platforms, Jiang et al. (2019) use a combination of behavioral modeling and controlled lab experiments considering driver behavioral factors. They find that regret aversion and ignorance of suggestion are the two major behavioral factors that influence drivers' relocation decisions. Sharing demand information is a better way of communicating demand compared with providing suggested actions to drivers, and the platform may also need to offer extra financial payment to compensate for drivers' relocation cost. A rich strand of literature examines the corresponding empty vehicle guidance and repositioning, which are discussed in Section 5.4.

If there are multiple ridesourcing platforms in the same local market, a driver may drive for multiple platforms at the same time and provide ride services for the platform that has a passenger nearby. This is called multi-homing behavior of drivers. Liu et al. (2017) study the impact of multi-homing in a ridesourcing market. By comparison with a single-homing duopoly, they find that multi-homing on either the passenger side or driver side improves overall welfare. However, multi-homing drivers potentially benefit themselves at the cost of single-homing drivers. In contrast, multi-homing passengers benefit themselves as well as single-homing passengers, which represents a more equitable distribution of gains from multi-homing. Some recent work examines platform competition strategies given the multi-homing behavior of passengers and drivers, such as studies by Cohen and Zhang (2017), Jeitschko and Tremblay (2019), Belleflamme and Peitz (2019), and Bryan and Gans (2019), which are discussed in Section 6.1.

Additionally, many studies examine driver behavior from highly diverse perspectives. For example, Lee et al. (2015) explore the impact of software algorithms and data-driven management on drivers' working practices in the context of Uber and Lyft. They conduct a qualitative study to describe how drivers respond when algorithms assign work, provide informational support, and evaluate driver performance, and how drivers use online forums to make sense of algorithm features; for example, a factor that influenced driver cooperation was whether the assignment made sense to them, which suggests that an explanation of why certain assignments were made might be an important feature. Malin and Chandler (2016) explore how Uber and Lyft drivers understand their own digital labor. They identify some unusual behavior from interviews with drivers; for instance, drivers may ask passengers to get out of the vehicle and cancel the ride when they have concerns about the vehicle's safety during the ride, since drivers are not employees of the platform and therefore risk liability. Ge et al. (2016) study drivers' racial and gender discrimination with regard to passengers and observe that removing passenger names from trip bookings may alleviate the immediate problem, but could introduce other pathways for unequal treatment of passengers. In examining how technological innovation in digital platform affects moral hazards and service quality, Liu et al. (2018) find that Uber drivers overall drive at a lower speed than taxi drivers, and taxi drivers tend to detour more relative to Uber drivers on metered airport routes in NYC, particularly when the airport passenger is non-local. Schwendau (2017) studies the dangers and self-protective behavior of drivers to understand their fears about the lack of safety and security provided by companies, and provides some suggestions from drivers to make the ride safer, such as more training by the platform, requiring a profile picture from a passenger, and vehicle dash cameras provided or offset by the platform. In the context of taxis, Noulas et al. (2018) find that experienced drivers are more likely to pick side streets that may help them to navigate away from heavy traffic, and demonstrate better routing skills in dense and complex urban environments than computer navigation systems. Xu et al. (2018a) study the factors that affect taxi drivers' response to ridesourcing requests. They find that taxi drivers working on ridesourcing platforms are more likely to respond to requests from the platform with economic incentives (especially a firm subsidy) and to requests with lower spatio-temporal demand intensity or higher spatio-temporal supply intensity when it is difficult to find street-hailing passengers. Drivers are more likely to respond to requests involving rides that cover a greater geographical distance and to those with a smaller number of repeated submissions. With the boom in ridesourcing platforms, we can expect more, either theoretical or empirical, studies on driver behavior in the future.

4.4. Wage and incentives

Wage and incentive mechanism for drivers affect the supply side of ridesourcing systems, in both the short- and long-term. In Section 3.3, we reviewed the literature on pricing problems for ridesourcing platforms, which include the determination of the fare charged to passengers, the wage paid to drivers, the commission withheld by the platform, and the interactions and endogeneity between these factors.

Several studies just focus wage and compensation on the supply side. For example, Angrist et al. (2017) examine the different wage structures of conventional taxis and Uber. Specifically, drivers on Uber pay a proportion of the fare to the platform, and conventional taxi drivers make a fixed payment independent of their earnings—usually a weekly or daily medallion lease—but keep every fare dollar net of expenses. They argue that the crucial difference between drivers comes down to the need to lease a medallion to drive a taxi as opposed to the *pro rata* fee the platform charges. Using an experiment that offered random samples of Boston Uber drivers the opportunity to lease a virtual taxi medallion that eliminates the commission, they find that many high-volume drivers display "lease aversion" and opt for the pro rata scheme, despite the better return offered by the lease model for taxis. They also compute the average compensation required to render drivers indifferent when choosing between ridesourcing platforms and conventional taxis. The results suggest that drivers on ridesourcing platforms gain considerably from the opportunity to drive without leasing.

To address the spatial-temporal imbalance between demand and supply, ridesourcing platforms often deploy spatial-temporal bonus and incentives programs in various formats. One commonly used spatial-temporal incentive is called *Boost* by Uber and *PanGu* by Didi. Boost multiples drivers' income by a certain amount for all trips within specified hotspots during specified times. Boost schemes operate in different zones across the city, while how much Boost the driver can earn depends on when and where they drive. Boost differs from surge pricing/wage in that (i) Boosts only affects the supply side, and (ii) Boosts are set in advance and available for longer periods of time. Uber also claims that when both surge and boost occur in the same area and at the same time, drivers will receive the higher one, so essentially Boost is like a space- and time-dependent guarantee of a minimum surge. Another commonly used incentive program is a *Streak* bonus or consecutive trips bonus. When drivers complete multiple trips within specified hotspots during specified times, they will receive a Streak bonus and the amount depends on the number of trips that meet certain requirements. There are many other incentives programs. For example, *Quest* is a target-based bonus, i.e., if drivers reach a specific number of trips during a particular period, they unlock certain incentives. In a *minimum wage guarantee*, platforms top-up driver earnings if their earnings are less than a guaranteed amount.

Some recent works have modeled and evaluated various incentives. For example, Leng et al. (2016) analyze taxi drivers' behavior in response to monetary promotions during a battle between two ridesourcing apps (i.e., Didi and Kuaidi in China in 2014) and demonstrate how several important service indices (e.g., travel distance and idle time) of taxi drivers changed. They show that the number of taxi trips made by every vehicle per day increases during the money promotion; also, idle times become shorter. However, drivers prefer to pick up passengers who travel shorter distances and passengers going to "hot" locations, since they could serve more passengers and thus collect more subsidies. Kabra et al. (2016) find that over a term as short as a week, passenger incentives are more effective than similar driver incentives. In the longer term, such as over three months, the opposite is true: Driver incentives are more effective than passenger incentives. This is because of the differential stickiness of passengers and drivers to the platform, as well as differential response to evolving service levels. Passengers are less sticky on the platform in the long term and more sensitive to their service level. When structuring driver incentives, it is more effective to use threshold incentives based on a certain level of usage rather than linear incentives. Fang et al. (2018) study a loyalty program for drivers and show that optimal revenue in a heterogeneous market can be achieved by a class of multi-threshold loyalty programs that include a simple implementation-friendly structure. They also argue that sophisticated loyalty programs that reward drivers through stepwise linear functions outperform simple sign-up bonuses that give drivers a one-time reward for participating.

Like passenger promotions on the demand side, the practice of wage and bonus incentives by ridesourcing companies on the supply side are both innovative and down-to-earth across countries and markets. We expect more studies and investigation, either empirical findings or theoretical models, of these diverse types of industry initiatives, regardless of their success or failure.

5. Platform operations

Ridesourcing platforms employ diverse operational strategies to enable and improve an on-demand shared transportation service. These operational strategies largely affect service quality for passengers, working status and income for drivers, overall system efficiency and platform performance—such as market share, revenue and profit—and social welfare and other externalities. In this section, we review research into six areas of platform operations: estimated time of arrival (ETA) in Section 5.1, matching and order dispatching in Section 5.2, ridesplitting operations in Section 5.3, empty vehicle guidance and repositioning in Section 5.4, information sharing and disclosure in Section 5.5, and rating mechanism in Section 5.6.

5.1. Estimated time of arrival

Estimated time of arrival (ETA) is the estimated travel time between an origin and a destination. It is one of the most important location-based services for ridesourcing platforms, and is also a key concern for both passengers and drivers. It has been used widely as the foundation for many real-time decisions by the platforms, such as matching and order dispatching, ridesplitting assignment, routing and navigation, guidance and repositioning, and price and wage estimation. An accurate and reliable ETA increases the efficiency of the ridesourcing system by reducing the travel cost for users, energy consumption, and vehicular pollution. However, this is a challenging task, because ETA is affected by diverse complex factors, including spatial correlations, temporal dependencies, and external conditions (e.g., weather, traffic lights, congestion; see Wang et al., 2018a).

Various methods have been used to estimate ETAs using various sources of data. For example, Wu et al. (2004) apply support vector regression (SVR) to highway traffic data and compare the results with other baseline travel-time prediction methods. They find that the SVR predictor can substantially reduce both the relative mean errors and root-mean-squared errors in predicted travel time, because SVR is believed to perform well for time series analysis with greater generalization ability and guaranteed global minima. De Fabritiis et al. (2008) present a large-scale working application of a Floating-Car Data (FCD) system. They propose two algorithms, based on artificial neural networks and pattern-matching, using floating car data designed to perform online short-term predictions of link travel speeds using current and near-past link average speeds. Test results show that these approaches are very effective for short-term predictions. Jenelius and Koutsopoulos (2013) present a model estimated using maximum likelihood to estimate travel time on urban road networks using vehicle trajectories obtained from low frequency GPS probes as observations where vehicles typically cover multiple network links between reports. The network model separates trip travel times into link travel times and intersection delays and allows travel times on different network links to be correlated based on a spatial moving average (SMA) structure. A case study of a network in Stockholm shows that link attributes and trip conditions have significant effects on travel times, and that there is a significant positive correlation between segments. Wang et al. (2014) estimate travel times on different road segments in different time slots by means of a three-dimensional tensor, using GPS trajectories of vehicles received in current time slots and over a period of history in addition to map data sources. They fill in the tensor's missing values using a context-aware tensor decomposition approach combined with geospatial, temporal, and historical contexts learned from trajectories and map data. Numerical experiments using GPS trajectories from more than 32,000 taxis in Beijing over a period of two months demonstrate the effectiveness. Woodard et al. (2017) propose a statistical model to predict the distribution of travel time using GPS data from mobile phones or other probe vehicles, taking into account the variation of local traffic patterns by time of week. They discuss a case study in the Seattle metropolitan region and find that the proposed method provides improved interval predictions relative to Bing Maps' predictions. Leveraging a network optimization framework and insights, Bertsimas et al. (2019b) develop a method that exploits taxi origin-destination data and other sources of traffic information tractably to extract travel time estimation. Using synthetic instances, they establish the robustness of the algorithm to high variance data and the interpretability of its results.

Given the availability of large amounts of data resulting from the wide penetration of ridesourcing platforms, machine learning techniques, especially deep learning techniques, have played a key role in the estimation of ETA recently. For example, Wang et al. (2018a) present an end-to-end deep learning framework to estimate the complete path travel time. They present a geo-convolution operation which is capable of capturing spatial correlations by integrating geographic information with classic convolution. By stacking recurrent units on the geo-convolution layer, they also capture temporal dependencies. Wang et al. (2018c) formulate ETA as a pure spatial-temporal regression problem using a large set of effective features and adapt different existing machine learning models to solve the regression problem. They also propose a wide-deep-recurrent (WDR) learning model and jointly train wide linear models, deep neural networks, and recurrent neural networks together. They deploy the solutions on Didi's platform and demonstrate good performance.

In the future, with more types of data with multiple dimensions from diverse sources, we expect that more statistical, econometric, and machine learning techniques will be developed and synergies with structural models to obtain more accurate ETA.

5.2. Matching and order dispatching

Ridesourcing platforms are a typical two-sided market, so matching demand and supply—i.e., dispatching passenger orders to drivers—is a key feature of the service. For single-rider services such as UberX and Didi Express, one passenger order is dispatched (i.e., matched) to one driver, which is very like the conventional taxi order dispatch. For multi-rider ridesplitting services such as Uber Pool, Didi Pool, Lyft Line, and Grab Share, multiple passenger orders with similar itineraries may be combined and dispatched to one driver. In this subsection, we focus on single-rider matching between one passenger and one driver. In Section 5.3, we focus on multi-rider matching and assignment for ridesplitting services. Note that there is a large stream of literature on the matching problem in dynamic ridesharing systems that aim to match travelers with similar itineraries and time schedules at short notice, and both passengers and drivers have their own travel needs (see Agatz et al., 2012, for a review). A dynamic ridesharing system is more like peer-to-peer shared travel services such as Didi Hitch and Grab Hitch, which are outside the scope of this review.

Matching and order dispatching algorithms affect the overall performance and efficiency of ridesourcing systems greatly. A good matching algorithm provides not only better service for passengers, but also an efficient fleet with better utilization and requiring fewer vehicles. For example, Vazifeh et al. (2018) address the minimum fleet problem in an on-demand shared transportation service. Given a collection of trips (specified by origin, destination, and start time), they determine the minimum number of vehicles needed to serve all of the trips without incurring any delay for passengers if an ideal order dispatching and empty vehicle repositioning system is used. Using taxi trip data from NYC for one year, they find that a method with near-optimal service levels would allow a 30% reduction in fleet size by comparison with current operations. In the context of peer-to-peer dynamic ridesharing, Lee and Savelsbergh (2015) investigate the benefits, complexities, and costs of employing a small number of dedicated drivers to serve riders who would otherwise remain unmatched. They find that the benefits and costs of employing dedicated drivers depend on three main factors: the number of trips in a service area, the time flexibility of trips, and the similarity between travel patterns of the trips. The dedicated drivers can be seen as a dedicated fleet working on ridesourcing platforms such as Uber and Didi. Although the contexts have some differences, these studies provide a reference for how well ridesourcing systems can perform with an ideal matching and dispatching algorithm. On the other hand, Feng et al. (2017) build a stylized model of a circular road and compare the average waiting times of passengers using various matching mechanisms. Surprisingly, they find that the on-demand matching mechanism could result in higher or lower efficiency than the conventional street-hailing mechanism, depending on the parameters of the system.

Matching and order dispatching pose fundamental challenges to platform operators that are difficult to surmount for the following reasons. First, ridesourcing systems are highly dynamic, with time-varying stochasticity and uncertainty in decision scenarios, such as those that involve demand and supply. Second, strong endogeneity is present between current decisions and future scenarios; matching decisions in the current period will affect demand and supply scenarios strongly in subsequent periods. Third, the platform must consider multiple short-term and long-term objectives, such as instant rewards from passenger pick-up time and fare charged, midterm service level and fleet efficiency, long-term passenger and driver fairness and satisfaction, and platform revenue, profit, and reputation; these objectives may conflict with each other. And fourth, in addition to these challenges, the scale of the matching problem in ridesourcing systems is large or even huge. This causes the curse of dimensionality, with decision variables that can number in the hundreds of thousands (e.g., up to $10 \sim 100$ thousand) and even more constraints, which must be considered quickly or even instantaneously. Such a large-scale problem requires reliable and high-quality solutions in a very short time—typically, within a few seconds.

Since the match between one passenger and one driver has a clear bipartite structure, the matching problem *per se* is often modeled using an integer optimization and combinatorial optimization formulation. Due to the stochasticity and uncertainty of ridesourcing systems, stochastic programming and robust optimization methods are often adopted. Due to the endogeneity between current decisions and future scenarios, dynamic programming models are also used to capture the complex state transitions between demand and supply scenarios with decisions. In addition, because of the sophisticated tradeoffs between multiple short-term and long-term objectives with spatio-temporal characteristics, machine learning techniques have been integrated into matching and dispatching algorithms recently to address intractable structures and complex estimations of rewards. Finally, because of the large scale of the problem and the strict requirement for computational speed, in current industry practice various heuristic algorithms play critical roles in solving these problems quickly in real time.

In the context of taxi order dispatching, much work has been conducted recently using diverse assumptions with different objectives, such as minimizing pick-up time and passenger waiting time, maximizing matched ratio and system profit, and minimizing taxi idle distance; see Lee et al. (2004), Wong and Bell (2006), Seow et al. (2010), Miao et al. (2016), and Zhang et al. (2017b). Many recent studies have addressed matching problems in the specific context of ridesourcing systems, such as Dickerson et al. (2018), Xu et al. (2018b), Ozkan and Ward (2019), Bertsimas et al. (2019a), and Lyu et al. (2019). Some work on peer-to-peer ridesharing hitch matching is also valuable for ridesourcing systems, such as the stable matching proposed by Wang et al. (2017b). Since the research problems in these papers are mainly standard optimization problems that can be summarized well by their objectives, methodologies and approaches, and instance performance, we use Table 2 to summarize these papers.

In practice, in addition to greedy matching of pairs of passengers and drivers within the closest distance, *batch matching* is a common strategy used by ridesourcing systems. Instead of dispatching a vehicle immediately an order arrives, platforms often hold unserved orders and empty vehicles for a certain matching interval, e.g., 2–10 s, and conduct batch bipartite matching. There are two key decision parameters in this batch matching strategy: length of the matching interval and the maximum allowed pick-up time/distance (i.e., matching radius) in each matching batch. Intuitively, as the matching interval increases, more demand/supply information can be revealed, but more passengers may cancel orders because of long waiting times. As the matching radius increases, more pairs can be matched in each batch, but the actual pick-up time/distance may also increase. Akbarpour et al. (2018) discuss the thickness of information in dynamic matching markets which is relevant to batch matching and corresponding information. They show that if the platform can identify passengers who are about to cancel, then waiting to thicken the market substantially reduces the fraction of unmatched passengers. If the platform cannot identify such passengers, then matching agents greedily is close to optimal. They specify conditions under which local algorithms that choose the right time to match, but do not exploit the global network structure, are close to optimal. Liu et al. (2019) argue that a centralized matching algorithm can increase the number of matches by making matches less frequently and matching agents more assortatively. Considering the impacts of matching radius, by constructing a double-ended queuing model, Xu et al. (2019) prove that the supply curve in the ridesourcing system with a finite matching radius is always backward bending, but a smaller matching radius leads to a weaker bend. They also argue the possibility of completely avoiding the bend by adaptively adjusting the matching radius. Further discussion of the matching interval and matching radius, as well as insights on implementable matching algorithms, are anticipated.

There is also a growing literature on the online algorithm for general dynamic matching. For example, Baccara et al. (2018) study a dynamic matching problem in which demand units can wait, and there is a trade-off between waiting for a thicker market with higher-quality match and incurring higher waiting costs. They show that the welfare difference between centralized matching and a discretionary process can be substantial, even for low waiting costs. Truong and Wang (2018) study dynamic matching, in which supply units can wait a deterministic amount of time, whereas demand units must be matched irrevocably upon arrival to existing supply units if any, or rejected. They propose an online algorithm with a worst-case performance guarantee and prove an upper bound on the best performance guarantee. Ashlagi et al. (2019) study dynamic matching in an infinite-horizon stochastic market while considering both hard- and easy-to-match agents who can be matched either bilaterally or indirectly through chains. They propose an asymptotic approach and compute tight bounds on the limit of waiting time under myopic policies. Ashlagi et al. (2018) study the problem of matching agents who arrive at a marketplace over time and leave after some time period without *a priori* information about the match values or arrival times. They propose a 1/4-competitive algorithm and also show that no algorithm is 1/2-competitive.

In the future, deriving efficient matching models and algorithms with both good theoretical performance guarantees and practical computational advantages will be extremely valuable. Specifically, computational algorithms to solve matching problems in a hybrid context with stochastic programming, dynamic programming, and machine learning, are worth investigating.

Table 2
Summary of some papers on matching and order dispatching.

	Literature	Objective	Methodology and approach	Instance performance
Taxi order dispatch	Lee et al., al.(2004)	Minimize pick-up time	Greedy matching with shortest pick-up time considering real-time traffic conditions	Simulation using Singapore taxi data. Reduce more than 50% passenger pick-up time and average travel distance
	Wong and Bell (2006)	Minimize passenger request waiting time	Heuristic with rolling horizon considering anticipation of future requests and traffic conditions	Simulation using synthetic instances. Perform well but the “curse of dimensionality” is a bottleneck
	Seow et al. (2010)	Maximize quality-of-service or minimize total cost	Multi-agent taxi dispatch architecture with linear assignment	Simulation using synthetic instances. Reduce customer waiting time and empty taxi cruising time
	Miao et al. (2016)	Maximize matching ratio with minimum taxi idle driving distance	Receding horizon control framework using spatio-temporally demand/supply, real-time GPS location, and occupancy information	Simulation using San Francisco taxi data. Reduce average total idle distance by 52% and supply demand ratio error by up to 45%
	Zhang et al. (2017b)	Maximize global order success rate considering driver acceptance	Linear logistic regression and gradient boosted decision tree to predict driver acceptance; hill-climbing to dispatch orders	Simulation in Didi online taxi system. Improve order success rate from 80% to 84%
Ridesourcing matching	Wang et al. (2017b)	Multiple objectives: systemwide measures and individual benefits	Stable matching with rolling horizon	Simulation using Atlanta ridesharing data. Increase stability of solutions a lot at the cost of a small degradation in systemwide measures
	Dickerson et al. (2018)	Maximize a generic matching reward	LP-based adaptive algorithm	Simulation using NYC yellow cabs data. Online competitive ratio of $1/2 - \text{epsilon}$ for any given $\text{epsilon} > 0$
	Xu et al., al.(2018b)	Maximize an overall global gain	Combinatorial optimization with reinforcement learning considering immediate rewards and future gains	Testing on Didi platform. Improve platform's revenue by a range of 0.5% to 5% in some cities in China
	Ozkan and Ward (2019)	Maximize the total cumulative number of matchings	Continuous linear program (CLP) and linear program (LP) based policy	Simulation using synthetic instances. Asymptotic optimality of CLP-based policy and LP-based policy under some conditions
	Bertsimas et al. (2019a)	Maximize total profit	A backbone algorithm with a restricted set of candidate actions for a sparser problem	Simulation using NYC yellow cabs data. Outperform some existing heuristics in large-scale cases
	Lyu et al. (2019)	Multiple objectives: platform revenue, pick-up time, service quality	Debt-based optimization with dynamically adjusted weights on multiple objectives	Simulation using Didi data. Improve service quality and platform revenue with a slight sacrifice of pick-up time

5.3. Ridesplitting operations

Ridesplitting services—i.e., transportation services with multi-rider trips that combine passenger orders with close itineraries—are becoming steadily more important and prove of great value, especially during peak demand hours. Uber Pool, Didi Pool, Grab Share, and Lyft Line can serve more demand using limited vehicles or serve certain fixed levels of demand using fewer vehicles for fewer trips and a shorter cumulative trip length. To study the potential impacts of ridesplitting, Santi et al. (2014) introduce the notion of a shareability network, which models the collective benefits of ridesplitting as a function of passenger inconvenience and computes optimal sharing strategies efficiently. They show that in a ridesplitting service with increasing but still low passenger discomfort, cumulative trip length can be cut by 40% or more for taxi trips in NYC. d'Orey et al. (2012) perform an empirical evaluation of ridesplitting taxis using simulation and show that full deployment of ridesplitting taxis provides an increase of 48% on the average occupancy per traveled kilometer. Korolko et al. (2018) consider a mechanism with joint optimization of dynamic pricing and dynamic waiting for ridesplitting passengers and determine the passenger waiting window. From simulations using Uber data, they find that the mechanism can mitigate price variability and increase capacity utilization, trip throughput, and welfare.

To generate value better from ridesplitting services, platforms must address operational challenges regarding how to assign multiple passengers/orders to a driver given stochastic and dynamic demand and supply information. Platforms must consider multiple objectives, such as additional waiting/delay times and detour travel distances for passengers, total travel distance and overall occupancy for drivers, number of served orders, and system revenue and profit. The difficulties and challenges of single-rider matching problems—stochasticity and uncertainty, endogeneity between current decisions and future scenarios, sophisticated tradeoffs between multiple objectives, and the quick response required for large-scale systems—are also faced by operators on multi-rider ridesplitting operations. As in Section 5.2, we use Table 3 to summarize some recent papers on multi-rider matching and assignment for shared-taxi and/or ridesplitting systems; see Santos and Xavier (2013), Hosni et al. (2014), Ma et al. (2015), Pelzer et al. (2015), Jung et al. (2016), Alonso-Mora et al. (2017), Qian et al. (2017), Korolko et al. (2018), and Simonetto et al. (2019). These studies have been conducted using diverse assumptions with different objectives, such as minimizing passenger waiting/delay time and detour, minimizing vehicle travel distance and mileage, maximizing the number of served requests, and maximizing system profit and welfare. In the literature, mixed integer linear programming (MILP) is often used to formulate the problem, while heuristics, such as simulated annealing and adaptive searching algorithms, are often deployed to solve the problem in real time with good computational speed. From the numerical examples in these papers, we can identify the significant potential benefits offered by ridesplitting services.

To reduce waiting delay and detours, some platforms also require ridesplitting passengers to meet at specific locations for easy pick-up and quick boarding. In these cases, the choice of meeting points are important for user experience and system efficiency. Work on meeting points in the context of peer-to-peer ridesharing systems are worth referring to; for example, Stiglic et al. (2015) introduce a ridesharing system with meeting points instead of pick-ups or drop-offs at a series of points. They validate the efficiency in terms of number of shared trips and system-wide travel distance savings. Aïvodji et al. (2016) consider the cost of ridesharing user privacy when setting meeting points, and develop a privacy preserving procedure to deploy meeting points without sacrificing system usage. Experiments carried out on a real transportation network demonstrate that it is possible to achieve a trade-off in which both privacy and utility levels are satisfactory.

In ridesourcing systems, preselection of meeting points in a static setting and real-time selection of meeting points in a dynamic setting both merit exploration. Another interesting research direction is routing in-service vehicles with available seats to increase the probability of them being shared and to improve the overall vehicle occupancy, given limited detour from the route and passenger inconvenience. We also expect more empirical findings on general demand and supply patterns and diverse passenger and driver behavior in ridesplitting services (e.g., passenger discriminatory attitudes in Moody et al., 2019, and impacts on ridesplitting from delay, detours, degraded travel time reliability, and built environment factors in Li et al., 2019). Additionally, as discussed by Shaheen and Cohen (2019), policies related to and support for shared ride services, including ridesplitting services—for instance, infrastructure and access to public rights-of-way, such as park-and-ride-facilities, HOV lanes, and loading zones—also warrant examination. More importantly, the pricing and fare-splitting mechanism for shared-ride passengers is critical for ridesplitting services (e.g., design price-service menus in Jacob and Roet-Green, 2018). Given that current practices for passenger fare-splitting and ridesplitting driver wage and incentives are typically simple and immature, future avenues for research include modeling fare-splitting, wages, and incentive design, along with ridesplitting matching and in-service vehicle routing.

5.4. Empty vehicle guidance and repositioning

In addition to matching and order dispatching, a critical operational strategy that platforms focus on is guidance to and repositioning of empty vehicles awaiting new passengers. Specifically, as introduced in Section 4.3, idle drivers and empty vehicles behave very differently when they are not serving passengers. Some tend to stay and wait in certain places, some tend to cruise the city randomly, and some may go to particular target places that they anticipate will offer a higher chance to get orders in a short time, or a higher chance of high-value orders. How to improve the guidance and repositioning of these idle drivers and empty vehicles awaiting new passengers from a system-wide perspective is important to increase the system efficiency. With an ideal repositioning and matching strategy, Vazifeh et al. (2018) demonstrates a 30% reduction in

Table 3
Summary of some papers on ridesplitting matching and assignment.

	Literature	Objective	Methodology and approach	Instance performance
Ridesplitting matching and assignment	Santos and Xavier (2013)	Maximize the number of served requests and minimize cost paid by the served passengers	Greedy randomized adaptive search procedure	Simulation using Illinois survey data. Save average of 18.58% cost for each travel request
	Hosni et al. (2014)	Maximize total profit	Mixed integer programming with Lagrangian decomposition and heuristics	Simulation using synthetic instances. Provide tighter bounds than CPLEX in shorter computational times
	Ma et al. (2015)	Minimize increase in travel distance	Single-side and dual-side searching algorithms with taxi scheduling	Simulation using Beijing taxi data. Reduce 11% in total travel distance and 7% in taxi fare per rider when the ratio of requests to taxis is 6
	Pelzer et al. (2015)	Minimize total mileage driven with limited detours	Divide network into distinct partitions that define the search space for ride matches	Simulation using Singapore taxi data. Reduce 42% number of trips, save 230,000 km in daily mileage, outperform greedy method
	Jung et al. (2016)	Minimize passenger travel time and maximize system profit	Hybrid simulated annealing	Simulation using Korea Transport Institute (KOTI) regional transportation planning model. Increase productivity and improve system efficiency
	Alonso-Mora et al. (2017)	Minimize sum of delays	Greedy assignment improved by constrained optimization	Simulation using NYC taxi data. 15% taxi of capacity 10 or 22.5% of capacity 4 can serve 98% demand with 2 to 3 min waiting time and 2 to 3 min trip delay
	Qian et al. (2017)	Maximize total saved travel miles	Integer linear programming converted into an equivalent graph problem considering incentives for taxi ridesplitting	Simulation using NYC, Wuhan, and Shenzhen taxi data. Save over 47% of total taxi trip mileage with a proper level of incentives
	Korolko et al. (2018)	Maximize welfare for drivers and passengers	A dynamic waiting mechanism (decide passenger waiting and walking before dispatch) with dynamic pricing	Simulation using Uber data in San Francisco. Mitigate price variability and increase capacity utilization, trip throughput, and welfare
	Simonetto et al. (2019)	Minimize a general cost such as detour cost	Linear programming with fleet reactive rebalancing and insertion cost given by dial-a-ride heuristic	Simulation using NYC taxi data and Melbourne metropolitan dataset. Similar service level as state-of-the-art algorithm but faster computation

fleet size, and Santi et al. (2014) a 40% reduction in cumulative trip length in a ridesplitting situation, using taxi trip data from NYC.

One way to guide empty vehicles is to provide historical and/or real-time demand information to drivers. In the context of taxi guidance, Powell et al. (2011) study a so-called spatio-temporal profitability (STP) map to guide cruising taxicabs. They claim that the STP map is useful in guiding for better profitability by showing a positive correlation between the cruising profitability score based on the STP map and the actual profitability of taxicab drivers by experiments using Shanghai taxi data. In the context of ridesourcing systems, Lu et al. (2018) study the short-run effect of displaying a surge pricing heat map to Uber drivers. Using a natural experiment and difference-in-difference approach, they find that the ability to see a surge pricing heat map has a statistically significant impact on drivers' decisions to relocate and their revenue: The heat map explains 10%–60% of Uber drivers' self-positioning decisions and increases drivers' revenue on surged trips by up to 70%. Afeche et al. (2018) study the interplay between passenger admission control and driver repositioning using a steady-state fluid network model and argue that it may be optimal to reject demand at the low-demand location strategically, even though there is an excess of drivers, to induce repositioning to the high-demand location. They evaluate performance in this context and show that the benefits may be more significant when capacity is moderate and when cross-location demand imbalance is significant.

In addition to demand information display, platforms can provide direct guidance and relocation suggestions to idle drivers. Godfrey and Powell (2002a, 2002b) propose an adaptive dynamic programming algorithm for dynamic fleet management with single-period and multi-period travel times, which is valuable for fleet guidance and repositioning in ridesourcing systems. Recently a literature on optimization models and algorithms for empty vehicle routing and repositioning for both taxi and ridesourcing systems has arisen; see Braverman et al. (2016), Zhang and Pavone (2016), Wallar et al. (2018), Iglesias et al. (2018), Iglesias et al. (2019), and Yu et al. (2019b); machine learning techniques, particularly reinforcement learning algorithms, have been applied, such as Wen et al. (2017), Gao et al. (2018), and Lin et al. (2018). These studies have been conducted with diverse assumptions and different objectives, such as minimizing the imbalance between supply and demand, minimizing the number of rebalancing vehicles, minimizing fleet size, maximizing the number of served requests, and maximizing driver and system profit. As in Section 5.2, we use Table 4 to summarize the objectives, methodologies and approaches, and instance performance for these papers.

For future research directions, operations related to empty vehicle guidance and repositioning could be more easily integrated with other operational strategies and decisions, such as matching and order dispatching, ridesplitting assignment, information sharing, monetary tools such as pricing and wage incentives, and parking provision to vacant ridesourcing vehicles (e.g., Xu et al., 2017). The efficient operation of empty vehicles is critical—and even essential—for transportation services that will use emerging autonomous fleets with driverless vehicles, which are expected to be available for use by both industry companies and the general public in the next few decades.

5.5. Information sharing and disclosure

The centralized planners and operators of ridesourcing systems employ historical and real-time information from both passengers and drivers to connect demand and supply better. The availability of information for platform operators raises two questions: (1) How much information about passengers should be displayed to drivers, and vice versa; and (2) how the privacy of passengers and drivers can be protected given necessary information sharing and disclosure.

What information should be collected and how it should be revealed to users are critical choices for system efficiency and user experience. Different platforms use diverse practices in different regions. Some studies examine information-reveal mechanisms and their impacts on ridesourcing platforms. For example, Rosenblat and Stark (2016) describe Uber drivers' "blind passenger acceptance and minimum fare" in some cities; i.e., drivers are not shown destination or fare information before they accept a ride. On one hand, hiding the destination before a driver chooses to accept or decline a ride request can potentially prevent destination-based discrimination; on the other, it can also foster reduced wages for drivers. Romanyuk (2017) develops a model for information intermediation faced by a generic platform to connect buyers and sellers. The author shows that full information disclosure is inefficient because of potential excessive rejection by sellers: a simple policy with partial disclosure to restore full efficiency when the platform observes the sellers' preferences, and a disclosure policy to maximize total surplus when sellers' preferences are unknown to the platform. Romanyuk also develops an approach to solve the information disclosure problem with heterogeneous and forward-looking sellers. Chu et al. (2018) study ridesourcing platforms that broadcast passenger request's origin and destination to idle drivers, who accept or ignore the request depending on the profitability considerations. They show that providing such information may reduce drivers' equilibrium profit, hence information provision is a double-edged sword: the drivers may choose to take more profitable requests via "strategic idling". They also show that routing more profitable requests to drivers according to the "shortest idle server first" policy while routing less profitable requests according to either the "random routing" policy or the "longest idle server first" policy can align the incentives and achieve the first-best outcome for the systems. Yaraghi and Ravi (2017) note that more information shared can lead to greater trust between users, but it can also lead to racial and gender biases. Lingenbrink and Iyer (2018) formulate an infinite linear program to study optimal information sharing in an unobservable single-server queue offering service at a fixed price to a Poisson arrival of delay-sensitive customers. They show that the optimal signaling mechanism requires the service provider to conceal information strategically in order to incentivize customers to join, and a binary signaling mechanism with a threshold structure is optimal. Romanyuk and Smolin (2019)

Table 4
Summary of some papers on empty vehicle guidance and repositioning.

	Literature	Objective	Methodology and approach	Instance performance
Empty vehicle guidance and repositioning	Godfrey and Powell (2002a, 2002b)	Maximize expected profits over finite horizon	Adaptive dynamic programming algorithm with nonlinear value functional approximations	Simulation using deterministic and stochastic synthetic instances. Produce high-quality solutions quickly
	Braverman et al. (2016)	Maximize a systemwide utility function	A fluid-based optimization problem on a queueing network. An optimal routing policy with an upper bound	Simulation using Didi data. Show benefits of fluid-based optimal routing policy compared to various other policies
	Zhang and Pavone (2016)	Minimize the number of rebalancing vehicles	A linear optimization program model on a closed Jackson network with passenger loss	Simulation using NYC taxi data. Meet current demand in Manhattan using 8000 vehicles (i.e., 60% of current fleet)
	Wen et al. (2017)	Maximize the expected number of served requests considering rebalancing cost	A reinforcement learning approach that adopts a deep Q network	Simulation using data in London. Outperform local anticipatory method by reducing 14% fleet size with little extra vehicle distance
	Gao et al. (2018)	Maximize total profit of a cabdriver in a working day	Markov decision process for the whole taxi driving sequence with Q learning algorithm	Simulation using Beijing taxi data. Improve profits and efficiency for drivers and increase opportunities for passenger to find taxi
	Lin et al. (2018)	Maximize gross merchandise volume of the platform	Deep reinforcement learning with two algorithms: contextual deep Q-learning and contextual multi-agent actor-critic	Simulation using Didi data in Chengdu. Outperform state-of-the-art approaches
	Wallar et al. (2018)	Maximize the number of requests that vehicles are able to serve	Integer linear program on discretized regions with demand estimation from an inhomogeneous Poisson process	Simulation using NYC taxi data. Serve 99.8% of requests using 3000 vehicles with significantly reduced waiting time and in-car delay
	Iglesias et al. (2018)	Minimize vehicle rebalancing, passenger waiting and dropping costs	Model predictive control algorithms that leverage short-term forecasts of customer demand from LSTM neural network	Simulation using Didi data. Outperform a state-of-the art algorithm with up to 89.6% reduction in mean customer waiting time
	Iglesias et al. (2019)	Minimize the number of serving and rebalancing vehicles on the road	A closed multi-class BCMP queuing network. Linear programming for the infinite fleet size	Simulation using NYC taxi data. Asymptotically recover existing models based on network flow approximation
	Yu et al. (2019b)	Maximize long-term expected profit over working period	Markov Decision Process solved by value iteration algorithm utilizing parallelized matrix operations	Simulation using Shanghai taxi data. Improve average unit profit (by 23% and 8.4%) and occupancy rate (by 23.8% and 8.3%) over random walk and local hotspot heuristic

consider short-lived buyers who arrive on a platform over time and are randomly matched with sellers. The sellers stay on the platform and decide whether to accept incoming requests. They argue that if sellers are homogeneous, then coarse information policies can restore efficiency; if sellers are heterogeneous, then the optimal information disclosure policy depends on seller payoff functions.

The efficiency of sharing information also comes with concerns about privacy for users, such as location privacy. Some research examines offering privacy-preserving ridesourcing services, which are particularly important in peer-to-peer ridesharing hitch services. For example, Rigby et al. (2013) discuss a dynamic, intuitive interface technique called "launch pads" and a centralized system architecture, which together simplify the ride-matching process while preserving location privacy. Aïvodji et al. (2016) develop a privacy-preserving service to compute meeting points (i.e., pick-up and drop-off points) such that each user remains in control of his location data. They propose a decentralized architecture providing strong security and privacy guarantees and integrate privacy-enhancing technologies and multimodal shortest path algorithms to compute mutually interesting meeting points for both drivers and passengers privately. Experiments demonstrate that the privacy-preserving approach does not impact the quality of solutions significantly and provides lower running time as an additional benefit. Hallgren et al. (2017) develop secure multi-party computation techniques for endpoint and trajectory matching, establish formal privacy guarantees and investigate how different riding patterns affect the privacy, utility, and performance trade-offs between approaches based on the proximity of endpoints or the proximity of trajectories. They show the effectiveness of this approach using real data from the NYC Taxi and Limousine Commission. For future research, we anticipate more empirical evidence on and theoretical models of passenger and driver behavior—in terms of user reaction and privacy and system performance and efficiency—under different information-sharing mechanisms in different options for ridesourcing services.

5.6. Rating mechanism

Ratings, of both drivers and passengers, is an innovative feature and function in ridesourcing systems. The rise of ridesourcing systems has led to a previously unrated transportation service being rated, providing measure of quality of service. To some extent, realization of transportation services on ridesourcing platforms and interactions between passengers and drivers rely on trust and endorsement from the platforms, while the rating system helps to digitize "word of mouth" by aggregating information from both passengers and drivers and serves as an endorsement from the platform. Long before the arrival of ridesourcing systems, some work in the literature discuss the promise and challenges of general online feedback systems (e.g., see Dellarocas, 2003). In the ridesourcing systems, ratings influence the behavior of both passengers and drivers; they also, in some cases, play a key role in the priority of order dispatching and even whether drivers can work on the platform.

The wide use of ratings by ridesourcing platforms offer significant value and benefits. For example, Thierer et al. (2015) argue that the sharing economy, through the use of the Internet and real-time reputational feedback mechanisms, is providing a solution to the "lemons problem" that many regulators have spent decades attempting to overcome. The lemons problem refers to the situation in which high-quality service providers leave a market because potential buyers are unable to assess the quality of service, and consequently depressing the average quality of service in the market. The rating system on ridesourcing platforms essentially provides more information about the quality of the product (i.e., ride service), and hence helps to mitigate or even solve the lemons problem. Rosenblat and Stark (2016) argue that by rating drivers, passengers are empowered to act as middle managers over drivers, whose ratings impact their employment eligibility directly. This redistribution of managerial oversight and power away from formalized middle management and toward passengers is part of a broader trend in the flexible labor market: Platforms can create expectations about their service that drivers must fulfill through the mediating power of the rating system. Jin et al. (2018a) study bilateral rating systems (BRS) on sharing economy platforms in which service providers and customers rate each other, and compare BRS with the unilateral rating systems (URS). They argue that BRS facilitates supply-demand balancing and can improve the average quality of passengers that drivers encounter, while the impacts on the average quality of drivers that passengers may face depend on passengers' valuation of the service. They also find that BRS always improves drivers' welfare but may reduce the platform's revenue. Since drivers' ability to reject low rating passengers in BRS can help remove excess demand and hence alleviate the demand-supply imbalance issue, the passengers' welfare may also be improved.

Despite these benefits, rating systems may also encounter problems, such as inflated, unfair, or biased ratings, and hence can cause unexpected outcomes. For example, Filippas et al. (2018) show that the effectiveness of a rating system will deteriorate over time because of the inflation of ratings. They argue that raters (e.g., passengers) feel pressure to leave "above average" ratings for the rated sellers (e.g., drivers), which in turn pushes the average higher. This pressure stems from raters' desire not to harm the rated seller. As the potential to harm is what makes ratings effective, reputation systems, as currently designed, sow the seeds of their own irrelevance. Kapoor and Tucker (2017) use data from a ridesourcing platform in India and empirically evaluate the performance and consequence of reviews that are unfair or unrepresentative of the true quality provided. They find that if passengers experience a ride cancellation, they are more likely to blame the replacement driver unfairly; drivers are more likely to respond negatively to a bad rating, and subsequently receive bad ratings if they were blameless for the previous negative rating. They also show that these potentially unfair ratings can motivate drivers to leave the platform, suggesting a broader negative effect of unfair negative ratings on platform participation. In a different context of hotel ratings, Eslami et al. (2017) study how users discover and behave in response to a biased rating. They study whether, how, and in what ways users perceive and manage this bias. They also show that users' awareness of biased rating might motivate them to reverse-engineer the rating, correct the bias, and demonstrate broken trust. This study could be valuable in studying the impact of different rating mechanisms on ridesourcing platforms. Stemler (2017) argues that the platform might be relying on the collective bias of the crowd to its detriment, instead of relying on the wisdom of the crowd. Rosenblat et al. (2017) point out that a rating system may represent a potential avenue for employment discrimination. Specifically, they use the Uber platform as a case study to explore how bias may creep into evaluations of drivers through rating systems. While platforms are legally prohibited from making employment decisions based on protected characteristics of drivers, their reliance on potentially biased passenger ratings to make material determinations may nonetheless have a disparate impact on employment outcomes.

There are also some studies of the behavior of both drivers and passengers regarding rating systems. For example, using receipt data from Uber, Kooti et al. (2017) find that matching passengers and drivers influences ratings: passengers and drivers with smaller age differences result in higher ratings. In future, we anticipate more empirical findings and theoretical models, and also anticipate research and practices to reduce unexpected problems with rating systems. The combination of ratings with other operational strategies, such as order dispatching, information sharing, pricing, and incentives design warrant future exploration.

6. Competition, impacts, and regulations

The boom in the ridesourcing industry entails tough competition between multiple platforms. It is unsurprising that it has significant direct impacts on existing transportation services, but it has also introduced other societal and environmental impacts. As a pioneer in the general sharing economy, regulation of the ridesourcing market is critical and has attracted strong attention from industry players, users, scholars, and policy makers. In this section, we review research into platform competition in Section 6.1, the impacts and interactions of ridesourcing platforms on other transportation services in Section 6.2, other societal and environmental impacts in Section 6.3, and a brief discussion of regulations in Section 6.4.

6.1. Competition

Multiple ridesourcing platforms may exist and compete in a local market. They compete not only on the demand side for passengers, but also on the supply side for flexible self-scheduling drivers who may work for multiple platforms. For example, Didi and Uber were engaged in fierce competition in China until late 2016, and Grab and Uber did the same in Southeast Asia until mid-2018. As of mid-2019, Uber and Lyft compete in the US; Bolt and Uber in Europe; Grab and Go-Jek in Southeast Asia; Didi and Uber in Australia; Careem and Uber in the Middle East; Ola and Uber in India; and Cabify, 99 Taxi and Uber in Brazil. Some studies have compared platforms and/or provided case studies of platform performance in specific markets. For example, Jiang et al. (2018) compare Uber, Lyft, and conventional taxis with respect to several key market features (e.g., supply, demand, price, and waiting time) in San Francisco and NYC to investigate competitive dynamics, and find that transportation infrastructure and socioeconomic features have substantial effects on market features. Other case studies include Wirtz and Tang (2016) on Uber's development and growth, first in the US and then in China and the causes of its failure in China; and Täuscher and Kietzmann (2017) on some failed firms in the sharing economy in the US, Germany and India.

A rich strand of economics studies of competition between two-sided platforms includes the work of Rochet and Tirole (2003), Armstrong (2006), and Armstrong and Wright (2007). The recent surge in ridesourcing systems has attracted attention to driver/passenger multi-home behavior and corresponding platform competition. For example, Jeitschko and Tremblay (2019) consider two-sided markets in which consumers (e.g., passengers) and firms (e.g., drivers) endogenously determine whether they single-home (patronize only one platform), or multi-home (join competing platforms). They find that the standard competitive bottleneck allocation in which all consumers single-home and all firms multi-home is always an equilibirum, and allocations with a mix of multi-homing and single-homing on both sides of the market. They also find that lower prices coincide with multi-homing: agents find multi-homing more attractive when faced with lower prices. Bryan and Gans (2019) examine competition between ridesourcing platforms in which platforms compete on both price and the waiting time induced with idled drivers. They show that when passengers are the only agents who multi-home, idleness is lower in duopoly compared with the case in which passengers face a monopoly ridesourcing platform. When drivers and passengers multi-home, idleness falls further to zero as it involves costs for each platform that is appropriated, in part, by their rival. Belleflamme and Peitz (2019) explore the allocative effects of change from single- to multi-homing. They argue that it is not always true that multi-homing hurts the side that can multi-home while benefiting the other side, as either the opposite may happen or both sides may benefit.

Much work focuses on platform competition. For example, Zha et al. (2016) argue that under the first-best scenario, profits for the platform and drivers will be negative if the matching function exhibits increasing returns to scale and the cost function of the platform shows economies of scale; the second-best scenario may be achieved by regulating the commission charged by the platform alone under some conditions; and competition does not necessarily lower the price level or improve social welfare. Cohen and Zhang (2017) study the setting in which two-sided platforms choose their prices and wages simultaneously to compete for both sides of the market, and show that a unique equilibrium exists and can be obtained using a tatonnement scheme. They explore the impact of "coopetition" between two-sided platforms—i.e., the business strategy of cooperating with competitors—and analyze the outcome if competing platforms engage in a profit-sharing contract by introducing a new joint service. The authors find that a well-designed profit-sharing contract will benefit every party in the market, including passengers, drivers, and both platforms. Fang et al. (2018) study platform competition with driver loyalty programs and show that the degree of driver heterogeneity is a crucial factor for both loyalty programs and pricing strategies. Séjourné et al. (2018) quantify how much platform fragmentation degrades the efficiency of the system. They study the increase in the supply rebalancing cost in a setting where demand is exogenously split between multiple platforms. They show, under a large-market scaling, that the additional cost due to fragmentation either vanishes or grows unboundedly depending on the nature of the exogenous demand.

For future research, more empirical analysis of platform competition from diverse perspectives would be highly worthwhile, because of the difficulty of accessing real data from multiple competing platforms. We also expect future work on platform competition with collaboration under different market conditions and regulations.

6.2. Impacts on other transportation services

It is not surprising that the emergence and popularity of ridesourcing systems has had large direct impacts on existing transportation services. A rich strand of literature discusses the impacts and interactions of ridesourcing platforms on public transportation services, especially as potential substitutes for and/or complements to public transit. In ongoing debates, the literature offers widely differing results that depend on specific assumptions and contexts.

Some work illustrates ridesourcing systems complementing public transit. For example, Zhang and Zhang (2018) examine the relationship between the frequency and probability of ridesourcing use and the frequency of public transit use in the US utilizing individual-level travel frequency data from the 2017 National Household Travel Survey. They show that, in general, a one-unit increase in public transit use is significantly positively related to a 1.2% increase in the monthly frequency of using ridesourcing services and a 5.7% increase in the probability of using ridesourcing services. Additionally, the positive relationship between ridesourcing services and public transit use is more pronounced for people who live in areas with high population density or in households with fewer vehicles. Differentiating short- and long-distance public transit trips, Babar and Burtch (2017) evaluate the effects of ridesourcing service entry on the use of public transit over the subsequent 12 months by constructing a difference-in-difference model using agency-level data. They find that Uber substitutes for road-based short-distance public transit trips, which is evidenced by a 1.05% decrease in the use of city buses over the 12 months following Uber's entry. They also find that Uber complements rail-based long-distance public transit trips; Uber's entry is related to a 2.59% increase in the use of subways and a 7.24% increase in the use of commuter rails over the subsequent 12 months.

Some work studies the substitutions of public transit by ridesourcing systems. For example, in the case of NYC, Schaller (2017) finds that growth in ridesourcing ridership accelerated at the same time as subway and bus ridership began to decline. The mileage added to city streets by ridesourcing is more than the total yellow cab mileage in Manhattan in 2016. Hoffmann et al. (2016) mention that ridesourcing and subway usage are positively correlated on the surface in data from NYC; however, expoiting a series of exogenous shocks to the system—the closing of subway stations—they suggest that the average shock results in an increase of over 30% in the use of ridesourcing services, indicating the potential for crowd-based systems to serve as infrastructure that helps smooth unexpected supply and demand surges. Using survey results for San Francisco, Rayle et al. (2016) find that while ridesourcing replaces taxi trips, at least half of the ridesourcing trips replaced modes other than taxi, including public transit and driving. Using the Transit app and Uber data in NYC and assuming users who request Uber through the Transit app are signaling their intent to try transit first—but are willing to move on to other modes when transit does not meet their needs—Davidson et al. (2017) find that Transit app users request Uber at a higher rate, both within 250 feet of a public transit station and with greater dispersion across the entire city than the general population of Uber ride-hails, which suggests that Transit app users attempt to use Uber to make up for gaps in their transit options. Hampshire et al. (2018) use Uber and Lyft service suspension in Austin as a natural experiment to measure the impact of the suspension of ridesourcing on travel behavior. The results reveal that of the population surveyed, 42% of respondents who had used Uber or Lyft prior to the suspension transitioned to another platform after suspension, 41% transitioned to a personal vehicle, 3% transitioned to public transit, and 9% purchased an additional vehicle in response to the service suspension.

There is a growing body of literature on the comparisons between ridesourcing platforms and conventional taxis. For example, using survey data from San Francisco, Rayle et al. (2014) find that ridesourcing waiting times are markedly shorter and more consistent than those of taxis, while ridesourcing users tend to be younger, own fewer vehicles, and travel more frequently with companions. Cramer and Krueger (2016) show, using data from five cities in the US, that drivers for UberX service have captured a higher capacity utilization rate than taxi drivers, which can be explained by four factors: (i) the platform's efficient matching technology, (ii) the platform's larger scale, (iii) inefficient taxi regulations, and (iv) the platform's flexible labor model and surge pricing.

Ridesourcing platforms have especially large impacts on conventional taxi services, and much of the literature focuses on the impacts. For example, Wallsten (2015) explores a dataset from the NYC Taxi and Limousine Commission, taxi consumer complaints from NYC and Chicago, and information from Google Trends on the popularity of Uber. The author finds that Uber's increasing popularity is associated with a decline in consumer complaints per trip about taxis in NYC. In Chicago, Uber's growth is associated with a decline in particular types of complaints about taxis, including broken credit card machines, air conditioning and heating, rudeness, and talking on cell phones. The author provides evidence that Uber has created an alternative for consumers who would otherwise have complained to the regulator and encouraged taxis to improve their own service in response to the new competition. Alley (2016) studies the impact of Uber on the taxi industry in NYC and argues that the price of taxicab medallions has declined precipitously since the arrival of Uber in the city by a factor of approximately 30% in three years. Harding et al. (2016) argue that the ridesourcing platforms solve the credence goods and thin market problems for the taxi industry and largely mitigate the problem related to open access, but they also bring potential problems such as instability of supply and demand, collusion and monopoly. Nie (2017) studies the impacts of ridesourcing platforms on the conventional taxi industry using taxi GPS trajectory data in Shenzhen, China. The author finds that (i) ridesourcing platforms cause significant loss in the ridership of taxis; (ii) taxis compete more effectively with ridesourcing in peak periods and in areas with high population density; (iii) e-hailing platforms help lift the capacity utilization rate of taxis; and (iv) ridesourcing platforms worsen congestion for taxis in the city, but the impact is relatively mild. From an inverse perspective, Murphy (2016) suggests some ways that public transit can learn from, build on, and interface with new transportation services, including ridesourcing services, based on in-depth interviews with transportation officials, a survey of shared mobility users, and analysis of transit and ridesourcing capacity and demand.

In the future, creating positive synergies between ridesourcing services and other transportation and urban services—with the aim of making the entire transportation and urban system more efficient—will introduce many promising and important research questions. Examples include integrating the design of ridesourcing and fixed-route transit systems (e.g., zone-based and line-based ridesourcing e-hailing services along a fixed-route transit line as in Chen and Nie, 2017), schedule and route optimization of public transit (e.g., buses and metro) while considering ridesourcing's complementary and feeding effects (e.g., last-mile and first-mile services as in Wang and Odoni, 2014; Wang, 2017), and the integrated design and operation of ridesourcing systems with other urban services, such as food delivery and urban freight logistics.

6.3. Societal and environmental impacts

Ridesourcing systems also have impacts in a much broader societal context. Some studies discuss these impacts from an environmental perspective, such as the effects on car ownership, energy and fuel consumption, air pollutant emissions, and traffic congestion. In particular, private car ownership in the presence of emerging ridesourcing services has attracted strong attention from researchers, but has reached no conclusions. While sharing mobility is assumed to reduce private car ownership on the surface, Anderson (2014) raises the concern that ridesourcing can serve as a prop for private car ownership because some drivers use their ridesourcing income to support their own use of a private vehicle or even to purchase a vehicle. Based on survey results for San Francisco, Rayle et al. (2016) find that the presence of ridesourcing might not affect car ownership behavior; Clewlow and Mishra (2017) find that 91% of ridesourcing users did not make any changes to car ownership in survey results for seven major cities in the US.

Some research finds evidence of positive environmental impacts of ridesourcing systems using specific datasets. For example, using data from Didi in the case of Beijing, Yu et al. (2017) argue that ridesourcing systems yield substantial energy savings and air pollutant emission reductions from the long-term perspective attributing to the weakening willingness on purchasing new cars. Li et al. (2016) investigate Uber's effects on traffic congestion and the environment (e.g., carbon emissions) in urban areas of the United States using data from Uber and the Urban Mobility Report. Specifically, they examine how the entry of Uber affects traffic congestion using a difference-in-difference framework and provide empirical evidence that ridesourcing services significantly decrease traffic congestion. Zheng et al. (2019) analyze ridesplitting data from Didi in the case of Hangzhou and argue that ridesplitting can reduce vehicles on road. Alexander and González (2015) propose a method to assess the impacts of ridesourcing services on urban traffic and congestion using mobile phone data. They extract average daily trips from mobile phone records and estimate the proportions of these trips made by auto and non-auto travelers. They match similar trips spatially and temporally and assume a range of adoption rates for auto and non-auto users to distill vehicle trips on ridesourcing platforms. Using data from Boston, they estimate a reduction in vehicles if non-auto users' adoption rate is less than about three times auto users' adoption rate.

On the other hand, some research finds evidence of more neutral and/or negative environmental impacts from ridesourcing systems. For example, Anderson (2014) argues that due to the relative lack of regulatory oversight of vehicle standards and quantity, ridesourcing could prove less ecologically desirable than conventional taxis: In San Francisco, for example, nearly 100% of the conventional taxi fleet is composed of recent-model "clean air" vehicles, while only 17% of ridesourcing vehicles dropping passengers at the airport are clean air vehicles estimated by San Francisco Police Department. They also raise the concern that ridesourcing services could increase congestion by drawing more drivers into the city and increase vehicle-miles-traveled by drivers deadheading long distances to and from work. Using survey data collected in San Francisco, Rayle et al. (2016) find that 8% of ridesourcing trips were induced travel, which is not an insignificant amount in terms of causing more congestion and emissions. Schaller (2017) argues that a continuation of ridesourcing-led growth in travel is not a sustainable way to grow the city. Adding ridesourcing mileage to already congested streets will lead to mounting costs for businesses and consumers from increasing traffic delays and hinder progress toward goals for mobility, economic growth, and environmental improvement. Jin et al. (2018b) argue that the impact of ridesourcing systems on traffic congestion near city centers is still unclear. Even though ridesourcing has promoted a green image, its true environmental impact has not been investigated thoroughly and its impact on energy consumption and greenhouse gas emissions are still uncertain.

An emerging literature studies societal impacts on other areas from diverse perspectives. For example, Rogers (2015) argues that a platform's partial consolidation of the car-hire sector and its compilation of data on passenger and driver behavior may enable both platform and regulators to ensure safety and root out discrimination against passengers with relative ease; while other work such as Ge et al. (2016) point out some discriminatory behavior and unequal treatment of passengers by drivers. Greenwood and Wattal (2015) find that the entry of Uber services into markets in California between 2009 and 2014 brought a significant drop in the rate of vehicle homicides using a difference-in-difference approach to exploit the natural experiment. Zhang and Li (2017) use a quasi-experiment to estimate the impact of ridesourcing services on urban consumer patterns. They identify an associated increase in the frequency and total amount spent on local food/drink businesses from Uber/Lyft entry and its strong relationship with Uber/Lyft usage intensity, but no notable increase in the amount spent per food or drink transaction. Burtch et al. (2018) examine how the entry of gig-economy platforms influences local entrepreneurial activity. On the one hand, such platforms may reduce entrepreneurial activity by offering stable employment for the unemployed and underemployed; on the other, such platforms may enable entrepreneurial activity by offering work flexibility that allows the entrepreneur to redeploy resources strategically in order to pursue the nascent venture. Results indicate a negative and significant relationship between Uber's entry and two measures of entrepreneurial activity: crowdfunding campaign launches at Kickstarter and levels of self-employment. Results also suggest that gig-economy platforms predominantly reduce lower quality entrepreneurial activity, seemingly by offering viable employment for the unemployed and underemployed. In the future, we expect more empirical research that explores the impacts of ridesourcing systems from diverse perspectives, such as safety, privacy, employment, and the social ties of users.

6.4. Regulations

Conventional legacy taxis in most cities are heavily regulated. These regulations often govern who can operate a taxicab, in which areas they can operate (e.g., King and Saldarriaga, 2018, estimate that up to 500,000 km per week of deadhead travel are associated with restrictions on pick-up locations for taxis in NYC), and how much they can charge for their services. In contrast, most drivers working on ridesourcing platforms do not need a certificate or license for commercial ride services; i.e., they operate personally owned or leased vehicles for a commercial purpose in legal gray areas. They can choose when and where to work, and the fare charged can be adjusted dynamically. In addition, ridesourcing services are not yet subject to taxes in some countries, which essentially confers advantages on ridesourcing platforms over legacy taxi service providers, who claim that these platforms open the door to unfair competition. In addition, the unclear regulation also raises concerns about user privacy, public safety, and the limited liability of ridesourcing platforms. One can refer to Malhotra and Van Alstyne (2014) for a discussion of so-called "dark side" of the sharing economy.

In practice, regulators behave differently across countries. Shaheen et al. (2016) and Cohen and Shaheen (2018) provide detailed reports for current practices of shared mobility in the US. Other reports and cases include Wahyuningtyas (2016) on Indonesia, Dudley et al. (2017) on London, Defossez (2017) on Brazil and the European Union, de Souza Silva et al. (2018) on Brazil, Li et al. (2018) on Singapore, and Puche (2019) on Mexico City and Bogota. In fact, regulating ridesourcing platforms triggers a dilemma, as Ranchordás (2015) points out: On the one hand, innovation in the sharing economy should not be stifled by excessive and outdated regulation; on the other hand, there is a real need to protect the users of these services from fraud, liability, and unskilled service providers. The author suggests that innovation in the sharing economy requires fewer, but broader, rules that do not stifle innovation, but also impose a minimum of legal requirements that take into account the specificities of innovative sharing economy practices. Rogers (2015) argues that Uber's success stems not just from regulatory arbitrage or other malfeasance, but from having created a far more efficient market for car-hire services. Yu et al. (2019a) evaluate the regulation of ridesourcing platforms in China using a two-period dynamic game that incorporates various competing goals and argue that without government intervention, the ridesourcing platform can drive conventional taxis industry out of the market under some conditions. They also find that a carefully designed regulatory policy can strike a better balance of multiple competing objectives. Aarhaug and Olsen (2018) point out that as market segments differ and shift in relative importance, possible and suitable forms of regulation for ridesourcing markets should change in comparison with conventional markets. A report from the International Transport Forum (see ITF, 2016) argues that regulation should focus on the needs of passengers and society, be kept as simple and uniform as possible, encourage innovative and more flexible regulation, and embrace data-led regulation. Rauch and Schleicher (2015) offer three predictions of the approaches governments will take toward the sharing economy in the medium-term future: Cities will (i) subsidize sharing firms to motivate them to enter or expand certain services; (ii) harness sharing firms for economic redistribution; and (iii) hire sharing firms as contractors to provide city services.

A growing literature on law and public policy discusses the regulation of business in a sharing economy. For example, Edelman and Geradin (2015) suggest a need to adapt laws and regulations to allow ridesourcing platforms to operate legally, that platforms should comply with regulatory requirements that are necessary to correct genuine market failures, and that these requirements should remain in force. Katz (2015) argues that instead of forcing platforms to conform to the same rules as conventional taxi services, the government may loosen restrictions for conventional taxi services while increasing protection for passengers and drivers on ridesourcing platforms. Posen (2015) argues that the solution is not to force platforms to comply with outdated regulations; rather, regulators should rely on experimental regulations for safety, which will allow passengers to make their own choices regarding which service they would prefer to use while ensuring their safety. Harding et al. (2016) argue that instead of restricting the growth of the platforms, regulators should focus on reducing the likelihood of monopoly and collusion. In terms of the interests of the platform, Cannon and Summers (2014) list ways that platforms can increase their business better under regulations, such as sharing data and presenting a well-researched case for the value of the platform. Other discussions can be found in Koopman et al. (2014), Witt et al. (2015) and others.

A critical controversy for ridesourcing platforms is the driver's legal role—i.e., whether drivers are independent contractors, freelancers or platform employees. Conflicts arise when drivers allege that they are denied employment benefits, while platforms counter that they do not employ drivers but merely license access to a platform that matches those who need rides with available drivers. Means and Seiner (2015) argue that the classification of drivers as independent contractors or employees should be determined by an overarching inquiry: How much flexibility do individuals have in determining the time, place, price, manner, and frequency of the work they perform on the platform? Hagiu and Wright (2019) show that being too strict or too liberal in classifying drivers as independent contractors (relative to the actual degree of control drivers have) can be detrimental, not just to firms and welfare, but sometimes to the drivers themselves. They also explore the extent to which an intermediate classification of drivers between employees and independent contractors may lead to better outcomes. Other discussion of the employment relationship and classification can be found in Acevedo (2016) and Redfearn (2016).

The unclear legal role of drivers also gives rise to a critical problem regarding tax rules and enforcement in ridesourcing systems, which has attracted the attention of researchers in auditing and law. For example, Oei and Ring (2015) point out that tax enforcement and compliance regarding ridesourcing may present challenges arising from two features: First, the business opportunistically picks the more favourable regulatory interpretation if there is ambiguity regarding which rule applies or whether a rule applies. Second, the "microbusiness" nature of sharing raises unique compliance and enforcement concerns. Bruckner (2016) also points out that taxpayers working on on-demand platforms face potential exposure to audit and penalties for failure to comply with filing rules that are triggered by relatively low levels of earned income and inconsistent adoption of reporting rules. Oei and Ring (2016) investigate the tax issues and challenges faced by ridesourcing drivers by analyzing their interactions in internet discussion forums. They find that while forum participants generally displayed accurate understanding of tax filing and income inclusion obligations, their approaches to expenses and deductions were less accurate and more varied in sophistication and willingness to comply with tax law. Zoepf et al. (2018) study the fact that the drivers of Uber and Lyft are able to use a standard mileage deduction to account for vehicle expenses for tax purposes. The deduction was \$0.54/mile in 2016 in the US, which is substantially larger than the calculated costs of \$0.30/mile for the driver population in a survey of over 1100 drivers for Uber and Lyft. The authors find that 73.5% of an estimated U.S. market of \$4.8B in annual ridesourcing driver profit is untaxed if drivers are able to capitalize on their losses fully for tax purposes.

Another critical question is the safety of ridesourcing services. Feeney (2015) argues that the cash-free transactions and self-identified passengers on ridesourcing platforms substantially mitigates one of the worst risks associated with conventional taxis: violent crime. On another note, using U.S. county-level data from 2007 through 2015, Dills and Mulholland (2018) find a lower rate of DUI (i.e., driving under the influence) and fatal accidents and a decline in arrests for assault and disorderly conduct after Uber's entry; conversely, they observe an increase in vehicle thefts. In China, the Supreme Court published a comparison of crime cases between ridesourcing platforms and conventional taxi services (see Supreme Court of China, 2018, source in Chinese). The data in China show that the crime rate for ridesourcing platform drivers is much lower than for conventional taxi drivers. Specifically, the crime rate for ridesourcing platform drivers is 0.048 per 10,000 in 2017 in China, while the crime rate for conventional taxi drivers is 0.627 per 10,000. However, several serious criminal incidents in the peer-to-peer ridesharing services in various countries has raised huge concern from the general public regarding the safety of ridesourcing services.

With technological development and business innovation, ridesourcing systems will certainly continue to evolve. Regulating the ridesourcing industry in diverse cultures and environments, while considering the welfare of all stakeholders—i.e., passengers, independent freelance drivers, taxi drivers, ridesourcing platforms, legacy taxi companies, and the general public—will offer avenues for long-term research.

7. Summary

With the rapid development and popularization of mobile and wireless communication technologies, ridesourcing companies have been able to leverage internet-based platforms to operate e-hailing services in many cities around the world. These companies connect demand (i.e., passengers with travel requests) and supply (i.e., drivers providing transportation services) and are disruptively changing the transportation industry, and especially the conventional taxi industry. These shared transportation companies are often viewed as pioneers in a general sharing economy.

The ridesourcing platforms consist of a typical two-sided market, which is a meeting place for passengers and drivers who interact and provide each other with network benefits. Passengers and drivers are sensitive to the prices and wages of the service, which are critical decisions the platform makes to coordinate and balance demand and supply. On the demand side, passengers with temporal and spatial characteristics consider fare and service quality with alternative travel modes in making their travel decisions. On the supply side, drivers, as freelancers, make working decisions flexibly regarding whether to work on the platform—and if so, when and how long to work—in response to many variables and factors, including their income level from the platform by comparison with other job options. The objectives of ridesourcing systems exist in multiple dimensions and may change according to the specific developmental stage, market conditions, platform competition, and government regulations. Some common objectives include balancing demand and supply over time and space, maximizing platform revenue and profit, maximizing market share and penetration, and social welfare. To operate the transportation service and achieve these objectives, platforms must employ various operational strategies and make decisions from diverse perspectives. Designing and operating ridesourcing systems is vital—and challenging—for all stakeholders: passengers/users, drivers/service providers, platforms, policy makers, and the general public.

In this paper, we propose a general framework to describe ridesourcing systems, which illustrates the intrinsic relations between variables and factors for the relevant stakeholders, agents and attributes. In general, trip service quality, driver income level, passenger demand, and driver supply are strongly endogenous and interactively dependent, while the endogenous influences and interactions are highly dynamic. These variables are thus crucial factors influencing operational strategies and decisions and the resulting efficiency of the ridesourcing market. The framework can aid understanding of the interactions between endogenous and exogenous variables, their changes in response to platforms' operational strategies and decisions, multiple system objectives, and market equilibria in a dynamic manner.

We summarize important research problems concerning ridesourcing systems and the corresponding methodologies that have been and are being developed and implemented to address these problems. These methodologies, both classic and novel, include statistics and econometrics, labor economics, microeconomics, queuing theory and stochastic process, integer and combinatorial optimization, stochastic and dynamic programming, game theory and mechanism design, and machine learning techniques. We conduct a comprehensive review of the literature in different areas from diverse perspectives, including demand and pricing, supply and incentives, platform operations, and competition, impacts and regulations.

On the demand side, important research problems include (1) spatio-temporal demand estimation for ridesourcing systems, (2) passenger mode choice with other travel alternatives, (3) mechanisms and algorithms for static and dynamic pricing, and (4) other passenger promotions. On the supply side, important research problems include (1) driver supply models to describe short- and long-term platform service capacity, (2) driver supply elasticity with respect to wage and incentives, (3) other driver behavior, and (4) mechanisms and algorithms for static and dynamic wages and incentives. To operate platform services better and improve system performance and efficiency, research problems for operators include (1) estimated time of arrival (ETA) for both pick-up and ride trips; efficient operational strategies and algorithms for (2) order dispatching and matching between passengers and drivers, (3) ridesplitting operations related to assignment and fare splitting, and (4) guidance and repositioning of empty vehicles awaiting new passengers; and (5) information sharing and disclosure and (6) rating mechanism. Considering ridesourcing services as a part of a larger urban transportation system, research problems arise from (1) platform competition, (2) impacts on other transportation services, (3) societal and environmental impacts, and (4) relevant governmental regulations and policies.

The proposed framework and the review suggest many avenues requiring future research, such as the improvement of various components and their integration to form a more efficient ridesourcing system, and the system's integration with other urban and mobility services under a general sharing economy and smart city context. Ridesourcing systems are booming and still evolving. We expect more exciting research will emerge to improve and reshape both shared transportation, and the entire transportation and urban system to the benefit of all.

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