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Shared autonomous vehicles and agent based models: a review of methods and impacts

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Abstract
Shared Autonomous Vehicles (SAVs) are expected to have a transformative role in future transportation systems, by reducing vehicle ownership, helping in alleviating congestion, improving accessibility and traffic safety, and changing travel behavior and urban infrastructure. The potential introduction of SAVs in transportation systems has triggered the need of exploiting suitable tools for designing and planning SAV operations and services and assessing their impacts. An explicit category of such tools are agent-based models (ABMs), whose advantage in efficiently representing transportation systems with a fine level of detail, has allowed them to gain importance in modeling SAVs. This paper systematically reviews and organizes the current state-of-the-art on ABMs dealing with SAVs. The review is two-fold: first, the methodological aspects of exploiting ABMs in the context of SAV services and operations are analyzed and second, ABM-based findings on the anticipated impacts of SAVs to traffic, travel behavior, land uses, the environment and so on, are presented and discussed. The paper concludes with recommendations for future research on SAVs and other, potential ABM applications for that purpose.

Keywords Shared autonomous vehicles, Autonomous mobility on demand, Agent-based simulation, Autonomous shared mobility impacts, Systematic review

1 Introduction

The introduction of AVs will become a challenge in the coming years. Given the rapid technological advances in autonomous driving, the question is no longer how, but when AVs will be introduced for full commercial use [9]. It is claimed that 75% of vehicles will be autonomous by 2040, while conservative reports suggest that this will be the case by 2060 [76]. AVs are likely to have significant impacts on trip patterns, traffic, and transportation operations [76]. Indeed, if AVs dominate, congestion is expected to worsen [45, 96], urban sprawl will be encouraged [31, 118], and the culture of "automobility" will be maintained [92].

On the contrary, the option of using AVs in the context of shared services (Shared Autonomous Vehicles – SAVs) is a case of promoting sustainable mobility, as SAVs are envisaged to help reduce traffic congestion [32, 72], limit the need for parking, and free more public space for other activities [55]. Furthermore, since most traffic accidents are attributed to human behavior [56, 97], SAVs will have a positive impact on road safety [6, 103]. What is more, SAVs will compete with conventional, taxi-type and ridesharing services [10, 32], thus redressing the way transport providers operate in an urban environment. It is therefore evident that the development of suitable methodological tools to study and assess that impact is essential for the efficient planning and design of future transportation systems. Indeed, emerging technologies and new modes, (such as SAVs, Mobility-as-a-Service (MaaS) and so on), set new challenges for transportation planning, as they create the need to investigate travel patterns at a more refined, microscopic scale [62].

Agent-based models (ABMs) can replicate transportation systems at a fine-granular level and as such, they

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are widely used for modeling SAV systems. ABMs are dynamic simulation processes that converge after a series of iterations; they consist of agents, the environment, and rules [62, 133]. Agents are the actors in a system (either travelers or vehicles), the environment is the place where agents act and/or interact (the road network, land uses, and transportation services), and rules describe the behavior and interaction of agents. Since ABMs represent travel behavior at a highly disaggregated level, it is possible to analyze the effects of transport policies on travel behavior and traffic in detail [66]. Given this inherent advantage, the research community has adopted such models to study the role, behavior, and impact of SAV systems.

Considering the extensive use of ABMs in SAV-related studies, this paper systematically reviews and organizes the literature on agent-based modeling of SAVs. The paper goes beyond the previously published state-of-the-art reviews on AVs [60, 73, 93] and critically analyzes and assesses the application of ABMs and their attributes, in the case of SAVs. Also, this paper provides a systematic analysis of the impacts of SAVs, derived through the application of ABMs. This allows to depict the suitability of ABMs in modeling SAV services and operations and to shed light on the impacts of SAVs on the urban environment.

The remainder of the paper is organized as follows: The second section addresses the methodological framework used to conduct the review. The third section explores various aspects of agent-based modeling in SAV related studies, and the fourth section offers a discussion of the findings and recommendations for future research. Finally, the conclusions and contribution of the paper are presented.

2 Methodology

A systematic literature review refers to the process of systematically finding and compiling all available information on an effect or topic area [26],it can be briefly described as a research method for identifying and critically appraising relevant research [18] and collecting and analyzing data from that research [75]. The research themes considered in the context of the review, are referred to as primary studies, while the review itself is a secondary study. This method is an acceptable way to synthesize research findings and show evidence at a meta-level [115], and it is therefore sufficient for the purpose of identifying critical concepts and questions on the topic reviewed. A systematic literature review exploits qualitative approaches developed to assess the quality and strength of findings from different types of studies and to compare these findings [37]. In particular, the processes of systematic literature review may differ depending on the scope and objectives of individual studies.

In this paper, a systematic review is used to gain a thorough understanding of ABMs and their use in the context of SAVs. various trusted databases such as Google Scholar, Web of Science, ScienceDirect, SPRINGER LINK, TRID, IEEE Xplore, Taylor and Francis, SAGE Publishing, etc. are exploited for finding relevant peer-reviewed articles (journals or conference proceedings) since 2013, using keywords that appear in the title, abstract, and body of the articles. Three categories of search terms were used, either separately or in various combinations: (1) agent, agent-based modeling, and agent-based simulation; (2) autonomous vehicles (AVs), autonomous taxi, autonomous mobility on demand (AMoD), shared autonomous vehicles (SAVs), and shared autonomous electric vehicles (SAEVs); (3) impact(s), implication, and effect. These terms were adapted to the specific structure and requirements of each database. Duplicate and irrelevant papers were ignored, and references within identified papers were carefully reviewed. Although some of the articles found were not peer-reviewed (gray literature), such as some pioneering scientific reports, they are still important for broad understanding interests in this field. To ensure the high quality of the review, the articles meet the following criteria: (1) they should be written in English; (2) they should use agent-based modeling (ABM) or agent-based simulation as analysis tools; and (3) they should include research on shared autonomous vehicles (SAVs). The final review pool consists of 98 scientific papers.

3 Agent based modeling in SAVs research

For the purposes of this review, three main aspects of ABM applications in SAVs are identified: conceptual, methodological, and impacts. The conceptual aspect refers to specific research questions on SAVs that ABM applications attempt to answer, and especially those related to the design, planning, and evaluation of SAVs services. The methodological aspect includes the framework, attributes, and use of ABMs in SAV related studies; the review revealed two broad categories for ABM applications in the context of SAVs: (a) studies focusing on the planning/design of SAVs systems and services, and (b) work analyzing the potential impact of SAVs on transport supply, mobility, the environment, and so on. Figure 1 illustrates the categorization of impacts related to ABM application in SAVs:

3.1 ABMs in the planning and design of SAV systems

Given the potential of SAVs in future transportation systems, the first category covers all aspects of SAV service development using ABMs, including planning, their

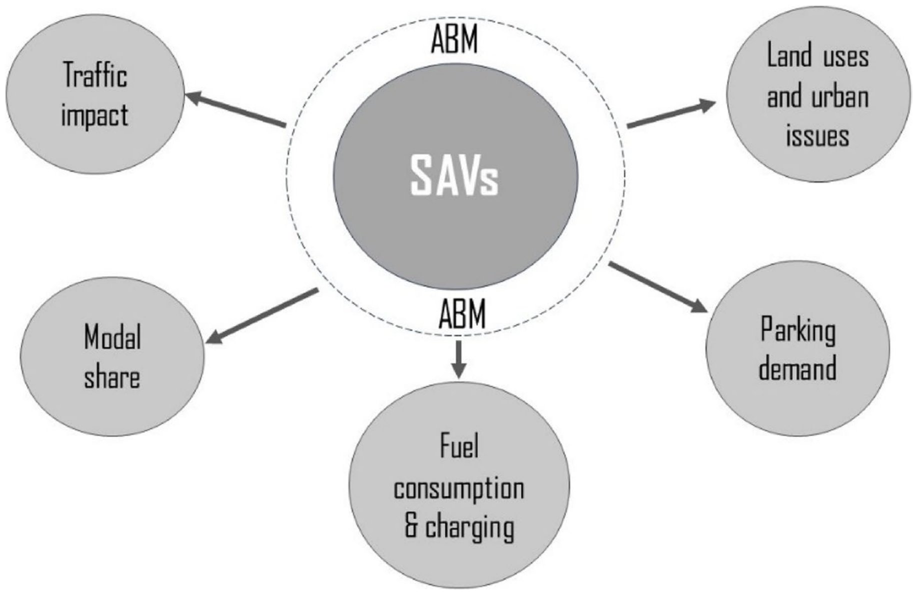

Fig. 1 Investigated SAV impacts by ABMs

application as first/ last mile solutions, taxi and ridesharing services, pricing, charging infrastructures and user behavior analysis.

3.1.1 Designing SAVs services

Several studies have addressed the design and planning of SAV services using ABMs, with focus on fleet sizing, costing, vehicle location and parking decisions. In this context, Fagnant and Kockelman [32] estimated fleet size requirements and assessed vehicle location strategies for a SAV service in Austin, TX. Their subsequent work delved into the effects of low SAV market penetration within the same city, simulating a fleet's operational dynamics Fagnant et al. [33]. They later expanded their research by considering dynamic ridesharing in SAV operations [34]. Building on these studies, Chen et al. [21] explored the management of a fleet of SAVs using a regional ABM, for assessing different vehicle ranges and charging infrastructures.

A study by Bösch et al. [16] extended the ABM platform MATSim (see Horni et al. [52] for further details on MATSim) to estimate the required fleet of SAVs needed for a SAV service in Zurich, Switzerland. Another ABM multiscale platform, SimMobility (see Adnan et al., [1] for further details on SimMobility) was used by Marczuk et al. [90] to investigate interplay of land-use, transportation, and communications, in the context of planning an Autonomous Mobility on Demand (AMoD) service in Singapore. Heilig et al., [47] used a microscopic travel demand model to simulate mode choice behavior and calculate fleet size needs for an AMoD service when private vehicles are not available, using the Stuttgart region as a case study. In the same direction, Dia & Javanshour [30] also proposed an AMoD service for Melbourne, Australia, and used the ABM platform Commuter (see Liyanage and Dia [80] for further details on Commuter) for assessing fleet size and parking requirements. Extending previous studies, Loeb & Kockelman [82] evaluated the fleet performance and costs of a SAV service in Austin, TX, identifying key profitability and customer satisfaction factors. Zhou et al. [140] introduced a collaborative model integrating park-and-ride facilities, public transportation, and SAVs in Nagoya, Japan, leveraging ABM insights. Concurrently, Ben-Dor et al. [12] evaluated the feasibility of ridesharing with SAVs in Tel-Aviv, Israel, using MATSim. Finally, Wang et al., [127] employed the ABM platform AnyLogic (see more in Borshchev [15], to examine the impact on travel and energy consumption by strategically formulating SAV platoons.

3.1.2 First/last mile transportation

Some studies have explored the role of SAVs in serving First/Last mile trips; In this context, Scheltes & De Almeida Coreira [109] utilized an ABM to design an Automated Last-Mile Transport system (ALMT), in Delft, Netherlands for connecting the city's train station and the university campus. Shen et al., [111] tackled the first/last mile problem to and from Mass Rapid

Transit stations in Singapore, by integrating a SAVs service and public transport. Using an ABM framework, they assessed the potential replacement of low-demand bus routes with such a service. In Sejong, Korea, Kim et al., [67, 68] examined the viability of an autonomous minibus service using the MATSim simulation framework. Concurrently, Gurumurthy et al., [42] investigated the potential of SAVs as a collective distribution mechanism in Austin, TX, highlighting the versatility of SAVs in enhancing urban mobility and addressing specific transportation challenges.

3.1.3 Planning Autonomous Taxi (AT) services

Autonomous taxi services, a specific subset of Shared Autonomous Vehicles (SAVs), have attracted considerable attention in academic research. Bischoff & Maciejewski [14] were the first to simulate a citywide replacement of private vehicles by autonomous taxi (AT) fleets in Berlin, Germany, using the MATSim simulation platform. Concurrently, Hörl et al. [50] exploited MATSim for simulating autonomous taxis in an integrated population and network-based transportation environment, which considered dynamic demand. Llorca et al. [81] used the same platform to simulate a fleet of autonomous taxis for partial substitution of transport demand in Munich, Germany. ABMs were also exploited by Martinez & Viegas [91] for evaluating different autonomous taxi services, in Lisbon, Portugal. Merlin [94] and Lu et al., [87] explored the potential of automated taxis in Ann Arbor, MI, in the context of either complementing public transport or the replacement of private vehicles. Other ABM applications planning for autonomous taxi services were presented by Hörl [48], Jäger et al., [57], Kim et al., [67, 68], Alisoltani et al., [5], and Chouaki & Puchinger [22].

3.1.4 Dynamic ride sharing

SAVs can play a transformative role in the ride-sharing ecosystem, fundamentally reshaping how ride-sharing services operate and are consumed. Exploiting ABMs, Zhang et al., [138] simulated the performance and estimate the likely benefits of a SAV system with dynamic ridesharing, and Lokhandwala & Cai [84] investigated the benefits of dynamic ridesharing in AT services in New York City, NY compared to traditional taxi services. Later, Wang et al. [124] applied AnyLogic to simulate dynamic ridesharing systems with both station-to-station and door-to-door services. Hörl et al., [51] exploited MATSim and its dynamic vehicle routing extension to simulate different operational strategies for controlling an automated mobility-on-demand system with sequential vehicle sharing. In a series of studies, Gurumurthy et al., [41] used MATSim to simulate travel behavior in Austin, TX, in the presence of private and shared AVs, with dynamic ridesharing and advanced road pricing policies. Subsequently, Gurumurthy et al., [40] used POLARIS (see further in Auld et al., [7] to assess dynamic ridesharing choices of AVs with geofencing in the Chicago region, IL, and Gurumurthy & Kockelman [39] studied the effects of pick-up and drop-off points on dynamic ridesharing rates in Bloomington, IL.

3.1.5 Costs and pricing of SAV services

Service costs and pricing of SAV services are critical for assessing their potential introduction. Using Austin, TX as a testbed and ABMs, Chen et al., [21] measured the impact of fare structures on the market potential of SAVs, Liu et al., [79] explored the relationship between the level of SAV fares and their impact on modal split of private trips, and Simoni et al., [113] examined the impact of different congestion pricing and tolling strategies. Bösch et al., [17] scrutinized policy combinations for SAV services in Zug, Switzerland, and identified pricing of public and private motorized transport as a suitable one. The impact of utility-based dynamic pricing for Autonomous Transportation Network Companies, using an ABM for Greater London, UK, under monopoly and competitive conditions, was investigated by Karamanis et al., [65].

Wen et al., [126] explored various pricing and hailing strategies for SAVs in a European city, while Nahmias-Biran et al., [102] combined the demand simulator of SimMobility with a meso-micro supply model to analyze service costs for both individual and shared Autonomous Mobility on Demand (AMoD) journeys in Tel-Aviv, Israel. Bucchiarone et al., [19] examined the introduction of autonomous shuttles in Trento, Italy, evaluating their service costs through an Agent-Based Model (ABM). Mo et al., [98] investigated the competitive dynamics between public transportation and SAVs in Tampines, Singapore, focusing on revenue generation and passenger costs. Ben-Dor et al., [13] used the MATSim platform to study the effects of various congestion and parking pricing strategies, as well as different SAV fleet compositions on SAV services in Jerusalem, Israel. Finally, Stevens et al., [119] analyzed the financial sustainability of AMoD systems in Rotterdam, Netherlands, considering strategies for vehicle relocation, ridesharing, and charging through the AnyLogic ABM platform.

3.1.6 Charging infrastructures

Since SAVs are expected to be electric (EV) or hybrid electric vehicles (HEV), some researchers have investigated the performance of SAVs with respect to the available charging infrastructure. Vosooghi et al. [122] related the performance of SAVs to their charging infrastructure in Rouen Normandy, France and found that performance is significantly improved by the placement of fast chargers and battery replacement infrastructures. Charging infrastructure for SAVs was also addressed by Zhang and Chen [134], who proposed a smart charging framework and argued that EVs with larger batteries respond better to charging opportunities with low electricity costs and have greater potential to reduce total energy-related costs. Ahadi et al. [2] argued that charging station locations for SAV depend mainly on the spatial distribution of installation costs and charging demand, with optimal locations in both central areas where demand is high and suburbs where installation costs are lower. Dean et al. [29] coupled repositioning and charging strategies in Austin, TX, resulting in 39% lower average wait times, 28% more daily trips, and 1.6% fewer empty trips. Furthermore, ridesharing is expected to downsize the fleet and reduce the number of charging stations required to keep the fleet operational. Compared to traditional ride-hailing service, in the case of a city model resembling Austin, TX, ridesharing decreases the fleet size and the number of charging stations from 57,279 and 1562 to 25,368 and 1058, respectively [35]. Last, Wang et al. [127] demonstrated that formulating platoons could reduce the existing system-wide energy consumption up to 9.6%. However, Loeb and Kockelman [82], who conducted a dynamic ridesharing model, found that the gasoline hybrid electric (HEV) fleet outperformed the EV fleet while being more profitable, offering response times of 4.5 min compared to 5.5 min of the electric fleet.

3.1.7 User behavior

Modeling user behavior in the presence of SAVs is critical for planning and designing such systems. In this context, Auld et al. [8] used the POLARIS ABM platform to test different levels of penetration of SAVs in the Chicago metropolitan area, IL. Hao and Yamamoto [44] investigated travel behavior in Nagoya, Japan, considering travelers' intention to use SAVs and their perceptions about ownership and sharing of their private vehicles. In their paper, Kamel et al. [63] investigated user preferences towards choosing SAVs, using an ABM in MATSim. Factors considered included age, gender, and income, which affected preferences for SAVs. Lokhandwala and Cai [86] developed an ABM in which different types of driver preferences for SAV were assumed. A study by Wang et al. [128] developed an ABM for simulating platooning formation and the interactions between SAVs and real-time travel requests,the objective was to capture the real-time behavior of SAVs as trip makers and then to evaluate the performance of an AMoD system with coordinated platooning formation. From a different perspective, Al Maghraoui et al. [4] examined travelers' willingness to use a SAV service depending on their current transportation mode in Paris, France. Nahmias-Biran et al. [101] used the ABM platform SimMobility in Singapore to analyze AMoD policies with respect to income and accessibility. Finally, Zhou et al. [139] investigated the relationship between AMoD services, accessibility levels and relocation decisions of urban residents; again, SimMobility was used for that purpose.

3.2 SAV impacts

The identified studies on SAVs and ABMs have yielded remarkable and at times contradictory results, which provide valuable insights into the impact of integrating SAV services in urban road networks. It should be emphasized that the modeling techniques used, and especially the simplifications or assumptions applied, play an important role in the expected results [116]. The impacts are grouped with respect to traffic, modal shift, land uses, parking, the environment, energy consumption, and operational and service aspects.

3.2.1 Traffic

Several papers have examined impacts to traffic at the network level, resulting in interesting, yet contradicting findings. According to Fagnant and Kockelman [32], a system of SAVs could save users ten times as many cars as they would need for private-vehicle travel, but that would induce about 11% more trips. Along the same lines, Fagnant et al. [33] argued that SAVs are expected to generate 8% more VKT in a low SAV penetration case, due to unoccupied trips or relocation issues. A study by Auld et al. [8] reported that SAVs could increase total VKT by about 4%, if an 80% increase in SAV service capacity is achieved. According to Javanshour et al. [58], an AMoD system with 10% penetration has the potential to radically reduce the existing private vehicle fleet by 84%, while maintaining the same travel demand. However, this would result in an increase of 29% to 77% in VKT depending upon the type of SAV service.

In line with previous studies, Dia and Javanshour [30] found that reducing the number of vehicles travelling in the case of an AMoD system, increased total VKT by 29% in case of zero waiting time and by 10% when the waiting time is up to 5 min, using Melbourne, Australia; these findings were later verified by Javanshour et al. [58]. Another study conducted by Oh et al. [105] concluded that an unrestricted implementation of AMoD could lead to a significant increase in network congestion and VKT in Singapore. Harper et al. [46] demonstrated that SAVs in downtown Seattle, WA, averaged an 5.6–6.4 km/day (3.5–4.0 mi/day) additional distance of travel, and that at a high penetration rate (50–100% AV), AVs would travel an additional 9.0–13.5 km/day (5.6–8.4 mi/day).

Finally, a study by the ITF [55] for Lisbon, Portugal as a case study, found that different autonomous taxi services would yield an increase of up to 89% in VKT. Similarly, Hörl et al. [50] found that the use of autonomous taxis for individuals in Zurich, Switzerland would increase VKT up to 60%. Other studies have demonstrated that the use of SAVs will lead to reduced vehicle trips and VKT. In this context, Heilig et al. [47] argued that in the case of Stuttgart, Germany, if 85% of private vehicle trips were undertaken by SAVs this would result in a 45% reduction in vehicle trips and a 20% reduction in vehicle kilometers. Lokhandwalaa and Cai [84] found that SAV based ridesharing in New York, NY, increased occupancy from 1.2 to 3, and reduced overall mileage up to 55%. Finally, Yan et al. [130] reported that the introduction of SAV ridesharing services could decrease VKT by 17%.

In terms of travel times, Bischoff & Maciejewski [14] reported that an increase of 17% in total network travel times due to idling would be expected because of SAVs, but higher congestion in certain points would not necessarily be expected. Llorca et al. [81] again found that total network travel times for both autonomous vehicle and conventional trips would increase when SAV fleets are introduced, but also argued that peak hour congestion would be reduced. According to Bösch et al. [17], if a small percentage of the population would use SAV, SAV systems can only reduce travel times at the cost of significant modal shifts. On the contrary, Hamadneh & Esztergár-Kiss [43] observed a reduction in both travel time and travel distance. Venkatraman and Levin [121] found encouraging results in reducing the total travel time of people for different SAV fleet sizes and demand levels.

3.3 Modal split

In addition to travel behavior and kilometers or miles traveled, the literature reports that SAVs will certainly affect the modal split. According to Chen and Kockelman [20], the potential share of SAVs in Austin, TX, would likely to range from 14 to 39%, when competing with conventional cars and public transportation. Liu et al. [79] showed that travelers who travel longer distances prefer SAVs over private human-driven vehicles because of avoiding driving burdens. ITF [55] indicated that in Lisbon, Portugal, SAVs would reduce the use of private vehicles, by 23%-65% and Kamel et al. [63] found that in Paris, France, the share of SAV trips would range from 3.8% to 5.3%. The findings of Ishibashi & Akiyama [54] for Tokyo, Japan showed that about 14%-32% of the population would switch to SAVs, and that those who traveled 2.0–8.0 km by train or bicycle would likely switch to SAVs. On the contrary, a study by Cyganski et al. [24] for Braunschweig, Germany, showed only minor changes in the modal split because of SAVs, primarily due to the short distances involved. Similarly, Nahmias-Biran et al. [102] found that the mode shift from active transportation and public transport to AMoD in Tel-Aviv, Israel, was insignificant, due to the travel costs of AMoD services. Regarding taxis, Liu et al. [77] concluded that SAVs could attract more users than conventional taxis due to lower costs. Finally, Ben-Dor et al. [13] reported that if parking or congestion pricing schemes would be applied, SAV users would come equally from PT and private vehicles.

3.3.1 Interaction with land uses

With respect to SAVs impact on land uses, Kim et al. [69] showed that the full integration of SAVs into the urban street environment was expected to lead to dispersed spatial structures; the authors simulated the spatial impacts of SAVs and assumed that the introduction of SAVs would change the location choices of travelers in addition to the attractiveness of regions. On the contrary, Zhou et al. [141] demonstrated that the implementation of AMoD would not lead to outward migration nor intensify the disparity between home and work locations.

3.3.2 Parking demand

Due to their operational model, SAVs will change parking demand; this potential change has been explored in a few studies. Zhang et al. [137] estimated the impact of SAVs on demand for parking demand and reported that SAV systems would be able to eliminate up to 90% of parking demand for customers using SAVs, for a low SAV penetration rate of 2%. According to Dia and Javanshour [30], demand for parking would decrease from 58 to 83%, depending upon travelers waiting time for SAV service. The study of Harper et al. [46] showed in the case of Seattle, WA, parking revenues would radically decline if SAV penetration increased, and that parking services would eventually become economically not viable.

3.3.3 Environment

There are several studies looking at the environmental footprint of SAVs. Zhang, et al. [138] first reported that SAVs can be environment friendly for cities in the long run. In the same direction, Martinez and Viegas [91] emphasized that if private vehicle were replaced by shared ones, this would significantly reduce CO2 emissions. According to Liu, et al. [78], found that different SAV operating strategies could reduce emissions by up 19%. Lokhandwala and Cai [85] showed that a SAV taxi fleet could reduce taxi CO2 emissions in New York City, NY by up to 861 tons/day. Lokhandwala and Cai [84] claimed that dynamic ridesharing of SAVs could decrease carbon emissions by up to 866 tons/day in New York City, NY. Yao et al. [132] found that exhaust emissions from the SAVs fleet in Hangzhou, China, would be 12.3% lower than those from the human-run fleet. According to Oh et al. [106], the application of AMoD in Singapore was found to lead to a reduction in vehicular emissions, particularly NOx and PM, by 4.3–5.7% and 5.6–8.2%, respectively. In contrast, Lu et al. [87] found that the environmental impact of SAVs, when these replace conventional vehicles, does not show significant improvement, because of the emission intensity of the local power grid. When it comes to traffic noise, Zwick et al. [142] demonstrated that replacing all car trips with an autonomous ride-pooling system based on bus stops leads to a dramatic reduction in noise in residential areas in Munich, Germany.

3.3.4 Energy consumption

As SAVs are expected to largely adopt electric propulsion and technologies (Kovačić et al., 2022), energy consumption and charging are important and have been addressed by different studies. According to Chen et al. [21] each SAV with a range of 80 miles would replace 3.7 private vehicles and each SAV with a range of 200 miles replace 5.5 private vehicles, under Level II (240-V AC) charging. Sheppard et al. [112] found that all mobility in USA could be served by 12.5 million SAVs, with an energy demand of 1142 GWh/day (8.5% of the national electricity demand in 2017) and a peak charging load of 76.7 GW (11% of the U.S. electricity peak). In a study by Oh et al. [106], the implementation of AMoD services in Singapore was estimated to result in a rise in energy consumption by 16.94–24.33%.

3.3.5 Operations and services

The last category refers to the operational and service-related impacts of SAVs, including costs and revenues, waiting times, vehicle fleet size, and other trip parameters. It should be underlined that many papers have laid their interest in this specific area. Beginning with costs and revenues, Fagnant and Kockelman [34] reported that dynamic ridesharing reduces total service times and travel costs for SAVs users, even after accounting for extra passenger pick-ups, drop-offs and non-direct routings. The authors also showed that a private fleet operator paying $70,000 per new SAV could earn a 19% annual (long-term) return on investment. When offering SAV services at $1.00 per mile of a non-shared trip. Among other studies, Hörl et al. [50] found that even under conservative pricing a large share of travelers would be attracted to SAVs, and Liu et al. [79] indicated that higher SAV fare rates allow for a larger private vehicle replacement (ranging from 5.6 to 7.7 private vehicles per SAV). In a subsequent study, Liu et al. [78] argued that the non-detour and detour sharing SAV strategies can reduce operational costs by 16% and 24% respectively. Farhan and Chen [35] focused on vehicle occupancy and demonstrated that allowing multiple occupants improves service rate as well as system-wide benefits from $1.34 M to $1.52 M. Yao et al. [131] found the revenue of a SAV system in Hangzhou, China to be approximately four times as the daily system operation costs. Finally, a study by Zhang and Guhathakurta [135] for Atlanta, GA, also indicated that a SAV service would yield reduced commute costs.

Regarding passenger waiting time, Shen and Lopes [110] proposed an algorithm for a SAV system, which could reduce average passenger waiting time by up to 29.82%. As noted by Chen and Kockelman [20], pricing strategies that attempt to match available SAVs supply with expected travel demand can reduce average waiting times by 19 to 23%. Liu et al. [78] claimed that SAV detour and non-detour sharing strategies can reduce waiting times by 62% and 82%, respectively. In the same direction, Hyland and Mahmassani [53] found that SAV dynamic strategies involving drop-off SAVs on the route in the assignment problem reduce traveler waiting times. Findings by Luo et al. [88] indicated that average passenger waiting times fell within an acceptable range in different SAV operations in Gunma, Japan. Wang et al. [128] reported that an AMoD system with vehicle platooning formation significantly affects the average waiting time of users. According to Pulhès and Berrada [108], for different levels of SAV fleet size and penetration, the maximum average waiting time is 15 min, and during peak periods this value can be as high as more than 17 min. Also, De Souza et al. [27, 28], who focused on the impact of a repositioning method for SAVs, also observed an improvement in SAVs waiting times.

Concerning SAVs fleet size itself, Wen et al. [126] noted that SAVs fleet size is the outcome of a tradeoff between service levels and operating costs. Also, according to Javanshour et al. [58], there is a strong quadratic relationship between the SAVs fleet size and VKT when demand is kept constant.

When it comes to the impact of SAVs on the total vehicle fleet in a region, SAVs have the potential to dramatically reduce the number of vehicles needed to meet current travel demand [55]. Looking at the results of various studies, Spieser et al. [117] reported that the fleet size of SAVs needed to serve the entire population of a city is up to 66% smaller than the fleet of private cars. Dia and Javanshour [30] claimed that SAVs in Melbourne, Australia, could lead to a large reduction in the total number of vehicles needed to meet travel demand (reduction of 43% to 88%). In the same direction, Lu et al. [87] pointed out that the needed SAV fleet to meet daily commuter demand with waiting times of less than 3 min is only

20% of the conventional single occupant car fleet. Wang et al. [123] found that during rush hour, about 240–250 SAV vehicles are needed to meet demand, while during off-peak hours, only about 30 vehicles should be in operation. Liu et al. [78] found that non-detour and detour vehicle sharing strategies can reduce total vehicle fleet size by 19% and 27%, respectively. Another study by Lokhandwalaa and Cai [84], highlighted that switching from traditional taxis to shared autonomous taxis could potentially reduce fleet size by 59% while maintaining service levels and not significantly increasing travelers waiting time. In the same line, Llorca et al. [81] showed that it is possible to replace three conventional cars with one autonomous taxi while meeting the demand for trips with reasonable waiting times. In addition, it is found that SAVs could replace 5 to 9 private vehicles in Austin, TX, while maintaining adequate service levels [21, 33]. Bischoff and Maciejewski [14] displayed that a fleet of 100,000 autonomous taxis is sufficient to replace the passenger car fleet in Berlin, Germany on a typical weekday with a high quality of service for customers.

4 Discussion, policy, and future research recommendations

From the papers reviewed, critical insights were gleaned regarding the use of ABMs to explore the impact of SAVs on future urban environments. One notable observation from the analysis of the selected papers is the uneven geographic distribution of case studies examining SAVs and their effects on urban environments. It appears that specific cities or regions are more actively engaged in investigating the potential impacts of SAVs (Table 1).

Notably, Singapore leads with 10 studies on ABMs for SAVs, followed by Austin (TX) with 8, Sioux Falls (SD) with 6, New York City (NY) with 5, Munich with 3, Melbourne with 3, Bloomington (IL) with 3, Zurich with 3 and Chicago (IL) with 3. These numbers indicate varying levels of research activity in different regions, possibly reflecting the interest, funding, or academic and industry focus in these areas on the topics indicated.

ABMs were also found to be extensively used for analyzing and assessing impacts of SAV services; these impacts are summarized in Fig. 2. Overall, most publications (regardless of the assumptions and the setup of the ABMs employed) conclude that both vehicle-kilometers travelled, and vehicle hours will increase, implying a negative impact in the performance of transportation networks, because of SAV operations. In addition, SAVs are expected to affect the modal split in their favor, reshape the spatial structure of cities, creating conditions for more compact urban agglomerations (due to their intrinsic property of being shared), and contribute to a noticeable reduction in parking demand, supporting the transformation of public spaces. As for environmental impacts, several papers argue that SAVs will support

Table 1 Case studies per city worldwide

City	Number of studies
Singapore	10
Austin, TX	8
Sioux Falls, SD	6
New York City, NY	5
Chicago, IL	3
Munich, Germany	3
Melbourne, Australia	3
Bloomington, IL	3
Zurich, Switzerland	3
Lisbon, Portugal	2
Berlin, Germany	2
Ann Arbor, MI	2
Nagoya, Japan	2
Seattle, WA	2
Paris, France	2
Hangzhou, China	2
Atlanta, GA	2
Tel-Aviv, Israel	2
Delft, Netherlands	1
Stutgart Region, Germany	1
London, UK	1
Brunswick, Melbourne, Australia	1
Zug, Switzerland	1
Sejong, South Korea	1
Seoul, South Korea	1
Jerusalem, Israel	1
Gunma, Japan	1
Budapest, Hungary	1
Izu Oshima, Japan	1
The Hague, the Netherlands	2
Palaiseau, France	1
Lyon, France	1
Rouen Normandie, France	1
Minneapolis–Saint Paul, MN	1
Paris-Saclay University	1
Trento, Italy	1
Tampines, Singapore	1
Amsterdam, the Netherlands	1
Tokyo, Japan	1
Kozoji, Japan	1
Rotterdam, the Netherlands	1

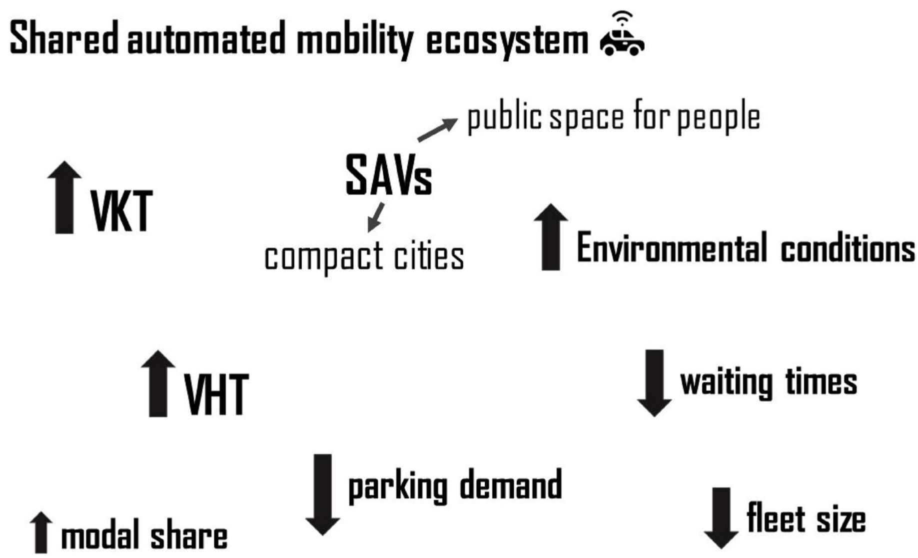

Fig. 2 Shared automated mobility ecosystem through ABM simulation studies

the reduction of emissions and noise pollution. Finally, impacts related to SAV operations include the improvement of traveler waiting times, and the replacement of conventional vehicles.

4.1 Policy recommendations

Identified SAV impacts can serve as the foundation for documenting policy recommendations that ensure an appropriate transition to an automated age, which still puts humans at the center [107]. First and foremost, there is a consensus among studies indicating an increase in VKT and VHT due to the introduction of SAVs. This means that urban environments are dominated by motorized vehicles for most of the day, affecting sociality and interaction between people in public spaces [25]. Therefore, it is suggested to prioritize constraints regarding the use of SAVs in urban areas, e.g. by excluding them from certain central areas. Most importantly, urban development should focus on proximity solutions, such as x-minutes cities [83], which can reduce the distances and time between home and facilities and thus create suitable conditions for active and non-motorized travel [70]. This future endeavor could mitigate the negative impacts of more VKT, and time spent traveling.

In terms of modal split, the literature argues that SAVs will gain travelers over other modes, implying that motorization will again prevail in urban areas. Therefore, SAVs should act as a substitute for private vehicles, and not as a competitor to active transportation and public transport [61]. Therefore, planning will need to consider fruitful synergies of SAVs with conventional public transport and active modes, such as a common street classification systems and coordination of services.

As for land uses, SAVs were found to be much better suited to compact urban areas than private AVs, which are expected to lead to dispersed urban patterns [38]. Therefore, future cities should encourage mixed land uses and densification to combat urban sprawl trends and facilitate the movement of SAVs compared to AVs. Another issue that should be of concern are the inequalities that can arise from the geographical distribution of SAV services [95]. To this end, SAV deployment schemes (standard or on-demand routes) should sufficiently serve the urban fabric (taking into account strategic visions for urban development and potential exclusion areas), ensuring solid accessibility for all who live and work in a city.

Moving on to parking demand, as significant decrease is anticipated, focus should be given on transforming these liberated spaces into human-oriented places [36]. The reallocated space should be reserved for pedestrians, cyclists and people with reduced mobility to encourage active mobility and reclaim urban space for vulnerable road users. As for policies related to the environmental impact of SAVs, apart from the potential benefits for the urban environment of replacing private cars with SAVs, synergies with active transportation modes are also a promising approach.

4.2 Future research

Research on planning and analyzing SAV services and the exploitation of ABMs for that purpose has been extensive in the recent years [11, 49, 59, 64, 74,

Fig. 3 Directions for future research

89, 100, 125, 129, 136]. However, there are research areas on SAV operations and services, for which ABMs can be used for investigating, assessing, and validating this upcoming mobility landscape (Fig. 3). First, SAVs cannot fully function in today's road network and therefore need suitable road infrastructure. This implies that new road functional categories that facilitate the circulation of SAVs should be introduced [120], and evaluated with suitable tools such as ABMs. Second, it is widely acknowledged that in the complex and dynamic urban structures of the 21st century, conventional public transportation may not be enough. Therefore, public transport should deploy automated mobility solutions [114], which can benefit urban transport systems, and become a driving force towards multimodality [3, 23, 99]. Third, SAVs can be a solution to the transportation needs of often captive travelers, such as elders, children, and people with disabilities (see also Nahmias-Biran et al., [102]). Therefore, future studies should concentrate on designing, implementing, and evaluating multimodal transportation networks and systems focusing on targeted traveler groups, with Shared Autonomous Vehicles (SAVs) playing a crucial role. Obviously, given the complexity of such systems, ABMs can be invaluable tools for their planning, analysis and evaluation.

Finally, the adoption of SAVs as a transportation mode will depend on public acceptance and user preferences. Research should focus on individuals' willingness to share rides with others and factors that influence this decision. For instance, Lavieri and Bhat [71] found that people are less sensitive to the presence of strangers when commuting to work than for leisure activities. In terms of acceptance, Nikitas et al. [104] also demonstrated that people across the globe perceive SAVs as a crucial employment disruptor. Consequently, it is a challenge for future studies to consider public acceptance parameters in the design and evaluation of SAVs services, and their subsequent introduction in ABMs.

5 Conclusions

This paper reviewed the literature on the use of ABMs on planning, analyzing, and assessing the impacts of SAV operations and services. The first part of the review identified different ABM applications in the context of SAV services and operations, suggesting the wide acceptance and suitability of these tools for tackling SAV problems. The second part of the review investigated the impact of SAVs in the network performance mode choice, land uses, the environment and parking demand. Most of the studies reviewed suggested, that while network performance will worsen and demand will shift to SAV usage, there will be environmental, operational and land use related benefits because of SAV services. Based on the review outcomes, policy suggestions for the introduction of SAVs and future research recommendations included the need to consider SAV services in conjunction with land use measures, and the integration of SAV in multimodal transportation systems. Overall, this paper aspires to serve as a valuable basis for future research and help policy makers, stakeholders, and local communities into considering appropriate, efficient and sustainable ways of introducing SAVs in future cities.

Appendix A

Assumptions

#	Author	Year	Study area	Framework	Assumptions
1	Fagnant, D.J., & Kockelman, K.M	2014	Hypothetical city	N/A	Gridded city, Fixed fleet size, Fixed distance per time period travel
2	ITF	2015	Lisbon, Portugal	N/A	Mode of shared and self-driving operation for the simulated fleet, availability of high-capacity public transport, penetration rate of the shared and self-driving fleet, time period
3	Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G	2015a	Hypothetical city	Matlab	Grid based hypothetical city, 2% SAVs penetration rate, trip generation based on National Household Travel Survey
4	Fagnant, D.J., Kockelman, K.M., & Bansal, P	2015	Austin, TX	MATSim	low level penetration of SAVs, sample of trips derive from the region's planning model to generate demand across traffic analysis zones
5	Kim, K.-H.; Yook, D.-H.; Ko, Y.-S. & Kim, D	2015	Seoul, South Korea	N/A	Future road condition, step-by-step adoption by road type, travel demand estimated based on Korea Transport DataBase. Travel demand was distributed to road network based on Wardrop's principle. Only household agents were considered, only urban and non-urban land used were considered
6	Zhang W., Guhathakurta S., Fang, J., & Zhang, G	2015b	Hypothetical city	Matlab	DR-SAV System: off-peak speed 30, peak speed 21, fleet size 700, willingness to share ride 50%
7	Azevedo, C.L	2015	Singapore	SimMobility	Car Access was forbidden in Central Business District of Singapore, Buses—Mass Rapid Transit—Taxis had access in this area, AMoD service was 40% cheaper than regular taxis, buses and MRT kept their frequencies, fares and capacities and the taxi fleet and cost remained the same, carpooling was not enabled
8	Shen, W., & Lopes, C	2015	New York City, NY	Mobility Testbed/ Agent-Polis	Vehicle speed limit 25miles/hour, load capacity of AV equal to 4, maximum speed capacity 100miles/hour
9	Marczuk, K.A., Hong, H.S., Azevedo, C.L., Adnan, M., Pendleton, S., Frazzoli, E., & Lee, D	2015	Singapore	SimMobility	Individual rides were considered, where each trip was served by a single vehicle In station-based model, after servicing a trip, AMoD vehicles always drove back to the nearest station and waited for new requests (and re-charge if necessary). In free-floating model, AMoD vehicles self-parked at drop-off locations, where they waited for new requests. It is assumed that all drop-off locations contained parking facilities where the vehicles could wait and optionally recharge.

#	Author	Year	Study area	Framework	Assumptions
10	Bosch, P., Ciari, F., & Axhausen, K.W	2016	Zurich, Switzerland	MATSim	Small percentage of population would use AVs, only trips made with cars would be substituted by AV trips (no modal shift)
11	Chen, D., Kockelman, K.M., & Hanna, J	2016	Hypothetical city (Austin, TX)	N/A	Gridded city divided into 4 zones. Each zone has its own average trip generation rate and average peak and off-peak travel speeds.
12	Marczuk, K., Soh, H., & Azevedo, C.L	2016	Singapore	SimMobility	Three rebalancing methods: (i) no rebalancing (vehicles are only moved when assigned to customers and parked at the destination of the trip), (ii) offline rebalancing (run based on the historical data and the rebalancing counts are decided before starting the simulation), and (iii) online rebalancing (is run during the simulation time and the rebalancing counts are optimized based on the predicted requests).
13	Hörl, S., Erath, A., & Axhausen, K.W	2016	Sioux Falls, USA	MATSim	actual data from city of Sioux Falls were used AVs are randomly distributed based on population density
14	Bischoff, J., & Maciejewski, M	2016	Berlin, Germany	MATSim	Synthetic population represents a typical weekday in Berlin, only trips with privates were kept and replaced with autonomous taxis.
15	Chen, D., & Kockelman, K.M	2016	Hypothetical city (Austin, TX)	N/A	Hypothetical city 100 × 100 mile, SAVs serve 10% of all trips, multinomial logit model to allow all trips in the region to choose among private vehicle, transit, and SAEV modes, all trips more than 1 mile in length.
16	Fagnant, D.J., & Kockelman, K.M	2016	Austin, TX	coded in C + +	3.02 person trips per day, 0.99 licensed drivers per conventional vehicles
17	Hörl, S	2017	Sioux Falls, SD	MATSim	Assumption of 2.6 pax from the cost calculator
18	Merlin, L	2017	Ann Arbor, MI	NetLogo	All transit riders in a small city could be served by an automated taxi system For a single-rider taxi system, passengers are assumed to have a boarding time of one minute and an alighting time of one minute. For the shared-ride system, the same fleet size would almost certainly perform at least as well as the single-rider system with respect to wait times. 18 Vehicle depreciation based upon either time or distance. Diversion travel time 19constraint. All passengers within the system must be willing to share rides.
19	Auld, J., Sokolov, V., & Stephens, T	2017	Chicago, IL	POLARIS	based on existing regional travel demand, different penetration rate of autonomous vehicles
20	Liu, J., Kockelman, K.M., Bosch, P., & Ciari, F	2017	Austin, TX	MATSim	SAVs have the same driving characteristics with human driven cars Not all travelers would choose SAVs

#	Author	Year	Study area	Framework	Assumptions
21	Llorca, C., Moreno, A., & Moeckel, R	2017	Munich, Germany	MATSim	Travel demand was generated using the population synthesizer of SILO, all workers were sent to their workplace during the morning hours, mode was selected according to distance
22	Martinez, L., & Viegas, J.M	2017	Lisbon, Portugal	N/A	Two scenarios: shared taxi and taxi-bus. In first scenario bookings were made in real time, maximum waiting time was 5 min (for trips less than 3 km) & 10 min (for trips more than 12 km), trips were served by 6-seat minivans; in second scenario bookings are made 30 min in advance, maximum waiting time was 10 min from preferred boarding time, trips were served by minibuses.
23	Dia, H. & Javanshour, F	2017	Melbourne, Australia	Commuter	Two AMoD scenarios; in the first one waiting time was 0 and privately owned self-driving cars (25%) and shared self-driving cars with capacities ranging from two to four people (75%) replaced all private vehicle travel; in the second scenario waiting time was up to 5 min.
24	Jäger, B., Agua, F.M.M., & Lienkamp, M	2017	Munich, Germany	JADE	Control Center Agent, Dispatching Algorithm, Taxi Agent, Fleet Management Agent
25	Scheltes, A., & De Almeida Correia, G.H	2017	Delft, Netherlands	Anylogic	A fleet of small fully automated electric vehicles, a dispatching algorithm distributes travel requests amongst the available vehicles using a FIFO sequence, vehicles are picked based on a set of specified control conditions.
26	Hao, M., & Yamamoto, T	2017	Nagoya, Japan	artisoc	Only intra-zone travel considered within the study area Travel fee of SAVs 55 JPY/kilometer, waiting time 1 min, travel time set to be the same as conventional vehicles. People with intention of owning private cars own vehicles, while people with no intention of having a private car stop owning vehicles. Customers will be picked up by the nearest AV and the appointment will be canceled if the waiting time is more than one minute.
27	Heilig, M., Hilgert, T., Kagerbauer, M., & Vortisch, P	2017	Stutgart Region, Germany	mobiTopp	All private cars are replaced by autonomous vehicles, each ride is shared by up to four people
28	Basu, R., Araldo, A., Akkinepally, A. P., Nahmias Biran, B. H., Basak, K., Seshadri, R., & Ben-Akiva, M	2018	Hypothetical city (with patterns observed in Singapore)	SimMobility	Generalized travel cost of AMoD based on literature. Change on travelers' knowledge of the system.
29	Karamanis, R., Angeloudis, P., Sivakumar, A. & Stettler M,	2018	London, UK	N/A	Each traveler evaluates the utility of each option AVs exist in the system throughout the whole simulation period, travelers appear once at the time of their travel request and exit when they are served.

#	Author	Year	Study area	Framework	Assumptions
30	Harper C., Hendrickson C., & Samaras C	2018	Seattle, WA	N/A	Gridded network, simulation ignores the actual roadway geometry, each AV makes a decision based on parking cost & searches for cheaper parking, all AVs are aware of the amount of available parking
31	Lu, M., Taiebat, M., Xu, M. & Hsu, S.-C	2018	Ann Arbor, MI	GAMA	Start times of trips to work and trips home both follow a normal distribution, personal cars replaced by autonomous taxis, people could choose whether to share an autonomous taxi with others or not
32	Liu, Z., Miwa, T., Zeng, W., & Morikawa, T	2018	Sioux Falls, SD	MATLAB	taxis cannot be hailed at the roadside, other traffic modes are not considered, taxis are shared by a maximum of two customers, every request for a taxi is for a single customer
33	Lokhandwalaa, M., & Cai, H	2018	New York City, NY	AnyLogic	All rider groups that are willing to share will first try to find a shared ride before searching for an idle taxi, a rider group who is not willing to share will search for a ride for 5 min. If no match is found, the ride group will exit the system unserved. Capacity of all taxis limited to 4, a rider is only eligible to share a ride if they allow a distance overage of at-least 100 m. Similarly, the maximum a rider can deviate has been capped to 10,000 m., time required for refueling is negligible.
34	Wang, B., Ordonez Medina, S.A., & Fourie, P	2018	Sioux Falls, SD	MATSim	All agents executed exactly two legs per day; home to work or secondary & work or secondary to home, initial fleet size was 0, vehicle capacity was 8 seats & vehicle idle time was 1800 secs.
35	Javanshour, F., Dia, H., & Duncan, G	2018	Melbourne, Australia	Commuter	10% market penetration rate, travel demand for each transport mode is unchanged, people use ride-sharing in groups of two, people traveling as a group have the same origin, destination and time schedule, station-based one way AMoD system, people walk from home to stations, empty travels for recharge or refuel are overlooked.
36	Cyganski R., Heinrichs M., Von Schmidt, A., & Krajzewicz, D	2018	Brunswick, Melbourne, Australia	TAPAS	Factors for value of time obtained from a stated preference user survey, advantages of riding in an automated vehicle only applied after a ramp-up time.
37	Shen, Y., Zhang, H. & Zhao, J	2018	Singapore	AnyLogic	Planning and regulation, transit fare and subsidy, coordination and competition, fare, ticketing and information integration.
38	Hyland, M., & Mahmassani, H.S	2018	N/A	N/A (coded in Python)	Share use of AVs as a mobility service, central operator, direct origin-to-destination service, operator assigns AVs to traveler requests in real-time, travelers' requests enter the system dynamically and stochastically.

#	Author	Year	Study area	Framework	Assumptions
39	Farhan, J., & Chen, T. D	2018	Hypothetical city (100 × 100 mile)	N/A (coded in C++)	Time-discrete SAEV simulation model, clustering using similarity evaluation, rideshare matching optimization model
40	Wen, J., Chen, Y. X., Nassir, N., & Zhao, J	2018	N/A (spread out residential area)	N/A	Autonomous Vehicles and Public Transport are operated or regulated by public authorities
41	Bosch, P., Ciari, F., & Axhausen, K.W	2018	Zug, Switzerland	MATSim	Existing modes include mass transit public transport (PT), the slow modes (SM) walk and bike, and motorized individual transport (MIT). For PT and MIT, the respective autonomous version was assumed (aPT and aMIT), Future modes are all based on autonomous taxis, which can be operated as a traditional taxi service (aTaxi) with exclusive single user service or as a ride-sharing service (aRS) which can carry multiple passengers at the same time.
42	Nahmias-Biran, B., Oke, J.B., Kumar, N., Basak, K., Araldo, A., Seshadri, R., Akkinepally, A.P., Lima Azevedo, C., & Ben-Akiva, M.E	2019	Singapore	SimMobility	Two modes of AMoD: AMoD as a non-shared, driverless ride (AMoD) and AMoD as a shared ride (AMoD Pool). A single AMoD ride will be 50% cheaper compared with MoD, and that a shared ride will be 30% cheaper than a single ride.
43	Kim, C., Jin, Y.-G., Park, J., & Kang, D	2019	Sejong, South Korea	MATSim	Transportation network data simplified to save computing time. External trips were excluded.
44	Zhou, Y., Li, Y., Hao, M., & Yamamoto, T	2019	Nagoya, Japan	Artisoc 4	Three user groups: park-and-ride commuters who park SAEVs at the station and take the train to their workplaces; inbound commuters who disembark from trains at the station and use the vehicles to reach their workplaces within the target area; elderly and disabled residents, who use shared autonomous vehicles for trips within the target area. In the evening peak hours, the same number of P&R commuters reverse their morning commuting trips by transferring at the same stations and returning to their origins.

#	Author	Year	Study area	Framework	Assumptions
45	Li, L., Lin, D., Pantelidis, T., Chow, J., & Jabari, S. E	2019	Brooklyn, New York, NY	N/A	The simulation considers two types of agents, SAEV agents and customer agents The pick-up distance is set to 1 km, maximum waiting time is set to 30 min Number of chargers per charging station is 6, the battery range for all SAEVs is set to a constant of 200 km. All SAEVs are assumed to be fully charged and uniformly distributed among all stations at the beginning of the simulation. The percent of charging stations in the area was varied from 10 to 50% in 10% increments. Fleet sizes were varied from 200 to 2000 in 200-vehicle increments. 5 different kinds of charging speeds were simulated. Both no relocation and relocation were tested and compared.
46	Gurumurthy, K.M., Kockelman, K.M., & Simoni, M	2019	Austin, TX	MATSim	AV ownership for 10% of the simulated population. Personal AVs are expected to travel empty (hypothetically) and not incur significant parking costs. A shared ride in a SAV is expected to cost less, approximately half as much as a solo trip in a SAV.
47	Ben-Dor, G., Ben-Elia, E., & Benenson, I	2019	Tel Aviv, Israel	MATSim	SAV when not in use – park near the end of the previous journey. Each scenario is examined with and without the possibility to reject an agent's request. The travel time of the marginal passenger cannot be 1.5 times longer than the travel time of a direct OD car trip; maximum waiting time cannot exceed 12 min.
48	Luo, L., Troncoso Parady G., Takami, K., & Harata, N	2019	Gunma, Japan	MATSim	Five travel modes considered: human-driven vehicle (HV), SAV, PAV, bicycle and walking. HV and PAV are exclusive to an agent, that is, they are not shared with other agents. AVs are assumed to have a positive effect in road capacity. Driver and passenger mode are separated for the car mode in the PT data since these two are assumed to differ in marginal utility of time. Scenarios for different market penetration.
49	Wang, S., Correia, G. H. de A., & Lin, H. X	2019	Hypothetical urban area	Anylogic	No induced travel demand is taken into account. All travelers are willing to share rides with strangers. The battery capacity can support full-day operations for each SAV. The parking spaces are enough for all the SAVs in each station. The speed of the SAV is 20% lower than that in off-peak hours. Travelers will give up requesting a SAV when the waiting time for a vehicle assignment exceeds 5 min. Maximum number of travelers in a shared car is two.

#	Author	Year	Study area	Framework	Assumptions
50	Loeb, B., & Kockelman, K.M	2019	Austin, TX	MATSim	Six scenarios: 1) Gasoline Hybrid-Electric SAV, 2) Short-Range SAEV, 3) Long-Range SAEV, 4) Long-Range SAEV Fast Change, 5) Short-Range SAEV Fast Change, 6) Long-Range SAEV Fast Charge, Reduced Fleet. Simulation process features charging strategies, dynamic ridesharing, mode choice, and a multi-step search algorithm, up to 4 people share a ride
51	Hamadneh, J., & Esztergár-Kiss, D	2019	Budapest, Hungary	MATSim	Scenarios: 1) the activity chain of travelers without changes on available modes. SAsV park at the destination, when there is no call for drive to pick up a traveler. 2) the impacts of SAVs on the car users (i.e. car ownership). All car users switch to SAVs. 3) the impact of SAVs on a certain type of travelers (high income, and long-time commuter). All travelers who spend more than 40 min for one trip and belong to the high-income class are candidate to use SAVs.
52	Sheppard, C.J.R., Bauer, G.S., Gerke, B.F., Greenblatt, J.B., Jenn, A.T., & Gopal, A.R	2019	USA (national level)	N/A	Hypothetical future where SAEVs are a dominant mode of transportation. Price and mobility demand exogenously defined. The mobility assumptions only cover a typical weekday. Impact of congestion on travel times, battery lifetimes and parking costs ignored. The model does not attempt to optimize the seating capacity of the vehicles.
53	Pöhler, L.D., Asami, Y., & Oguchi, T	2019	Izu Oshima, Japan	N/A (long-term ABM with Dijkstra algorithm)	Neglecting traffic congestion and induced traffic. Assumed fixed hours of departure and number of trips for different groups of travelers. One conventional vehicle needs to be replaced once in the timespan of the simulation of 13 years.
54	Kim, C., Jin, Y.-G., Park, J., & Kang, D	2019	Sioux Falls, SD	MATSim	All commuters used autonomous taxis instead of private cars.
55	Simoni, M., Kockelman K.M., Gurumurthy, K.M., & Bischoff, J	2019	Austin, TX	MATSim	Two scenarios are simulated; AVs and SAVs, cost of AVs is lower than car cost, in AV scenario there is one SAV per 30 agents, in SAVs scenario there is one SAV per 10 agents, decrease of availability of privately owned vehicles to 60%
56	Hörl, S., Ruch, C., Becker, F., Frazzoli, E., & Axhausen, K. W	2019	Zurich, Switzerland	MaTSim	Fleet size, operational policy of the fleet, single occupancy taxi service, free speed travel time, rebalancing of AVs was disabled

#	Author	Year	Study area	Framework	Assumptions
57	Kamel, J., Vosooghi, R., Puchinger, J., Ksontini, F., & Sirin, G	2019	Paris, France	MATSim	Three scenarios: 1) the transportation system without SAVs, 2) SAVs added without considering user preferences, 3) SAVs added, and user preferences are considered. SAVs services are only car-share and not the ride-share. Four main modes for the basic scenario are considered (PT, private car, walk and bike)
58	Wang, B., Medina, S.A., & Fourie, P.J	2019	Waterfront Tanjong Pagar area, Singapore	MATSim	Four parking strategies: roaming, street parking, depot parking (and a mixed strategy (combination of street and depot parking) Different levels of PT demand
59	Wang, S., Correia, G. H. de A., & Lin, H. X	2020	The Hague, Netherlands	AnyLogic	dynamic time-dependent demand generation and vehicle assignment, vehicle platooning and a mesoscopic traffic simulator, central operator responsible for vehicle assignment, route calculation and formation of platoons, central operator for vehicle assignment has no knowledge about travel requests in advance, Pre-booking of SAVs is not considered, no proactive rebalancing of SAVs
60	Pulhès, A., & Berrada, J	2019	Palaiseau, France	MATLAB	Different levels of fleet size and penetration rate of AVs were considered; fleet size: 10–40 vehicles; two kinds of vehicles: 30-seat minibuses & 5 seat mid-sized cars
61	de Souza, F., Gurumurthy, K.M., Auld, J. & Kockelman K.M. (a)	2020	Bloomington, IL	POLARIS	Three different fleet sizes of 650, 700, and 750 SAVs were tested with, and without, repositioning.
62	Yao, F., Chen, X.(M.), Angeloudis P., & Zhang, W	2020a	Hangzhou, China	N/A (Dijkstra algorithm)	The number of charging piles is assumed to equal the actual number of charging piles in the study area multiplied by the SAEV market penetration rate.
63	de Souza, F., Gurumurthy, K.M., Auld, J., & Kockelman, K.M. (b)	2020	Bloomington, IL	POLARIS	Repositioning decisions are made at constant time steps (e.g., every 5 min).
64	Liu, J., Jones, S., & Adanu, E.K	2020	Chicago, IL	N/A	SAVs and taxis have the same out-of-vehicle travel times. The tolls to be collected are the same as taxi services. SAVs services will be 75%, 100% and 125% of non-driver-wage costs of taxi services.
65	Gurumurthy, K.M., Kockelman, K.M, & Zuniga-Garcia, N	2020	Austin, TX	MATSim	SAVs costs include a base fare, time-varying fare, and distance-varying fare. One SAV is available for every 10 travelers (or approx. every 35 person-trips), fleet size of 4,500 SAVs. 3 policy scenarios: door-to-door, FMFL, and both.

#	Author	Year	Study area	Framework	Assumptions
66	Zhang, W., & Wang, K	2020	Atlanta, GA	N/A (Monte-Carlo method Python 2.7)	Consumers are willing to pay an extra 10% of the current vehicle price A 10% decline in technology price (over time?). NHTSA's current and possible technology adoptions (e.g., adoption of electronic stability control (ESC) from year 2015 and connectivity from year 2020 on all new vehicles) are enacted.
67	Alisoltani, N., Zargayouna, M., & Leclercq, L	2020	Lyon, France	N/A	The cars can have two situations: they are either waiting in depots for new passengers or they are servicing the assigned passengers
68	Vosooghi, R., Puchinger, J., Bischoff, J., Jankovic, M., & Vouillon, A	2020	Rouen Normandie, France	MATSim	The population of the case study area has been downscaled to 10% and the network capacity has been modified in the performed simulations. The price of the service is 0.4 Euro per kilometer for all scenarios. The maximum number of stations is limited to 12.
69	Yan, H., Kockelman, K.M, & Gurumurthy, K.M	2020	Minneapolis–Saint Paul, MN	MATSim	All trips are made by a SAV here to gauge the service based on trip demand and fleet parking restrictions. When SAVs are allowed to park on curbs, there is no impact on traffic flow. All SAVs remain at the curb where they dropped off their passenger(s) in most scenarios. When considering parking availability in lots, each parking lot in a scenario has equal capacity that totals to accommodate 80% of the fleet.
70	Al Maghraoui, O., Vosooghi, R., Mourad, A., Kamel, J., Puchinger, J., Vallet, F., & Yannou, B	2020	Paris, France	MATSim	Two types of SAV services: 1) individual-rides, and 2) ridesharing. 2000 standard 4-seats SAVs have been integrated into the simulations. The service cost is considered to be 0.48 €/km for individual-rides and 0.4 €/km for ridesharing.
71	Lokhandwala, M., & Cai, H. (a)	2020	New York City, NY	N/A	A known total budget is available to develop the charging infrastructure. No charging stations in the first phase; the model starts with existing charging infrastructure. For all next phases, all charging stations in the previous ones will continue their service. Lifetime of charging stations longer than the time horizon of the model. Same charging rate for all stations.

#	Author	Year	Study area	Framework	Assumptions
72	Zhang, T.Z., Chen, T.D	2020	Seattle metropolitan region, WA	N/A	Trip patterns from the Puget Sound Regional Council (PSRC) Regional Travel Demand Model, reflecting local travel demand. Time of use (TOU) pricing rates from Seattle City Light and simulated real-time pricing (RTP) environments using locational marginal price (LMP) data. Renewable energy sources (RES), specifically photovoltaic (PV) generation, were modeled using data from the National Renewable Energy Laboratory (NREL). Two types of EVs (short range [SR] and long range [LR]) and two types of charging infrastructure (level 2 [LV2] and DC fast chargers [FC])
73	Lokhandwala, M., & Cai, H. (b)	2020	New York City, NY	N/A	Five rider types (unwilling to pool a ride, prefer not to pool, indifferent to pooling, prefer to pool, will only accept a pooled ride). All types distributed evenly among all the riders using the system.
74	Oh, S., Seshadri, R., Azevedo, C.L., Kumar, N., Basak, K., & Ben-Akiva, M.E	2020	Singapore	SimMobility	The baseline scenario consists of all existing modes, which are Car, Carpooling, Bus, Rail, Private bus, Taxi, MOD Single/Shared, and Walk. The price of a shared AMoD taxi is assumed to be 75% that of a single-ride AMoD taxi. Utilization is close to 100% during the peak period, request satisfaction rates are close to 100% and waiting times are sufficiently low.
75	Nahmias-Biran, B., Oke, J.B., Kumar, N., Lima Azevedo, C., & Ben-Akiva, M.E	2020	Singapore (virtual city)	SimMobility	The following AMoD modes were added in addition to existing modes: (1) AMoD as a single ride, (2) AMoD as a shared ride, (3) AMoD as a first/last connector to Mass Rapid Transit (MRT) stations, (4) AMoD as a first/last connector to MRT stations as a shared ride. In the near future scenario, AVs operate only in the Central Business District. In the long-term scenario, all mobility-on-demand services will be operated by an automated fleet city-wide. MoD modes and traditional taxis will no longer be available.
76	Venkatraman, P., & Levin, M	2021	Sioux Falls, SD	N/A (Tabu Search heuristic)	A SAV serves only one traveler at any time. SAVs routing problem with static demand, travelers with a desired departure time, without a time window for arrival. Each traveler has a desired time of departure from his origin and does not have a constrained time of arrival at his destination.

#	Author	Year	Study area	Framework	Assumptions
77	Gurumurthy, K.M., Kockelman, K.M., & Auld, J	2021	Chicago, IL	POLARIS	Maximum response time, which 30 min. SAVs operate on the roadway like traditional ride sourced vehicles. All travelers were willing to share rides if using the SAVs fleet. Four scenarios were proposed with three distinct geofences, and one without a fence for baseline comparison.
78	Chouaki, T. & Puchinger, J	2021	Paris-Saclay, France	SUMO	6 scenarios in an incremental manner, from a fixed schedule bus service to a complex one mixing demand responsive buses and robo-taxis. In all these scenarios, conventional vehicles are not considered.
79	Zwick, F., Kuehnel, N., Moeckel, R., & Axhausen, K.W	2021	Munich, Germany	MATSim	Two mode choice scenarios, one substituting all car trips by ride-pooling, another one with free mode choice. The public transport network is fairly optimized for the current PT system. The vehicles operate 24 h. In the second scenario, most people would probably not use another mode from/to the boundary of the study area and change from/to ride-pooling if it is not enforced.
80	Bucchiarone, A., De Sanctis, M., & Bencomo, N	2021	Trento, Italy	N/A	Scenarios: (i) each user is assigned a different working place, meaning that diversified and mainly non overlapping travel destinations are considered; (ii) each user is assigned one of the only two available working places; (iii) each user is assigned the same unique working place. The cost for the service is of 1 Euro/Km.
81	Mo, B., Cao, Z., Zhang, H., Shen, Y., & Zhao, J	2021	Tampines, Singapore	N/A	Five regulation scenarios: four with constrained competition while the other one focuses on unconstrained competition to find the Nash Equilibrium. Other important regulation aspects, such as service fare, pricing, and bus routes, are fixed in all scenarios. Before AV entering the market, walking, bus, and ride-hailing are the only travel modes available for the first-mile trips. After AV emerges, ride-hailing will be replaced by the AMoD. Signal system and driving behavior not considered.
82	Yao, F., Zhu, J., Yu, J., Chen, C., & Chen, X. (M)	2020b	Hangzhou, China	implemented in Go	Maximum waiting tolerance of passengers is 30 min. The time interval for passengers to get on and off the vehicle is 40 s. Routing results are calculated based on the static shortest path algorithm. Either HVs or AVs pick up one passenger at one time in the hybrid ride-hailing market.

#	Author	Year	Study area	Framework	Assumptions
83	Kang, D., & Levin, M	2021	Sioux Falls, SD	implemented in Java	Central SAVs dispatcher. Passengers are willing to be picked up instantaneously after sending out a request. Parking space unlimited. Passengers are assumed to wait until picked up by a SAV. We assume that each SAV serves one passenger request at a time, unlike ridesharing studies.
84	Javanshour, F., Dia, H., & Duncan, G	2021	Melbourne, Australia	Commuter	AV market penetration would be 10% and that remaining trips will continue to rely on conventional privately-owned vehicles. Services are station-based in which each centroid has a station with shared AVs to service customers. People need to walk a distance from their residences to the AMoD station. All trips were assumed to be one-way between origins and destinations. Passenger waiting time threshold was assumed 15 min.
85	Winter, K., Cats, O., Martens, K., & van Arem, B	2021	Amsterdam, Netherlands	MATSim	Three strategies (heuristics): Demand Anticipation, Supply Anticipation, Demand–Supply Deflcit Minimization In the third strategy, open requests are dispatched to idle vehicles located within the same zone. SAVs and private cars share the same road infrastructure. SAVs are operated as a centrally dispatched fleet. Car-pooling is not considered.
86	Zhang, W., & Guhathakurta, S	2021	Atlanta, GA	implemented in Python	Fifty rounds of warm-up simulation runs suggest: Approximately 367,160 vehicles will be sufficient to serve ten-county travel demand to ensure that more than 99 percent of the clients can be picked up within fifteen minutes after calling for services. The average waiting time is 7.13 min on a daily basis. The average waiting time increases to 10.59 during evening peak hours. Each SAV can serve around 24.5 trips on a daily basis.
87	Ahadi, R., Ketter, W., Collins, J., & Daina, N	2021	Berlin, Germany	N/A	Charging demand must be covered fully by installing charging stations (CSs). All CSs and SAEVs are homogeneous. Grid constraints are considered as a limit on the number of chargers for each zone in the optimization part. Land costs and grid constraints vary across the service region.

#	Author	Year	Study area	Framework	Assumptions
88	Zhou, Y., Sato, H., & Yamamoto, T	2021	Kozoji, Japan	Artisoc	Two vehicle dispatching strategies: initial dispatching and redispatching. All vehicles in the fleet comprise two seats. Level of service mainly defined by the wait time. Three experimental scenarios, namely the high-speed, low-speed, and no-sharing ride scenarios.
89	Zhou, M., Le, D., Nguyen-Phuoc, D.Q., Zegras, P.C., & Ferreira, J	2021	Singapore	SimMobility	Service operation: door-to-door service or as a feeder to the rail transit system. Pricing: Single ride: 75% of that of conventional taxis / Shared ride: 70% of single-ride service's price (or 52.5% of that of conventional taxis). Level of service: waiting time and access time are both specified the same as taxis and MOD services, which are assumed to be 5 min for both door-to-door and feeder services. Fleet: assumed to consist of a combination of 4- and 6-seaters
90	Oh, S., Lentzakis, A.F., Seshadri, R., & Ben-Akiva, M.E	2021	Singapore	SimMobility	Three scenarios are considered about the price or fare of the AMoD services: AMoD single-ride price: 75%, 100% and 125% of taxis & AMOD shared-ride price: 75% of single-ride. AMoD fleet is fully composed of battery electric vehicles (BEV) and the other vehicle categories are composed of gasoline/diesel-fueled vehicles
91	Hörl, S., Becker, F., & Axhausen, K.W	2021	Zurich, Switzerland	MATSim	The service region: Only journeys that begin and conclude within the service area's geographic bounds are eligible for the AMoD service. The minimum distance requirement: Trips shorter than 0.25 km in Euclidean distance between the origin and destination coordinates are not supported by the AMoD mode. The maximum waiting time constraint: Trips with an anticipated waiting time of over 15 min will not be provided with AMoD as an alternative mode of transportation.
92	Ishibashi, Y., & Akiyama, E	2022	Tokyo, Japan	MATSim	Time spent trave ling by SAVs has no effect on the agent's utility. Maximum possible waiting time at 20 min, fixed when boarding and alighting times for passengers. Fixed walking and bicycling travel speeds, and distance traveled.
93	Gurumurthy, K.M., & Kockelman, K.M	2022	Bloomington, IL	POLARIS	All trips choosing to use a SAV/TNC are currently single-party trips. All travelers opting to use the fleet are willing to share. A proportional increase in network capacity is also assumed for certain scenarios.

#	Author	Year	Study area	Framework	Assumptions
94	Dean, M.D., Gurumurthy, K.M., de Souza, F., Auld, J., & Kockelman K.M	2022	Austin, TX	POLARIS	Time step of 15 min to react to zonal demand. Taxi and ride-sourcing vehicles were estimated as SAEVs in the mode choice model, with assumed fare components.
95	Wang, S., Correia, G.H., & Lin, H.X	2022	Hague, Netherlands	AnyLogic	All travel demand is produced and attracted between what have been designated as service points which are connected to the network nodes. Vehicles wait at service points to form platoons instead of using slow-down and catch-up strategies. There are enough parking places for SAEVs to form a platoon at the service points. AMoD services are used to serve all private car trips in an urban area.
96	Ben-Dor, G., Ogulenko, A., Klein, I., & Benenson, I	2022	Jerusalem, Israel	MATSim	Various congestion and parking pricing schemes and active SAV fleets of different sizes (250–1,000 vehicles) are simulated. The SAV service to the trips between the central and the outer area; at least one SAV's origin or destination should be in the center. The price of the SAV trip is set equal to that of the PT.
97	Stevens, M., Correia, G.H., Scheltes, A., & van Arem, B	2022	Rotterdam, the Netherlands	AnyLogic	The AMoD service is used only as a first- and last-mile mode in a multimodal public transport trip Ride pooling is only possible when the required detour to pick up the second passenger is smaller than 25% of the direct travel time of the traveler that has been picked up first. The charging facilities are located at the PT station and their location is fixed. The number of chargers required is not fixed and depends on the charging demand. Both fast and slow charging strategies are tested.
98	Nahmias-Biran, B., Dadashev, G., & Levi, Y	2022	Tel Aviv, Israel	SimMobility (with Aimsun Next)	AMoD services are introduced in replacement of MoD at a discount from regular taxi fares. 6 cost reduction scenarios were considered: 30%, 40%, 50%, 60%, 70% and 80% discount from taxi fares. The AMoD service will offer both single and shared ride (pooling) options to enable further reduction in fares and in energy consumption. Travel time in AMoD Pool includes the waiting time for passengers (5 min for each passenger) and the extra time for pickup and drop-offs (3 min for each pickup/drop-off).

Appendix B
Results

#	Author	Year	Study area	Results
1	Fagnant D. & Kockelman K	2014	Hypothetical city	A system of SAVs may save members ten times the number of cars they would need for self-owned personal-vehicle travel, but would induce about 11% more travel
2	ITF	2015	Lisbon, Portugal	Shared self-driving fleets have the potential to drastically reduce the number of vehicles necessary to deliver the same travel as today's fleet (approx. 10%). The overall volume of car travel will likely increase (6% more car-kilometers travelled than today) Reduced parking needs will free up significant public and private space
3	Zhang W., Guhathakurta S., Fang J. & Zhang G	2015a	Hypothetical city	It would be able to eliminate up to 90% of parking demand for clients who adopt the system, at a low market penetration rate of 2%. Different SAVs operation strategies and client's preferences may lead to different spatial distribution of urban parking demand.
4	Fagnant D., Kockelman K. & Bansal P	2015	Austin, TX	Each SAV can replace around 9 conventional vehicles within the study area while still maintaining a reasonable level of service. 8 percent more vehicle-miles traveled (VMT) may be generated
5	Kim, K.-H., Yook, D.-H., Ko, Y.-S., & Kim D.-H	2015	Seoul, South Korea	The full integration of autonomous vehicles in the urban road environment is expected to lead to more dispersed spatial structure
6	Zhang W., Guhathakurta S., Fang J. & Zhang G	2015b	Hypothetical city	A DR-SAV system can provide more satisfactory level of service compared with an NR-SAV system, in terms of shorter trip delays, more reliable services (especially during peak hours), less VMT generation, and less trip costs. Moreover it is demonstrated that a DR-SAV system can be more environment-friendly in the long run
7	Azevedo, C.L	2015	Singapore	The average waiting time decreases with the increase in the fleet size, and it is equal to 5 min when AMoD fleet size is around 2200 vehicles. Further increase in the fleet size is not able to significantly decrease the waiting time.
8	Shen, W., & Lopes, C	2015	New York City, NY	The proposed algorithm improves passengers' experience by reducing the average passenger waiting time by up to 29.82% and increasing the trip success rate by up to 7.65%.

#	Author	Year	Study area	Results
9	Marczuk, K.A., Hong, H.S., Azevedo, C.L., Adnan, M., Pendleton, S., Frazzoli, E., & Lee, D	2015	Singapore	In both station-based and free-floating models, increasing the vehicle fleet size resulted in an increase in the number of passengers served. The free-floating model was able to serve 90% of the demand, while the station-based model 68%. Increasing the AMoD fleet size resulted in a fall in waiting times. With 20 initial stations, the median waiting time decreased from 20.74 to 1.80 min as the fleet size grew from 2000 to 7500.
10	Bosch, P., Ciari, F., & Axhausen, K.W	2016	Zurich, Switzerland	For a given fleet performance target, the relationship between served demand and required fleet size is non-linear and the ratio increases as demand increases. If waiting times of up to 10 min are accepted, a reduction of up to 90% of the total vehicle fleet can be possible even without active fleet management like vehicle redistribution
11	Chen, D., Kockelman, K.M., & Hanna, J	2016	Hypothetical city (Austin)	Fleet size is sensitive to battery recharge time and vehicle range, with each 80-mile range SAEV replacing 3.7 privately owned vehicles and each 200-mile range SAEV replacing 5.5 privately owned vehicles. Each SAEV replace 5 to 9 privately owned vehicles
12	Marczuk, K., Soh, H., & Azevedo, C.L	2016	Singapore	Rebalancing reduces the required fleet size and shortens the customers' wait time. We observe a decrease in waiting time with the increase in the fleet size.
13	Hörl, S., Erath, A., & Axhausen, K.W	2016	Sioux Falls, SD	Even under conservative pricing a large share of travelers is attracted by autonomous vehicles, though it is highly depended on the provided fleet size. For sufficiently large supplies, the vehicle miles travelled of autonomous single-passenger taxis, increase up to 60%.
14	Bischoff, J., & Maciejewski, M	2016	Berlin, Germany	A fleet of 100.000 vehicles will be enough to replace the car fleet in Berlin at a high service quality for customers. One autonomous taxi could replace the demand served by ten conventional vehicles in Berlin.
15	Chen, D., & Kockelman, K.M	2016	Hypothetical city (Austin, TX)	The mode share of SAEVs in the simulated city is predicted to lie between 14 and 39%, when competing against privately-owned, manually driven vehicles and city bus service. Pricing strategies that attempt to balance available SAEV supply with anticipated trip demand can decrease average wait times by 19 to 23%.

#	Author	Year	Study area	Results
16	Fagnant, D.J., & Kockelman, K.M	2016	Austin, TX	Dynamic ride sharing reduces total service times and travel costs for SAVs users, even after accounting for extra passenger pick-ups, drop-offs and non-direct routings. A private fleet operator paying 70,000 per new SAV could earn a 19% annual (long-term) return on investment while offering SAVs services at $1.00 per mile of a non-shared trip.
17	Hörl, S	2017	Sioux Falls, SD	The overall mode share for the Taxi operator is higher than for the Pool operator at peak and off-peak hours. The Taxi service performs better regarding travel times throughout the day. The simulated Pool operator has a competitive advantage due to the low price, but realistically this would not be economical. In the combined case, while the Taxi service is favoured at peak times, the Pool service attracts the larger share of customers at off-peak hours.
18	Merlin, L	2017	Ann Arbor, MI	The automated shared-ride taxi transit service could provide a higher level of service at lower cost and lower carbon emissions than the current bus system An automated taxi service without ride-sharing would provide high levels of service at lower cost, but with higher levels of carbon emissions than the current bus system. Ridesharing is essential to obtaining the full cost savings and environmental benefits for an automated taxi system. Both automated taxi systems would likely increase peak-hour congestion by increasing peak-hour vehicle kilometers traveled.
19	Auld, J., Sokolov, V., & Stephens, T	2017	Chicago, IL	Changes in capacity increase overall VMT, although only to a small degree, with about 4% induced additional VMT for an 80% increase in capacity. The elasticity of VMT with respect to capacity of 0.05 is in line with values reported in the literature. Changes in travel time cost, or the value of travel time savings, have a significant effect, especially at very low levels of VOTT, increasing VMT by up to 59%, while average travel time increases from about 20 min to more than 70 min.
20	Liu, J., Kockelman, K.M., Bosch, P., & Ciari, F	2017	Austin, TX	Higher fare rates allow for greater vehicle replacement (ranging from 5.6 to 7.7 HVs per SAV). Empty vehicle miles traveled by the fleet of SAVs ranged from 7.8 percent to 14.2 percent.

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21	Llorca, C., Moreno, A., & Moeckel, R	2017	Munich, Germany	The total travelled distance and the travel time for both autonomous and conventional trips increased when autonomous vehicles fleets are operating. Congestion levels in the peak hour were reduced. It was possible to replace three conventional cars with one autonomous taxi while satisfying the travel demand with reasonable waiting times.
22	Martinez, L., & Viegas, J.M	2017	Lisbon, Portugal	A full implementation scenario where the existing metro service is kept and private car, bus and taxi mobility would be replaced by shared modes would significantly reduce travelled vehicle-kilometres and CO2 emissions.
23	Dia, H. & Javanshour, F	2017	Melbourne, Australia	Significant reduction in both the number of vehicles required to meet the transport needs of the community, and the required on-street parking space. This reduction in both the number of vehicles was achieved at the expense of a less significant increase in the total VKT.
24	Jäger, B., Agua, F.M.M., & Lienkamp, M	2017	Munich, Germany	The feasibility of operating a shared autonomous vehicle fleet with both high service levels and vehicle utilization is confirmed.
25	Scheltes, A., & De Almeida Correia, G.H	2017	Delft, Netherlands	The automated last-mile transport system was only able to compete with the walking mode, additional measures were needed for the system to be competitive with cycling. Relocating empty vehicles or allowing pre-booking reduced average waiting time. Allowing passengers to drive at a higher speed reduced average travel time. Reducing system capacity increased in energy use.
26	Hao, M., & Yamamoto, T	2017	Nagoya, Japan	20 to 30% of trips are served by SAVs, and that 50 to 70% of the vehicles provided by households are sufficient to serve the demand without significant waiting time. Young generation, car owners and frequent car users are less likely to get rid of their car and just use SAVs. People who take part-time jobs are more likely to give away their personal vehicle
27	Heilig, M., Hilgert, T., Kagerbauer, M., & Vortisch, P	2017	Stutgart Region, Germany	About 45% of all vehicle movements and 20% of all vehicle kilometers could be saved. About 85% of all vehicles in the Stuttgart region might be dispensable
28	Basu, R., Araldo, A., Akkinepally, A. P., Nahmias Biran, B. H., Basak, K., Seshadri, R., & Ben-Akiva, M	2018	Hypothetical city (with patterns observed in Singapore)	Without mass (public) transit, congestion seems to intensify. Mass (public) transit has a fundamental role, despite the high efficiency of AMoD, when aiming to avoid congestion and maintain acceptable levels of service.

#	Author	Year	Study area	Results
29	Karamanis, R., Angeloudis, P., Sivakumar, A. & Stettler M,	2018	London, UK	In monopoly, dynamic pricing provides higher revenues than static pricing at non-peak hours. In competition, dynamic pricing is superior at peak hours where increased waiting times are observed. In both market structures, shared trips are more popular in dynamic pricing compared to static pricing.
30	Harper C., Hendrickson C., & Samaras C	2018	Seattle, WA	As AV penetration rates increase, parking lot revenues decrease significantly and could likely decline to the point where operating a lot is unsustainable economically, if no parking-demand management policies are implemented.
31	Lu, M., Taiebat, M., Xu, M. & Hsu, S.-C	2018	Ann Arbor, MI	For meeting daily commute demand, the optimized autonomous taxi fleet size is only 20% of the conventional solo-commuting personal car fleet. Commuting cost decreases by 38% when using internal combustion engine a Taxis, Energy consumption, greenhouse gas emissions, and SO2 emissions are higher than conventional solo commuting, mainly because of unoccupied repositioning between trips. The environmental impacts of electric aTaxis do not show significant improvement over conventional vehicles.
32	Liu, Z., Miwa, T., Zeng, W., & Morikawa, T	2018	Sioux Falls, SD	The non-detour and detour sharing strategies can respectively reduce fleet size by 19% and 27%, reduce waiting time by 62% and 82%, reduce operational costs by 16% and 24%, and reduce CO2 emissions by 17% and 19% in comparison with a non-sharing strategy
33	Lokhandwalaa, M., & Cai, H	2018	New York City, NY	Switching from traditional taxis to shared autonomous taxis can potentially reduce the fleet size by 59% while maintaining the service level. Ride sharing increases occupancy rate (from 1.2 to 3), decreases total travel distance (up to 55%), and reduces carbon emissions (up to 866 metric tonnes per day).
34	Wang, B., Ordonez Medina, S.A., & Fourie, P	2018	Sioux Falls, SD	During the peak hour, around 240—250 vehicles are needed to satisfy the demand while during the off-peak hour, only around 30 vehicles are in use. More than 90% of total trips share rides, and more than 40% of total trips are with high occupancy (more than 6 passengers during the trip). In both morning and afternoon peak, the spatial distribution of initial vehicle position is close to travel demand.
35	Javanshour, F., Dia, H., & Duncan, G	2018	Melbourne, Australia	An AMoD system could reduce the current fleet size by 84% while meeting the same travel demand. The increase in VKT is significant (around 77% for scenarios where the vehicles are used in car-sharing systems, and 29% for vehicles used as ride-sharing systems). A strong quadratic relationship between AMoD fleet size and VKT exists

#	Author	Year	Study area	Results
36	Cyganski R., Heinrichs M., Von Schmidt, A., & Krajzewicz, D	2018	Brunswick, Melbourne, Australia	Only minor changes in the modal split and the number of rides for the city of Brunswick due to the relatively small travel distances prevailing
37	Shen, Y., Zhang, H. & Zhao, J	2018	Singapore	The proposed integrated system has the potential of enhancing service quality, occupying fewer road resources, being financially sustainable, and utilizing bus services more efficiently
38	Hyland, M., & Mahmassani, H.S	2018	N/A	Optimization-based AV-traveler assignment strategies allow en-route pickup AVs to be diverted to new traveler requests Strategies that incorporate en-route drop-off AVs in the assignment problem, reduce fleet miles and decrease traveler wait times More-sophisticated AV-traveler assignment strategies improve operational efficiency when fleet utilization is high The spatial distribution of traveler requests significantly impacts the empty fleet miles generated.
39	Farhan, J., & Chen, T. D	2018	Hypothetical city (100 × 100 mile)	Allowing multiple occupants improves service rate as well as system-wide benefits from $1.34 M to $1.52 M. Ridesharing decreases fleet size and the number of charging stations. Compared to traditional ride-hailing service, with ridesharing, the fleet size and the number of charging stations reduce.
40	Wen, J., Chen, Y. X., Nassir, N., & Zhao, J	2018	N/A (spread out residential area)	The trade-off between the level of service and the operational cost, provides insight for fleet sizing to reach the optimal balance. The encouragement of ridesharing, that allows in-advance requests, and combines fare with transit, could facilitate service integration and sustainable travel.
41	Bosch, P., Ciari, F., & Axhausen, K.W	2018	Zug, Switzerland	Considering the existing spatial distribution of the demand and the existing transport system, AV systems are solely capable of decreasing travel times at the cost of substantial mode shifts and additional vehicle kilometers driven. Among the tested policy measures, even though all indicated causality, only the organizational form of the AV service demonstrated a statistically significant effect.

#	Author	Year	Study area	Results
42	Nahmias-Biran, B., Oke, J.B., Kumar, N., Basak, K., Araldo, A., Seshadri, R., Akkinepally, A.P., Lima Azevedo, C., & Ben-Akiva, M.E	2019	Singapore	In the "AMoD only" scenario, where AMoD services are offered as a substitute for traditional MoD services, we see a significant reduction in PT mode share of more than 6%, with a shift toward AMoD, which consists of 13.2%. In the AMoD case, the fleet is more efficiently managed, as they are introduced incrementally, while MoD drivers are introduced according to their shift starting time. The shared requests experience higher waiting times. The increase in fleet size is clearly beneficial for non-shared requests, while its impact is less pronounced for the shared.
43	Kim, C., Jin, Y.-G., Park, J., & Kang, D	2019	Sejong, South Korea	Minibuses did not replace the trunk traffic, and the minibus service should be used as an auxiliary for the trunk traffic. The minibus service increased the public transport mode share by 3–5%.
44	Zhou, Y., Li, Y., Hao, M., & Yamamoto, T	2019	Nagoya, Japan	In the residential area, approximately 400 shared autonomous vehicles can facilitate more than 10,000 trips at an appropriate level of service. For the commuter town, fewer than 400 vehicles can provide rapid responses with a wait time of approx. 5 min for more than 5000 trips per day.
45	Li, L., Lin, D., Pantelidis, T., Chow, J., & Jabari, S. E	2019	Brooklyn, NY	Improvements in performance of an SAEV system with en route relocation when compared to no relocation, in terms of reductions in average waiting times and lost customers. Lost customers, average waiting times and average waiting customers all decrease with an increase in fleet size.
46	Gurumurthy, K.M., Kockelman, K.M., & Simoni, M	2019	Austin, TX	The cost-effectiveness of traveling with strangers overcomes inconvenience and privacy issues at moderate-to-low fare levels. A moderately sized fleet (one SAV for every 25 people) serves nearly 30% of all trips made during the day. This same fleet performs better when road pricing is enforced in the peak periods, moderating VMT by 2%, increasing SAVs demand and in turn fleet-manager revenue
47	Ben-Dor, G., Ben-Elia, E., & Benenson, I	2019	Tel Aviv, Israel	Fleets of 50-150 K vehicles could well serve the entire intra-metropolitan travel demand, with an average occupancy of ~ 2 compared to 1.1 passengers per vehicle today. Minimal fleet size of 50 K SAVs is sufficient for serving Tel Aviv Metropolitan Area users' activities but carries a high level of daily rejections 6%. A larger fleet does not seem to improve the level of service significantly.

#	Author	Year	Study area	Results
48	Luo, L., Troncoso Parady G., Takami, K., & Harata, N	2019	Gunma, Japan	SAVs share increases with the fleet size in general. Most scenarios indicate a considerable market penetration for SAVs given relatively optimistic settings. Average passenger waiting time in all scenarios falls in an acceptable range. Fleet average served requests and average inactive ratio suggest supply efficiency for the whole fleet, which increases with size. An increase in total VKT observed with the SAVs introduction, while accessibility increases.
49	Wang, S., Correia, G. H. de A., & Lin, H. X	2019	Hypothetical urban area	SAVs systems together with dynamic ridesharing can significantly reduce average waiting time, VKT and empty SAVs trips. The proposed vehicle assignment algorithm can reduce the empty VKT for the pickups for all tested SAVs systems up to about 40% and improve the system capacity. The tailored time-varying transit service system, compared with the parallel transit service systems, can achieve a similar system performance in terms of average waiting time, service time and system capacity.
50	Loeb, B., & Kockelman, K.M	2019	Austin, TX	The gasoline hybrid-electric (HEV) fleet performed better than EV fleets, while remaining more profitable, providing response times of 4.5 min compared to 5.5 min. The HEV fleet is the more profitable option until the cost of gasoline exceeds $10 per gallon or the cost of a long-range EV falls below $16,000. Of all the EVs studied, the long-range fast-charging scenario provides the best service and is the most profitable.
51	Hamadneh, J., & Esztergár-Kiss, D	2019	Budapest, Hungary	1 SAV can replace 8 conventional vehicles with acceptable average waiting time and usage of 4-seats (shared trip). Travel time decreased by 17% and the travel distance decreased by 20% after 100 iterations performed. The long commuter and high-income travelers can be served by 20 SAVs with waiting time of 10 min and trip duration of 20 min. In this case 1 SAV can replace 6 conventional vehicles.
52	Sheppard, C.J.R., Bauer, G.S., Gerke, B.F., Greenblatt, J.B., Jenn, A.T., & Gopal, A.R	2019	USA (national level)	If all U.S. mobility was satisfied by SAEVs with a sharing factor of 1.5, a fleet of only 12.5 million vehicles and 2.4 million charge points would be required, consuming 1,142 GWh of energy per day (or 8.5% of daily U.S. electricity demand) with a peak load of 76.7 GW (or 11% of the U.S. non-coincident peak) at a cost of $ 0.27/mi.

#	Author	Year	Study area	Results
53	Pöhler, L.D., Asami, Y., & Oguchi, T	2019	Izu Oshima, Japan	In all three land use policies as possible scenarios of future settlement, the AMoD is cheaper than the conventional transportation system. The land use policies have a stronger impact on the AMoD system in reducing the total costs than the conventional system.
54	Kim, C., Jin, Y.-G., Park, J., & Kang, D	2019	Sioux Falls, SD	Many commuters could not depart at the desired time and had to adjust. A travel reservation system or a dynamic pricing system will be required before autonomous taxis become popular.
55	Simoni, M., Kockelman K.M., Gurumurthy, K.M., & Bischoff, J	2019	Austin, TX	All pricing strategies reduce congestion. However, their social welfare impacts differ in meaningful ways. More advanced strategies perform better in terms of traffic conditions and traveler welfare. The possibility to refund users by reinvesting toll revenues as traveler budgets plays a salient role in the overall efficiency of each strategy as well as in the public acceptability.
56	Hörl, S., Ruch, C., Becker, F., Frazzoli, E., & Axhausen, K. W	2019	Zurich, Switzerland	The choice of fleet operational policy determines customer-vehicle assignment and repositioning of empty vehicles (rebalancing) heavily influences system performance, e.g., wait times and cost.
57	Kamel, J., Vosooghi, R., Puchinger, J., Ksontini, F., & Sirin, G	2019	Paris, France	Neglecting user preferences in multiagent simulations can significantly change the outputs for future scenarios. Specifically, SAVs modal shares are estimated to be 5.3% without, and 3.8% with introducing preferences. The overall modal split of the SAVs after introduction of user preferences decreases by 28%, the use of this mode decreases by 38% among the travelers. Demographic structure plays an important role regarding the use of SAVs.
58	Wang, B., Medina, S.A., & Fourie, P.J	2019	Waterfront Tanjong Pagar area, Singapore	The in-vehicle travel time of most strategies increases with more demand. The increment of high demand scenarios is within 10 s, which is tolerable for a 10-min trip. Agents travel longer with the road strategy due to more congestion and spend less in-vehicle time when vehicles park inside depot. The ATOD system with a fixed fleet size was found to be flexible and robust enough to serve from 70 to 130% of normal demand with an acceptable level of service.

#	Author	Year	Study area	Results
59	Wang, S., Correia, G. H. de A., & Lin, H. X	2020	The Hague, Netherlands	- The impact of vehicle assignment strategies in the AMoD system with vehicle platooning formation predominately affects the average waiting time and system capacity to transport travelers as a whole. - However, vehicle platooning, to some extent, could lengthen the travel time of platoon vehicles. - The hold-on time of leading vehicles in order to form a platoon could affect the average time delay of vehicles part of those platoons.
60	Pulhès, A., & Berrada, J	2019	Palaiseau, France	Dispatcher based vehicle assignment is clearly beneficial for users and operators but restrictive for drivers. A service with large-capacity vehicles is less efficient than a fleet of 5-seat vehicles, even in a network with high demand and limited station numbers. With a sufficient number of vehicles, an acceptable maximal waiting time value is achieved.
61	de Souza, F., Gurumurthy, K.M., Auld, J. & Kockelman K.M. (a)	2020	Bloomington, IL	On average, the wait times were lower with repositioning for all adequate fleet sizes. With repositioning enabled, a higher share of demands were served.
62	Yao, F., Chen, X. (M.), Angeloudis P., & Zhang, W	2020a	Hangzhou, China	Platform's daily revenue is approx. four times as the daily system operation costs, therefore it can operate at a satisfactory level of profit. The simulated average waiting time of clients is 6.8 min (close to the empirical waiting time).
63	de Souza, F., Gurumurthy, K.M., Auld, J., & Kockelman, K.M. (b)	2020	Bloomington, IL	On average, the wait times were around 20% lower with repositioning for all adequate fleet sizes. In addition, enabling repositioning led to a higher share of demands being served. These benefits are achieved at the expense of 6% added vehicles miles traveled.
64	Liu, J., Jones, S., & Adanu, E.K	2020	Chicago, IL	SAVs may attract more users than conventional taxis due to reduced driver costs. Lower SAVs speeds can cause longer travel times and increase the time-associated travel costs. However, the influence of non-wage cost is clear. If the travel demand and SAVs speed are held constant, the required fleet size decreases with increase in tolerate waiting times. SAVs could serve over 85% of trips if SAVs services remove all driver-wage cost in taxi services.

#	Author	Year	Study area	Results
65	Gurumurthy, K.M., Kockelman, K.M, & Zuniga-Garcia, N	2020	Austin, TX	SAVs have the potential to help solve First-Mile-Last-Mile transit problems when fare benefits are provided to transit users. Restricting SAVs use for FMLM trips increases transit coverage, lowers average access and egress walking distance, and shifts demand away from park-and-ride and long walk trips. When SAVs are available for both door-to-door use and FMLM trips, high SAVs fares help maintain transit demand.
66	Zhang, W., & Wang, K	2020	Atlanta, GA	Transition scenarios from year 2020–2040 suggest the parking demand may be significantly reduced in the future. Market penetration of car-sharing rather than vehicle automation is the key to parking demand reduction. The reduction rate in parking space during the transition period increases from 6.5% in 2020 to 34.9% in 2040. Spatial shifts in parking demand are also observed.
67	Alisoltani, N., Zargayouna, M., & Leclercq, L	2020	Lyon, France	The proposed multi-agent system is efficient in terms of serving all the requests in a short time satisfying both passengers and providers objectives.
68	Vosooghi, R., Puchinger, J., Bischoff, J., Jankovic, M., & Vouillon, A	2020	Rouen Normandie, France	Because of the lower service availability due to going to charging stations and charging times along the day, the fleet usage ratio is decreased in all SAEV scenarios compared to the base-case scenario. By providing one normal charger per approximately four SAEVs, the performance indicators become dramatically worse in all scenarios compared to a non-electric SAVs service. However, after replacing normal chargers with rapid chargers and by increasing the number of outlets of normal chargers, important improvements are observed. The choice of charging and battery swapping station placement strategy is found to have a profound effect on service performance indicators
69	Yan, H., Kockelman, K.M, & Gurumurthy, K.M	2020	Minneapolis–Saint Paul, MN	The average SAVs in this region can serve at most 30 person-trips per day with less than 5 min average wait time, but generates 13% more VMT. With dynamic ride-sharing, SAVs VMT fell, on average, by 17% and empty VMT fell by 26%. Compared to idling-at-curb scenarios, parking restricted scenarios generated 8% more VMT. Relying on 52 mi/gallon hybrid electric SAVs, as opposed to a 31 mi/gallon conventional drivetrain SAVs, is estimated to lower travelers' energy use by 21% and reduce tailpipe emissions by 30%

#	Author	Year	Study area	Results
70	Al Maghraoui, O., Vosooghi, R., Mourad, A., Kamel, J., Puchinger, J., Vallet, F., & Yannou, B	2020	Paris, France	Estimating demand of SAVs service, and relatively its configuration and design must take into account the demographic structure of the city/region of and the taste variations of its inhabitants. Introducing traveler profiles into the system has the potential to enhance the quality of the service provided, as it can increase the overall satisfaction of VIP travelers, as well as having a positive effect on non-VIP travelers in terms of their detour and waiting times.
71	Lokhandwala, M., & Cai, H. (a)	2020	New York City, NY	EV adoption in a traditional fleet requires charging infrastructure with fewer stations that each has more charging ports, compared to the future fleet (fully autonomous vehicles with ride sharing) which benefits from having more scattered charging stations. Charging will only reduce the service level by 2% for a future fleet with 100% EV adoption. EV adoption can reduce CO2 emissions of NYC taxis by up to 861 Tones/day for the future fleet and 1100 Tones/day for the traditional fleet.
72	Zhang, T.Z., Chen, T.D	2020	Seattle metropolitan region, WA	In the absence of electricity price signals, SAEV charging demand is likely to peak the evening. Under Smart Charging management, EVs with larger battery sizes are more responsive to low-electricity cost charging opportunities and have greater potential to reduce total energy related costs for a SAEV fleet, especially under Real Time Pricing structure.
73	Lokhandwala, M., & Cai, H. (b)	2020	New York City, NY	Higher service levels are reached when all of the riders in the system are open to pooling, with the majority willing to accept non-pooled rides and a few (30%) unwilling to accept a non-pooled ride. In order to achieve a higher system service level, a small number of riders who accept only pooled rides is desired. The most flexible rider type has relatively high service level, low waiting time, and the least variability in both service level and waiting time.

#	Author	Year	Study area	Results
74	Oh, S., Seshadri, R., Azevedo, C.L., Kumar, N., Basak, K., & Ben-Akiva, M.E	2020	Singapore	In the case that total vehicle ownership is not capped, the introduction of AMoD leads to a significant increase in VKT of up to 17% in the case of moderate introduction and an increase in the ratio of congested to free travel time during peak hours of up to 14%. The increase in network congestion can be mitigated by caps on vehicle ownership. The VKT increase is mitigated and decreases from 11% to 7.7% if total vehicle ownership is fixed. The fleet sizes required to serve AMoD demand in an island-wide rollout range from 27,500 to 43,200 in the moderate adoption scenario, in addition to an on-demand and taxi fleet of around 20,000 each.
75	Nahmias-Biran, B., Oke, J.B., Kumar, N., Lima Azevedo, C., & Ben-Akiva, M.E	2020	Singapore (virtual city)	The city-wide deployment of AMoD results in greater accessibility and network performance. Mid and high-income individuals are gaining less accessibility as compared to low-income groups.
76	Venkatraman, P., & Levin, M	2021	Sioux Falls, SD	Encouraging results in reducing the total person travel time for differing fleet sizes and demand levels. Reduction of Average Vehicle Travel Time and Average Person Travel Time.
77	Gurumurthy, K.M., Kockelman, K.M., & Auld, J	2021	Chicago, IL	Service areas need a balanced mix of trip generators and attractors, and an SAVs fleet's empty VMT can be noticeably reduced through suitable geofencing and DRS. Geofences can also help lower response times, reduce systemwide VMT across all modes, and ensure uniform access to SAVs. DRS is most useful in lowering VMT and eVMT that arises from sprawled land development, but with insufficient demand to share rides, savings from the use of geofences is higher.
78	Chouaki, T. & Puchinger, J	2021	Paris-Saclay, France	A mobility service that relies on AVs aided by connected road side units that allow to retrieve information about the traffic would perform better than a regular service. Introducing communications between the buses and the road side units (bus stops and traffic lights) allows a significant reduction in trip duration.
79	Zwick, F., Kuehnel, N., Moeckel, R., & Axhausen, K.W	2021	Munich, Germany	Replacing all car trips by a stop-based ride-pooling system leads to a drastic noise reduction in residential areas, whereas door-to-door systems may even increase noise exposure due to additional pick-up/drop-off rides and detours. Reduction in VKT with the pooling system observed. Assuming that each private vehicle is on average used for 3 rides per day, more than 600,000 private vehicles are necessary to transport the same amount of rides as 12,000 stop-based ride-pooling vehicles.

#	Author	Year	Study area	Results
80	Bucchiarone, A., De Sanctis, M., & Bencomo, N	2021	Trento, Italy	Managing a considerable set of users sharing the same working place contributes to making the autonomous shuttles (AS) service less expensive and thus, more convenient for companies who may at the same time wish to offer it to their employees, at the expense of increase of waiting time. When diversified working places are considered, travel costs are subject to a high variance that might discourage the use of a shared ride. The waiting time for users served by the AS, decreases with the increasing size of the fleet.
81	Mo, B., Cao, Z., Zhang, H., Shen, Y., & Zhao, J	2021	Tampines, Singapore	The competition can result in higher profits and higher system efficiency for both operators (AV & PT) compared to the status quo. On average, the competition reduces the travel time of passengers but increases their travel costs. Nonetheless, the generalized travel cost is reduced when incorporating the value of time. The bus supply adjustment increases the average vehicle load and reduces the total VKT measured by the passenger car equivalent, while the AV supply adjustment does the opposite.
82	Yao, F., Zhu, J., Yu, J., Chen, C., & Chen, X. (M.)	2020b	Hangzhou, China	A small proportion of AVs in the hybrid ride-hailing market can significantly reduce the average waiting time of passengers. The average waiting time for passengers in human driving is longer than that of AVs by 1.9 min. The total VKT for the fleet of AVs are smaller, and their exhaust emissions are 12.3% fewer than those of the human driving fleet.
83	Kang, D., & Levin, M	2021	Sioux Falls, SD	The maximum stable demand is linearly related to the fleet size given. The max-pressure dispatch policy can serve as much demand as any other dispatch policy.
84	Javanshour, F., Dia, H., & Duncan, G	2022	Melbourne, Australia	While AMoD can meet the demand for travel using only 16% of the current vehicle fleet, they would produce 77% increase in VKT.
85	Winter, K., Cats, O., Martens, K., & van Arem, B	2021	Amsterdam, Netherlands	All pro-active relocation strategies are outperformed by a naïve remain-at-drop off-location strategy in a scenario where curbside parking capacity is in abundance. The demand-anticipation heuristic leads to the highest average waiting times due to vehicle bunching at demand-hotspots which results in an uneven usage of parking facilities. The most favourable results in regard to service efficiency and equity are achieved with the heuristics balancing demand and supply, at the costs of higher driven mileage due to the relocation of idle vehicles.

#	Author	Year	Study area	Results
86	Zhang, W., & Guhathakurta, S	2021	Atlanta, GA	All market segments are going to be less attached to their workplaces. The properties with preferred structural characteristics, school districts, and neighborhood features will become more appealing to home buyers. Therefore, the SAVs-induced reduction in transportation cost provides more freedom for home buyers regarding where they may choose to live. The model outputs suggest an increase in commute VMT generation across all market segments.
87	Ahadi, R., Ketter, W., Collins, J., & Daina, N	2021	Berlin, Germany	Charging station locations depend mostly on the spatial distribution of installation costs and charging demands. Optimal CSs are located in both central areas where demand is high, and suburbs where installation costs are lower. Charging strategies and fleet size affect the charging patterns, the required number of chargers and the fleet performance.
88	Zhou, Y., Sato, H., & Yamamoto, T	2021	Kozoji, Japan	In the case of a high-speed scenario, the same fleet size improved the level of service (LOS) by reducing the average wait time and halving the in-vehicle time. By contrast, the wait time in terms of the average and 95th percentile of the no-sharing ride scenario drastically deteriorated to an unacceptable level. Preparing for the potential fleet insufficiency periods from 7:00–13:00 and 15:00–18:00 can improve the LOS.
89	Zhou, M., Le, D., Nguyen-Phuoc, D.Q., Zegras, P.C., & Ferreira, J	2021	Singapore	In the full automation scenario, an average decrease of 4.17 min is observed in accessibility and the median is a 0.65-min decrease. Accessibility increases for 47.29% of the population and drops for 52.70% of them. The female group experiences a small average increase in accessibility while the male group encounters an average decrease in accessibility. Middle-age groups experience moderately larger increase in accessibility and the increase for the oldest group is exceptionally small. Middle-age groups show the largest reduction in accessibility in the full automation scenario when private modes become unavailable

#	Author	Year	Study area	Results
90	Oh, S., Lentzakis, A.F., Seshadri, R., & Ben-Akiva, M.E	2021	Singapore	Introduction of AMoD services may potentially lead to increased vehicular traffic, resulting in heightened congestion levels compared to the standard scenario. Factors contributing to network congestion in AMoD scenarios include both demand patterns and operational requirements such as dead-heading and empty trips. Vehicle accumulation and production increase by 8.7–14.5% and 5.6–8.8%, respectively, following the introduction of the AMoD service. Additionally, the total magnitude of hysteresis loops grows by more than 24% in these scenarios. While the introduction of AMoD results in higher energy consumption (16.94–24.33% increase from the baseline), vehicle emissions in terms of NOx and PM are reduced by 4.3–5.7% and 5.6–8.2%, respectively. The travel delay of IVTT for vehicles increases up to 23% in the AMoD scenario with an increase in VKT.
91	Hörl, S., Becker, F., & Axhausen, K.W	2021	Zurich, Switzerland	4,000 AMoD vehicles lead to the maximum demand of around 150,000 requests per day Customers are willing to accept average waiting times of around 4 min at a price of 0.75 CHF/km
92	Ishibashi, Y., & Akiyama, E	2022	Tokyo, Japan	Approximately 14%–32% of the population would shift to SAVs, and those who traveled 2.0–8.0 km by rail or bicycle were likely to shift to SAVs. If the total number of SAVs is increased too much, it is possible that people who used to walk or bicycle, will shift to SAVs. It is important to limit the total number of SAVs to an appropriate amount from the perspectives of environmental impact and health impact.
93	Gurumurthy, K.M., & Kockelman, K.M	2022	Bloomington, IL	Results reveal that greater pickup and drop off location (PUDO) spacing or distances between stops and higher levels of SAVs use or trip demand increase average vehicle occupancy and decrease SAVs VMT (by up to 27%) compared to door-to-door SAVs fleet operations without DRS or PUDOs. At 0.25 mi PUDO spacings, travelers walked less than 5 min at either trip end.
94	Dean, M.D., Gurumurthy, K.M., de Souza, F., Auld, J., & Kockelman K.M	2022	Austin, TX	On average, wait times were 39% lower, and average daily trips served per SAEV increased up to 28% compared to SAEV repositioning with heuristic charging. Coupling repositioning with charging decreased the fleet's percent empty travel on average by 1.6%, relative to the scenario treating them as independent events. Sparser charging stations reduce investment costs.

#	Author	Year	Study area	Results
95	Wang, S., Correia, G.H., & Lin, H.X	2022	Hague, Netherlands	Forming platoons could save up to 9.6% of the system-wide energy consumption for the most efficient car model. Forming platoons reduces the travel times for travelers even if they experience delays while waiting for a platoon to be formed. Delays lead to longer travel times for the travelers with the platoon leaders, similar to what people experience while traveling in highly congested networks when platoon formation does not happen. The platoon delay increases as the volume of AMoD requests decreases; in the case of an AMoD system serving only 20% of the commuter trips (by private cars in the case-study city), the average platoon delays experienced by these trips increase by 25%.
96	Ben-Dor, G., Ogulenko, A., Klein, I., & Benenson, I	2022	Jerusalem, Israel	In case of zero congestion/parking price, two-thirds of users of SAVs are former PT users. In case of parking or congestion price, the PT/car split is half-half.
97	Stevens, M., Correia, G.H., Scheltes, A., & van Arem, B	2022	Rotterdam, the Netherlands	Relocation scenario: The required vehicle fleet to serve all the demand decreased by 6.45%, but led to an increase in total system driving distance of 28%. Dynamic ride pooling: No change compared to baseline scenario for required fleet. The average waiting time for a vehicle to arrive increased by 42%. Ride pooling & relocation: Compared to the base scenario, the ridepooling & relocation scenario can serve the same passenger demand requiring 10% fewer vehicles. Fast charging scenario: all the demand can be served in the fast-charging scenario using 6% less vehicle fleet compared to the base scenario. Fast chargers also led to lower investment costs, because 20% fewer chargers are required.
98	Nahmias-Biran, B., Dadashev, G., & Levi, Y	2022	Tel Aviv, Israel	While at the Base Case scenario MoD share was about 0.6% of total trips, with 30% reduction in fare the total share of AMoD services was about 1.8%, and it increases to 3.8% with 80% reduction in fare. Only with 80% reduction in fare did the AMoD services become slightly more attractive than Car, and AMoD-pool travel costs became lower than Motorcycle costs but still higher than Bus costs. In both single and shared AMoD services, the maximum number of trips obtained for trips between 10 and 20 km.

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