PRODUCTION AND OPERATIONS MANAGEMENT

PRODUCTION AND OPERATIONS MANAGEMENT

Vol. 31, No. 4, April 2022, pp. 1595–1612
ISSN 1059-1478 | EISSN 1937-5956 | 22 | 3104 | 1595

DOI 10.1111/poms.13633

Service Operations for Mixed Autonomous Paradigm: Lane Design and Subsidy

Lan Lu
International Institute of Finance, School of Management, University of Science and Technology of China, Hefei 230000, China, lluae@ustc.edu.cn

Zheng Zhu
College of Civil Engineering and Architecture, Zhejiang University, Hangzhou 310058, China
Alibaba-Zhejiang University Joint Research Institute of Frontier Technologies, Hangzhou 310058, China, zhuzheng89@zju.edu.cn

Pengfei Guo
College of Business, City University of Hong Kong, Hong Kong, China, penguo@cityu.edu.hk

Qiao-Chu He*
SUSTech Business School, Southern University of Science and Technology, Shenzhen, Guangdong Province 518055, China, heqc@sustech.edu.cn

This study aims to examine and design operational strategies for mixed flows of autonomous vehicles (AVs) and human-driven vehicles (HVs). We propose a stylized model wherein utilitarian individuals either drive HVs or take privately operated AVs that are collectively dispatched. In the baseline mixed policy where AVs and HVs share the same lanes, we find that AVs under-join the traffic (queue) while HVs over-join. We identify a "crowding-out effect" such that AVs will tend to mitigate the over-joining HVs and reduce overall congestion/throughput. To improve the traffic efficiency of the baseline mixed policy, we consider a fully dedicated policy in which both AVs and HVs are segregated to different lanes and a partially dedicated policy in which only AVs enjoy dedicated lanes. We find that dedicated policies outperform the mixed policy in both social welfare and the aggregate throughput when the platooning effect is moderate or strong. Exact conditions are derived for the selection of fully dedicated policy and partially dedicated policy. Furthermore, we find that a carefully designed subsidy is necessary for the dedicated policy to simultaneously improve the social welfare and the throughput when the platooning effect is very weak. These results shed interesting light on the policy regulation for the emerging mixed autonomous paradigm: a dedicated policy with proper lane design and subsidy (if necessary) will improve both social welfare and aggregate throughput.

Key words: service operations; flexible queueing systems; queueing game; autonomous vehicles
History: Received: July 2020; Accepted: November 2021 by Prof. Michael Pinedo, after 1 revision.
*Corresponding author.

1. Introduction

The development of industry 4.0 has brought disruptive technologies to the world, therefore implies new paradigms regarding most management problems. We begin to see a number of papers that study operations management problems concerning disruptive technologies in the context of Industry 4.0, such as blockchain (Gao et al. 2021), cloud computing (Arbabian et al. 2021, Chen et al. 2019, Jain et al. 2021, Zhang et al. 2020), and data analysis and processing (Dong et al. 2018, Ghoshal et al. 2020). The Internet of Things (IoT), which represents the use of various intelligent devices to carry out the communication and presentation of information, is one of the fundamental technologies of Industry 4.0. The accelerated development of IoT in mobility and accessibility makes travel faster and more convenient, and the upcoming wave of developments lies in vehicle-based innovations (Mahmassani 2016). Within the past decade, the substantial developments of sensing, wireless communication, digital image acquisition, artificial intelligence technologies gave birth to autonomous vehicles (AVs). The development of AVs, which is the combination of the developments of IoT, automation technologies, and cyber-physical systems (CPS), stands in the center of Industry 4.0. Therefore, motivated by the disruptive technologies brought by Industry 4.0, we consider the operations management of AVs in this study.

Since the 1950s, there have been four phases of research and development (R&D) on autonomous driving (Shladover 2018). In the first three phases, the major focus was on the lateral and longitudinal (spacing and speed) control of individual vehicles (Fenton and Mayhan 1991, Shladover et al. 1991), autonomous cruise (Glathe 1994, Ioannou et al. 1993), and video image processing for driving scene recognition (Dickmanns 2002). By adopting headway safety policies (Shladover et al. 1991), and vehicle-to-vehicle sensing and communication technologies (Tsugawa et al. 1992), AV could be formed into platoons with small distances, resulting in automated highways (Rillings 1997). The fourth phase of R&D continues today, and it began with the Defense Advanced Research Projects Agency's (DARPA) Grand Challenges Program in 2004. While the concept of "Autonomous Vehicles (AVs)," which used to denote the use of electronic or mechanical devices to replace human labor, has been changing over time (Shladover 2018), the Society of Automotive Engineers (SAE) proposed a five-level classification of AVs (SAE On-Road Automated Vehicle Standards Committee 2014). Based on the classification, level 1 automation means adaptive cruise control or lane-keeping assistance, and only level 5 automation refers to a fully self-driving vehicle that can run on roadways and take actions without any assistance from a human driver.

In this study, the research is based on a fully developed AV industry, such that AVs are with level 4 or 5 in automation. Specifically, we highlight the following salient features of AV fleet: (i) Low uncertainty and variation in vehicle operations. Under the control of computers, an AV can change speed or lane smoothly. Accurate sensing and well-designed control mechanism help AVs to detect and react to sudden changes in the driving environment, thereby improving traffic safety (Pomerleau and Jochem 1996). (ii) Systematic coordination. The coordination among the AVs fleet is achieved with wireless information technology, enabling AVs to communicate with each other or with transportation infrastructure. A vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), or even vehicle-to-anything (V2X) system is commonly referred to as a connected vehicle (CV) system (Shladover 2018).

These potential benefits of AVs are generally concluded based on simulation studies due to limited real-world evidence on roadway testing of AVs. A detailed review is provided in section 2. Based on sound travel behavior and traffic flow theorems, the simulation-based studies illustrate us insightful senses of future mobility with AVs. However, the macro-level operation design receives little attention, especially when the traffic flow consists of both AVs and human-driven vehicles (HVs), that is, mixed flows. The existing efforts from both the industry and the academics mainly focus on the technical improvements and advanced operation of AVs. Thanks to the previous studies, we have developed comprehensive perspectives on different aspects (i.e., safety, travel demand, and control) of AVs. While standing on the planning and political horizon, it is necessary to understand the mobility and economic characteristics of a traffic system with both AVs and HVs.

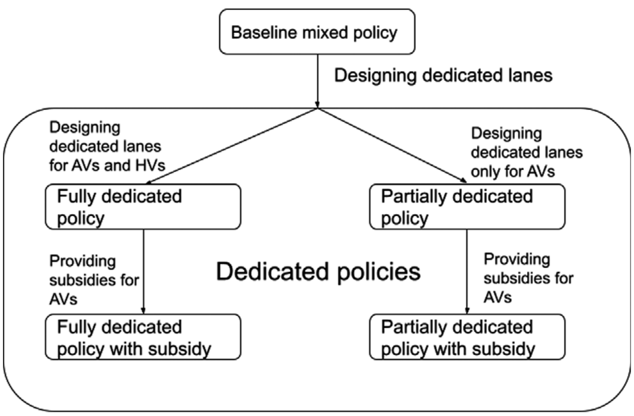
This study aims to examine and design operational strategies for mixed flows of AVs and HVs. Specifically, we consider a queueing-game model to characterize the dynamics of the mixed traffic flows, where AVs and HVs make self-interested queue-joining decisions based on the traffic conditions. The decision processes of AVs and HVs are different, which is one of the key salient features identified in our model. HVs make queue-joining decisions to maximize their own utilities. In particular, we focus on shared-AV fleets operated by a private AV company, for example, Waymo and Zoox, which charges passengers a service fee. The assumption of company-operated AVs is realistic since platform-based companies are leading the autonomous revolution in the real world. They are most likely to embrace AV technology due to considerable reductions in labor costs. For example, in October 2020, Waymo opened the commercial ride-hailing service with fully autonomous rides to the public in the East Valley of Phoenix, Arizona. In May 2021, Baidu provided the first commercial self-driving taxi service in China. Due to the financial strength and technology leadership, the company-operated AVs will play leading roles for a long time in the future. In our model, the AV company maximizes its profit by deciding the unit service price, while AV passengers make their travel decisions to maximize their own utilities based on this price. To characterize the traffic flows, we first build a general model without a specific queueing process to generate some basic insights. Then we concentrate on a heavy traffic M/G/c/c queueing model for the mixed flow of AVs and HVs. The characterization of the platooning effect captures the other key salient feature that AVs have low uncertainty and variation in vehicle operations. Therefore, the core attributes of such a traffic system can be summarized by the coexistence of two types of users: (i) one type makes individual-level decisions, while the other makes grouped-level decisions; (ii) the individual users receive unstable level-of-service, while the grouped users enjoy smooth services. From the perspective of policy-makers (the government), we consider two policy instruments, that is, dedicated lane design and subsidy, to improve the traffic system. Two critical metrics are utilized to evaluate the performance of policies: social welfare (i.e., aggregate utilities for stakeholders) and aggregate throughput (i.e., roadway usage).

To improve traffic efficiency, we consider a fully dedicated policy in which AVs and HVs are segregated to different lanes and a partially dedicated policy in which only AVs enjoy a dedicated lane. The consideration of dedicated policies is natural since the dedicated lanes can be beneficial in balancing the travel demand and roadway capacity, and eliminating the disturbance between AV platoons and individual HVs. We conduct comprehensive analyses of a baseline mixed policy and the dedicated policies with varying exogenous variables. These three policies are compared to each other concerning social welfare and aggregate throughput. We find that the dedicated policies always dominate the mixed policy in both metrics when the platooning effect is moderate or strong. The other policy instrument, that is, the subsidy for AVs, is considered as a complement for the dedicated policies when the platooning effect is very weak. We find that compared to the baseline mixed policy, the dedicated policies with subsidy can improve both social welfare and aggregate throughput as long as the subsidy is high enough. See Figure 1 as an illustration of the relationship of different policies.

We summarize the main highlights and contributions in what follows.

An innovative model framework. We conceptualize the emerging mixed autonomous mobility paradigm through a stylized queueing game model wherein individual decision-making agents (HVs) interact with group decision-making agents (AVs). In particular, we focus on shared-AV fleets operated by a private platform company, for example, Waymo and Zoox, which charges passengers a usage fee. This model framework is essentially different from previous studies since it innovatively incorporates the travel decisions of vehicles, especially the group decision feature of AVs, into the traffic system. To our best knowledge, our study is the first one in the operations management field to investigate the service operations for the mixed flow of AVs and HVs using the queueing game. This novel perspective not only fills the gap of the research between transportation and operations management but also generates different results from the literature. Particularly, we identify a "crowding-out effect" such that AVs will tend to mitigate the over-joining HVs and reduce overall congestion/throughput, which is contrary to the result in the prior literature that the introduction of AVs can always benefit the throughput (Mirzaeian et al. 2021).

Figure 1 The Relationship of Different Policies



Metrics from a new perspective. While the capacity (i.e., maximum throughput), throughput, and average travel time are commonly considered as the measure of traffic system performance in prior literature (Chen et al. 2017, Ghiasi et al. 2017, Mirzaeian et al. 2021), social welfare receives little attention, and this study fills in the gap. We start from the perspective of OM and consider social welfare as an important metric to evaluate the performance of traffic policies. Since we incorporate the travel decisions of AVs and HVs into our model, social welfare, which integrates the impact of throughput and average travel time, can be a more comprehensive measure to evaluate the performance of policies. Therefore, we also contribute to the OM literature concerning managerial insights toward policy regulation for IoT-enabled autonomous driving.

Various policies suggestions. In particular, based on the baseline mixed policy, we propose a series of dedicated policies, that is, the fully dedicated policy, the partially dedicated policy, the fully (partially) dedicated policy with subsidy, to improve the traffic system. We introduce capacity allocation into the dedicated policy design to make our policies more flexible. We compare these dedicated policies and identify the conditions for different policies to adopt. We find that dedicated policies always outperform the mixed policy in both social welfare and the aggregate throughput. Consequently, we are able to provide policy suggestions for various traffic conditions and always achieve a Pareto-improvement. The superiority of our dedicated policies generates different insights from the literature (Mirzaeian et al. 2021) where the dedicated policy has poor performance. Our results shed interesting light on the policy regulation for the emerging mixed autonomous paradigm: a dedicated policy with proper lane design and subsidy (if necessary) will improve both social welfare and aggregate throughput.

The paper is organized as follows. In section 2 we present a comprehensive review on the related research. Section 3 provides a mathematical characterization of the mixed flow in terms of the decision-making process of HVs/AVs and the general traffic flow stochasticity. In section 4, the heavy traffic M/G/c/c queueing model is built, and the performances of different traffic policies are examined. We summarize the main findings of this study in section 5. The proofs for the main results are given in the Appendix.

2. Literature Review

Our research is related to three streams of research: (i) AVs and the platooning effect; (ii) the mixed flow of AVs and HVs and operations management of AVs; and (iii) traffic flow modeling and queueing game.

There is an emerging pool of literature on AVs. In the context of traffic science, traffic flow is described by the interrelation between space (i.e., distance from the rear of the leader and the front of the follower), speed, density, and volume (Greenshields et al. 1935). Theoretically, AVs need much shorter reaction times for taking an acceleration or a break than human drivers, leading to the capability of running at high speed with smaller spaces and thereby a higher volume (Shladover et al. 1991). CV systems can further increase the volume by simultaneously controlling a platoon of AVs (Tsugawa et al. 1992, Varaiya 1993). Besides, the heterogeneity in human driving behavior (e.g., the preferred following distance, braking force, lane-changing habits) can result in unstable traffic flows, which can be avoided by a platoon of AVs with homogeneous control Monteil (2014). Platooning, as one of the most salient features of AVs, is expected to promisingly improve the traffic efficiency (Milanés and Shladover 2014, Ploeg et al. 2011, Shladover et al. 2012). Various aspects of platooning are studied, such as the formation process (Xiong et al. 2019) and the impact of platoons on highway bottlenecks (Jin et al. 2018). These results can support one of the key assumptions, that is, the platooning effect in our model.

With the emerging research concerning the promising features of AVs, an important question receives much attention: whether and how will the introduction of AVs into the traffic system improve traffic efficiency? To answer this question, a number of studies conduct analyses for the mixed flow of AVs and HVs to investigate the impact of AVs. The microscopic traffic simulation models that capture car following (acceleration and deceleration) behavior (Gartner 2001) and lane-changing behavior (Talebpour et al. 2016) of each vehicle on the roadway is a state-of-art approach for the examination of AV flows. There has been a heatwave of simulation-based AV studies during the last decade, which covered different aspects of roadway traffic, such as the stability and throughput of connected AVs (Talebpour and Mahmassani 2016), intersection control with AV platoons (Lee and Park 2012, Lioris et al. 2017), and lane control of mixed flows (Talebpour et al. 2017). However, for theoretical research, there are only a limited number of studies that conduct analytical models to characterize the mixed flow. For example, Chen et al. (2017) investigate how will the introduction of AVs affect the traffic capacity based on a theoretical framework considering spacing characteristics and platoon size. Ghiasi et al. (2017) propose a Markov chain model to formulate the mixed flow with stochastic headways. They take both the platooning intensities and the penetration rate of AVs into consideration to investigate the change of traffic capacity. (Naumov et al. 2020) study the impact of AVs and pooling, concluding that the adoption of AVs and pooling may lead to worse traffic quality and more congestion. While these studies provide valuable insights into the improvement brought by AVs, most of them focus on the benefits from the technical superiority of AVs (e.g., the platoon control). However, another important feature of AVs, that is, the group decision, is overlooked in the literature. Some studies that focus on the operational strategy for autonomous vehicles reveal the decision process of AVs in contrast to human drivers (who do not necessarily comply with global optimal guidance). For example, (Abouee-Mehrizi et al. 2021) consider a car sharing company and explore when it is optimal to use AVs in the car sharing market. Liu and Whinston (2019) propose an information-based approach to guide the routing decisions for autonomous vehicles. Baron et al. (2018) consider the sharing of AVs and its impact on social welfare. In this study, we combine both the two salient features, that is, the technical superiority of platooning and the distinct decision process of AVs, to characterize the mixed flow of AVs and HVs. By considering the travel decisions of AVs and HVs in the mixed flow traffic, this novel perspective fills the gap of the research between transportation and operations management.

We apply a queueing game framework to model the traffic flow and the decision processes of AVs and HVs. Queueing models are widely adopted to characterize the traffic flow in the literature. Heidemann (1996) adopt M/M/1 and M/G/1 queues to model the uninterrupted flow. Heidemann (2001) further extend the M/M/1 model to study the non-stationary traffic flow. Vandaele et al. (2000) develop several queueing models, such as M/M/1 and M/G/1 queues, to analyze the uninterrupted traffic flow based on traffic counts. Van Woensel and Vandaele (2006), Van Woensel et al. (2006) use empirical data and simulations to evaluate the queueing models and conclude that the normal traffic flow on a highway can be best described by the M/G/1 model. A more complicated M/G/c/c model is also used in the literature to characterize the traffic flow (Jain and Smith 1997, Mirzaeian et al. 2021). In this study, we follow Mirzaeian et al. (2021) to adopt the M/G/c/c model to describe the mixed traffic flow.

Classical results in both observable and unobservable queues are reviewed in Hassin and Haviv (2003) and are recently updated in Hassin (2016).

Since we consider the decision processes of AVs and HVs, our research is most closely related to the literature on service operations, particularly queueing models with rational agents. In this study, we consider two policy instruments: dedicated policy, that is, segregating AVs and HVs, and subsidies. Several papers in the traffic research literature considering the mixed flow study the dedicated policy. Chen et al. (2017) evaluate three dedicated policies with exogenous arrival rates of AVs and HVs. Mirzaeian et al. (2021) consider a designated-lane policy in which a single lane is designated to AVs and the other lanes are assigned to HVs. While both of them provide valuable insights that the dedicated lane will be underutilized when the penetration rate of AVs is low, they do not consider the capacity allocation of lanes. In this study, we extend the literature and consider the capacity allocation as a decision in the dedicated policy. A similar policy in the literature is that Ghiasi et al. (2017) consider a lane management model to maximize the highway throughput by deciding the number of lanes designated to AVs. Subsidizing AVs is also a practical policy that is considered in the literature. Luo et al. (2019) also propose a policy instrument—subsidy—to promote AVs but focus on a game between the government and AV manufacturer instead of considering the traffic dynamics. Cui et al. (2021) investigate the impact of slugging and focus on the role of HOV lanes where drivers who participate in slugging can take the HOV lanes with less travel time. They also consider the subsidy (or tax) as an instrument of the government to optimize social welfare, which provides good support for our subsidies policy. While these studies assume exogenous arrival rates of AVs and HVs, in this study, we endogenize the travel decisions of AVs and HVs in a game-theoretical framework.

Specifically, in terms of AVs and HVs' queue-joining decision framework, our research is related to the literature of customers' strategic behavior in the queueing system. HVs' joining decision is the self-optimization. Naor (1969) study the decisions of selfish customers who do not consider their negative externalities in an observable queue. They find that selfish customers over-join and result in suboptimal user welfare. The result of selfish customers is extended in several aspects, such as generalized arrival process (Yechiali 1971) and multi-server queue (Chr 1972, Edelson and Hilderbrand 1975, Yechiali 1972). The case of unobservable queue is studied by Littlechild (1974) and Hassin (1986). Unlike HVs, AV passengers' travel decision is restricted by the service price charged by the AV company that maximizes its profit. Therefore, the decision process of AVs finally turns to be the social optimization. The performances of self-optimization and social optimization are well studied in the literature (Guo and Hassin 2011, 2012, Hassin and Snitkovsky 2017). The study of the mixture of these two in the same queueing system, however, is very limited (Gilboa-Freedman and Hassin 2014). This study extends the literature by studying the mixed flow equilibrium of both AVs (social optimization) and HVs (self-optimization).

3. The Basic Model with Travel Decisions

In this section, we propose a basic model to characterize the mixed autonomous paradigm. In this traffic system, we consider a representative roadway segment on the highway. The two types of vehicles, that is, HVs and AVs, will make their own travel decisions to the roadway, while the government attempts to improve traffic efficiency by designing traffic policies. To capture the decisions on both sides, we build a game-theoretical model to evaluate the performances of different traffic policies with dependent travel decisions of vehicles. In section 3.1 we first characterize the travel decisions of HVs and AVs, respectively. In section 3.2 we compare the mixed policy and the dedicated policy using a general traffic model.

3.1. Different Decision Processes

We utilize a stylized model with both AVs and HVs in the transportation system to capture their interactions. Although drivers in the real world may have heterogeneity in trip lengths, route choices, departure time choices, and value of time (VOT), our stylized model enables us to highlight the equilibrium mobility behaviors of both AVs and HVs and obtain analytical results. (Yang and Yang 2011).

Suppose that the mixed autonomous driving paradigm is non-constrained by technology hurdle and both the HVs and AV fleet make mobility decisions based on their utility maximization. In particular, we assume that HVs and AVs will decide on a representative trip whether they want to use the roadway segment.

We consider three parties of players in the game: the AV company, AV passengers, and HVs. For AV passengers and HVs, if they decide to join the queue, they will obtain a corresponding utility, and otherwise, they choose outside options (e.g., subway) with utility z. Without loss of generality, we set $z = 0$. AV passengers and HVs make decisions on whether to join the queue, while the AV company charges a unit service price p_a to maximize its profit. Collectively, these travel decisions will induce an equilibrium travel intensity (throughput).

HVs' travel decisions. Since human drivers make individual queue-joining decisions, they are referred to as the atomic customers who join the queue when the individual customer receives a non-negative utility:

$$U_h = V_h - C_h EW_h \geq 0, \tag{1}$$

where U_h denotes the utility of an individual HV driver, V_h denotes the payoff for an HV to complete the trip, C_h denotes the homogeneous VOT of HV drivers, and EW_h denotes the expected travel time of HVs. Finally, human drivers will keep the throughput θ_h such that $U_h = 0$.

AVs travel decisions. Unlike HVs, we assume that AVs are operated by a private shared-mobility company (e.g., Waymo or Zoox). This assumption is consistent with the reality that platform-based companies are leading the autonomous revolution. They are most likely to embrace AV technology due to considerable reductions in labor costs. For example, in October 2020, Waymo opened the commercial ride-hailing service with fully autonomous rides to the public in the East Valley of Phoenix, Arizona. In May 2021, Baidu provided the first commercial self-driving taxi service in China. Due to the financial strength and technology leadership, the company-operated AVs will play leading roles for a long time in the future. As a service provider, the AV company's objective is to maximize its profit by deciding the service price p_a, while AV passengers decide whether to make a trip based on individual utility. The decision problem for the AV company is as follows:

$$\max_{p_a} \pi_a = \max_{p_a} \theta_a p_a, \tag{2}$$

where θ_a is the AVs throughput in the equilibrium. For AV passengers, they will join the queue when the individual passenger receives a non-negative utility:

$$U_a = V_a - C_a EW_a - p_a \geq 0, \tag{3}$$

where V_a, C_a, and EW_a represent the payoff, VOT, and expected travel time of AVs when passing the roadway segment, respectively. Note that V_h, V_a, C_h, C_a, EW_h, and EW_a are non-negative. We generally assume $C_h \geq C_a$ because an HV driver needs to focus on driving, while an AV passenger can work, read, or do other things during the trip. Finally, in the equilibrium, AVs will keep the throughput θ_a such that $U_a = 0$.

The sequence of events is as follows: The AV company first decides the service price p_a. This decision is irreversible and cannot be changed. The AV company knows ex-ante that HVs and AV passengers can observe its action. Then HVs and AV passengers make their travel decisions simultaneously after observing the AV service price chosen by the AV company.

We summarize the first key salient features of our proposed mixed autonomous paradigm. HVs and AVs differ in their queue-joining behaviors. HVs are atomic agents who decide to queue or not to queue by maximizing their own utilities. In contrast, AVs are a fleet of vehicles coordinated by a private company (e.g., Waymo or Zoox). The AV company makes pricing decisions by maximizing its profit, while AV passengers decide whether to join the queue to maximize their own utilities. Now that we understand the drivers' mobility decisions, and we will start with a discussion on road lane operational policy for this mixed autonomous transportation system in the following sections.

3.2. The Traffic Policies

In this subsection, we consider the two traffic policies: (i) the mixed policy where AVs and HVs use the same traffic lanes and (ii) the fully dedicated policy where AVs and HVs travel on designated lanes. We assume that the throughput of the traffic system to be $\theta_a(\lambda_a, \lambda_h)$, $\theta_h(\lambda_a, \lambda_h)$ for AVs and HVs, respectively. The relationship between the throughput and arrival rate can be different for various queueing models. In an M/G/c/c queue, the throughput $\theta = \lambda(1 - \pi_c)$, while in some other queues such as M/G/1 with $\rho < 1$, we have $\theta = \lambda$. Therefore, this general model can be adapted to different queueing systems, and we will specify the case of M/G/c/c queue in the next section. We utilize a general function $W(\theta_a, \theta_h)$ to characterize the expected travel time of the traffic system, which is convex and increasing in the throughput θ_a, θ_h of AVs and HVs. To evaluate the performance of different traffic policies, we consider two important metrics: social welfare and aggregate throughput. Obviously, social welfare is the first consideration of the government in operations management. However, although social welfare consists of utilities for all the stakeholders, it might not comprehensively measure the effectiveness of mobility in traffic systems. That is, higher social welfare might reflect a comfortable travel situation in which drivers do not encounter traffic congestion. However, from the system perspective, this could imply a low utilization of roadway segments (i.e., measured by aggregate throughput) and a waste of system resources. Therefore, we also take the throughput into consideration, which is a common metric in traffic flow research.

3.2.1. Mixed Policy. In the baseline mixed policy, we consider a mixed autonomy such that HVs and AVs can take any lane of the roadway segment. In other words, the traffic flow on any lane of the segment is mixed with HVs and AVs. Without loss of generality, we assume HVs and AVs are uniformly distributed on different traffic lanes and vehicles do not change their lanes or pass the others. This assumption is a conservative perspective of the future such that the impact of waving and passing behaviors on the mixed flow will be minimized. Additionally, it also prevents potential liability issues related to traffic accidents.

In the mixed policy, AV passengers and HVs follow the decision processes in section 3.1 to maximize their own utility, while the AV company decides the service price p_a to maximize its profit π_a. According to Equations (1)–(3), we can obtain the optimal decisions via the following equations:

$$U_h = V_h - C_h W(\theta_a^*, \theta_h^*) = 0, \tag{4}$$

$$U_a = V_a - C_a W(\theta_a^*, \theta_h^*) - p_a^* = 0, \tag{5}$$

$$p_a^* = \arg\max_{p_a} p_a \theta_a. \tag{6}$$

According to Equations (4)–(6), we can obtain the equilibrium in the mixed policy by solving system equations (see details in the Appendix). Obviously, due to the individual decision process of HVs who will always join the queue with a non-negative utility, the expected travel time of the mixed flow will finally go to $\frac{V_h}{C_h}$ such that all HVs obtain zero utility. To ensure the existence of such a mixed flow, we have the following necessary condition:

Proposition 1. *The necessary condition for the mixed flow equilibrium of AVs and HVs to exist is*

$$\frac{C_a}{V_a} \le \frac{C_h}{V_h}. \tag{7}$$

Proposition 1 indicates that the existence of mixed flow equilibrium depends heavily on the ratio of drivers' VOT to their payoffs of the trip, that is, $\frac{C_a}{V_a}$ and $\frac{C_h}{V_h}$. We refer to $\frac{C_a}{V_a}$ and $\frac{C_h}{V_h}$ as the cost-benefit ratio of AVs and HVs, respectively. A higher cost-benefit ratio means that it is less worthy of conducting and completing the trip. The necessary condition $\frac{C_a}{V_a} \le \frac{C_h}{V_h}$ provides an upper bound for $\frac{C_a}{V_a}$ to ensure the existence of AVs in the traffic flow. Intuitively, this condition implies that AV technologies should bring convenience to travelers (i.e., by either increasing payoffs or decreasing costs) to maintain a positive market penetration. Otherwise, there is no reason for adopting AVs in the roadway segment. This condition is not harsh because AVs are generally believed to decrease drivers' VOT (i.e., $C_h \ge C_a$). Besides this necessary condition in Proposition 1, their should be a necessary condition for HVs to exist in the traffic flow ($\theta_h^* \ge 0$). Although the general formulation prevents us from deriving an explicit inequality like Equation (7), we can obtain some insights by analogy with Proposition 1. Similarly, the necessary condition for HVs to exist should also depend on the cost-benefit ratio, and it should provide an upper bound for $\frac{C_h}{V_h}$ to ensure the existence of HVs.

We then analyze the important measurements of the roadway segment under the equilibrium condition and obtain the following proposition.

Proposition 2. *In the equilibrium, the optimal throughput of AVs (θ_a^*) and HVs (θ_h^*), average travel time of AVs (EW_a^*) and HVs (EW_h^*), the aggregate utility of AV passengers (UW_a^*) and HVs (UW_h^*), and the profit of the AV company (π_a^*) are given by Table 1. Therefore, the social welfare is*

$$SW = \pi_a^* + UW_a^* + UW_h^* = \theta_a^* \left(V_a - \frac{C_a V_h}{C_h} \right). \tag{8}$$

According to Proposition 2, we note that the expected travel time equals the inverse value of the cost-benefit ratio of HVs. Based on the result in Proposition 1, the inverse cost–benefit ratio of HVs is smaller than that of AVs, and it guarantees positive utility for AVs. However, the aggregate utility of AVs is fully captured by the AV company as its profit, while AV passengers obtain zero utility as HVs. To maximize its profit, the company charges p_a to restrict the throughput of AVs. Therefore, we can identify AVs as under-joining the queue and the under-joining behavior is negative to AVs throughput but ensures positive utility. Another finding is that HVs do not obtain any utility. That is, as long as an HV driver observes the positive utility of taking a trip, he or she will join the roadway segment. Finally, the joining behavior stops when the utility for the marginal HV driver declines to zero, which results in zero aggregate utility of HVs. Similarly, we can identify HVs as over-joining the queue, and the over-joining behavior results in high HVs throughput but zero utility. The difference in utilities results from different travel decision processes of AVs and HVs, which is one of the key salient features of AVs in this study.

Table 1 Summary of Throughput, Travel Time, and Utilities for Mixed Policy

	Throughput	Travel time	Utility
Mixed HV	θ_h^*	$EW_h^* = \frac{V_h}{C_h}$	$UW_h^* = 0$
Mixed AV	θ_a^*	$EW_a^* = \frac{V_h}{C_h}$	$UW_a^* = 0,\ \pi_a^* = \theta_a^* \left(V_a - \frac{C_a V_h}{C_h} \right)$

3.2.2. Fully Dedicated Policy. As mentioned in the previous discussion, one potential advantage of AVs over HVs is the mitigation of congestion and a reduction of travel time due to the platoon control, named the platooning effect. However, in the mixed policy, this advantage is not fully utilized due to the interactions of HVs and AVs. Therefore, a potential improvement is to allocate dedicated lanes for AVs and HVs to reduce the disturbance from each other. In this subsection, we will discuss a dedicated policy where HVs and AVs are separated into different lanes, named the fully dedicated policy. More variants of dedicated policies will be discussed in the next section.

When designing a fully dedicated policy, a natural question is how to allocate the roadway capacity for AVs and HVs. Without loss of generality, we assume the total roadway capacity to be 1, and the government will allocate γ to AVs and $1-\gamma$ to HVs. The government's objective is to decide γ to improve the traffic system concerning the total throughput and social welfare. To avoid kinks due to integer numbers of lanes and simplify the analysis, we consider a continuous allocation of road capacity between HV lane and AV lane. Later we will consider the integer numbers of lanes in the next section with a specific queueing model. We abstract away from the microscopic driving behaviors such as lane-changing, waving (vehicles entering or exiting the road segment), to focus on policy discussion for a clear presentation.

In the fully dedicated policy, both AVs and HVs can only enter their designated lanes and form two independent traffic flows. For the traffic flow of AVs and HVs, we denote the travel time function as $W_a^d(\gamma,\theta_a)$, $W_h^d(\gamma,\theta_h)$, the throughput as θ_a^d, θ_h^d. We capture the platooning effect of AVs and use a dependent speed function to model the two mobility modes (HVs vs. AVs), and we have the following assumptions:

Assumption 1.

$$\frac{\partial W_a^d(\gamma,\theta_a)}{\partial\theta_a} \le \frac{\partial W(\theta_a,\theta_h)}{\partial\theta_a} \le \frac{\partial W(\theta_a,\theta_h)}{\partial\theta_h} \le \frac{\partial W_h^d(\gamma,\theta_h)}{\partial\theta_h}, \tag{9}$$

$$\frac{\partial W_a^d(\gamma,\theta_a)}{\partial\gamma} < 0,\ \frac{\partial W_h^d(\gamma,\theta_h)}{\partial\gamma} > 0. \tag{10}$$

The first assumption characterizes the platooning effect of AVs, implying AVs generate less marginal travel time than HVs by traveling in platoons. This reflects that AVs have a smoother travel process than HVs because they are operated by computers with high coordination and extremely low heterogeneity in driving behaviors. The effect of the platoon on traffic flow has been investigated by empirical data (e.g., Kerner et al. (2006)) and simulations (e.g., Pueboobpaphan and Van Arem 2010); and it was found that driving in platoons can improve the stability and efficiency of the traffic flow. Moreover, the pure AV flow is the fastest one, while the mixed flow is slower, and the pure HV flow is the slowest. The second assumption is natural, indicating that the travel time will decrease when the traffic lane is allocated with more capacity.

Similarly, following the decision processes in section 3.1, we can obtain the equilibrium throughput of AVs and HVs via the following equations:

$$U_h^d = V_h - C_h W_h^d(\gamma,\theta_h^{d*}) = 0, \tag{11}$$

$$U_a^d = V_a - C_a W_a^d(\gamma,\theta_a^{d*}) - p_a^{d*} = 0, \tag{12}$$

$$p_a^{d*} = \arg\max_{p_a^d} p_a^d\theta_a^d. \tag{13}$$

Although explicit formulations cannot be derived due to the general form of travel time and throughput, we can obtain some primary results by analyzing the structure of the problem. First, HV's expected travel time is also $\frac{V_h}{C_h}$ as in the mixed policy, and consequently, HVs obtain zero utility. Second, social welfare, that is, the aggregate utilities of all stakeholders, is fully captured by the AV company. Thus, social welfare is maximized when AVs throughput is maximized, that is, all of the capacity is allocated to the AV lane. Moreover, the government can improve social welfare in the fully dedicated policy by allocating enough capacity to AV lanes, which is described in the following proposition.

Proposition 3. *There exists* $\underline{\gamma}\in(0,1)$ *such that when* $\gamma > \underline{\gamma}$, $SW^d(\gamma) > SW$.

Proposition 3 indicates that the government can improve the mixed policy in social welfare by allocating a high capacity for AVs (a large γ). This result is intuitive since only AVs generate social welfare.

However, the situation is more complicated for the other metric, that is, the aggregate throughput. To understand the interactions behind, we first summarize two essential effects of AVs: the platooning effect and the crowding-out effect. Since AVs are controlled in platoons, they can enjoy a lower service time than HVs. This advantage, named the platooning effect, will encourage AVs to join the queue. However, the emergence of AVs occupies part of the roadway capacity for HVs, and some HVs are replaced by AVs. In other words, AVs crowd some HVs out of the system, named the crowding-out effect. Although reducing the throughput of HVs, the crowding-out effect may not necessarily reduce the aggregate throughput since more AVs join the queue. The interaction of the platooning effect and the crowding-out effect can generate complicated results for the aggregate throughput when the fully dedicated policy is adopted. When AVs and HVs are segregated to dedicated lanes, the platooning effect is enlarged for AVs because the disturbance from HVs on the travel time is removed. The advantage of platoon control is fully utilized. As a result, AVs can enjoy a better traffic condition on the dedicated lane, and the under-joining behavior will be mitigated. In other words, AVs are more willing to join the lane than in the mixed policy. Therefore, the dedicated policy benefits AVs in throughput. However, HVs are less willing to join the lane than in the mixed policy. In the mixed policy, although the platooning effect is small, HVs can enjoy part of it from the interaction of AVs. The mixed flow of HVs and AVs is better than the pure HVs flow with respect to travel time. When HVs and AVs are separated, HVs lose this benefit and face a worse flow. As a result, more HVs are crowded out of the system and the crowding-out effect is more significant. Therefore, the exact impact of the fully dedicated policy on the aggregate throughput is dependent on the specific mathematical formulations for the traffic system. We are particularly interested in examining the existence of a win–win condition where both social welfare and aggregate throughput are improved, which brings critical OM insights. Therefore, we will give a detailed discussion in the next section, where a specific queueing model is used to characterize the traffic system.

4. The Heavy Traffic M/G/c/c Model with Travel Decisions

In this section, we specify the general traffic model in section 3 as the heavy traffic M/G/c/c queueing model to characterize the traffic system. The travel decisions follow the basic model, while the specific queueing model will generate more detailed results. In section 4.1 we first introduce the queueing model. Then in section 4.2, we will discuss the mixed policy and several dedicated policies.

4.1. The Queueing Model

In this section, we consider an M/G/c/c queue to characterize the traffic flow on the highway. However, due to the complexity of the state-dependent M/G/c/c queue, we restrict our attention to the heavy traffic case, where the potential arrival rates λ_a and λ_h are so high that the highway is always full of vehicles. Such a congestion case is the most demanding situation for better traffic policies to implement.

We follow Mirzaeian et al. (2021) to use an M/G/c/c queue with c servers and capacity c to characterize the traffic system. The highway has N lanes with length L, where the jam density J is defined as the maximum number of vehicles per mile per lane on the highway. Therefore, the capacity of the highway is $c = JLN$. As long as a vehicle joins the queue, the service begins. When vehicles find c other vehicles already on the highway before them, they will turn away without waiting. Therefore, the travel time is exactly the service time, that is, the time of the vehicle passing the roadway segment. The mean speed of vehicles is denoted by S_n, where $n = 1, \ldots, c$ is the number of vehicles on the highway. S_n decreases as n increases, where S_1 is called the free-flow speed and S_c is called the jam speed.

According to Cheah and Smith (1994), the steady state distributions of an M/G/c/c queue, π_n, are expressed as follows.

$$\pi_n = \frac{(\lambda L)^n}{n! S_n \cdots S_1}\pi_0,\ n = 1, \ldots, c, \tag{14}$$

where

$$\pi_0^{-1} = 1 + \sum_{n=1}^{c} \frac{(\lambda L)^n}{n! S_n \cdots S_1}. \tag{15}$$

In the M/G/c/c queueing model, the proportion π_c of vehicles find c other vehicles already on the roadway and will turn away. Therefore, we can obtain the effective arrival rate (throughput)

$$\theta = \lambda(1 - \pi_c), \tag{16}$$

and the mean expected travel time

$$W = \frac{\sum_{n=1}^{c} n\pi_n}{\lambda(1 - \pi_c)}. \tag{17}$$

In this model, we concentrate on the heavy traffic case where λ is large enough, implying infinite potential vehicles arriving to the highway. According to Equation (17), we can obtain the limit of the mean travel time (Mirzaeian et al. 2021):

$$W_\infty = \lim_{\lambda\to\infty} W = \lim_{\lambda\to\infty} \frac{L\sum_{n=0}^{c-1}(L\lambda)^n/(n! S_{n+1}\cdots S_1)}{1 + \sum_{n=1}^{c-1}(L\lambda)^n/(n! S_n \cdots S_1)} = \frac{L}{S_c}, \tag{18}$$

where S_c is the jam speed when there are c vehicles on the highway.

Equation (18) implies that in the heavy traffic case, the expected travel time depends on the jam speed. Jain and Smith (1997) propose a linear model to characterize the jam speed as $S_c = \frac{S_1}{c}$, where S_1 is the free-flow speed. Since we consider a mixed traffic flow of

AVs and HVs, the characterization of the difference between AVs and HVs is the key point. Besides the different travel decision processes, the other important feature of AVs is the platooning effect which makes the traffic smoother and faster. Therefore, in the mixed flow traffic, even with the same total flow rate on the highway, different proportions of AVs and HVs will result in different performances of the queue. While Mirzaeian et al. (2021) propose a Markovian process with very detailed parameters to capture the platooning effect, the MAP is too complicated when travel decisions are endogenized into the model. Therefore, we consider a special form that is simple but still captures the salient feature of AVs, that is, the platooning effect that makes the traffic more smooth. Specifically, we consider the heavy traffic case with infinite potential vehicles, consisting of AVs and HVs. As we have mentioned in the queueing model, in the heavy traffic case, although the arrival rate λ goes to infinity, the throughput θ (effective arrival rate) is limited. θ, θ_a, θ_h are assumed to be observable since the navigation system is in popularity. Therefore, the AV company can control the throughput indirectly by deciding the service price p_a, while AV passengers and HVs' travel decisions will eventually induce an equilibrium travel intensity, that is, the effective arrival rates (throughputs) θ_a and θ_h (see Figure 2 as an illustration). Since the M/G/c/c queue has limited capacity, the performance of the queue in the heavy traffic case is heavily dependent on θ.

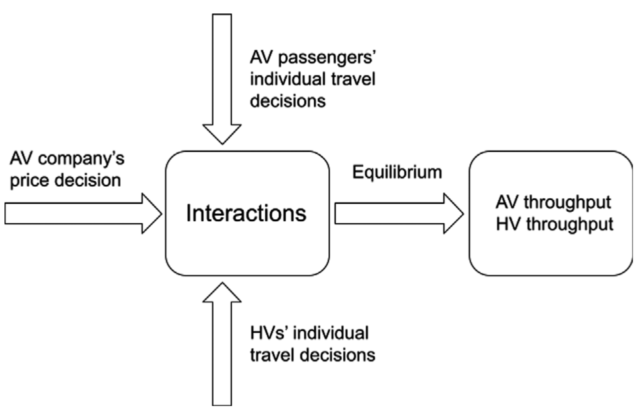
To characterize the platooning effect of AVs, we define the jam speed to be a function of the throughputs θ_a and θ_h, where $\theta_a + \theta_h = \theta$. To provide a sound formulation of jam speed with mixed flows, we refer to the empirical study of traffic fundamental diagram (Qu et al. 2015) and jam traffic (Kerner and Rehborn 1996), and macroscopic mixed flow model (Ngoduy 2013). The literature suggests that: (i) the theoretical maximal jam throughput monotonically increases with jam density (or capacity); (ii) as fewer vehicles are driving in platoons, platoon density will decrease, leading to a fluctuated traffic and a lower jam throughput. Based on the literature above and the linear speed model of Jain and Smith (1997), we also build a linear model for the jam speed:

$$S_c = u(c) - \alpha\theta_a - \beta\theta_h, \tag{19}$$

where $u(c)$ is the free-flow speed function increasing in the capacity c of the queue, $\beta > \alpha$ are coefficients implying the platooning effect of AVs makes the traffic faster. Therefore, both the total throughput and the proportion of AVs are important factors for the jam speed as well as the mean travel time. Without loss of generality, we normalize L to be $L = 1$ and the mean travel time W of the M/G/c/c queue with throughput θ_a, θ_h can be written as

$$W_c(\theta_a, \theta_h) = \frac{1}{u(c) - \alpha\theta_a - \beta\theta_h}. \tag{20}$$

Figure 2 An Illustration of the Three Decisions Inducing the Equilibrium



4.2. Traffic Policies

In this section, we adapt the model framework in sections 3.1 and 4.1 to different traffic policies. Similarly, to evaluate the performance of traffic policies, we consider two metrics: social welfare and aggregate throughput.

4.2.1. Mixed Policy. In the baseline mixed policy, we consider a mixed autonomy such that HVs and AVs can take any lane of the roadway segment. Substituting the expected travel time, that is, Equation (20) to Equations (1)–(3), we can obtain the aggregate throughput of atomic HVs (i.e., θ_h) and AVs (i.e., θ_a) via the following equations:

$$U_h = V_h - \frac{C_h}{u(c) - \alpha\theta_a - \beta\theta_h} = 0, \tag{21}$$

$$U_a = V_a - \frac{C_a}{u(c) - \alpha\theta_a - \beta\theta_h} - p_a^* = 0, \tag{22}$$

$$p_a^* = \arg\max_{p_a} \frac{\frac{C_a}{p_a - V_a} + u(c) - \beta\theta_h}{\alpha} p_a. \tag{23}$$

We analyze the important measurements of the roadway segment under the equilibrium condition and obtain the following proposition.

PROPOSITION 4. *In the equilibrium, the optimal throughput of AVs (θ_a^*) and HVs (θ_h^*), average travel time of AVs (EW_a^*) and HVs (EW_h^*), the aggregate utility of AV passengers (UW_a^*) and HVs (UW_h^*), and the profit of the AV company (π_a^*) are given by Table* 2.

Table 2 Summary of Throughput, Travel Time, and Utility for Mixed Policy

	Throughput	Travel time	Utility
Mixed HV	$\theta_h^* = \frac{C_a u(c) V_h^2 - V_a C_h^2}{\beta C_a V_h^2}$	$EW_h^* = \frac{V_h}{C_h}$	$UW_h^* = 0$
Mixed AV	$\theta_a^* = \frac{C_h (V_a C_h - C_a V_h)}{\alpha C_a V_h^2}$	$EW_a^* = \frac{V_h}{C_h}$	$UW_a^* = 0$, $\pi_a^* = \frac{(V_a C_h - C_a V_h)^2}{\alpha C_a V_h^2}$

A feasible solution of Equations (21)–(23) requires non-negative throughput, that is, $\theta_h \geq 0$ and $\theta_a \geq 0$. To avoid the trivial case where $\theta_h = 0$ and $\theta_a = 0$, we assume that $\frac{C_h}{V_h} < u(c)$ and $\frac{C_a}{V_a} < u(c)$. Otherwise, the individual utility in Equations (21) and (22) will always be negative and neither HVs nor AVs will conduct the trip. If both θ_h and θ_a are positive, then the system reaches an equilibrium with the mixed flow. Otherwise, one travel mode will dominate the other one. By examining the feasible regions of the equilibrium condition in terms of the exogenous variables, we have the following corollary.

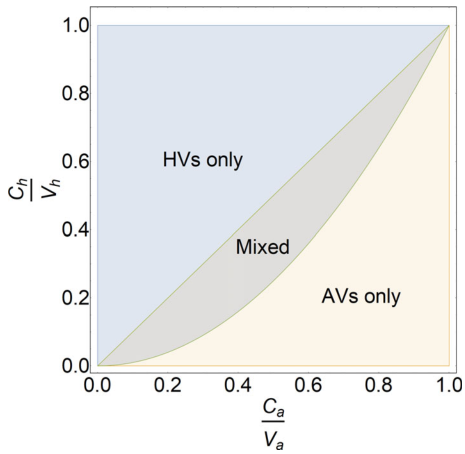
COROLLARY 1. *The pure-strategy Nash equilibrium for the mixed flow exists if* $\frac{C_h^2}{V_h^2 u(c)} \leq \frac{C_a}{V_a} \leq \frac{C_h}{V_h}$.

Similar as in the basic model, Corollary 1 indicates that the existence of mixed flow equilibrium depends heavily on the cost-benefit ratio of AVs and HVs, that is, $\frac{C_a}{V_a}$ and $\frac{C_h}{V_h}$. The necessary condition $\frac{C_a}{V_a} \leq \frac{C_h}{V_h}$ is the same as that in the basic model, which ensures the existence of AVs by the upper bound of $\frac{C_a}{V_a}$. However, as we have discussed in the basic model, $\frac{C_a}{V_a}$ cannot be too small, otherwise, AV technologies will dominate the traffic system and all HVs will be crowded out of the system by AVs. That is, the condition $\frac{C_h^2}{V_h^2 u(c)} \leq \frac{C_a}{V_a}$ ensures the participation of HVs into the traffic system. These two necessary conditions together provide the sufficient and necessary condition for the mixed flow to exist. Figure 3 illustrates the feasible region for the existence of mixed flow equilibrium when $u(c) = 1$.

With the specific queueing model, Proposition 4 provides more complicit results than that in the basic model. Therefore, we can calculate the social welfare and the aggregate throughput to evaluate the performance of the policy more accurately. The social welfare is

$$SW = UW_a^* + UW_h^* = \frac{(V_a C_h - C_a V_h)^2}{\alpha C_a V_h^2}, \tag{24}$$

Figure 3 Feasible Region for Mixed Flow Equilibrium [Color figure can be viewed at wileyonlinelibrary.com]



and the aggregate throughput is

$$\theta = \theta_a^* + \theta_h^* = \frac{(\beta - \alpha) V_a C_h^2}{\alpha \beta C_a V_h^2} + \frac{u(c)}{\beta} - \frac{C_h}{\alpha V_h}. \tag{25}$$

4.2.2. Fully Dedicated Policy. Similarly, in this subsection, we will discuss the fully dedicated policy where HVs and AVs are separated into different lanes.

Different from the basic model where continuous capacity is considered, here we assume that the government will assign K out of N lanes to AVs and the other $N - K$ lanes to HVs, where K is an integer. This assumption under the M/G/c/c queueing model is more practical. We denote the roadway capacity as $k = JLK$ for AVs and $c - k = JL(N - K)$ for HVs. Both AVs and HVs can only enter their designated lanes and form two independent queues, that is, an M/G/k/k queue for AVs and an M/G/c-k/c-k queue for HVs. The government's objective is to decide k to improve the traffic system concerning the total throughput and social welfare.

The expected travel time (and thus the congestion cost) is calculated based on two separate M/G/k/k and M/G/c-k/c-k queues. Following the decision processes in section 3.1, we can obtain the throughputs of the HV lanes and AV lanes via the following equations:

$$U_h^d = V_h - \frac{C_h}{u(c-k) - \beta \theta_h} = 0, \tag{26}$$

$$U_a^d = V_a - \frac{C_a}{u(k) - \alpha \theta_a} - p_a^{d*} = 0, \tag{27}$$

$$p_a^{d*} = \arg\max_{p_a^d} \frac{C_a + p_a^d u(k) - V_a u(k)}{\alpha (p_a^d - V_a)} p_a^d. \tag{28}$$

Table 3 Summary of Throughput, Travel Time, and Utility Under the Fully Dedicated Policy

	Throughput	Travel time	Utility
Dedicated HV	$\theta_h^{d*} = \frac{V_h u(c-k) - C_h}{\beta V_h}$	$EW_h^{d*} = \frac{V_h}{C_h}$	$UW_h^{d*} = 0$
Dedicated AV	$\theta_a^{d*} = \frac{\sqrt{V_a} u(k) - \sqrt{C_a}\sqrt{u(k)}}{\alpha\sqrt{V_a}}$	$EW_a^{d*} = \frac{\sqrt{V_a}}{\sqrt{C_a}\sqrt{u(k)}}$	$UW_a^{d*} = 0,\ \pi_a^{d*} = \frac{\left(\sqrt{C_a} - \sqrt{V_a}\sqrt{u(k)}\right)^2}{\alpha}$

Solving Equations (26)–(28) leads to the following proposition.

PROPOSITION 5. *The optimal throughput of AVs (θ_a^{d*}) and HVs (θ_h^{d*}), average travel time of AVs (EW_a^{d*}) and HVs (EW_h^{d*}), the aggregate utility of AV passengers (UW_a^{d*}) and HVs (UW_h^{d*}), and the profit of the AV company (π_a^{d*}) are given by Table* 3.

Note that the measurements in Proposition 5 are highly dependent on the exogenous variables and the allocation of the total capacity (i.e., k and $c - k$). When designing dedicated lanes, a natural problem for the government is how to allocate the capacity of the roadway segment to AVs and HVs. In our model, the government needs to decide $k \in [0, c]$ to implement a well-intended dedicated policy. Although in practice, the capacity of roadways should be discrete, the adoption of a continuous k is enough to reveal the relationship of the two metrics in our analytical model.

The decision-making process of the government can be formulated as optimization problems concerning the two metrics. In the fully dedicated policy, based on the results in Table 3, the government can maximize the total social welfare by solving the following problem

$$\max_k SW^d(\theta) = \max_k UW_h^{d*}(k) + UW_a^{d*}(k) = \max_k \frac{\left(\sqrt{C_a} - \sqrt{V_a}\sqrt{u(k)}\right)^2}{\alpha}, \quad (29)$$

or alternatively, it can maximize the aggregate throughput via

$$\max_k \theta^d(k) = \max_k \lambda_h^{d*}(k) + \lambda_a^{d*}(k) = \max_k \frac{u(c-k) - \frac{C_h}{V_h}}{\beta} - \frac{\frac{\sqrt{C_a}\sqrt{u(k)}}{\sqrt{V_a}} - u(k)}{\alpha}. \quad (30)$$

We summarize the results concerning the fully dedicated policy in the following two corollaries by solving these two optimization problems.

COROLLARY 2. *If $u(k) \geq \frac{C_h^2 V_a}{V_h^2 C_a}$, $SW^d(k) > SW$ and the social welfare is maximized at $k = c$ (AV lanes only).*

Corollary 2 implies that AVs contribute more to social welfare. The social welfare, that is, the aggregate utilities of all stakeholders, is fully captured by the AV company. Thus, social welfare is maximized when AVs throughput is maximized, that is, all of the capacity is allocated to the AV lane.

For the aggregate throughput, we have analyzed the complicated situation in the general model. Here we assume the free-flow speed function $u(x)$ to be a directly proportional function, as a special case of the linear function, to derive some analytical results. The linear assumption is widely used in the transportation literature (Manual 2000).

COROLLARY 3. *If $\frac{\alpha}{\beta} \leq 1 - \frac{C_a V_h^2 \sqrt{\frac{C_a u(k)}{V_a}}}{C_a V_h^2 u(k) + C_a C_h V_h - V_a C_h^2}$, $\theta^d(k) > \theta$ and the aggregate throughput is maximized at $k = c$ (AV lanes only); if $\frac{\alpha}{\beta} \geq 1 - \frac{C_a V_h^2 \sqrt{\frac{C_a u(c)}{V_a}}}{C_a V_h^2 u(c) + C_a C_h V_h - V_a C_h^2}$, $\theta^d(k) < \theta$ for all $k = 1, \ldots, c$;*

Corollary 3 shows two cases for the aggregate throughput. The first case holds when $\beta \gg \alpha$, where the platooning effect of AVs dominates the system and the optimal policy is to provide all of the limited roadway capacity to AVs. This case is trivial. However, AVs in real life cannot achieve such a high level, and the coexistence of AVs and HVs will be the reality for a long time. The second case holds when $\frac{\alpha}{\beta}$ is reasonable, implying the fully dedicated policy cannot improve the aggregate throughput. The reason is that the separated lanes will enhance the under-joining behavior for AVs and diminish the over-joining behavior for HVs. Therefore, as we have mentioned before, both the platooning effect and the crowding-out effect will be enhanced. However, the positive impact on throughput by platooning effect cannot compensate for the negative influence of the crowding-out effect, and the aggregate throughput will decrease.

4.2.3. Partially Dedicated Policy. In this subsection, we extend the fully dedicated policy such that AVs can drive on both the dedicated AV lanes and the HV lanes, while HVs can only drive on the HV lanes, named the partially dedicated policy. Therefore, the traffic system consists of dedicated AV lanes and mixed-flow lanes. We also assume that the government assigns the capacity k to the AV lanes and capacity $c-k$ to the mixed-flow lanes, and the function $u(x)$ is still a directly proportional function. When $k=0$, the partially dedicated policy is equivalent to the mixed policy and it degenerates to the fully dedicated policy with AV lanes only when $k=c$. Therefore, we only need to consider the case where $k \in (0, c)$. Then, repeating the analysis process in the fully dedicated policy, we have the following proposition.

PROPOSITION 6. *The optimal throughput of mixed AVs (θ_{ma}^{ed*}), dedicated AVs (θ_{da}^{ed*}), and HVs (θ_{mh}^{ed*}), average travel time of mixed AVs (EW_{ma}^{ed*}), dedicated AVs (EW_{da}^{ed*}), and HVs (EW_{h}^{ed*}), the aggregate utility of mixed AV passengers (UW_{ma}^{ed*}), dedicated AV passengers (UW_{da}^{ed*}), and HVs (UW_{h}^{ed*}), and the profit of the AV company on the mixed AV lane (π_{ma}^{ed*}) and dedicated AV lane (π_{da}^{ed*}) are given by Table 4.*

According to Proposition 4, we can calculate the social welfare and aggregate throughput as follows:

$$SW^{ed} = UW_{mh}^{ed*} + UW_{ma}^{ed*} + UW_{da}^{ed*} + \pi_{ma}^{ed*} + \pi_{da}^{ed*} = \frac{2(V_aC_h - C_aV_h)^2}{\alpha C_a V_h^2}, \tag{31}$$

$$\theta^{ed}(k) = \theta_{mh}^{ed*} + \theta_{ma}^{ed*} + \theta_{da}^{ed*} = \frac{2(\beta-\alpha)V_aC_h^2}{\alpha\beta C_a V_h^2} + \frac{u(c-k)+u(k)}{\beta} - \frac{2C_h}{\alpha V_h}. \tag{32}$$

COROLLARY 4. *In the partially dedicated policy, $SW^{ed}(k) \geq SW$ for all $k \in (0, c)$. $\theta^{ed}(k) > \theta$ for all $k \in (0, c)$ when $\frac{\alpha}{\beta} < \frac{V_aC_h - C_aV_h}{V_aC_h}$; $\theta^{ed}(k) < \theta$ for all $k \in (0, c)$ when $\frac{\alpha}{\beta} > \frac{V_aC_h - C_aV_h}{V_aC_h}$.*

Corollary 4 indicates that the partially dedicated policy can always improve social welfare regardless of the capacity allocation. This result is intuitive since the social welfare is captured by the AV company and the partially dedicated policy is providing inclination for AVs, while HVs are restricted. Similarly, for the aggregate throughput, it is improved when the platooning effect of AVs is strong enough. Interestingly, both the optimal social welfare and aggregate throughput are regardless of the capacity allocation when $u(x)$ is a directly proportional function. The AV company considers the profit of both the two types of lanes and can always adjust the service price to fit the government's capacity allocation decision. Finally, this group decision process of AVs will counteract the impact of the government's decision. This result provides more flexibility for the government's capacity allocation in the partially dedicated policy. Under certain circumstances$\left(\frac{\alpha}{\beta} < \frac{V_aC_h - C_aV_h}{V_aC_h}\right)$, the partially dedicated policy can improve social welfare and aggregate throughput simultaneously with any capacity allocation decision.

We then compare the partially dedicated policy with the fully dedicated policy. According to Corollary 2 and 3, if the fully dedicated policy can improve the traffic system, the optimal policy is to allocate all capacity to AV lanes. Therefore, we only consider the case where $k=c$ for the fully dedicated policy (also called the full AVs policy), while for the partially dedicated policy, the capacity allocation has no impact on the social welfare and aggregate throughput. The function $u(x)$ is still assumed to be a directly proportional function, where $u(c) \geq \frac{C_h^2 V_a}{V_h^2 C_a}$ for the mixed flow to exist. By comparing the two metrics of the two dedicated policies, we obtain the following corollary:

COROLLARY 5. *$SW^{ed} \geq SW^d(c)$ if $u(c) \leq \gamma_1$, while $SW^{ed} < SW^d(c)$ if $u(c) > \gamma_1$, where $\gamma_1 = \frac{2V_a^2C_h^2 + 2\sqrt{2}C_aV_aC_hV_h - 4C_aV_aC_hV_h - 2\sqrt{2}C_a^2V_h^2 + 3C_a^2V_h^2}{C_aV_aV_h^2}$. $\theta^{ed} \geq \theta^d(c)$ if $\frac{\alpha}{\beta} \leq \gamma_2$, while $\theta^{ed} < \theta^d(c)$ if $\frac{\alpha}{\beta} > \gamma_2$, where $\gamma_2 = \frac{C_a^{3/2}\sqrt{u(c)}V_h^2 - C_a\sqrt{V_a}u(c)V_h^2 - 2C_a\sqrt{V_a}C_hV_h + 2V_a^{3/2}C_h^2}{2V_a^{3/2}C_h^2 - C_a\sqrt{V_a}u(c)V_h^2}$.*

Corollary 5 provides two thresholds for the comparison of the two dedicated policies. It is easy to find that the comparison depends heavily on two

Table 4 Summary of Throughput, Travel Time, and Utility for the Partially Dedicated Policy

	Throughput	Travel time	Utility
Mixed HV	$\theta_{mh}^{ed*} = \frac{C_aV_h^2u(c-k)+C_aV_h^2u(k)-2V_aC_h^2}{\beta C_aV_h^2}$	$EW_{mh}^{ed*} = \frac{V_h}{C_h}$	$UW_{mh}^{ed*} = 0$
Mixed AV	$\theta_{ma}^{ed*} = \frac{-C_aV_h^2u(k)+2V_aC_h^2-C_aC_hV_h}{\alpha C_aV_h^2}$	$EW_{ma}^{ed*} = \frac{V_h}{C_h}$	$UW_{ma}^{ed*} = 0$, $\pi_{ma}^{ed*} = \frac{\left(V_a - \frac{cV_h}{C_h}\right)\left(-C_aV_h^2u(k)+2V_aC_h^2-C_aC_hV_h\right)}{\alpha C_aV_h^2}$
Dedicated AV	$\theta_{da}^{ed*} = \frac{u(k)-\frac{C_h}{V_h}}{\alpha}$	$EW_{a}^{ed*} = \frac{V_h}{C_h}$	$UW_{da}^{ed*} = 0$, $\pi_{da}^{ed*} = \frac{\left(V_a - \frac{cV_h}{C_h}\right)\left(u(k)-\frac{C_h}{V_h}\right)}{\alpha}$

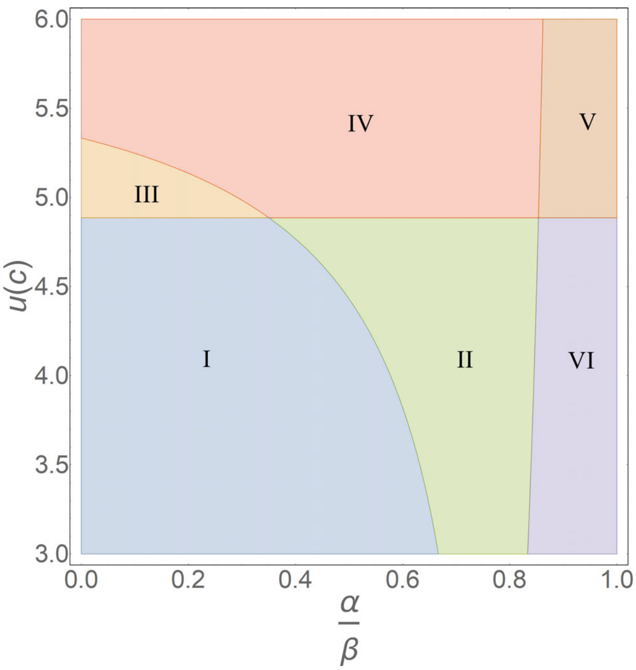
Production and Operations Management 31(4), pp. 1595–1612, © 2021 Production and Operations Management Society

parameters: $u(c)$ and $\frac{\alpha}{\beta}$. $u(c)$ can be regarded as the free-flow speed of the roadway with capacity c, characterizing the natural situation of the roadway. In the partially dedicated policy, due to the existence of HVs and the counteraction force of the AV company's group decision, $u(c)$ has no impact on social welfare. However, in the fully dedicated policy, a higher $u(c)$ provides a higher potential profit (social welfare) for the AV company and stimulates the policy inclination for AVs. Therefore, when $u(c)$ is high enough, the high potential welfare will induce a full AVs policy to optimize the social welfare. $\frac{\alpha}{\beta}$ characterizes the platooning effect of AVs, where a smaller $\frac{\alpha}{\beta}$ implies stronger platooning effect. Compared to the full AV policy, HVs' over-joining behavior in the mixed-flow lanes in the partially dedicated policy has a positive impact on the throughput of AVs because AV passengers are indifferent in the two types of lanes. However, this positive impact is insignificant when the platooning effect of AVs is weak. Only when the platooning effect is strong enough can the increased AV throughput in the dedicated AV lanes compensate for the loss of sharing some capacity with HVs. Therefore, when $\frac{\alpha}{\beta}$ is small enough, the partially dedicated policy is better than the full AVs policy in the aggregate throughput.

Combining the results in Corollary 2–5, we can obtain six scenarios for the comparison of the mixed policy, the fully dedicated policy and the partially dedicated policy. Figure 4 is an illustration of the six scenarios. In Scenario I, where $u(c) \le \gamma_1$ and $\frac{\alpha}{\beta} \le \gamma_2$, the partially dedicated policy dominates the fully dedicated policy in both social welfare and aggregate throughput. $u(c) \le \gamma_1$ implies the potential profit is limited, while $\frac{\alpha}{\beta} \le \gamma_2$ indicates the platooning effect of AVs is strong. Therefore, it will be better to keep the mixed-flow lanes instead of adopting the full AVs policy. In Scenario II, where $u(c) \le \gamma_1$ and $\frac{\alpha}{\beta} > \gamma_2$, the partially dedicated policy is superior to the fully dedicated policy in social welfare because the limited potential profit is not enough to support a full AV policy. For the aggregate throughput, the weak platooning effect restricts the positive impact of HVs' over-joining behavior in the partially dedicated policy, resulting in a lower aggregate throughput to the full AV policy. In Scenario III, the partially dedicated policy is superior to the fully dedicated policy in aggregate throughput due to the strong platooning effect. However, the high potential welfare makes it better to adopt full AV policy to optimize social welfare. In Scenario IV, the fully dedicated policy dominates the partially dedicated policy since the potential welfare is high and the platooning effect is weak.

In the first four scenarios, the fully dedicated or the partially dedicated policy always dominates the

Figure 4 **The Six Scenarios for the Comparison of the Mixed Policy, the Fully Dedicated Policy and the Partially Dedicated Policy. $V_a = 3$, $C_a = 1$, $V_h = 1$, $C_h = 1$ [Color figure can be viewed at wileyonlinelibrary.com]**



mixed policy in both social welfare and aggregate throughput, implying a Pareto-improvement. However, in Scenario V (VI), although the fully (partially) dedicated policy maximizes social welfare, the mixed policy dominates the aggregate throughput. More specifically, when $\frac{\alpha}{\beta} > \frac{C_a V_h^2\left(\sqrt{\frac{C_a u(c)}{V_a}} - u(c)\right) + V_a C_h^2 - C_a C_h V_h}{V_a C_h^2 - C_a u(c) V_h^2}$, where the platooning effect is relatively weak, the Pareto-improvement cannot be achieved. For this situation, we will introduce an additional policy instrument (subsidies) to enhance the dedicated policies.

4.2.4. Dedicated Policy with Subsidy.

In the dedicated policies, the government cannot improve the aggregate throughput in some cases (Scenario V, VI) because the crowding-out effect is more likely to dominate the platooning effect. Therefore, designing dedicated lanes for AVs, as an instrument aimed at enhancing platooning effect, is not enough to Pareto-improve the traffic system. In this section, we further consider mitigating the crowding-out effect in the dedicated policy, that is, to improve the aggregate throughput by encouraging more AVs to join the queue without reducing HV throughput. The low throughput of AVs is a result of the profit-maximization decision-making rule of the AV company, where the service price restricts some AV passengers from joining the queue. Providing an extra subsidy is one way to stimulate AV passengers' willingness to pay and increase the AV throughput without reducing the social welfare. Therefore, a Pareto-improvement is more likely to be achieved. Specifically, we first consider a partially dedicated policy with subsidy in which the government provides unit subsidy s to AV passengers but no subsidy to HV drivers. Thereby, HV drivers remain the same decision-making rule as in the partially dedicated policy, while AV passengers decide the throughput θ_a^{ds*} according to a modified utility function with subsidy:

$$U_{ma}^{eds} = V_a - C_a EW_{ma} - p_a^{eds*} + s = 0, \tag{33}$$

$$U_{da}^{eds} = V_a - C_a EW_{da} - p_a^{eds*} + s = 0. \tag{34}$$

Similarly, we can obtain the equilibrium results (See details in the Appendix) and the following proposition:

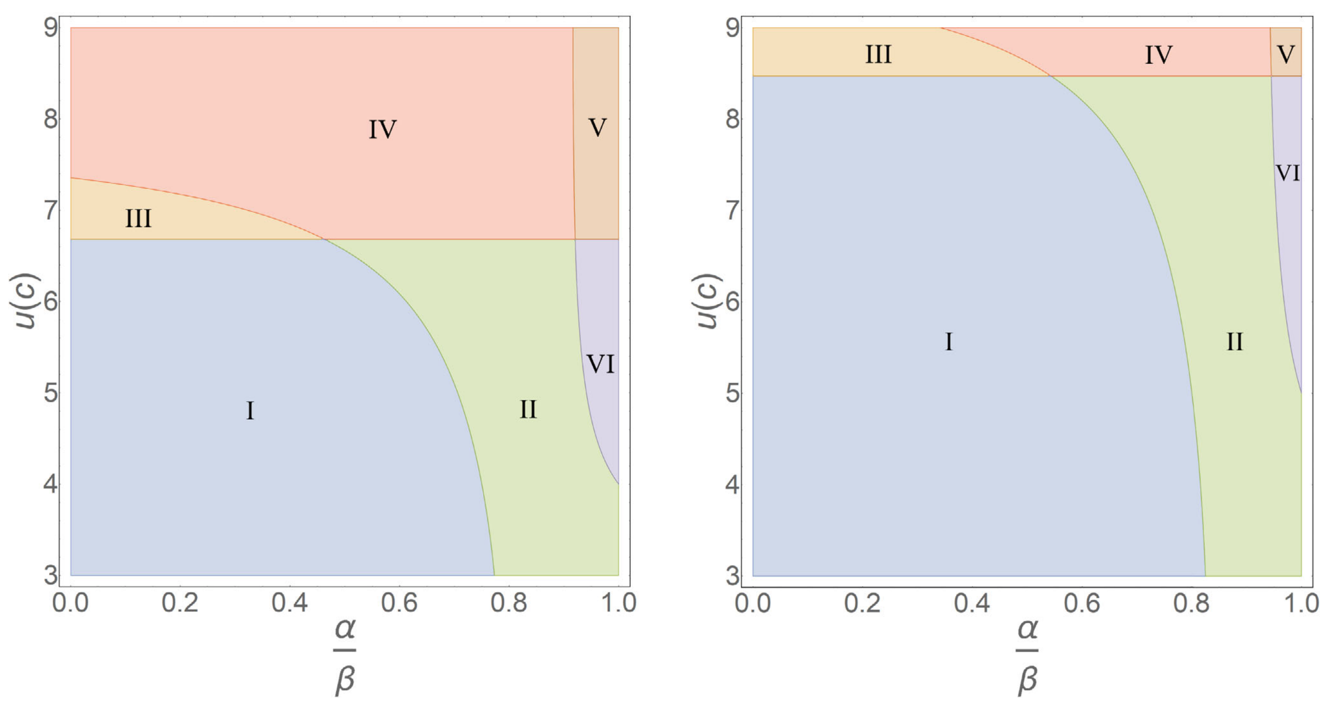
PROPOSITION 7. *In the partially dedicated policy with subsidy, $SW^{eds}(k) \geq SW$ for all $k \in (0, c)$. $\theta^{eds}(k) > \theta$ for all $k \in (0, c)$ when $\frac{\alpha}{\beta} < \frac{V_a C_h - C_a V_h + 2sC_h}{V_a C_h + 2sC_h}$.*

Proposition 7 provides a more relaxed condition for the aggregate throughput to be improved in the partially dedicated policy with subsidy. For AV passengers, the effect of offering a subsidy s is equivalent to increasing the payoff of the trip, which will stimulate the conservative throughput of AVs. Therefore, providing subsidy for AVs will encourage AVs to join the queue while not crowd out HVs. As a result, the crowding-out effect can be weakened and a win–win condition is more likely to be achieved. The analysis for the fully dedicated policy with subsidy is similar to before. We can obtain the following proposition:

PROPOSITION 8. *In the fully dedicated policy with subsidy, social welfare is maximized at $k = c$ (AV lanes only). If $\frac{\alpha}{\beta} \leq 1 - \frac{C_a V_h^2 \sqrt{\frac{C_a u(c)}{V_a + s}}}{C_a u(c) V_h^2 + C_a C_h V_h - V_a C_h^2}$, $\theta^{ds}(k, s) > \theta$ exists and the aggregate throughput is maximized at $k = c$ (AV lanes only).*

Similarly, providing subsidies to AVs relaxes the conditions for the Pareto-improvement to be achieved in the fully dedicated policy. Therefore, Scenario V and VI can be reduced by providing enough subsidies. Figure 5 is an illustration for the change of scenarios when $s = 1$ and $s = 2$. It is easy to see that with the increasing subsidy, the regions for Scenario V and VI shrink. Therefore, by increasing the subsidy s, the government can Pareto-improve both social welfare and aggregate throughput in more general cases. It is easy to see that $\lim_{s \to \infty} \frac{V_a C_h - C_a V_h + 2sC_h}{V_a C_h + 2sC_h} = 1$ and

Figure 5 An Illustration for the Change of Six Scenarios. $V_a = 3$, $C_a = 1$, $V_h = 1$, $C_h = 1$ [Color figure can be viewed at wileyonlinelibrary.com]



(a) s=1. (b) s=2.

$\lim_{s\to\infty} 1 - \frac{C_a V_h^2 \sqrt{\frac{C_a u(c)}{V_a+s}}}{C_a u(c) V_h^2 + C_a C_h V_h - V_a C_h^2} = 1$, implying as long as the subsidy is high enough, the Pareto-improvement can always be achieved.

5. Conclusion

Within the past decade, the developments of IoT, automation technologies, and CPS in the context of Industry 4.0 gave birth to AVs. We are witnessing the evolution of urban mobility from HVs to AVs. Mixed traffic flows of AVs and HVs are likely to turn our imagination into a reality in the near future. A stylized game-theoretical model is proposed to evaluate the consequences of this mixed autonomous paradigm. Two key features of the mixed traffic flow are included in the model: (i) HV drivers make individual travel decisions, while AV passengers' individual travel decisions are tuned by the AV company's pricing decision to maximize its profit; (ii) the travel time is more sensitive to HV throughput than AV throughput due to the platooning effect of AVs. We identify two important effects of AVs related to the features: the platooning effect and the crowding-out effect, and make comprehensive analyses about their interactions that generate complicated results. Based on the model, we ascertain the performance of two operational policies of mixed traffic flow: a baseline mixed (i.e., pooling) policy and a dedicated policy and its extensions. Our models focus on the Pareto-optimality of two important metrics: social welfare and aggregate throughput. Interestingly, these two metrics are usually not aligned, and therefore, it is significant for the government to take both of them into consideration. The major findings are summarized below.

First, we propose a series of dedicated policies, that is, the fully dedicated policy, the partially dedicated policy, the fully dedicated policy with subsidy, and the partially dedicated policy with subsidy to improve the traffic system. We identify the conditions for different policies to be adopted and provide straightforward policy recommendations. (i) When the free-flow speed is low and the platooning effect is strong, the partially dedicated policy is optimal in both social welfare and the aggregate throughput. (ii) When the free-flow speed is low and the platooning effect is moderate, the policy selection depends on which metric is more important. If the government concerns more about social welfare, the partially dedicated policy should be adopted; while if the aggregate throughput is in priority, the fully dedicated policy is the right choice. (iii) When the free-flow speed is high and the platooning effect is strong, the government should choose the partially dedicated policy if aggregate throughput is a major concern, while the fully dedicated policy is the solution for maximizing social welfare. (iv) When the free-flow speed is high and the platooning effect is moderate, the fully dedicated policy is the optimal choice concerning both two metrics. (v) When the platooning effect is very weak, subsidies must be considered to achieve a Pareto-improvement in both two metrics. Similarly, when the free-flow speed is high, the fully dedicated policy dominates. When the free-flow speed is low, if social welfare is prioritized, the government should choose the partially dedicated policy and vice versa.

Second, we introduce capacity allocation decision and the subsidy into dedicated policies and find that a Pareto-improvement in both social welfare and aggregate throughput can always be achieved compared to the baseline mixed policy. The superiority of dedicated policies in our model provides different insights from the literature (Mirzaeian et al. 2021) where the dedicated policy only outperforms the mixed policy in throughput with moderate AVs proportion. The difference mainly comes from three aspects: (i) The introduction of capacity allocation enables us to design different dedicated policies to fit different proportions of AVs. (ii) The endogenization of travel decisions provides more incentives for dedicated policies, for example, the smoother travel condition in the dedicated lane can attract more vehicles to join. (iii) The subsidy, as a complement for dedicated policies, provides more incentives for AVs to join the queue. In summary, Mirzaeian et al. (2021) find that the dedicated policy is only recommended when the proportion of AVs is moderate and the throughput is a major concern. In our paper, however, due to the flexible capacity allocation, self-interested travel decisions, and various dedicated policies, we conclude that dedicated policies can always dominate the mixed policy in both social welfare and throughput. In other words, since we focus on capacity allocation and different varieties of dedicated policies, we are more optimistic towards potential dedicated AV lanes for policy-makers to leverage on autonomous driving technology towards a more efficient and effective mobility market.

The insights from this research are not limited to service operations for mixed AVs and HVs, but can also be extended to other systems with similar attributes in users' decision-making processes and obtained services, for example, the system with two types of users. Especially, with the development of artificial intelligence (AI) in the context of Industry 4.0, many AI technologies are used to help people and the mixture of AI and human beings in the same service system becomes common. Here arise the problems of two types of users with different decision processes. The main methodology in our paper can be extended to solve this kind of service design problems.

A potential direction for future research is to consider privately owned AVs. Although the company-owned AVs are mainstream now, privately owned

AVs may become popular in the future. To incorporate privately owned AVs into analysis, we can use a discrete choice model in which uncertain utility is considered. We have tried to build a basic model and provide some simulation results in the appendix. This extension will make the problem more practical, which is more complicated but deserves investigation. Another interesting extension is to consider more variates of dedicated policy, for example, the inverse partially dedicated policy in which only HVs can enjoy dedicated lanes. Moreover, since the subsidy in this study is based on vehicle type (for AVs), another possibility is to consider providing subsidy based on lane type. This subsidy policy will incorporate the decision of lane choice and can influence the congestion levels of both lanes through the endogenous travel decision.

Acknowledgments

The authors sincerely thank the editors and the anonymous reviewers for their detailed comments and many valuable suggestions. This work was partially supported by the Research Grants Council of Hong Kong under grant no. 15502820, Hong Kong Research Grants Council (RGC) for General Research Fund 16208920, Alibaba-Zhejiang University Joint Research Institute of Frontier Technologies, NSFC (National Natural Science Foundation of China) grants 72071101, Hong Kong Research Grants Council (RGC) for General Research Fund 11215119, and Shenzhen Natural Science Fund (Grant No. GXWD20201230110313001, Program Contract No. 20200925160442005).

References

Abouee-Mehrizi, H., O. Baron, O. Berman, D. Chen. 2021. Adoption of electric vehicles in car sharing market. *Prod. Oper. Manag.* **30**(1): 190–209.

Arbabian, M. E., S. Chen, K. Moinzadeh. 2021. Capacity expansions with bundled supplies of attributes: An application to server procurement in cloud computing. *Manuf. Serv. Oper. Manag.* **23**(1): 191–209.

Baron, O., O. Berman, M. Nourinejad. 2018. Introducing Autonomous Vehicles: Formulation and Analysis. Available at SSRN: https://ssrn.com/abstract=3250557 (accessed date December 6, 2021).

Cheah, J. Y., J. M. G. Smith. 1994. Generalized m/g/c/c state dependent queueing models and pedestrian traffic flows. *Queueing Syst.* **15**(1): 365–386.

Chen, D., S. Ahn, M. Chitturi, D. A. Noyce. 2017. Towards vehicle automation: Roadway capacity formulation for traffic mixed with regular and automated vehicles. *Transport. Res. B. Meth.* **100**: 196–221.

Chen, S., H. Lee, K. Moinzadeh. 2019. Pricing schemes in cloud computing: Utilization-based vs. reservation-based. *Prod. Oper. Manag.* **28**(1): 82–102.

Chr, N. 1972. Individual and social optimization in a multiserver queue with a general cost-benefit structure. *Econom. J. Econom. Soc.* **40**(3): 515–528.

Cui, S., K. Li, L. Yang, J. Wang. 2021. Slugging: Casual carpooling for urban transit. *Manuf. Serv. Oper. Manag.* Forthcoming. https://doi.org/10.1287/msom.2021.0988.

Dickmanns, E. D. 2002. Vision for ground vehicles: History and prospects. *Int. J. Veh. Auton. Syst.* **1**(1): 1–44.

Dong, W., S. Liao, Z. Zhang. 2018. Leveraging financial social media data for corporate fraud detection. *J. Manag. Inf. Syst.* **35**(2): 461–487.

Edelson, N. M., D. K. Hilderbrand. 1975. Congestion tolls for poisson queuing processes. *Econom. J. Econom. Soc.* **43**(1): 81–92.

Fenton, R. E., R. J. Mayhan. 1991. Automated highway studies at the Ohio state university-An overview. *IEEE Trans. Veh. Technol.* **40**(1): 100–113.

Gao, Y., S. Kumar, D. Liu. 2021. Blockchain Technology Adoption in Digital Advertising: A Game-Theoretic Analysis. Available at SSRN: https://ssrn.com/abstract=3640784 (accessed date December 6, 2021).

Gartner, N. 2001. Traffic Flow Theory: A Sstate-of-the-Art Report. https://rosap.ntl.bts.gov/view/dot/35775 (accessed date December 6, 2021).

Ghiasi, A., O. Hussain, Z. S. Qian, X. Li. 2017. A mixed traffic capacity analysis and lane management model for connected automated vehicles: A Markov Chain method. *Transport. Res. B. Meth.* **106**: 266–292.

Ghoshal, A., S. Kumar, V. Mookerjee. 2020. Dilemma of data sharing alliance: When do competing personalizing and non-personalizing firms share data. *Prod. Oper. Manag.* **29**(8): 1918–1936.

Gilboa-Freedman, G., R. Hassin. 2014. Regulation under partial cooperation: The case of a queueing system. *Oper. Res. Lett.* **42**(3): 217–221.

Glathe, H.-B. 1994. Prometheus-a cooperative effort of the european automotive manufacturers. Technical report, SAE Technical Paper.

Greenshields, B. D., W. S. Channing, H. H. Miller, et al. 1935. A study of traffic capacity. *Highway research board proceedings*, vol. 1935. National Research Council (USA), Highway Research Board.

Guo, P., R. Hassin. 2011. Strategic behavior and social optimization in markovian vacation queues. *Oper. Res.* **59**(4): 986–997.

Guo, P., R. Hassin. 2012. Strategic behavior and social optimization in markovian vacation queues: The case of heterogeneous customers. *Eur. J. Oper. Res.* **222**(2): 278–286.

Hassin, R. 1986. Consumer information in markets with random product quality: The case of queues and balking. *Econom. J. Econom. Soc.* 1185–1195.

Hassin, R. 2016. *Rational Queueing*. CRC press, Boca Raton.

Hassin, R., M. Haviv. 2003. *To Queue or not to Queue: Equilibrium Behavior in Queueing Systems*, vol. **59**. Springer Science & Business Media, Berlin.

Hassin, R., R. I. Snitkovsky. 2017. Self, social and monopoly optimization in observable queues. *Proceedings of the 11th EAI International Conference on Performance Evaluation Methodologies and Tools*. 214–220.

Heidemann, D. 1996. A queueing theory approach to speed-flow-density relationships. *Transportation and Traffic Theory. Proceedings of the 13th International Symposium on Transportation and Traffic Theory, Lyon, France, 24–26 July 1996*.

Heidemann, D. 2001. A queueing theory model of nonstationary traffic flow. *Transp. Sci.* **35**(4): 405–412.

Ioannou, P., Z. Xu, S. Eckert, D. Clemons, T. Sieja. 1993. Intelligent cruise control: Theory and experiment. *Proceedings of 32nd IEEE Conference on Decision and Control*. IEEE, 1885–1890.

Jain, R., J. M. G. Smith. 1997. Modeling vehicular traffic flow using m/g/c/c state dependent queueing models. *Transp. Sci.* **31**(4): 324–336.

Jain, T., J. Hazra, S. Kumar. 2021. Pricing Strategies of Public Cloud Computing Instances: A Game-Theoretic Model.

Available at SSRN: https://ssrn.com/abstract=3326688. (accessed date December 6, 2021)

Jin, L., M. Čičić, S. Amin, K. H. Johansson. 2018. Modeling the impact of vehicle platooning on highway congestion: A fluid queuing approach. *Proceedings of the 21st International Conference on Hybrid Systems: Computation and Control (part of CPS Week)*. 237–246.

Kerner, B. S., H. Rehborn. 1996. Experimental features and characteristics of traffic jams. *Phys. Rev. E.* **53**(2): R1297.

Kerner, B. S., S. L. Klenov, A. Hiller, H. Rehborn. 2006. Microscopic features of moving traffic jams. *Phys. Rev. E.* **73**(4): 046107.

Lee, J., B. Park. 2012. Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment. *IEEE Trans. Intell. Transp. Syst.* **13**(1): 81–90.

Lioris, J., R. Pedarsani, F. Y. Tascikaraoglu, P. Varaiya. 2017. Platoons of connected vehicles can double throughput in urban roads. *Transp. Res. C. Emerg. Technol.* **77**: 292–305.

Littlechild, S. C. 1974. Optimal arrival rate in a simple queueing system. *Int. J. Prod. Res.* **12**(3): 391–397.

Liu, Y., A. B. Whinston. 2019. Efficient real-time routing for autonomous vehicles through bayes correlated equilibrium: An information design framework. *Inf. Econ. Policy.* **47**: 14–26.

Luo, Q., R. Saigal, Z. Chen, Y. Yin. 2019. Accelerating the adoption of automated vehicles by subsidies: A dynamic games approach. *Transport. Res. B. Meth.* **129**: 226–243.

Mahmassani, H. S. 2016. 50th anniversary invited articleautonomous vehicles and connected vehicle systems: Flow and operations considerations. *Transp. Sci.* **50**(4): 1140–1162.

Manual, H. C. 2000. Highway capacity manual. Washington, DC, 2, 1.

Milanés, V., S. E. Shladover. 2014. Modeling cooperative and autonomous adaptive cruise control dynamic responses using experimental data. *Transp. Res. C. Emerg. Technol.* **48**: 285–300.

Mirzaeian, N., S.-H. Cho, A. Scheller-Wolf. 2021. A queueing model and analysis for autonomous vehicles on highways. *Management Sci.* **67**(5): 2904–2923.

Monteil, J. 2014. Investigating the effects of cooperative vehicles on highway traffic flow homogenization: analytical and simulation studies. Ph.D. thesis.

Naor, P. 1969. The regulation of queue size by levying tolls. *Econom. J. Econom. Soc.* **37**(1): 15–24.

Naumov, S., D. R. Keith, C. H. Fine. 2020. Unintended consequences of automated vehicles and pooling for urban transportation systems. *Prod. Oper. Manag.* **29**(5): 1354–1371.

Ngoduy, D. 2013. Platoon-based macroscopic model for intelligent traffic flow. *Transp. B Transp. Dyn.* **1**(2): 153–169.

Ploeg, J., B. T. M. Scheepers, E. Van Nunen, N. Van de Wouw, H. Nijmeijer. 2011. Design and experimental evaluation of cooperative adaptive cruise control. *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 260–265.

Pomerleau, D., T. Jochem. 1996. Rapidly adapting machine vision for automated vehicle steering. *IEEE Exp.* **11**(2): 19–27.

Pueboobpaphan, R., B. Van Arem. 2010. Driver and vehicle characteristics and platoon and traffic flow stability: Understanding the relationship for design and assessment of cooperative adaptive cruise control. *Transp. Res. Rec.* **2189**(1): 89–97.

Qu, X., S. Wang, J. Zhang. 2015. On the fundamental diagram for freeway traffic: A novel calibration approach for single-regime models. *Transport. Res. B. Meth.* **73**: 91–102.

Rillings, J. H. 1997. Automated highways. *Sci. Am.* **277**(4): 80–85.

SAE On-Road Automated Vehicle Standards Committee. 2014. Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems. *SAE Standard J.* **3016**, 1–16.

Shladover, S. E. 2018. Connected and automated vehicle systems: Introduction and overview. *J. Intell. Transp. Syst.* **22**(3): 190–200.

Shladover, S. E., C. A. Desoer, J. K. Hedrick, M. Tomizuka, J. Walrand, W.-B. Zhang, D. H. McMahon, H. Peng, S. Sheikholeslam, N. McKeown. 1991. Automated vehicle control developments in the path program. *IEEE Trans. Veh. Technol.* **40**(1): 11–130.

Shladover, S. E., D. Su, X.-Y. Lu. 2012. Impacts of cooperative adaptive cruise control on freeway traffic flow. *Transp. Res. Rec.* **2324**(1): 63–70.

Talebpour, A., H. S. Mahmassani. 2016. Influence of connected and autonomous vehicles on traffic flow stability and throughput. *Transp. Res. C. Emerg. Technol.* **71**: 143–163.

Talebpour, A., H. S. Mahmassani, F. E. Bustamante. 2016. Modeling driver behavior in a connected environment: Integrated microscopic simulation of traffic and mobile wireless telecommunication systems. *Transp. Res. Rec.* **2560**(1): 75–86.

Talebpour, A., H. S. Mahmassani, A. Elfar. 2017. Investigating the effects of reserved lanes for autonomous vehicles on congestion and travel time reliability. *Transp. Res. Rec.* **2622**(1): 1–12.

Tsugawa, S., T. Saito, A. Hosaka. 1992. Super smart vehicle system: Avcs related systems for the future. *Proceedings of the Intelligent Vehicles92 Symposium*. IEEE, 132–137.

Van Woensel, T., N. Vandaele. 2006. Empirical validation of a queueing approach to uninterrupted traffic flows. *4OR* **4**(1): 59–72.

Van Woensel, T., B. Wuyts, N. Vandaele. 2006. Validating state-dependent queueing models for uninterrupted traffic flows using simulation. *4OR* **4**(2): 159–174.

Vandaele, N., T. Van Woensel, A. Verbruggen. 2000. A queueing based traffic flow model. *Transp. Res. D. Transp. Environ.* **5**(2): 121–135.

Varaiya, P. 1993. Smart cars on smart roads: Problems of control. *IEEE Trans. Autom. Control.* **38**(2): 195–207.

Xiong, X., E. Xiao, L. Jin. 2019. Analysis of a stochastic model for coordinated platooning of heavy-duty vehicles. *2019 IEEE 58th Conference on Decision and Control (CDC)*. IEEE, 3170–3175.

Yang, H., T. Yang. 2011. Equilibrium properties of taxi markets with search frictions. *Transport. Res. B. Meth.* **45**(4): 696–713.

Yechiali, U. 1971. On optimal balking rules and toll charges in the gi/m/1 queuing process. *Oper. Res.* **19**(2): 349–370.

Yechiali, U. 1972. Customers' optimal joining rules for the gi/m/s queue. *Management Sci.* **18**(7): 434–443.

Zhang, Z., G. Nan, Y. Tan. 2020. Cloud services vs. on-premises software: Competition under security risk and product customization. *Inf. Syst. Res.* **31**(3): 848–864.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

EC.1: Proofs.