Better be private, shared, or pooled? Implications of three autonomous mobility scenarios in Lyon, France

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ABSTRACT

Autonomous vehicles will be one of the most disruptive technologies of the automative industry. Their wider implications on society are expected to be considerable, even if these implications are still under debate. Meanwhile, various stakeholders, including cities and tech companies, are launching different AV pilot projects to test and help boost the technology readiness level. This research assesses some of the impacts of three AV mobility scenarios: private, shared, and pooled AVs in Lyon, France. An agent-based simulation framework is used (MATSim). Results suggest that AV services can reshuffle existing transportation dynamics by attracting a significant share of travel demand, especially from public transport and walking. If not regulated, these services can produce substantial excess travel distances and increase energy consumption and emissions of the transportation system. In this regard, pooled robotaxis are the least impactful introduction scenario of AVs compared to non-pooled robotaxis or private AVs.
Keywords: Autonomous vehicle, Shared autonomous vehicle, Pooled autonomous vehicle, Robotaxi, Impact, Agent-based model.

1 Introduction

Full vehicle automation will be one of the most disruptive developments of the years to come (Litman, 2022). From a technological point of view, many technical challenges mark the path of the introduction of autonomous vehicles (AVs), but constant progress is being made in this direction and many milestones have already been reached. From a societal point of view, the wider implications of this technology are, however, still under debate. Meanwhile, many cities and private stakeholders are engaging in AV pilot projects, sometimes with little regard to their broader implications (McAslan et al., 2021). In this context, the investigation of AV impacts is of critical importance.

Research has devoted many studies to the investigation of AV implications. Various direct and ripple effects following the introduction of AVs were discussed, and in some cases evaluated. These impacts include: car adoption and use (Soteropoulos et al., 2018; Lécureux et al., 2022; Gurumurthy & Kockelman, 2020), travel cost (Bösch, Becker, et al., 2018), mode competition (Bösch, Ciari, & Axhausen, 2018), network congestion (Maciejewski & Bischoff, 2018), safety (Koopman & Wagner, 2017), parking (Millard-Ball, 2019), energy consumption (Morfeldt & Johansson, 2022), road infrastructure (Saeed, 2019), social and spatial equity (Meyer et al., 2017), residential and firm location (Gelauff et al., 2017; Meyer et al., 2017), job creation and destruction (Nikitas et al., 2021).

If most studies agree that the introduction of AVs can have serious implications, no clear consensus has emerged yet on the magnitude of these implications (Lécureux et al., 2022). This is because these studies rely on: (i) various assumptions regarding the introduction, adoption, and use of AVs, (ii) different methodologies, and (iii) applied to different spatial and cultural contexts. Consequently, this makes the comparison of research findings on the implications of AVs not straightforward and in some cases misleading. Nevertheless,

most studies acknowledge that the implications of AVs will depend on their introduction scenario: private, shared, pooled, electric, or fossil-fueled.
Research supports that private AVs (PAVs) are likely to decrease car ownership since one PAV can be shared between all household members (Brandon Schoettle, 2015; May et al., 2020; Zhang et al., 2018; Saleh & Hatzopoulou, 2020). As a consequence, the introduction of PAVs can induce new travel demand and compete against existing travel modes. Research points to a potential reduction in the use of public transport (PT) and active modes to the benefit of PAVs (Meyer et al., 2017; May et al., 2020; Zhang et al., 2018; Brandon Schoettle, 2015). Other studies highlight the potential impact of PAVs on parking and urban space management (Bischoff et al., 2019; Bahk et al., 2022). Some authors show that PAVs can induce an increase in total Vehicle-Kilometers of Travel (VKT) and car Passenger-Kilometers of Travel (PKT) (Rodier, 2018; Bahk et al., 2022). This increase is due to empty-drive and induced demand (Saleh & Hatzopoulou, 2020; Zhang et al., 2018).
In comparison with PAVs, shared AVs (SAVs) have received more attention from research for their potential to be the most likely AV scenario during the first years of their introduction. Research shows that SAVs can substitute for many private conventional vehicles (PCV). Many authors find a substitution rate around 10%, i.e. 1 SAV replaces nearly 10 cars (Narayanan et al., 2020; Llorca et al., 2017; Moreno et al., 2018; Bischoff & Maciejewski, 2016; Liu et al., 2017). However, this rate can vary from one study to another (see (Narayanan et al., 2020) for a review). When AVs are shared, most studies point to a potential increase in car VKT, mainly due to empty-drive. The magnitude of this increase varies significantly between studies. This excess travel is reduced when SAVs are pooled, i.e. simultaneously shared between different passengers.
In this research, we investigate some of the direct implications of three mobility scenarios based on AVs: Private AVs (PAVs), Shared AVs (SAVs), and Pooled Shared AVs (PSAVs). This investigation is conducted in the city of Lyon, France and it relies on MATSim, a multimodal state-of-the-art agent-based simulation framework (Horni et al., 2016).

2 Methodology and assumptions

AV mobility scenarios

PAVs are personal AVs that are shared within the household and made available to all its members aged 5 years and above, regardless of their driving capabilities. SAVs are shared AVs that operate as robotaxis. Potential users can request an SAV and use it exclusively. PSAVs are SAVs that allow ride-pooling.
Each of these three scenarios relies on various assumptions.

- In the PAV scenario, we assume:
  - In all households that own one or more PCVs, the car is replaced with one and only one PAV.
  - The PAV is shared between all household members aged 5 years old and above regardless of their driving capabilities.
  - The marginal cost of using a PAV is similar to that of a conventional car, everything else is held constant.
  - The value of time (VoT) when using a PAV is 75% that of using public transit (PT) to value onboard activities and improved comfort.
  - PAVs cannot be pooled between different household members.
- In the SAV scenario, we assume:

  - Ban of PCVs for all households that live in the most densely populated areas of Lyon. In these areas, a service of robotaxis is operated. This results in a scenario with a mixed car fleet: SAVs + PCVs.
  - SAVs are shared but cannot be pooled between different users.
  - The distance fare of using an SAV has a 30% overhead in comparison with the PCV (0.26 € per kilometer) with a minimum fare of 0.53 €.

- In the PSAV scenario, we assume:
  - Ban of PCVs for all households that live in the most densely populated areas of Lyon. In these areas, a service of pooled robotaxis is operated. This results in a scenario with a mixed car fleet: PSAVs + PCVs.
  - PSAVs are shared and can be pooled between a maximum of 4 passengers.
  - The distance fare of using a PSAV has a 15% overhead in comparison with the PCV (0.23 € per kilometer) with a minimum fare of 0.45 €.

The time spent using PAVs, SAVs, or PSAVs is valued similarly. The initial parking location of SAVs and PSAVs is inferred from the location of taxi stands in Lyon.
Based on these assumptions, 410,240 PAVs are introduced in Lyon. For SAVs and PSAVs, various fleet sizes were tested, starting with the most common substitution rate of 10%. Results suggest that a rate of $\approx 1:7$ or 15% is a convenient trade-off, that limits the size of the fleet and keeps waiting times reasonable. This results in the introduction of 54,860 SAVs and PSAVs in replacement of 367,562 PCVs.
In the three scenarios, we assume that the AV technology does not significantly improve the capacity of the network in Lyon. Simulation outcomes of these scenarios are compared to the pre-pandemic reference mobility scenario of Lyon. The reference scenario has been calibrated to replicate observed pre-pandemic mobility behaviors.

Microsimulation framework

Agent-based models (ABM) are convenient tools to simulate AVs and their systemic implications. By design, these tools can simulate various microscopic interactions in space and time between travel demand and supply. This high modeling resolution is required for the simulation of AVs, especially when shared or pooled between users.
This research is conducted using MATSim, an open-source ABM adapted for the simulation of large-scale transportation scenarios (Horni et al., 2016). MATSim relies on a fine description of travel demand and supply. Travel demand is described by agents and their daily activity plans. MATSim agents are utility-maximizers. The performance of daily activities increases their utility, whilst the time and cost spent traveling between these activities decrease their utility. Each agent can optimize its daily plan by changing its (i) travel mode, (ii) route, or (iii) departure time. At the end of each iteration, agents score their daily plans and decide to keep or change them in the next iteration. Plan mutation is performed by a genetic algorithm. To limit large outcome fluctuations, only a limited portion of agents (i.e. less than 15%) can change their daily plans at once. After a number of iterations, simulation outcomes reach an equilibrium where the daily activity and mobility plans of agents are optimized, given their constraints, preferences, and choices made by other agents.
The simulation of AV scenarios is performed thanks to two MATSim extensions: *DRT* (Bischoff et al., 2016) and *TAXI* (Maciejewski & Nagel, 2013). The *DRT* extension simulates various mobility services based on the demand-responsive transport paradigm. The extension is used for the simulation of PSAVs. At the core of the *DRT*, is the central request dispatcher (CRD) that manages incoming taxi requests and their assignment to PSAVs. The assignment of requests can be subject to various constraints attached to several operational objectives: optimize waiting time, maximum detour, or maximum excess

travel times. For each incoming taxi request, the CRD checks the possibility to insert this request into the current taxi routing plans. This insertion can be rejected if it causes long excess travel times or detours for passengers (Bischoff et al., 2016).
For the simulation of PAVs and SAVs, the *TAXI* extension is used (Maciejewski & Nagel, 2013). This extension is based on the DVRP (Dynamic Vehicle Routing Problem) that is often used for on-demand transportation services (Maciejewski & Bischoff, 2015). Similar to the PSAV, a CRD manages incoming taxi requests and assigns these to vehicles. For PAVs, agents have only access to their corresponding private AV. For household members that might compete for the PAV, vehicle assignment is performed following the first come first served strategy. For robotaxis, any available taxi can be assigned to any request. This assignment algorithm changes according to the balance between taxi demand and supply (Maciejewski et al., 2016):

1. **Under-supply**: if taxi demand exceeds supply, requests are served according to the strategy of the first available taxi the first dispatched. Available taxis are assigned to the closest requests to minimize their waiting times, regardless of their incoming order.

2. **Over-supply**: if taxi supply exceeds demand, the first come first served strategy is adopted. For each request, the closest available taxi is assigned to minimize the taxi idle time of SAVs.

Case study of Lyon

The 3 mobility scenarios are evaluated in the case of the Métropole de Lyon (ML), France. ML has a population of 1.4 million and an area of $534 km^2$. The average population density is 2,645 $inhab/km^2$. 47% of this population lives in the municipalities of Lyon and Villeurbanne. The PT system of ML has 4 subway lines, 7 tramway lines, nearly 8 BRT lines, and 130 bus lines. In 2019, this network was used by nearly 1.8 million daily trips, which makes it the second-largest PT system in France
There are nearly 1.04 cars per household in ML. According to the 2015 household travel survey (SYTRAL, 2015), 42% of trips were conducted using the car, 36% by foot, 20% by PT, and 2% by bike.
The 3 scenarios are compared to the reference scenario of Lyon. This scenario is calibrated to replicate observations from the HTS of 2015 (SYTRAL, 2015). The calibration consists in finding appropriate parameters for the utility function of agents. These parameters are chosen to replicate observed modal shares and modal shares by distance (Fig. 1).

Data

For the description of travel demand, MATSim requires detailed information on the daily activity and mobility plans of each individual in the population of interest. For confidentiality reasons, this information is, at best, available for a small sample of the population. To overcome this limitation, most ABM, including MATSim, resort to using synthetic populations. A synthetic population is a set of artificial agents that replicate the most relevant aspects of the population of interest. The synthetic population of Lyon is generated by EQASIM (Hörl & Balac, 2021). By combining HTS (SYTRAL, 2015) and Census Data (CD) (INSEE, 2019), EQASIM reconstructs the population of Lyon at the individual and household levels. Each synthetic agent is characterized by its gender, age, residential location, household size, etc. Activity and mobility plans are inferred from the HTS and assigned to agents using a statistical matching algorithm. In this paper, activity plans describe the daily routines of a typical pre-pandemic workday.
For the description of travel supply, MATSim requires information on the transportation network: road links, PT stops, timetables, etc. MATSim relies, as much as possible, on open-source data: GTFS and OpenStreetMap.

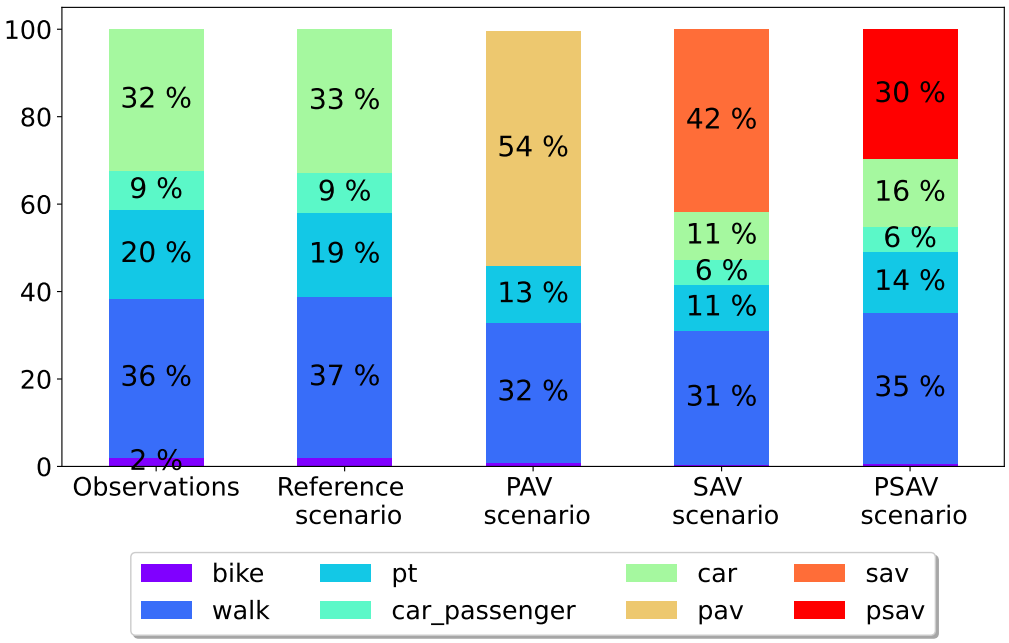


Figure 1: Observed and simulated modal shares in the reference, PAV, SAV, PSAV scenarios.

MATSim is a large-scale agent-based simulation framework that might require considerable computational time to reach convergence. In Lyon, the convergence is reached after 1,000 iterations. For the PAV scenario, for example, the simulation of 100% of the population can take more than a month[1]. To reduce this time, the simulation is down-scaled with a random draw of 5% of the total population. Travel supply is accordingly reduced. This down-scaling reduces computational times for the PAV scenario to nearly 6 days.

3 Results

Mode competition of AVs

Simulation results show that the AV mobility services can attract a considerable share of travel demand (Fig. 1). 54%, 41%, and 30% of total trips are performed using PAVs, SAVs, and PSAVs, respectively. Most of this demand is shifted from PCV drivers and passengers (Fig. 2). 70%, 53%, and 58% of the trips performed by PAVs, SAVs, and PSAVs, used to be performed by the PCV in the reference scenario (Fig. 2). The rest of AV demand is, however, shifted from car-alternative modes. 15% and 13% of PAVs' demand is shifted from walking and PT. 25% and 19% of SAVs' demand is shifted from PT and walking. 26% and 13% of PSAVs' demand is shifted from PT and walking.
From a modal share perspective, the introduction of AV services is mostly detrimental to PT. In the three scenarios, the share of PT decreases between 30% and 50%. Nevertheless, the competition brought by these services is partially attenuated by the reduction in car ownership and the increase in car-sharing. Between 10% and 12% of car users in the reference scenario shift to other car-alternative modes, especially PT and walking in the AV scenarios.

AV mobility patterns

The three AV scenarios have a significant potential to attract and induce travel demand. Mobility patterns associated with each scenario are however different. Simulation results

[1]On a personal computer with 12 cores and 32 Go of RAM

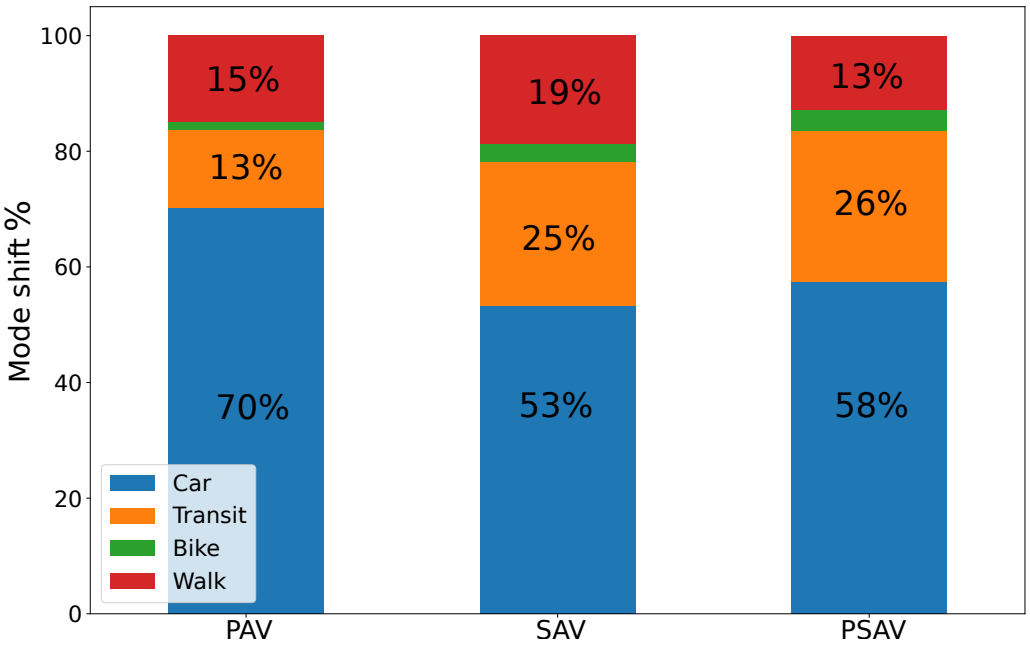


Figure 2: Modal transfers to PAVs, SAVs, and PSAVs.

highlight a variety of uses of AVs (Fig. 3). With automation and car-sharing, PAVs are used for different travel purposes: work (15% of trips), education (8%), return to home (41%), shopping (10%), leisure (13%), and other activities (13%). In comparison with the reference scenario, PAVs are more used for commuting to school than before. Trips to school that used to be performed by car, mainly as car-passenger, are 5% in the reference scenario and 8% in the PAV scenario.

This distribution is not only dictated by the weight of each trip purpose in daily routines, but also by their departure time distribution. As mentioned, PAVs are assigned to household members according to the first come first served strategy. In the morning peak period (7AM-9AM), the use of PAVs is dominated by commuting trip purposes (Fig. 3). During the evening peak period (4PM-7PM), PAVs are mostly used to return home. In between, PAVs are used for secondary activities, like shopping and leisure.

SAVs and PSAVs show similar use patterns to PAVs. Most of robotaxi requests during the morning rush period are for commuting. Secondary trip purposes are more prevalent during off-peak periods.

If PAVs, SAVs, PSAVs have similar travel patterns, their intensity of use is, however, different. Results show that PAVs are used, on average, for 3.5h (Std 3h) per day, instead of 42min (Std 30min) of use of PCVs in the reference scenario. SAVs are nearly used for 14h (Std 2h20min) a day, whereas PSAVs are used, on average, for 10h.

The increase in the use-intensity of AVs can also be illustrated by the number of daily trips of each service. In the reference scenario, the PCV is used, on average, for 3.2 daily trips (median 2, Std 1.7). PAVs are used for 6.3 daily trips (median 6, Std 4). SAVs are used for 35 daily trips (median 36, Std 7.2). PSAVs are used for 25 trips (median 25, Std 9.3).

The use of shared AVs (SAVs and PSAVs) is partly dependent on the trade-off between taxi supply and demand that translates into passenger waiting times. These times vary during the day (Fig. 4). Waiting times of SAVs and PSAVs are skewed to the right by extreme values. For the SAV service, their median and average values are 9min and 22min, respectively (Fig. 4a). For PSAVs, median and average waiting times are less than 7min and 15min respectively (Fig. 4b). As expected, waiting times increase during morning and evening peak periods (Fig. 4), especially for the SAV service. High waiting times for these services are due to their limited availability. From 8AM to 9PM, 100% of the SAV fleet is busy (red dashed curve in Fig. 4a). When demand exceeds supply, the first available robotaxi is dispatched to the closest waiting request. Consequently, SAV users

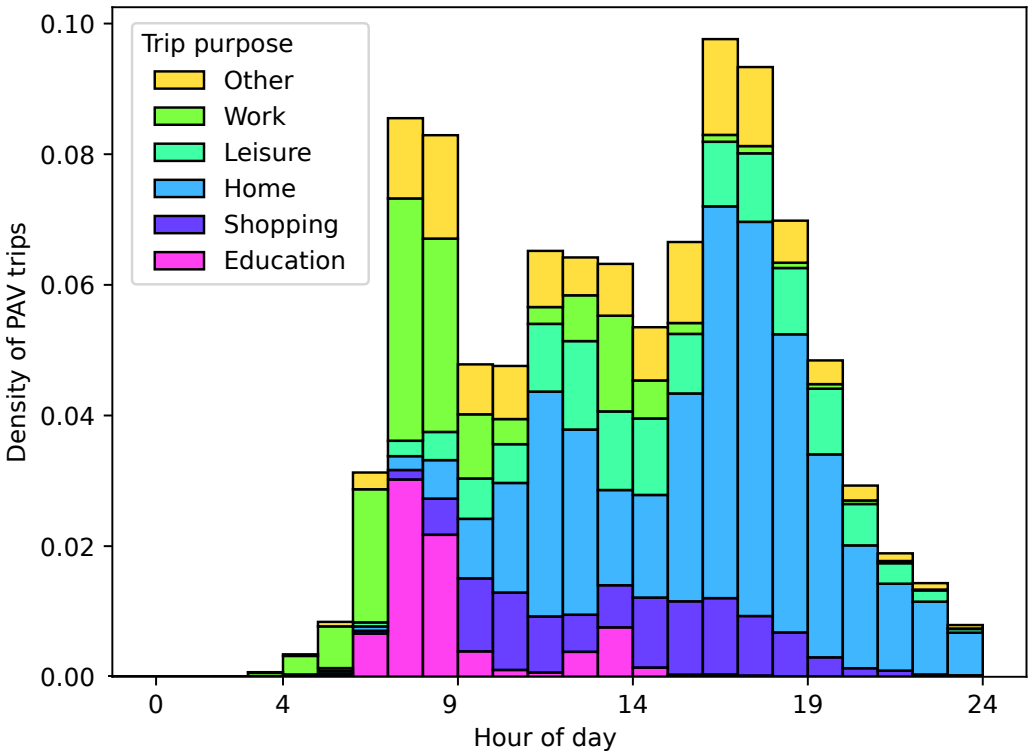
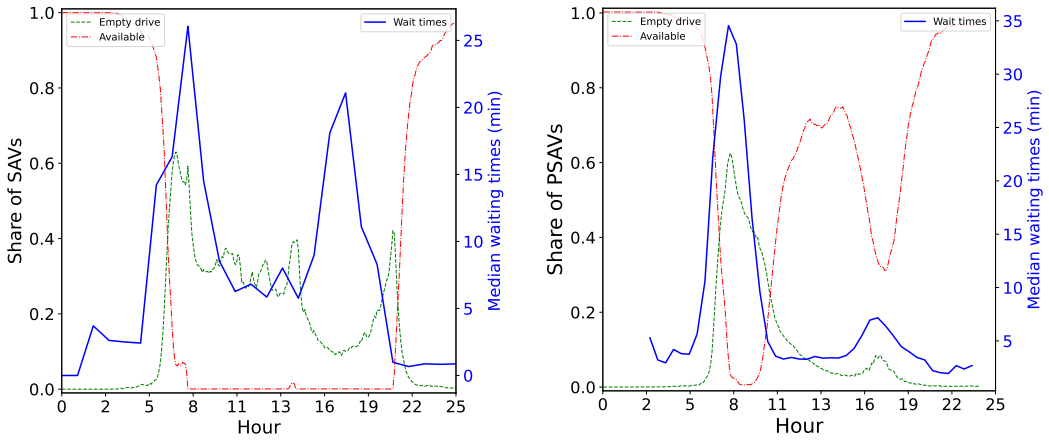


Figure 3: Density distribution of PAV trips by purpose and hour of the day.

can experience high waiting times, while robotaxis can incur high empty-drive distances. PSAVs show a similar pattern during the morning peak period, but less during the evening peak period (blue curve in Fig. 4b).
Due to their non-optimized initial parking location, waiting times of SAVs and PSAVs are higher during the morning than during the evening peak period. During the morning peak, requests stem from various places, not necessarily near the initial parking locations of AVs. Serving these requests requires significant waiting times due to empty-drive (green dashed lines in Fig. 4). During the evening peak, robotaxis are already located near potential "hot spots" of demand that have been served earlier in the day. Consequently, waiting times are lower and even lower for PSAVs than SAVs. PSAVs are less busy (more than 30% of PSAVs are available between 4PM and 9PM) and capable to serve several requests on their way. However, the use of PSAVs makes passengers incur excess travel times due to detours and pick-up/drop-off operations. On average, PSAVs have 1.48 (median 1.54, Std 0.15) passenger. During the morning and evening peak periods, PSAVs' average occupancy is 1.37 and 1.6 passenger, respectively.

Implications of AV use

If automation and car-sharing can boost car-use intensity and open new opportunities for their operation, the increased intensity comes at a price. To serve different distant travel requests, AVs are required to drive empty to satisfy these requests. In comparison with the reference scenario, VKT in the PAV scenario increases by 102%. 59% of this increase is due to empty-drive of PAVs. In the SAV scenario, the VKT increases by 66%, of which 27% is due to empty-drive. For PSAVs, the VKT increases by 22%, and 9% are due to empty-drive. For the three scenarios, the rest of the increase in VKT is attributable to car users and induced demand shifted from other modes.
The significant increase in total VKT due to AVs can have serious implications on network congestion, AV consumption, and emissions. If PAVs, SAVs, and PSAVs were electric, their total electricity consumption would be roughly proportional to their total VKT. Given this assumption, total PAVs, SAVs, and PSAVs' consumption can be 2.5, 2, and 1.4 times that



(a) Performance indicators of SAVs.

(b) Performance indicators of PSAVs.

Figure 4: Performance indicators: availability, empty distance, median wait times of SAV and PSAV services.

of the PCV, ceteris paribus. If these technologies were to run on fossil fuels, the ratios of emissions would also be of this order of magnitude.

4 Discussion

Findings emphasize that the three AV mobility services can have a significant modal share in Lyon. This popularity comes at the expense of car-alternative modes, especially, PT. The relatively reduced cost of use of AV services reduces its generalized cost and shifts demand to these services. Previous research confirms this finding (Morfeldt & Johansson, 2022; Saleh & Hatzopoulou, 2020; May et al., 2020; Llorca et al., 2017; Chen & Kockelman, 2016). The competition brought by AV services is not compensated for by the decrease in car ownership that follows their introduction. In the case of Lyon, $\approx 10\%$ of car users switch to car-alternative modes, while more than 30% of car-alternative travel demand switches to AVs. Other studies find that the reduction in car-ownership following the introduction of AVs can be beneficial to PT and slow modes (Soteropoulos et al., 2018).
Car automation and sharing help increase the car-use intensity in terms of the number of trips, daily use duration, and distance. This increase has already been highlighted by the existing literature (Horl et al., 2021). Consequently, car VKT increases as well. PAVs produce higher VKT than SAVs, and SAVs produce higher VKT than PSAVs. Other researchers confirm this ranking (Bischoff et al., 2017; Soteropoulos et al., 2018). Researchers also confirm the magnitude of the increase in VKT (Horl et al., 2021; Saleh & Hatzopoulou, 2020). Other studies, however, find much lower VKT values than this research. This can be due to differences in terms of methodologies, assumptions, and case studies. Findings from an ongoing work that compares two cities from France and Canada using the same methodology and similar assumptions will shed light on this subject.

5 Conclusion

This research investigates some of the implications of the introduction of AVs as a transportation alternative. Three AV mobility scenarios are assessed: PAVs, SAVs, PSAVs in the case of Lyon, France.
Findings highlight the considerable impact AVs can have on the urban mobility landscape. In the three scenarios, AVs compete against existing modes, especially PT to the benefit of AVs. Consequently, total car mileage increases significantly in comparison with the

reference scenario of Lyon. Part of this increase is due to empty-drive of AVs. In the increasing order of excess VKT, we find PSAVs, SAVs, and PAVs. This finding suggests that SAVs and PSAVs are the least impactful scenario of the introduction of AVs in Lyon, and most likely in other cities. In the case of Lyon, the potential of PSAVs is only reached when the private car is banned from dense areas of operation of these services.
This paper is subject to some limitations. It is noteworthy that PAVs are assumed to be non-pooled. When the PAV is used by an agent it becomes unavailable to other household members. This induces large waiting times and VKT for PAVs. This assumption will be addressed by using the *DRT* extension for PAVs.
It is also noteworthy that no dynamic rebalancing strategy is used in the SAV and PSAV scenarios. The implementation of rebalancing can increase demand for robotaxis, decrease waiting times, but also increase VKT due to empty-drive. Rebalancing requires also longer computational time.
Travel demand is kept constant and similar to the pre-pandemic situation. AVs are likely to induce new travel and activity demand and routines. Many studies have explored these futures through stated-preferences surveys that can be considered in the definition of the synthetic population.

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