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COMMENTS

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The impact of ride-hailing in city transportation

Abstract This paper investigates the impact of ride-hailing services, particularly the integration of autonomous vehicles (AVs), on urban transportation systems. The paper discusses the challenges faced by ride-hailing platforms in managing a fleet of both AVs and conventional vehicles (CVs) within the spatial network of a city. It examines the approaches and methods used to manage demand allocation for AVs and CVs, considering the strategic behavior of human drivers and considerations for possible regulations. Using mean-field game theory, this paper proposes efficient strategies for managing fleet operations along with those of traffic optimization and service efficiency. The analysis highlights the complexities of integrating AVs into existing transportation systems and advocates for the development of robust theoretical traffic models for regulatory decisions and improved urban mobility.

Keywords ride-hailing, autonomous vehicles, conventional vehicles, strategic behavior, mean-field game

1 Introduction

In the past decade, personalized transportation services have begun a new era. Ride-hailing platforms (RHPs), such as DiDi in China and Uber and Lyft in the US have opened a new chapter in the sharing economy for transportation. In the foreseeable future, driverless autonomous vehicle platforms (AVPs) may subsume traditional taxi services. As increased competition and pressure from regulators continue within this sector, operational and economic efficiency will likely become core issues.

A major challenge facing the platform is managing a fleet of both autonomous vehicles (AVs) and conventional vehicles (CVs) over the spatial network of a city. The fact that AVs are owing to and run entirely by the RHP allows it to efficiently design optimal strategies for repositioning and routing these vehicles to meet demand in various areas and maximize profits. However, unlike AVs, human drivers of CVs pursue their own interests and thus independently decide when and where to reposition themselves in response to an order by the platform (Afèche et al., 2023). Different control mechanisms for the two types of vehicles pose a real challenge: making optimal decisions for the AVs, while assigning demand to CVs so that inefficiencies resulting from self-interested behaviors are reduced.

A key issue in this optimization problem of mixed fleets is forecasting the behavior of CVs. Human drivers engage in strategic interactions with each other, indicating such interaction leads toward some kind of equilibrium. Interactions revolve around differing waiting times for customer assignments among various areas. If there are a number of drives flocking in an area, the waiting time for customer assignments is prolonged due to the excess supply.

These longer waiting times, much like repositioning (driving empty to a different region after dropping off a consumer), reduce the average profit a driver earns per unit of time, since drivers are spending more time without earning. While no individual driver can influence the system-wide average waiting times, each driver optimizes his/her actions taking these times as given. However, the collective behavior of all drivers does impact the system, making a game-theoretic model appropriate for this scenario.

The CVs would eventually reach an equilibrium if the demand is invariable for a sufficiently long time. With longer repositioning time than waiting time, strategic CV

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drivers would tend to queue up in areas with high revenues rather than reposition to other areas with unserved demand, leading to inefficient social outcome and reduced revenue for the platform. The integration of AVs enables the RHP to reduce these losses by assigning part of the demand in high-revenue areas to AVs, where CVs typically queue. This decline in available demand for CVs leads to higher waiting times, thus motivating them to change location and serve demands in less profitable, remote areas. Alternatively, the high-profit demand does not need to be allocated to the AVs by the platform or for the AVs to serve remote regions. Although AVs do produce a higher profit in comparison with CVs, this could indeed be counterintuitive toward the approach of having a balanced system. This highlights the complexity and interdependence of managing both AVs and CVs.

2 Related literature

The existing studies can be categorized into two primary fields: (i) optimizing the repositioning, matching, and pricing of conventional RHPs that exclusively utilize CVs, and (ii) RHPs that integrate AVs.

The first category centers on traditional vehicles. Previous research has highlighted the issue of empty vehicle repositioning in spatial networks. Specifically, Afèche et al. (2023) employed a steady-state fluid model to examine the strategic choices made by drivers of CVs; however, their analysis is confined to a two-region network and does not incorporate AVs. In the work by Braverman et al. (2019), a fluid model was proposed to analyze the repositioning strategies of centrally controlled CVs. Their findings indicate that, irrespective of the routing policy, the optimal utility derived from their model serves as an upper limit when the number of vehicles is restricted. Benjaafar et al. (2022) proposed a closed queuing network to model CV systems, assuming that customer demand follows a Poisson process, and provided precise upper and lower bounds for the minimum number of CVs required to achieve a specified service level. Furthermore, Candogan and Wu (2023) explored how platforms can leverage system state information to influence repositioning decisions, thereby enhancing commission revenues within the broader context of spatial resource allocation.

The second category of studies explores RHPs that integrate AVs. Most of the research focuses on assessing the impact of AVs on the payoffs for RHPs, CV drivers, and consumers (Lian and van Ryzin, 2023; Freund et al., 2022; Siddiq and Taylor, 2022; Castro and Frazelle, 2024; Wigand et al., 2020). In their study, Lian et al. (2023) examined the economic impacts of AVs across varying demand scenarios. Freund et al. (2022) analyzed how platforms determine wages for human drivers and establish AV fleet sizes. Siddiq and Taylor (2022) nvestigated the effects of AVs on the payoffs for RHPs, CV drivers, and social welfare through a game-theoretic framework. However, these studies largely overlook the spatial dynamics of vehicles and consumer demand within the systems.

Another relevant area in this context is mean-field games, which examine the interactions among a large number of strategic participants (Huang et al., 2006; Lasry and Lions, 2007). Courcoubetis and Dimakis (2023) analyzed equilibria in mean-field games and provided a solution method to characterize the CV equilibrium.

3 Navigating the challenges of mixed fleets: Balancing autonomous and conventional ride-hailing vehicles

In the near future, advancements in AV technology and its widespread implementation are poised to significantly transform the transportation landscape. This shift promises to enhance mobility, making transportation more accessible and efficient. However, it also presents significant challenges for RHPs and is likely to have notable repercussions on traffic patterns.

As AVs become increasingly prevalent, ridesharing services may need to adapt their business models to accommodate fleets of self-driving cars. This shift could result in heightened competition, as traditional rideshare drivers may experience job displacement. Platforms will need to reassess their strategies, including fleet management and maintenance for AVs, optimization of routes, and ensuring passenger safety in this new technological context. Furthermore, the introduction of AVs could lead to changes in traffic behavior. While these vehicles have the potential to reduce congestion by improving traffic flow and minimizing human errors, they could also contribute to increased traffic if deployed in large numbers without appropriate regulatory frameworks. The integration of these vehicles into existing transportation systems must be carefully managed to avoid unintended consequences on urban mobility, such as increased travel times or alterations in public transit usage. We will further detail the three key challenges.

First, a significant challenge for RHPs is the effective management of a mixed fleet comprising both autonomous and CVs within a city's road network. Since the AVs are fully owned and controlled by the platform, the operator can easily develop an optimal strategy for repositioning and routing empty AVs to meet demand across various areas and maximize profit. In contrast, human drivers make independent, self-interested decisions regarding when and where to reposition their vehicles and whether to continue working for the platform (as noted by Afèche et al., 2023). This difference in control between the two vehicle types presents a practical challenge: the platform must devise an optimal strategy for the AVs while also appropriately allocating demand to CVs to address the inefficiencies caused by the self-serving behavior of human drivers.

Furthermore, due to regulatory pressures concerning passenger safety, platforms that deploy AVs have recently proposed a new ‘hybrid’ mode: employing a pool of human operators, referred to as ‘virtual drivers,’ who remotely supervise the vehicle while it transports a passenger or navigates through accident-prone areas. The AV can operate unsupervised at other times. This suggests new constraints on the platform’s operations: if all virtual drivers from the pool are occupied, no new passengers can be accommodated. Additionally, virtual drivers may act strategically, selecting which rides to supervise or continuing to operate vehicles to ensure they receive priority in serving customers.

Second, a significant challenge in achieving efficiency in RHPs—both operationally and economically—lies in the dynamic matching of demand (the passengers) with supply (the drivers), particularly during short-term, unpredictable fluctuations. Successfully navigating these variations is vital, necessitating sophisticated algorithms and strategies that can swiftly adapt to changing conditions to optimize rider satisfaction and driver utilization. The RHP needs effective algorithms to determine the following:

(1) Assignment of passengers to cars. Once a customer submits a ride request, the platform must decide which car will provide the service. Travel delay until pickup plays a crucial role in this decision, and a matching algorithm must effectively balance minimizing pickup delay with overall optimality (McCurry, 2018).

(2) Platform Pricing Policy. The platform establishes ride fees based on various factors, including pickup and destination locations, time of day, and other variables. Critically, during periods of high passenger demand in regions with insufficient vehicle availability, ride fees are increased, reflecting the level of demand excess. This dynamic pricing model, known as surge pricing in Uber and Prime Time in Lyft, is commonly utilized to temporarily discourage additional ride requests while simultaneously attracting more drivers to areas experiencing surges.

(3) Car Mobility. In RHPs, drivers often mobilize without transporting passengers, aiming to maximize their individual earnings. This strategy involves relocating to areas with a higher likelihood of receiving well-compensated ride assignments from the platform. In the case of AVs, which are owned by the platform, mobility is optimized through central management by the platform.

The range of vehicle types includes CVs, electric vehicles (EVs), AVs, and hybrid autonomous vehicles (HAVs), each presenting distinct operational considerations for the platform. Notably, while EVs and HAVs require charging at designated locations, CVs and EVs are driven by self-optimizing individuals, whereas AVs operate entirely under platform control, and HAVs follow a hybrid model. Consequently, the integration of various vehicle types has significant operational implications for RHPs and the resulting traffic patterns.

Finally, the coexistence of a mixed fleet consisting of AVs, CVs, and HAVs poses considerable challenges to transportation authority regulations, particularly concerning traffic management. This complex integration necessitates that regulators address a range of issues that may affect traffic flow, safety, and overall transportation efficiency. For example, the operational dynamics of AVs—capable of communicating and making decisions independently—differ markedly from those of manually operated CVs. This discrepancy can result in unpredictable traffic behavior, as AVs and HAVs may interact with their environment in ways that are not characteristic of human-driven vehicles.

Additionally, the varying levels of automation among these vehicles can lead to inconsistencies in their responses to traffic signals, adaptation to shifting road conditions, and navigation around obstacles, potentially exacerbating congestion and heightening accident risks. Therefore, it is crucial for transportation authorities to formulate regulations that promote seamless communication among all vehicle types, fostering coherent traffic flow that optimizes efficiency while prioritizing safety.

Ultimately, to effectively manage a diverse range of vehicle types, transportation authorities must confront the challenge of developing a robust theoretical traffic model. Relying solely on existing data and past experiences proves insufficient. Instead, authorities need to construct a comprehensive model that integrates various theoretical perspectives and innovative methodologies. This holistic approach should incorporate principles from traffic engineering, urban planning, game theory, and behavioral science to gain a deeper understanding of the complexities of traffic flow and the interactions among different vehicle categories. By doing so, authorities can create predictive tools that enhance decision-making, improve traffic management strategies, and ultimately foster safer and more efficient transportation systems.

4 Approaches and strategies for optimizing ride-hailing platforms in urban transportation

In light of the challenges faced by RHPs in integrating a mixed fleet of conventional and AVs, it is pertinent to build upon the framework of mean-field games. Mean-field games are particularly effective in modeling scenarios where numerous agents—such as drivers in a ride-hailing context —compete for shared resources. As shown in Fig. 1, this research aims to apply this theoretical framework to enhance understanding of the dynamics and interactions within a large population of vehicles and drivers, thereby enabling the development of more efficient strategies for managing both conventional and autonomous fleet operations. This approach will address issues related to resource allocation, traffic optimization, and overall service efficiency in urban transportation systems.

First, it is essential to consider the strategic behavior of drivers on RHPs, as this significantly influences both the platform's efficiency and the overall transportation dynamics within a city. The decision-making processes of RHP drivers can be effectively modeled using Markov decision processes (MDPs). A fundamental MDP model can be introduced to represent the decisions of RHP drivers, where various locations within a city are defined as the state space —essentially, a driver's state corresponds to their current location. At any given moment, a driver faces a choice between waiting at their current location to be matched with a passenger by the RHP or moving to a different location, which represents the possible actions they can take. Although this simplified model can yield useful qualitative insights, such as regarding worst-case efficiency, it lacks the complexity needed for accurate predictions of driver behavior.

To enhance the model's predictive accuracy, we develop MDPs that incorporate a broader range of actions and states. This enhancement will enable us to consider critical factors such as recharging or refueling vehicles, as well as the simultaneous transportation of multiple passengers. For example, a driver might opt to move to an EV charging station when their battery is low, or they may decide to pick up a new passenger while already transporting another.

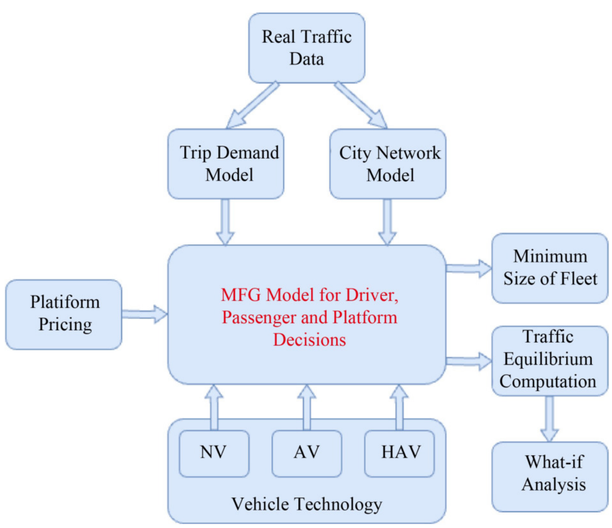

Fig. 1 A summary of the proposed approaches.

It is important to emphasize that, although the complexity of the state space increases, this complexity pertains to a single driver. Within the framework of mean-field games, there is no requirement to track each individual player's state; rather, we concentrate on the overall distribution of drivers within the single-driver state space, as detailed in Lasry and Lions, 2007. This approach contrasts with simulation models, which create sample paths within a more extensive product state space, often complicating the analysis and interpretation of collective driver behavior. By applying a mean-field game approach, we can effectively analyze and predict the dynamics of numerous drivers operating within a shared environment.

Secondly, it is important to model passengers' choices, as various travel modes exist alongside RHPs, which is essential for a comprehensive analysis of urban transportation. The availability of multiple transportation options, such as public transit and traditional taxis, indicates that passenger demand for RHPs is interdependent with the characteristics—such as travel times and costs —of these alternative modes. By integrating riders' choices into our models, we can develop more realistic simulations that reflect the interactions between RHPs and other public transportation forms. Furthermore, customer preferences for CVs and AVs introduce an additional layer of complexity to the analysis.

To achieve this, we should employ general discrete choice models, which are commonly used in transportation research to analyze how travelers make decisions among various transportation options. Referring back to the mean-field game model, it is essential that for any selected discrete model, an equilibrium can be established that provides clearly defined demand levels for different locations. This indicates that the impacts of RHPs on other transportation modes can be accurately quantified based on system parameters.

Incorporating this approach will enhance the findings presented by Banerjee et al., 2015 and Bimpikis et al., 2019, thereby broadening their applicability across a wider range of systems without imposing stringent conditions on discrete choice models. This flexibility fosters a more nuanced understanding of urban transportation dynamics, ultimately facilitating the development of more effective policies and strategies for managing multimodal transit systems.

Thirdly, it is crucial to acknowledge the hierarchical nature of decision-making between RHPs and their drivers. In this two-sided market, RHPs serve as intermediaries that connect passengers with drivers. With the emergence of AVs, these platforms are increasingly positioned to exert greater control over transportation services, assuming a dual role. This duality poses a challenge: balancing the interests of human drivers with those of the platform's fleet of AVs. These interests may occasionally conflict, as optimizing for one group may not necessarily yield benefits for the other.

Considering the unique urban landscape and distinct passenger demand patterns, an essential question arises: Is operating RHP a financially sustainable business model? To effectively analyze this complex dynamic, we can utilize a Stackelberg game framework to model the pricing strategy of RHPs. This approach allows us to capture the intricacies of decision-making among the RHP and its various stakeholders, providing a clearer understanding of how pricing and operational strategies can be optimized in a competitive environment. By doing so, we can assess the potential profitability of ride-hailing services in the context of evolving transportation options, including both AVs and traditional drivers.

The profit-maximization challenges faced by RHPs have been examined in studies by Banerjee et al., 2015 and Bimpikis et al., 2019, albeit within a more constrained framework utilizing a direct method. In this model, the RHP interacts with both drivers and passengers, with the latter two groups exerting minimal influence on decision-making processes. Conversely, the RHP plays a significant role in shaping the behavior of both drivers and passengers. This configuration results in a Stackelberg mean-field game, characterized by a single dominant player, the RHP. Courcoubetis and Dimakis, 2023 suggest that when the RHP is the sole transportation alternative, drivers and passengers collectively behave as a unified entity, seeking to maximize a specific concave function based on a predetermined reward scheme. By integrating the RHP into this framework, the overall game can be framed similarly to a two-player Stackelberg game, facilitating the efficient computation of a Nash equilibrium. This approach not only elucidates the strategic interactions among RHPs, drivers, and passengers but also enhances our understanding of how pricing and operational decisions can be optimized within the urban mobility context. Ultimately, this modeling framework allows for a clearer assessment of the profitability and sustainability of ride-hailing services amid diverse urban dynamics.

Fourthly, the myopic behavior of drivers represents another crucial aspect that requires deeper examination. It can be suggested that drivers aim to optimize their compensation rates on a per-unit-time basis. This assumption is plausible, particularly if drivers remain connected to the RHP for extended periods while completing multiple rides. However, it remains questionable whether all drivers behave as perfectly rational optimizers, willing to forego immediate earnings for potentially greater rewards later. Therefore, it is essential to model drivers' myopic behavior to determine the extent to which the findings can be generalized.

When we introduce the concept of drivers employing a discounted compensation strategy, we engage with a discounted MDP. This framework provides a more nuanced understanding of decision-making under uncertainty, as it enables drivers to weigh immediate rewards against future benefits. To analyze the equilibrium properties —such as existence, uniqueness, and efficiency—in this context, we must utilize advanced analytical techniques, including Bellman equations. These equations allow for the deconstruction of complex decision-making processes into simpler, recursive components, thereby helping us determine optimal strategies over time. Furthermore, the computation of equilibria in this setting draws parallels to concepts in reinforcement learning and best response dynamics from evolutionary game theory. Reinforcement learning offers a robust framework for understanding how agents, such as drivers, learn optimal strategies through experience and feedback from their environment. By integrating insights from both reinforcement learning and game theory, we can investigate how drivers adapt their strategies in response to changing circumstances, including variations in demand, competition, and platform policies. Ultimately, this inquiry may yield a deeper understanding of driver behavior within RHPs and contribute to the design of more effective systems that align incentives for sustained engagement, thereby enhancing the overall efficiency of the ride-hailing ecosystem.

Fifthly, computing and analyzing mean-field equilibria can be quite challenging and often lacks a systematic methodology. Within the mean-field games framework, any equilibrium corresponds to an optimal solution of a convex optimization problem. As these optimization problems can typically be solved in polynomial time, efficient algorithms are available for computing equilibria in this context. However, while this aspect holds true for the simpler RHP model, a similar variational characterization remains unknown for scenarios where passengers are modeled with discrete choice or where drivers use discounting.

Even in instances where such a variational characterization is not available, it is plausible that efficient algorithms may still exist. We anticipate this to be the case within the RHP pricing model, particularly since computing Stackelberg equilibria can be accomplished efficiently. Nonetheless, the development of concrete algorithms that reliably compute equilibria with strong performance in RHP models requires further exploration. Utilizing real data can inform the design of these high-performing algorithms.

It is well established that game equilibria can often be suboptimal; in other words, the total value derived from non-cooperative behavior can fall short of what would be achieved through cooperative optimization among all players. This phenomenon is also evident in mean-field games, which demonstrate that the inefficiency can be at least half of the optimal value, with the worst-case scenario experiencing an exact degradation to half. This inefficiency is likewise illustrated in the basic RHP model, where drivers tend to cluster around locations offering high-paying rides, even if it entails waiting time. This behavior is suboptimal since drivers waiting without serving passengers do not contribute to the overall value generated. A more complex challenge lies in determining the worst-case inefficiency across any given system. By examining these aspects in detail, it is important to shed light on the nature of inefficiencies in RHPs and contribute to more effective operational strategies that enhance overall system performance.

Finally, the game-theoretical model should be applied in real-world contexts, particularly within the transportation systems of major metropolitan areas. The data provided by transportation authorities and RHPs is integral to this testing process. This effort paves the way for developing a new generation of traffic analysis and prediction tools that can significantly enhance the capabilities available to city planners and traffic management authorities. The overarching goal of this initiative is to create a 'digital twin' of the city's transportation system. This digital twin would enable accurate predictions of car traffic and public transport usage across various scenarios that consider factors such as different vehicle technologies, the locations of charging stations, toll structures, congestion pricing, and incentive schemes designed to promote greener modes of transportation. Currently, the predominant method for forecasting such traffic patterns involves complex agent-based simulations, such as those produced by MITSIMLab.

An intriguing research direction involves the integration of discrete choice models that capture individual behaviors, detailed city maps, and a trip generation process into a comprehensive simulator. This simulator would monitor the movements of individual vehicles and analyze driver responses to traffic conditions, including congestion. However, achieving traffic equilibrium through such simulations can be time-consuming, often requiring several days to complete. Moreover, any adjustments to critical parameters —such as toll rates —necessitate restarting the entire simulation process, which can prove inefficient. Existing simulation tools struggle to accurately model the traffic patterns associated with RHPs, particularly when drivers are traveling without passengers. This limitation significantly diminishes the effectiveness of these tools for city planners, as they fail to account for the full dynamics of urban traffic. Consequently, establishing a robust suite of simulation tools has become an urgent and promising objective in urban transportation research. By developing advanced models that effectively incorporate real-time data and diverse transportation scenarios, city planners will gain crucial insights that facilitate informed decision-making, optimization of traffic flow, and enhancement of overall urban mobility. This innovation has the potential to transform how cities approach transportation planning, leading to more sustainable and efficient urban environments.

5 Conclusions

The emergence of ride-hailing services has significantly transformed urban transport system dynamics, making urban mobility more accessible and convenient for users but also providing a difficult challenge for city infrastructure and traffic management. As ride-hailing is evolving with the incorporation of AVs, possibilities to revolutionize the urban mobility system become brighter. AVs also promise to ease the operations of ride-hailing and thus potentially improve performance, reduce congestion, and lower costs. However, worthy of discussion is their impact on traffic patterning, public transit systems, and the broader urban landscape. The mean-field game model provides several insights that could simplify this interaction. It allows understanding of the collective behavior of a swarm of independent agents-such as drivers and passengers in a ride-hailing ecosystem-and resulting equilibrium states in large-scale urban environments to predict their collective behaviors. This means the mean-field game framework allows policymakers and urban planners to use simulation tools to evaluate different scenarios with respect to different ride-hailing strategies and AV integration for congestion, service quality, and overall transportation efficiency.

In summary, while ride-hailing and AVs provide new means for enhancing urban transportation, they come with challenges that must be well managed. Applications like mean field games will help stakeholders make decisions which maximize benefits and minimize potential risks thereby creating a more sustainable and efficient city transport system.

Competing Interests The authors declare that they have no competing interests.

References

Afèche P, Liu Z, Maglaras C (2023). Ride-hailing networks with strategic drivers: The impact of platform control capabilities on performance. Manufacturing & Service Operations Management, 25(5): 1890–1908

Banerjee S, Johari R, Riquelme C (2015). Pricing in ride-sharing platforms: A queueing theoretic approach. Available at SSRN 2568258

Benjaafar S, Wu S, Liu H, Gunnarsson E B (2022). Dimensioning on-demand vehicle sharing systems. Management Science, 68(2): 1218–1232

Bimpikis K, Candogan O, Saban D (2019). Spatial pricing in ride-sharing networks. Operations Research, 67(3): 744–769

Braverman A, Dai J, Liu X, Ying L (2019). Empty-car routing in ridesharing systems. Operations Research, 67(5): 1437–1452

Candogan O, Wu M (2023). Information design for spatial resource allocation. Available at SSRN 4505414

Castro F, Frazelle A (2024). Getting out of your own way: Introducing autonomous vehicles on a ride-hailing patform. Production and Operations Management, Available at SSRN 3912137

Courcoubetis C, Dimakis A (2023). Stationary equilibrium of mean field games with congestion-dependent sojourn times. In: Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems. London: United Kingdom, 2913–2915

Freund D, Lobel I, Zhao J (2022). On the supply of autonomous vehicles in platforms. Available at SSRN 4178508

Huang M, Malhame R P, Caines P E (2006). Large population stochastic dynamic games: closed-loop mckeanvlasov systems and the nash certainty equivalence principle. Communications in Information and Systems, 6(3): 221–252

Lasry J M, Lions P L (2007). Mean field games. Japanese Journal of Mathematics, 2(1): 229–260

Lian Z, van Ryzin G (2023). Capturing the benefits of autonomous vehicles in ride-hailing: The role of market configuration. Available at SSRN 3716491

McCurry J (2018). Driverless taxi debuts in tokyo in world first trial ahead of olympics. The Guardian, Available at the website of Theguardian

Siddiq A, Taylor T A (2022). Ride-hailing platforms: Competition and autonomous vehicles. Manufacturing & Service Operations Management, 24(3): 1511–1528

Wigand K M, Brandt T, Neumann D (2020). The effect of autonomous vehicles on consumer welfare in ride-hailing markets. Available at SSRN 3664415