



Introducing shared, electric, autonomous vehicles (SAEVs) in sub-urban zones: Simulating the case of Vienna[☆]

Stefanie Peer^{a,*}, Johannes Müller^b, Asjad Naqvi^{c,d}, Markus Straub^b

^a Vienna University of Economics and Business (WU), Vienna, Austria

^b Austrian Institute of Technology (AIT), Vienna, Austria

^c International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria

^d Austrian Institute of Economic Research (WIFO), Vienna, Austria

ARTICLE INFO

Keywords:

MATSim
Traffic simulation
Shared autonomous electric vehicles
Demand-responsive transport (DRT)
First-mile/last-mile
Micro-transit
Sub-urban

ABSTRACT

Shared, autonomous electric vehicles (SAEVs) are expected to enter the market in the coming decades. Using MATSim, we simulate a use case where SAEVs are introduced in multiple suburban zones at the outskirts of Vienna (Austria), which are characterized by relatively low population density, but have access to at least one rail-based public transport stop. For all combinations of different fleet sizes and fare levels, we find that a relatively small share of car trips by residents of these zones (7%–14%) are replaced by SAEVs, generating CO₂ emissions reductions of 5%–11%. Moreover, 23%–35% of trips previously undertaken by foot or bicycle are replaced by SAEVs, as well as 10%–20% of public transport trips. The potential of SAEVs to reduce the use and ownership of private vehicles in suburban areas therefore seems to be rather limited, which is also reflected in our finding that one SAEV usually replaces only 2–4 private vehicles. The potential becomes somewhat larger when the usage and ownership of private cars is assumed to become more expensive, leading to 17%–20% of car trips being replaced by SAEVs and generating CO₂ emissions reductions of up to 32%.

1. Introduction

Shared autonomous electric vehicles (SAEVs) are expected to be gradually released to the market in the upcoming decades (Adler et al., 2019). SAEVs are likely to substantially lower the generalized cost of travel and hence constitute an attractive transport mode for travelers (Meyer et al., 2017). Moreover, due to SAEVs being electric and the possibility to share the vehicles and rides, they are also expected to be beneficial from an environmental point of view. Nevertheless, recent studies shed doubt on the notion that SAEVs are always welfare-enhancing, as they may lead to a strong increase in vehicle kilometers traveled, which in turn may go hand in hand with an increase in congestion (Taiebat et al., 2019), limited greenhouse gas emission reductions, and – if active modes are replaced by SAEVs – negative public health effects (Nunes and Hernandez, 2020).

This article investigates transport-related, environmental and socioeconomic impacts of SAEVs in case their operational area is constrained to specific zones in the outskirts of urban regions. These are zones characterized by relatively low population density, which typically renders the provision of area-wide conventional (scheduled, high-capacity)

public transport inefficient. Nevertheless, here we have defined these operational areas such that they contain at least one subway or railway station with good service. The core idea is that SAEVs complement the regular public transport system, in particular by covering the first and last mile. In our simulations, they operate as demand-responsive vehicles with a capacity of four persons without fixed routes. Our use case hence corresponds closely to the setup presented in Stark et al. (2019), where a feeder system of shared, automated vehicles covers the first and the last mile. According to Stark et al. (2019), the advantages of this model include affordability (especially when SAEVs are included in the (subsidized) public transport fare system), promotion of multi-modal trips (feeding into mass public transport), potential reduction of traffic, and enhanced accessibility in poorly connected areas.

Besides simulating various fare levels and fleet sizes, we investigate the role of imposing higher taxes on private car ownership and usage. This is done to obtain an indication to which extent the potential of SAEVs to replace private car trips can be enhanced, and what the resulting implications are in terms of travel times and CO₂ emissions.

[☆] We gratefully acknowledge financial support from the Austrian Climate Research Programme (ACRP) for the project “Simulating the environmental and socioeconomic effects of Shared Autonomous Electric Vehicles: The case of Vienna” (SimSAEV) under grant number KR17AC0K13731. We thank two anonymous reviewers for their helpful comments.

* Corresponding author.

E-mail address: stefanie.peer@wu.ac.at (S. Peer).

<https://doi.org/10.1016/j.tranpol.2023.12.002>

Received 7 April 2023; Received in revised form 4 December 2023; Accepted 7 December 2023

Available online 14 December 2023

0967-070X/© 2023 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

We utilize a large-scale multi-agent MATSim model (Axhausen et al., 2016) recently developed and calibrated for the city of Vienna (Müller et al., 2022). For accurately capturing multi-modal trips, a routing algorithm that goes beyond the standard MATSim model is implemented. We track the impacts of the simulated scenarios on standard mobility measures like travel time and distance as well as on CO₂ emissions. Emissions are captured at the trip, car, and the road link level. Moreover, socio-economic characteristics, which also informs the assumed time preferences, are used to identify which population groups are more or less likely to benefit from the introduction of SAEVs.

Our results show that the willingness to switch to SAEVs is quite limited for trips made by private car in the baseline scenario (without SAEVs). Instead, most of the switches take place for trips in which active transport modes (walking, biking) or public transport have been used in the baseline scenario (see Kaddoura et al. 2020b for a similar finding). Unsurprisingly, overall SAEVs are chosen more frequently in the low-price scenarios and with the larger fleet size. When adding the assumption that owning and/or using private cars becomes more expensive, a substantial increase in SAEV usage can be observed, resulting in sizable emission savings. But this outcome comes at the cost of substantially higher travel times.

The key policy implication of our experiments is that the introduction of SAEVs to complement traditional public transport in suburban areas is unlikely to convince a large number of car users to switch to SAEVs and give up their private car. This is because the daily travel time increases substantially for most car users. For this use case of SAEVs to be competitive, accompanying pull measures (e.g., expansion of the conventional public transport system) and push measures (e.g., restrictions on cars in the inner city, road tolls) seem necessary.

Methodologically, this paper is most closely related to other agent-based simulation studies of employing SAEVs as demand-responsive transport service outside large urban agglomerations (Viergutz and Schmidt, 2019; Leich and Bischoff, 2019; Kaddoura et al., 2020b; Cyganski et al., 2018; Militão and Tirachini, 2021), or as first- and last-mile service inside urban agglomerations (Shen et al., 2018). Unlike several of the related papers (e.g. Leich and Bischoff, 2019; Shen et al., 2018), we allow for all types of mode shifts. We consider it unrealistic that only those agents who use a car in the baseline scenario (where SAEVs are absent) are able to switch to SAEVs. Moreover, our paper adds to the literature on the distributional (socio-economic) impacts of SAEVs, which have so far not received much attention. An exception is Whitmore et al. (2022) who come to the conclusion that using automated vehicles for first and last mile services can improve transport equity outcomes compared to the case where conventional buses are operated. Finally, we also add to the literature on environmental effects of SAEVs, which has recently been reviewed by Shaheen and Bouzaghrane (2019).

The remaining paper is structured as follows. Section 3 introduces the MATSim model for the city of Vienna, outlines how SAEVs are operated in the model, and provides an overview of the different scenarios that are simulated. Section 4 discusses the results of the policy experiments. Section 5 concludes and provides recommendations for future research.

2. Literature

Most papers that study the introduction of SAEVs conclude that it leads to a significant increase in vehicle kilometers traveled (see for instance the review by Pernestål and Kristoffersson (2019) of 26 simulation studies), in particular if SAEVs are left unregulated. The primary reason is induced demand due to the availability of SAEVs as efficient, comfortable, inexpensive, and safe travel mode (e.g. Meyer et al., 2017; Loeb and Kockelman, 2019; Becker et al., 2020; Wadud et al., 2016; Fagnant, 2015; Taiebat et al., 2019), which additionally offers the advantage that travel time can be used productively (e.g. Molin et al., 2020). SAEVs are also likely to attract new user groups

who are currently limited to the role of car passengers (mostly, elderly, disabled, and young people). Additional kilometers driven might further be due to idle rides, which may take place for different purposes including the avoidance of parking charges (Millard-Ball, 2019; Zhang and Wang, 2020)¹, the relocation of vehicles according to expected demand patterns (Bischoff and Maciejewski, 2020; Guan et al., 2020), or charging (Weiss et al., 2017; Lin et al., 2019). An increase in vehicle kilometers traveled can increase road congestion significantly, potentially slowing down also other modes that share a common infrastructure with SAEVs (Nguyen-Phuoc et al., 2023). To which extent a possible increase in travel times may be dampened by ride-sharing (e.g. Moreno et al., 2018; Tirachini, 2020; Zhang et al., 2015) as well as more by a efficient use of road space by automated vehicles (e.g. Am-bühl et al., 2016), is still fairly disputed. Existing ride-hailing platforms like Uber and Lyft may, however, provide a first indication: they have led to an increase in congestion during peak periods (Tirachini and Gomez-Lobo, 2020; Fielbaum, 2020).

The main environmental benefits of SAEVs, compared to cars with combustion engine, are due to electrification, which leads to a reduction in local air pollution (Rafael et al., 2020)², noise, and greenhouse gases. Other factors that play a role in determining the environmental footprint of SAEVs are less certain and often context-dependent (see the review article by Shaheen and Bouzaghrane (2019)). One important aspect concerns the mode choice behavior of travelers when SAEVs are introduced: the switch from a car with combustion engine to an SAEV has clear environmental benefits; in contrast, a switch from public transport, walking and cycling to SAEVs tends to have negative environmental consequences, while also being detrimental for the efficient use of public space and public health (e.g. Kaddoura et al., 2020b; Liu et al., 2017; Nunes and Hernandez, 2020). The effects of automation *per se* on energy use (and in turn on greenhouse gas emissions) are still uncertain, with some analyses projecting a reduced and others an increased impact (Wadud et al., 2016; Larson and Zhao, 2020; Taiebat et al., 2019; Kopelias et al., 2020). Induced demand for travel due to being able to use in-vehicle time more productively (Malokin et al., 2019) as well as the direct energy consumption related to the automation (for sensors etc.) (Gawron et al., 2018) are important determinants of the overall effect. For automated first-/last-mile services (similar to the services analyzed in this paper), Grahn et al. (2023) emphasize the importance of the driving range and capacity of the SAEVs in determining the potential of reducing energy consumption.

Various policy options exist that are likely to improve the welfare impacts of an SAEV introduction. For city centers where private fleet providers are likely to enter the market (if granted access), road tolls that are designed such that they lead to an internalization of external costs (including costs associated with time losses imposed on others, local and greenhouse gas emissions, and noise) have been advocated (Kaddoura et al., 2020a), and will become easier to implement for automated vehicles (Adler et al., 2019). In less densely populated areas, subsidies are likely to be required to render SAEVs an attractive alternative to using a private vehicle (Nunes and Hernandez, 2020). This implies a relevant use case where SAEVs are part of, or a complement to the public transport system. While most papers consider SAEVs to be in private fleet ownership, there are some studies that have investigated

¹ The main currently available steering instruments with respect to road transport will become widely obsolete with the introduction of SAEVs: parking charges will induce automated vehicles to keep cruising or park elsewhere, and taxes on fuel do not apply to electric vehicles (Adler et al., 2019).

² The reduction in local pollution due to electrification can be substantial. But it should not be neglected that up to 50% of external air pollution from vehicle use are from sources other than fuel combustion, such as PM_{2.5} and PM₁₀ particulate matter that originate from tires and brakes (Grigoratos and Martini, 2015).

cases in which SAEVs were integrated in the public transport system.³ For instance, [Kassens-Noor et al. \(2020\)](#) and [Chee et al. \(2020\)](#) study how automated public transport services are perceived by potential users, and what drives their intention to use them in the context of the USA (Michigan) and Europe (Stockholm), respectively. Unsurprisingly, comfort and service frequency are identified as crucial factors, while a perceived lack of safety acts as a barrier. [Stark et al. \(2019\)](#) discusses different use cases of automated vehicles (AVs) in relation to public transport, based on a stakeholder process conducted in Germany. They identify three main use cases: (a) traditional bus model with automated buses, (b) feeder system to cover first and last mile, (c) individualized on-demand mobility.

While most studies on SAEVs focus on urban areas ([Lin et al., 2019](#); [Pernestål and Kristoffersson, 2019](#); [Guan et al., 2020](#)), those studies that model SAEVs (or shared autonomous vehicles (SAVs))⁴ as being part of the public transport system have mostly focused on the complementary role of SAEVs in rural and sub-urban areas as well as small and mid-sized towns where mass public transport cannot be provided efficiently, and where, due to a lack of profitability, private fleet operators would not provide their services. Moreover, the alternative to allow SAEVs to operate in inner, densely populated city centers may largely be detrimental to welfare, as SAEVs add to congestion (e.g. [Kaddoura et al., 2020a](#)). Among the papers that study SAEVs outside urban areas are [Viergutz and Schmidt \(2019\)](#) who simulate the operation of a demand-responsive system of SAVs in the rural town of Colditz (Germany), [Leich and Bischoff \(2019\)](#) who focus on implementing AV-based public transport in suburban areas of Berlin, and [Cyganski et al. \(2018\)](#) and [Wang et al. \(2018\)](#) who study the use of SAVs in the mid-sized towns of Brunswick (Germany) and Sioux Falls (US), respectively.

Different designs of using SAEVs (or SAVs) as part of the public transport system have been studied. [Kaddoura et al. \(2020b\)](#) simulate on-demand SAVs that are added to existing modes of transportation. They compare a setting where the service area contains only the inner-city area of Berlin and one where it contains the entire city. They find that for small service areas and low prices, undesirable mode switches away from cycling and walking towards the newly introduced mode are common. Larger service areas make switches away from cars more attractive. Again for the case of Berlin, [Leich and Bischoff \(2019\)](#) simulate the replacement of conventional bus lines in suburban areas of Berlin by on-demand SAVs. They find an increase in operating costs and only a slight decrease in travel time. Using a similar setup, [Shen et al. \(2018\)](#) and [Ongel et al. \(2019\)](#) find more promising results for Singapore: they find that replacing low-demand bus routes by on-demand SAVs leads to improvements in service quality and cost efficiency ([Shen et al., 2018](#)), and that using automated vehicles for scheduled and on-demand vehicles leads to substantial cost savings ([Ongel et al., 2019](#)). Also for the case of Singapore [Nguyen-Phuoc et al. \(2023\)](#) find that, unless all private cars are removed, introducing automated mobility on-demand reduces the demand for traditional public transport and increases road congestion.

Multiple studies compare a fully flexible, demand-responsive fleet of SAVs with a less flexible system. [Viergutz and Schmidt \(2019\)](#) come to the conclusion that in rural areas too much flexibility may be too costly or suffer from poor service quality (such as long wait times). Similarly, [Chen and Nie \(2017\)](#) find that running e-hailing vehicles along a fixed-route transit line and with a stable headway outperforms a more flexible, on-demand, zone-based system. In contrast, [Whitmore](#)

[et al. \(2022\)](#) come to the conclusion that first and last mile services by autonomous vehicles or shuttles are more cost-efficient than conventional buses, while also leading to improvements in public transport coverage and transport equity.

Finally, [Militão and Tirachini \(2021\)](#) investigate the highly relevant question whether demand-responsive transport systems can achieve economies of scale. For the city of Munich (Germany), they find that even for automated systems this is only the case if certain trips can be rejected. It seems safe to assume that the possibility of achieving economies of scale is even more limited in peripheral areas.

3. Simulation setup and scenarios

3.1. Overview

Our model is based on the MATSim software, which is an agent-based simulation framework in which agents perform a given sequence of activities at fixed locations over a day. The model is set up for the city of Vienna and its surroundings in a radius of approximately 30 kilometers from the city center. The simulated area covers approximately 4,100 square kilometers and contains a population of around 2.3 million including 1.7 million inhabitants who reside in Vienna. The road network data (comprising 156,000 links) is taken from OpenStreetMap (OSM). Data on potential activity locations (facilities) – categorized into home, work, education, shopping, leisure, and errands – are based on land use categories and points of interest, both derived from OSM, as well as open data on population density ([Eurostat, 2019](#)) and employment density ([Wirtschaftskammer Österreichs, 2019](#)).⁵ [Fig. 3.1](#) shows a map of the simulated zone and the location patterns of the facilities.

3.2. Population and plan generation

MATSim requires the definition of agents. We simulate 12.5% of the population living in the area taken into account in our simulations (see [Fig. 3.1](#)). A simulation of the full population would not be feasible for computational reasons. The socio-economic characteristics of the agents have been assigned such that they are in line with the most recent national travel survey undertaken in Austria (*Österreich Unterwegs* ([Tomschy et al., 2016](#))). Note that one of these assigned characteristics is the extent to which each agents can access a car.⁶ Moreover, an initial set of daily schedules (or so-called “plans”) have been defined for each agent. These were created by cleaning, geo-constraining, and re-sampling data from “Österreich unterwegs 2013/2014” for the simulated region. As the mobility survey contains activity location information only at the municipal level, an algorithm is applied to assign realistic geo-coordinates for the agents’ home locations and the destinations visited on the simulated day. This optimization algorithm relies on the reported travel times and trip distances from the survey data. From this, we obtain geo-coded locations for each agent’s sequence of activities (for details see [Müller et al. 2022](#)).

The baseline scenario (without SAEVs) is calibrated to the travel diaries contained in the *Österreich Unterwegs 2013–2014* survey and traffic count stations. More details on the calibration can again be found in [Müller et al. \(2022\)](#).

³ In some instances (such as in Berlin, Bern and Vienna) autonomous buses have already been added to the public transport system. So far, however, they mostly operate at low speeds and under direct human supervision.

⁴ Most related studies do not discuss the environmental implications and for that reason also do not differentiate whether shared autonomous vehicles run on fuel or electricity.

⁵ To account for heterogeneity in the capacity of facilities, the number of facilities at a specific location is defined to equal to the capacity of a facility. For instance, in the case of an employer with 1000 employees, 1000 facilities are generated at the same location.

⁶ Note that having access to a car is defined as a time-invariant variable at the agent level (but does not necessarily imply that the agent owns the car; car ownership is captured in a separate variable in the *Österreich Unterwegs* survey but is not used here).



Fig. 3.1. MATSim simulation area. Note: Facilities are marked as colored dots. Background map: ©OpenStreetMap.

3.3. Mode choice, routing, and calibration

Overall, we account for five transport modes — walking, bicycle, car, public transport (PT), and SAEVs (see also Müller et al. (2021) for a more extensive description of the model setup). Two modes, cars and SAEVs, are simulated on the MATSim road network. The trips of the other modes (walk, bicycle, and PT) are not simulated on the network. Instead the agent is teleported with the assumed travel times provided by the router, which in turn takes into account timetables, topography, and average walking/cycling speeds. The SAEVs are enabled using the Demand-Responsive Transport (*drt*) module of MATSim (Maciejewski and Nagel, 2013). The module interacts with MATSim's dynamic vehicle routing problem (*dvrp*) module which enables dynamic changes of agents' plans within one iteration of the simulation. The difference to the other four conventional modes is that SAEVs require dynamic manipulation of an agent's travel plan (such as sending requests for a vehicle, routing of the SAEVs and matching a ride with other agents) (Maciejewski et al., 2017). The *drt* module enables ride-sharing in SAEVs (the extent of sharing is determined by the algorithm inherent to the *drt* module rather than being decided upon by agents) and automatic re-location of vehicles according to the demand patterns of the agents. Furthermore, we assume for SAEVs a boarding and alighting time of one minute and a maximum waiting time of 10 min. Requests of agents that cannot be served within this time constraint will be rejected and scored poorly. The parameter `maxTravelTimeAlpha` has been assigned a value of 1.3, while `maxTravelTimeBeta` is set to 400. These parameters define the upper limit for an agent's travel time, which is defined as $\text{maxTravelTimeAlpha} \times \text{estimated travel time} + \text{maxTravelTimeBeta}$. Requests resulting in a travel time exceeding this calculated value will be rejected. The typical duration of an SAEV trip is set to 20 min, which corresponds to realistic trip durations in larger zones.

MATSim runs several iterations in which agents may choose a different plan (plans with a higher score have a higher likelihood of being chosen), which may involve re-routing of the car or public transport route, or a change in the transport mode. The iterations last

until an equilibrium of the total scores is reached (which in our case happened after roughly 250 iterations). Plan innovations are turned off after 80% of the iterations so that poorly scored plans are unlikely to be included in the final result. As a result, only a very small number of agents (≤ 3 agents/scenario) are not picked up by an SAEV due to the maximum waiting time of 10 min being exceeded.

Between the iterations of the simulation, plausible inter-modal plans for the entire day are calculated for each agent and cached. The availability of transport modes and the location of personal vehicles is thereby taken into account. For instance, personal vehicles must be brought back home at the end of the day and can only be used at the location where the agent used it last. The plans of the agents are fed into an inter-modal routing algorithm to generate the transport mode and route for each trip. The inter-modal routing algorithm is not part of MATSim, but instead we make use of the inter-modal routing algorithm Ariadne (Prandtstetter et al., 2013). Inter-modal trips are an essential feature of our simulation, since it allows agents to use SAEVs in combination with public transport. If the routing algorithm yields a car or SAEV choice, the corresponding information including location and time, is added to the MATSim simulation. The coherent integration of routing and mode choice outside of MATSim significantly increases the performance and reduces computational time, as also explored by Hörl et al. (2019).

3.4. Utility functions

MATSim works with a scoring function to evaluate the success of an agent's travel diary at the end of the day. The basic logic behind this utility function is to consider the time spent on activities other than travel positively, while travel time is penalized. The parameters for the mode-specific travel time penalties reflect what is usually referred to as value of travel time (savings), often abbreviated by VOT or VTTS, respectively. In our case, these are derived from stated and revealed preference data collected from a representative diary-based survey of Austrian workers (Hössinger et al., 2020; Jokubauskaite et al., 2019; Schmid et al., 2019), where an essential finding was that public

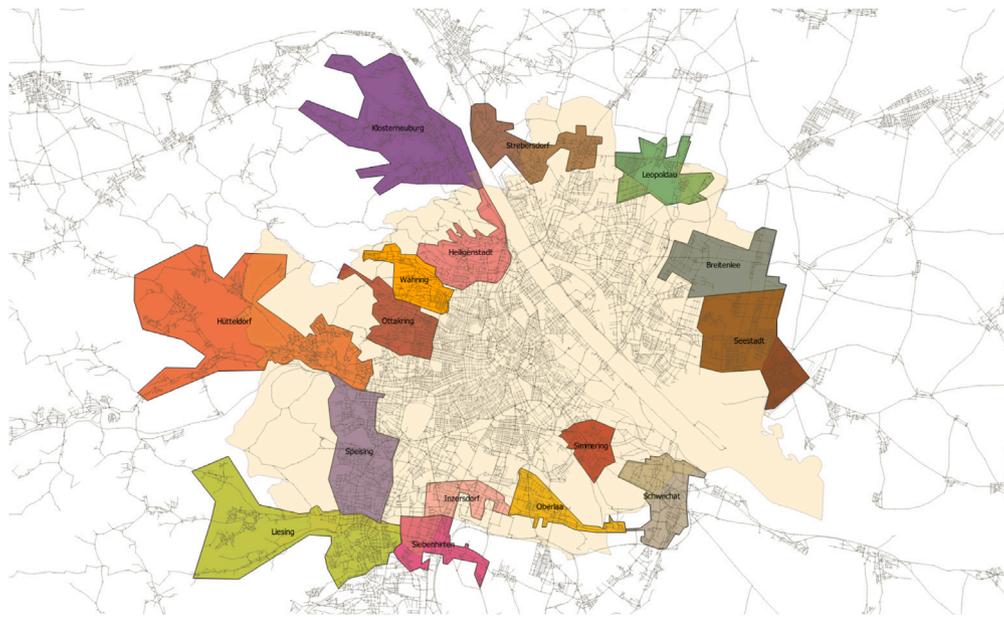


Fig. 3.2. Simulation zones with separate SAEV fleets in the outskirts of Vienna.

transport travel times are valued lower (hence, cause less dis-utility per hour of travel) than car travel times.⁷ We estimate a reduced version of the mixed logit model presented in Schmid et al. (2019), namely a latent class discrete choice model with two classes, where class membership (i.e. the relative weight each class of coefficients has for a specific individual) is determined by various socio-economic variables. The resulting time valuations amount to 11.1–14.1 Euro/hour for walking, 9.4–19.6 Euro/hour for cycling, 5.3–6.9 Euro/hour for public transport, and 12.2–13 Euro/hour for car travel. These estimates (and their dependency on socio-economic characteristics) are then used to define ten sub-population groups, which differ in terms of their travel time penalties (see Müller et al. (2022) for a more detailed explanation), hence capturing heterogeneity in the valuation of travel times. For SAEVs, we assume that in-vehicle time is valued at 75% of the corresponding value attached to time spent driving a car, hence reflecting that travel time in SAEVs can be used more productively as travelers are released from the driving task and can focus on other activities (Fosgerau, 2019; Ho et al., 2015).

For SAEVs, we assume that in-vehicle time is valued at 75% of the corresponding value attached to time spent driving a car, hence reflecting that travel time in SAEVs can be used more productively as travelers are released from the driving task and can focus on other activities (Fosgerau, 2019; Ho et al., 2015).

3.5. Zoning

The scenarios discussed in this paper are based on the assumption that SAEVs are only allowed to operate within restricted areas at the outskirts of Vienna. These areas usually do not have a dense public transport network which is why car ownership and car usage are substantially higher than in the city center. SAEVs can help to solve the first and last mile problem by improving connectivity to prioritized (usually rail-based) public transport. For the simulations, we define 16 zones in the outskirts of Vienna consisting of low-density residential areas with low-frequency public transport (busses), but also access to

⁷ A potential explanation brought forward by the authors of the cited studies is that smartphones and other mobile devices have rendered public transport travel times more enjoyable and productive compared to car travel times.

at least one subway or railway station with good service (more than one connection every 20 min during rush hour). While the Viennese public transport system is generally of very high quality, it thins out significantly as the distance from the city center increases.

The exact selection of the zones can be seen in Fig. 3.2. Each area contains between 2000 to 11,000 facilities, and the SAEV fleet size in the corresponding area is proportional to that number.⁸ Each SAEV is assigned to one zone and only picks up and drops off passengers within that zone. In order to ensure that the SAEVs are used strictly as a last mile service, and not for routes from one zone to another, each zone has its own zone-specific SAEV fleet.

3.6. CO₂ emissions

In our simulation model, private cars are the only transport mode that causes CO₂ emissions (we ignore emissions accruing for energy generation and vehicle production processes). Since MATSim simulates the traffic at the car level, emissions can be estimated very accurately and assigned to locations in the road network as well as to the trips of specific agents.

The emissions for each car that is present in the simulation are calculated after the last iteration using the Emissions Module (“ev”) for MATSim, developed by Hülsmann et al. (2011) and further extended by Kickhöfer et al. (2013). The parameter values assumed in the emissions calculations are based on average values from the Handbook Emission Factors for Road Transport version 4.1 (HBEFA 4.1: Notter et al. 2019). MATSim distinguishes between warm emissions and cold emissions. While warm emissions are emitted during the whole trip and are independent of the engine’s temperature, cold emissions occur during the warm-up phase of the engine. For the computation of the warm emissions, MATSim uses driving speed, stop duration, and vehicle characteristics; for the computation of the cold emissions it uses driving speed, distance traveled, parking time and vehicle characteristics (André and Rapone, 2009; Weilenmann et al., 2009). Other factors such as air conditioning and different road gradients are ignored. A detailed description of the calculation of emissions in the context of MATSim can be found in Kickhöfer (2014) and Axhausen et al. (2016).

⁸ In the MATSim framework, zones are implemented as a *shape-area-based* operational scheme (Maciejewski and Nagel, 2013).

Finally, note that we unfortunately are not able to model the charging behavior of electric vehicles (the SAEVs), as MATSim's extension for electric vehicles (Waraich et al., 2013) is not compatible with the use of multiple SAEV fleets (which in turn enables us to define distinct SAEV zones).

3.7. Scenarios

A baseline simulation without SAEVs is used as a benchmark to compare changes across key variables. It reflects the status-quo in the larger Vienna region in terms of its population (and characteristics thereof), existing infrastructure and vehicle ownership characteristics, and hence does not account for demographic or technological changes (e.g. more people switching to privately owned electric vehicles) that might occur over time. In addition to the baseline simulation without SAEVs, we conduct the following nine experiments:

- 12 SAEVs per 1000 facilities at 00 cents per minute
- 12 SAEVs per 1000 facilities at 10 cents per minute
- 12 SAEVs per 1000 facilities at 30 cents per minute
- 25 SAEVs per 1000 facilities at 00 cents per minute
- 25 SAEVs per 1000 facilities at 10 cents per minute
- 25 SAEVs per 1000 facilities at 30 cents per minute
- 25 SAEVs per 1000 facilities at 00 cents per minute and 100% increase in fuel costs
- 25 SAEVs per 1000 facilities at 00 cents per minute and 25% increase in the costs of owning a car
- 25 SAEVs per 1000 facilities at 00 cents per minute with a 100% increase in fuel costs and a 25% increase in the costs of owning a car

Hence, in all experiments the supply of SAEVs is fixed to either 12 or 25 vehicles per 1000 facilities located inside the zones. In total, these sum up to 1,118 and 2,338 SAEVs respectively, representing medium to large fleet size scenarios. For comparison, there are 4800 taxis in the entire city of Vienna (Kluge et al., 2020), which would correspond to 600 in our simulation (as only 12.5% of the population is simulated).

In the simulations, SAEVs are introduced at three price levels: 0 cents, 10 cents, and 30 cents per minute. The lower fares, especially the 0 cent price, reflect a strongly subsidized fare, as common with most public transport systems (including the Viennese one).⁹ The highest price corresponds closely to what studies predict to be the fare level charged by private SAEV fleet operators (Bösch et al., 2018; Compostella et al., 2020). Also note that the fares are always calculated based on direct routes; agents are hence not charged for possible detours in the case of ride-pooling.¹⁰

The last three experiments are defined such that SAEV usage is relatively attractive, hereby providing an upper bound for the usage rates of SAEVs in suburban zones at the outskirts of Vienna. They hence assume the larger fleet size (25 SAEVs per 1000 facilities) and a fee of zero. Additionally, they assume that usage and/or ownership of private cars becomes more expensive (not just for agents residing inside the SAEV zones, but all car drivers in the Greater Vienna Area). Higher usage costs are represented by fuel costs doubling from 9.1 ct/km to 18.2 ct/km. Higher ownership costs are reflected by a 25% increase in the costs associated with owning a car (incl. insurance, depreciation

⁹ According to the website of the local public transport provider (Wiener Linien, 2023), 1.17 million individuals (out of 2.3 million living in the Greater Vienna region, which is simulated here) have a public transport subscription card and hence face 0 marginal costs when using public transport. Given the rather low prices of subscription cards (an annual ticket for the entire network amounts to 365 Euro) and a price for a single trip of 2.40 Euro, most persons who regularly use public transport will be inclined to buy a subscription card.

¹⁰ <https://www.matsim.org/apidocs/av/12.0/org/matsim/contrib/av/robotaxi/fares/drt/package-summary.html>

etc.) from 13.5 Euro/day to 16.9 Euro/day. Car ownership costs only accrue if an agent uses the car on the day of simulation.

For comparisons across the different scenarios, we can make use of the fact that within the MATSim framework, the same trip, defined by a specific origin and destination, exists across all simulations and can thus be assigned a unique identifier. This allows us to track and compare changes in key statistics like travel times, distances, modal split, and emissions across the simulations. Data is also recorded on the road network, which provides an additional set of variables to measure speeds, congestion levels, and emissions.

4. Results

This section provides an overview of the results obtained from the simulations.

4.1. Who is switching to SAEVs?

Table 4.1 shows the modal split in the baseline scenario (for all agents residing inside the SAEV operating zones), as well as the (mode-specific) share of trips that switch to SAEVs for each of the other scenarios. For multi-modal trips we assign a main mode using the following ranking: SAEVs > PT > Car > Bicycle > Walk. The main mode for a specific trip is then always defined as the mode that ranks highest, irrespective of the travel time or the distance traveled by different modes within a trip. This methodology is consistent with the “Österreich Unterwegs 2013–2014” report (Tomschy et al., 2016), based on which the agent population has been defined.

The statistics concerning the baseline scenario show that the modal split of public transport is substantial (47%), which can be attributed to the relatively good public transport connectivity in the SAEV operating areas (by definition). Active modes account for 23% of trips, while the car accounts for 30%.

Table 4.1 shows, as expected, that switches to SAEVs are more common at lower prices and larger fleet sizes. Among the trips that involve SAEV usage, around 1/4 to 1/3 of trips combine SAEV and public transport usage; the majority of SAEV trips, in contrast, are uni-modal. Moreover, we can observe that around 10%–20% of trips that were undertaken by traditional public transport in the baseline scenario, are undertaken by SAEVs (or at least partially by SAEVs) in the scenarios where SAEVs have been introduced. Such switches may impose negative external costs on society, for instance when the resulting lower public transport ridership numbers lead to a down-scaling of the public transport system (for financial reasons), hence decreasing its attractiveness.

Similarly, we also find that SAEVs are often adopted for trips that have been conducted with active modes (walking and biking) in the baseline scenario. Also these switches tend to be undesirable from a societal perspective from several perspectives: active transport modes have no emissions, are beneficial from a health perspective, and very space-efficient.

Those mode switches that tend to be most desirable from a societal point of view are those where private car trips are replaced by SAEVs. We find that these switches take place to a fairly limited extent in the first six scenarios (7%–14% of car trips are replaced; as expected, the percentage is lowest for the scenario with the low fleet size and the high price). This share increases substantially in those scenarios where private car usage and/or ownership becomes more expensive. In these scenarios, 17%–20% of private car trips are replaced with SAEV rides.

In the Appendix, we also provide graphical information (Figs. A.1) on how the modal split evolves in the different SAEV zones (see Fig. 3.1), when comparing the baseline modal split to the modal split of the scenario with the smaller fleet size and a fare of 30 cents per minute. We find some variation in the modal split of SAEVs, with a noticeably higher SAEV share occurring in the larger areas of Klosterneuburg, Liesing, Hütteldorf, and Heiligenstadt (these results are qualitatively similar for other SAEV scenarios that we analyzed).

Table 4.1
SAEVs as main mode (all agents residing inside the SAEV zones).

	Baseline						Increase in cars costs			
	(%)	12 SAEVs			25 SAEVs			25 SAEVs 0 cents		
		0 cents	10 cents	30 cents	0 cent	10 cents	30 cents	100% gas	25% cost	Both
SAEV main mode (%)	18.56	16.06	11.72	21.23	17.84	12.54	22.56	22.71	24.04	
SAEV main mode & PT use (%)	6.04	4.32	2.40	6.69	4.82	2.61	7.60	7.60	8.44	
Switch from PT	47.39	18.25	14.27	9.55	20.28	15.62	10.29	20.43	20.52	
Switch from Car	29.62	11.61	10.02	7.04	13.81	11.59	7.58	16.62	16.84	
Switch from Walk + Bike	22.99	30.85	28.91	22.77	35.24	31.65	24.19	35.73	36.06	

Note: In the last three lines of the table, the first results column represents the modal split in the baseline scenario (without SAEVs). The remaining columns show the percentage shares of agents switching to SAEVs (including trips that combine SAEVs with other modes in the second row of the table).

Table 4.2
Characteristics of SAEV users.

	Baseline						Increase in cars costs			
		12 SAEVs			25 SAEVs			25 SAEVs 0 cents		
		0 cents	10 cents	30 cents	0 cent	10 cents	30 cents	100% gas	25% cost	Both
Males (%)	49.47	46.84	46.05	44.22	46.14	45.56	44.40	46.65	46.62	47.00
Average age	41.81	42.12	41.68	40.97	41.37	40.97	40.67	41.58	41.62	41.79
Urban (%)	81.46	75.33	73.29	69.73	73.29	71.30	68.95	73.31	73.36	73.40
Single (%)	21.28	19.86	19.38	18.53	19.51	19.39	18.81	19.55	19.77	19.76
Has kids (%)	37.30	38.34	39.53	41.65	39.51	40.75	41.95	39.19	39.22	39.06
Educated (%)	32.17	28.68	27.59	25.44	28.16	26.61	25.10	28.79	29.03	29.81
High income (%)	42.24	42.86	43.05	43.48	43.40	43.30	43.21	43.48	43.17	43.46
Has a Car (%)	61.35	53.03	51.30	47.99	51.79	49.98	47.36	53.63	53.81	55.49

Note: The first results column shows the baseline population shares. The remaining columns show the characteristics of shares of agents that switch to SAEVs.

4.2. Socio-economic impacts

Table 4.2 provides an overview of the socio-economic characteristics of SAEV users, and how they compare to the average characteristics of the agents residing in the zones (first column).

Overall, the characteristics of SAEV users differ only to a limited extent from the average characteristics of the population of agents residing in the SAEV zones. The table shows that agents who make use of SAEVs are somewhat less likely to be male and single, and more likely to have children than the population average. SAEV users also tend to be slightly less educated but somewhat richer than the average. They are also relatively less likely to be resident of an area with a fairly high urbanity level as well as less likely to have a car. SAEVs therefore seem to over-proportionally benefit those who live in peripheral locations without car access, which makes sense, as this is a population segment with currently rather limited mobility options.

4.3. SAEV trips

Table 4.3 provides statistics on the SAEV trips for the different scenarios. The first row shows the total (exogenously determined) number of SAEVs in each scenario and the next row shows the total distance traveled. At lower prices, the average distance that an SAEV travels increases since the lower prices induce a higher demand for SAEVs. The total distance traveled by SAEVs goes up further when private car use/ownership is priced more heavily.

Since SAEVs can be shared by up to four passengers, the *Ride sharing* section in Table 4.3 shows what percentage of the total distance traveled is either empty, single rides, or shared. The share of empty kilometers increases at higher prices and smaller fleets sizes (and hence in those scenarios with less overall demand), ranging from 27 to 34% of the total distance traveled by SAEVs. Similarly, the number of passengers per km driven by SAEVs is lowest (0.29–0.31) for the three scenarios with the smaller fleet size, but similar for all remaining SAEV scenarios (0.33–0.34). Single occupancy rides account for 45%–52% of

the total SAEV distance and their share goes up at higher prices. At lower prices, we can observe relatively more sharing among the agents, likely due to the higher demand. Overall, ride-sharing is rather rare, which is not surprising as ride-sharing was not incentivized financially (even when sharing a vehicle, all passengers needed to pay the full fare).

As to be expected, the number of SAEV rides is substantially higher at lower prices and at the larger fleet size. For instance, if the price goes up from 0 cents to 30 cents, the number of SAEV rides decreases by about one third. Similarly, holding prices constant at 0 (10) cents, while doubling the fleet size from 1118 to 2338 vehicles results in a 8.8% (6.5%) increase in SAEV rides.

These demand patterns for SAEVs are also reflected in the average wait times for hailed SAEV rides. Across the scenarios, the average wait time does not vary much and generally amounts to only 2.5 to 3 min (the low waiting times are a consequence of the relatively large fleet sizes and the maximum waiting time being limited to 10 min). It slightly decreases as the fleet size goes up, which is plausible, as more cars will better cater to the demand. Similarly, at higher prices, the average wait time for SAEVs declines as a result of lower SAEV demand (which increases the availability of idle SAEVs).

Those scenarios in which the costs of private car usage and/or ownership are increased assume the larger fleet size and a usage fee of zero. As a consequence, it is not surprising that the demand patterns associated with these scenarios are fairly similar to the scenario with the larger fleet and a fee of zero where no changes in the costs related to private cars have been assumed. This is particularly true in terms of the extent to which SAEVs drive around idle and are being shared by multiple agents, respectively. Also the average wait time and travel time are similar to that reference scenario. Differences can be observed with respect to overall distance driven and the number of SAEV trips: both indicators exhibit a 7%–14% increase relative to the larger fleet size and no-fee scenario in which private car costs are unaffected, reflecting the larger demand due to higher costs associated with using

Table 4.3
Characteristics and consequences of SAEV demand.

	12 SAEVs			25 SAEVs			Increase in cars costs		
	0 cents	10 cents	30 cents	0 cent	10 cents	30 cents	25 SAEVs 0 cents		
							100% gas	25% cost	Both
SAEVs									
Total SAEVs (count)	1,118	1,118	1,118	2,338	2,338	2,338	2,338	2,338	2,338
Total distance (km)	139,773	126,309	99,434	142,328	124,802	93,128	152,594	152,913	161,950
Nr. of passengers (count)	43,943	38,658	29,027	47,790	41,174	30,549	51,070	51,040	54,369
Avg distance/SAEV (km)	125.02	112.98	88.94	60.90	53.38	39.83	65.27	61.13	68.27
Passengers/km	0.31	0.30	0.29	0.34	0.33	0.33	0.33	0.33	0.34
Total empty distance (km)	43,692	40,676	33,915	38,762	34,269	24,936	41,066	41,631	43,316
Ride sharing									
0 passengers (%)	31.26	32.20	34.11	27.23	27.46	26.78	26.91	27.23	26.75
1 passenger (%)	45.24	46.00	47.05	46.34	48.40	51.97	46.19	46.24	45.71
2 passengers (%)	17.51	16.89	14.92	19.55	18.37	16.56	19.61	19.49	20.05
3 passengers (%)	4.37	3.80	2.89	5.10	4.37	3.56	5.32	5.18	5.34
4 passengers (%)	1.62	1.10	1.02	1.78	1.41	1.14	1.97	1.86	2.15
Customers									
Average wait time (mm:ss)	03:05	02:58	02:49	02:43	02:41	02:31	02:44	02:43	02:44
Average travel time (mm:ss)	09:50	09:31	08:56	09:36	09:17	08:40	09:38	09:35	09:38
CO₂ Emissions									
Change inside SAEV zones (%)	-9.94	-8.47	-6.43	-10.94	-9.96	-7.33	-20.99	-20.22	-30.34
Change outside SAEV zones (%)	-3.78	-3.20	-2.60	-3.75	-3.62	-3.02	-16.05	-13.31	-25.92
Number of private cars (SAEV zones)									
Difference (Δ) to baseline (17167 cars)	-4638	-4276	-3758	-4854	-4574	-3865	-6362	-6682	-8138
Δ /nr. of SAEVs	4.15	3.82	3.36	2.08	1.96	1.65	2.72	2.86	3.48

and/or owning private vehicles. Similarly, a fairly pronounced difference can be observed with respect to the CO₂ emissions, where the decline relative to the baseline is 10–20 percentage points higher than for the higher fleet and no-fee scenario without changes in the costs for private car usage and/or ownership.

Table 4.3 also provides information on the change in CO₂ emissions for roads inside the zones compared to the baseline scenario. For the first six scenarios, the drop in emissions is between 6 and 11% in the zones. The higher bound occurs for those scenarios where more car trips are replaced by SAEV trips (i.e. those with low prices and the higher fleet size). This result is a direct consequence of our assumption that cars are the only source of direct CO₂ emissions. The table also shows changes in CO₂ emissions produced along the road network outside the SAEV zones. These amount to reductions in the range of -3 to -4% for the first six scenarios (where the costs associated with the usage and ownership of private cars are unchanged). This spillover effect is mostly due to agents switching from cars to other modes (among them, SAEVs) when traveling to and from destinations outside the SAEV-zones.¹¹ For the three scenarios in which private car ownership and/or usage is assumed to become more expensive, the decline in CO₂ emissions outside the zones is much stronger than in the first six scenarios, namely between 13 and 26%. This decline can, however, not be exclusively attributed to spillover effects, but is mainly due to car usage and/or ownership becoming more expensive for all agents that own a car, not only those that reside inside the SAEV zones.

Finally, Table 4.3 shows how the number of private cars used during the simulated day by agents living inside the SAEV zones is affected by the introduction of the SAEVs. For cars that are not used during that day, no car ownership fees are charged, hence indicating that the number of cars used is here a direct proxy for the cars owned by agents. We see that the number of cars used goes down considerably compared to the 17167 cars used in the baseline. This is particularly the case in the last three scenarios, where the higher car usage and/or ownership costs discourage car usage and ownership (the last scenario

is associated with a 50% decline in cars being used). Finally, we can also relate these reductions to the number of SAEVs introduced in each of the scenarios. This provides us with an indication of how many private cars can be replaced by an SAEV. The last row in Table 4.3 shows that this ratio is between 1.65 and 4.15, which is lower than what is usually found in studies that investigate the introduction of SAEVs in more urban areas (e.g. Chen et al., 2016).

4.4. Impact of SAEVs

For all agents who reside in the SAEV zones and all scenarios, Table 4.4 shows descriptive statistics for the following four key indicators: travel time, distance traveled, and CO₂ emissions.

For the first six scenarios, where the costs associated with private cars are unchanged, the introduction of SAEVs leads to relatively small shifts in these indicators. The average daily travel time of the agents residing in the SAEV zones decreases by two to three minutes (2.5%–4%). Average distances increase only very slightly compared to the baseline (at most by 0.63 km in the scenario with the larger fleet size and 0 price). These small changes are a direct consequence of the agents' activity location choices remaining identical across scenarios. The largest change can be observed for CO₂ emissions, which decline by 5%–11% when SAEVs are introduced. The reduction in emissions, as expected, is higher for the lower price scenarios and for the larger fleet size scenarios, as more agents switch to SAEVs under these conditions.

The last three columns of Table 4.4 show the results of the three scenarios, in which SAEVs are introduced with a fee of zero and the larger fleet size, and at the same time also private car usage and/or ownership become more expensive. Unlike for the first 6 scenarios (where the average daily travel time is somewhat shorter than in the baseline scenario), the average daily travel time in these three scenarios is above (by at most 2 min) or equal to the average travel time in the baseline scenario. This is because (in the wake of higher costs associated with private car usage/ownership) agents switch from their private car to SAEVs, which goes hand in hand with travel time increases. The average distance traveled remains almost the same as in the baseline (just as in the first six scenarios). The CO₂ emissions decline substantially as more private car owners switch to SAEVs than

¹¹ We find no evidence that the presence of SAEVs affects travel times outside the zones.

Table 4.4
Mobility-related statistics for all agents residing in zones (aggregated over the simulated day).

Averages	Baseline	Increase in cars costs								
		12 SAEVs			25 SAEVs			25 SAEVs 0 cents		
		0 cents	10 cents	30 cents	0 cent	10 cents	30 cents	100% gas	25% cost	Both
Travel time (hh:mm)	01:17 (00:47)	01:15 (00:44)	01:14 (00:43)	01:14 (00:43)	01:15 (00:43)	01:14 (00:43)	01:14 (00:43)	01:17 (00:44)	01:17 (00:44)	01:19 (00:45)
Change in travel time by mode										
Walk + Bike (%)		-18.58	-17.89	-15.45	-21.55	-19.51	-16.06	-16.59	-15.52	-10.34
Car (%)		-10.60	-8.25	-5.43	-11.16	-10.13	-6.77	-23.33	-23.54	-34.63
PT (%)		-0.76	-0.88	-0.57	-1.37	-0.02	-0.02	6.59	6.28	13.58
Distance traveled (km)	25.29 (20.31)	25.82 (20.32)	25.71 (20.27)	25.55 (20.27)	25.92 (20.33)	25.79 (20.29)	25.58 (20.27)	25.92 (20.30)	25.97 (20.35)	25.98 (20.35)
Change in dist. traveled by mode										
Walk + Bike (%)		-19.27	-18.11	-14.26	-22.87	-20.19	-14.99	-17.15	-15.56	-9.47
Car (%)		-10.56	-8.30	-5.65	-11.46	-10.13	-6.72	-22.89	-21.88	-32.40
PT (%)		1.97	1.03	0.44	1.35	2.02	1.12	10.87	9.71	18.34
CO ₂ emissions (kg)	18.74 (33.73)	16.82 (33.71)	17.20 (33.97)	17.72 (34.13)	16.64 (33.80)	16.89 (33.85)	17.50 (34.03)	14.46 (32.01)	14.63 (32.75)	12.65 (30.95)
Change in CO ₂ emissions (%)		-10.27	-8.24	-5.47	-11.22	-9.87	-6.63	-22.85	-21.93	-32.49

Note: The table shows averages and percentage changes at the trip level.

Table 4.5
Mobility-related statistics for all agents residing in zones who use a car in the baseline scenario but switch to SAEVs for the specific experiment (aggregated over the simulated day).

Averages	Increase in cars costs								
	12 SAEVs			25 SAEVs			25 SAEVs 0 cents		
	0 cents	10 cents	30 cents	0 cent	10 cents	30 cents	100% gas	25% cost	Both
Number of agents	2862	2510	1811	3351	2816	1897	4027	4111	4758
Travel time (hh:mm)									
Baseline	00:41	00:39	00:36	00:41	00:40	00:35	00:45	00:44	00:47
Experiments	01:19	01:13	01:01	01:18	01:12	00:59	01:28	01:26	01:34
Time costs (Euro)									
Baseline	8.69	8.35	7.55	8.75	8.40	7.46	9.48	9.22	9.81
Experiments	12.34	11.56	9.81	12.28	11.36	9.47	13.54	13.42	14.42
Distance traveled (km)									
Baseline	21.61	20.13	16.77	21.74	20.18	16.49	25.18	23.83	26.45
Experiments	24.19	22.30	18.35	24.47	22.51	18.20	28.32	26.90	29.79
CO ₂ emissions (kg)									
Baseline	33.38	30.90	25.63	33.51	31.01	25.17	39.06	36.92	41.10
Experiments	1.89	1.18	1.22	1.57	1.74	1.34	0.00	0.00	0.00

in the first six scenarios. The average decrease is highest (−32%) for the last scenario where both the costs for private car usage and for private car ownership are increased.

To investigate more specifically the impact of the SAEV introduction on car users, Table 4.5 shows the simulation results only for those agents who use a car in the baseline, who reside in one of the SAEV operating areas, and who use an SAEV at least once in a given scenario (due to the last criterion, the number of agents per column differs). We find that for these agents, the average daily travel time goes up substantially, and amounts on average to double the travel time that these agents had in the baseline scenario without SAEVs. This effect can only partially be attributed to switching to SAEVs (which are usually not much slower than cars) but is also a consequence of switching to public transport, cycling, and walking, all of which tend to be slower than car travel (if they were faster, many of these trips would have been undertaken with modes other than private cars already in the baseline scenario).

The average time costs also increase significantly, although less so, as the switch to SAEVs (and public transport) is associated with lower time valuations. Average distances are affected only slightly — in all scenarios they go up by around 10 to 13%. Finally, the CO₂ emissions

drop to close to or equal to 0 for all scenarios for the groups considered in the table. The reason is that it is very rare that an agent uses both a car and an SAEV over the course of the simulated day, as cost-wise such a mobility pattern is very unfavorable due the fixed costs associated with making use of a car.

Finally, we can conduct a back-of-the-envelope calculation on whether the social benefits associated with a reduction in CO₂ emissions exceed the increase in time costs for the groups of agents included in Table 4.5. Assuming an average reduction in time costs of 3.5 Euro and a reduction in CO₂ emissions of 30 kg (both values close to what several of the scenarios yield), it is straightforward to derive that if the negative societal impacts per ton of CO₂ are valued higher than 116.7 Euro, the social benefits associated with a reduction in CO₂ emissions are greater than the disutility caused by the travel time increase. Recent studies suggest that this condition is fulfilled. For instance, Rennert et al. (2022) state a preferred estimate of 185 USD (approx. 170 EUR) per ton of CO₂ savings.

5. Conclusions and directions for future research

In this paper, we simulated the introduction of shared, autonomous, electric vehicles (SAEVs) in zones outside of the city center of Vienna

(Austria), where population density is relatively low but access to prioritized (rail-based) public transport is available. We compared the results associated with a small (12 SAEVs/1000 facilities) and a large (25 SAEVs/1000 facilities) fleet of demand-responsive SAEVs with a maximum capacity of four persons. In terms of pricing schemes, we investigated the effects of SAEVs being available for free, a low SAEV fare (10 cents/minute) and a high SAEV fare (30 cents/minute). For all combinations of price and fleet size, we find that only a fairly small share of agents switches from cars to SAEVs, and that SAEVs are mainly used by agents that have traveled on zero-emission modes (cycling, walking, public transport) in the baseline scenario (i.e. the status quo without SAEVs). This finding is consistent with earlier simulation studies on automated and non-automated demand-responsive transport (e.g. [Thao et al., 2023](#)). Moreover, unlike most earlier studies that do not account for multi-modal trips, we can show that only for 1/4 to 1/3 of SAEV trips, the SAEV usage is combined with a public transport trip, indicating that the underlying idea of introducing SAEVs in zones that have a reasonably good public transport connectivity has some appeal but is not the dominant way of how SAEVs are used. As a result of these findings, CO₂ emissions savings relative to the baseline (for the agents residing in the SAEV zones) are fairly low: 5%–11%. Moreover, a switch away from cycling and walking may also have negative public health impacts ([Nunes and Hernandez, 2020](#)).

We also simulated scenarios in which not only SAEVs are introduced, but also the ownership and/or usage of private cars is assumed to become more expensive. We find that under such conditions, more agents who used cars in the baseline scenario can be convinced to switch to alternative modes including SAEVs. For that reason, substantially higher CO₂ emission reductions (up to 32%) can be generated, as car users increasingly use SAEVs as well as active modes and public transport. Nevertheless, even in these favorable conditions, we find that an SAEV replaces on average only 2.7 to 3.5 private cars.

From a policy perspective, our results thus imply that introducing demand-responsive SAEVs as part of the public transport system at the outskirts of the cities will lead to some reductions in CO₂ emissions, but may have negative societal consequences when pedestrians, cyclists and public transport users switch to SAEVs. Substantial emission reductions can only be expected if accompanying policies are implemented that render car usage and ownership unattractive. However, our simulations show that such emission reductions come at the cost of significantly longer travel times. These time costs could likely be lowered by investing in better cycling infrastructure and conventional mass public transport also in the less densely populated areas of Vienna.

Our findings are broadly in line with the relevant literature. Also [Kad-doura et al. \(2020b\)](#) found that with smaller zones, mainly “undesirable switches” away from walking, cycling and public transport towards SAEVs take place. Similar to [Cyganski et al. \(2018\)](#) we also find that the uptake of SAEVs is fairly moderate, and similar to [Viergutz and Schmidt \(2019\)](#) we can conclude that SAEVs will likely not be the panacea for public transport provision in areas with fairly low population density. In contrast to these studies, we emphasize also environmental and socio-economic impacts of SAEVs. Regarding the latter, a main finding is SAEVs are especially adopted by those who live in non-urban areas but do not having access to a car.

Our simulations are of course not without limitations. For instance, we assume there is no latent demand for additional trips. Instead, our simulation approach assumes that the daily planning of the agents is unaffected by the introduction of SAEVs. This assumption has been made to ensure tractability and allow for comparisons of specific trips across experiments. But it is inconsistent with other studies that predict changes – and more specifically, an increase – in overall travel demand (due to changes in trip origins and destinations, trip timing, or in the planned activities) (see overview paper by [Pernestål and Kristoffersson, 2019](#)). Not only is the introduction of an additional, attractive transport mode likely to increase the number of trips, it may also lead to longer trips, not at least because in the longer run people may relocate to

more remote (and hence cheaper) locations, inducing further urban sprawl ([Duarte and Ratti, 2018](#); [Meyer et al., 2017](#)). While this is certainly an important aspect to consider for simulations in which SAEVs can operate throughout the entire city, it may, however, be somewhat less relevant for our simulation scenarios, as our focus is on first- and last-mile trips.

Overall, we look at a situation where SAEVs are only introduced in the designated zones at the outskirts of Vienna, while otherwise assuming that the status-quo (associated with the timing of the most recent representative Austrian mobility survey ([Tomschy et al., 2016](#))) remains. This scenario might be somewhat unrealistic in several dimensions, including the assumptions that private car ownership rates remain unchanged, that private cars operate on fossil fuels, and that the demographic characteristics of the Greater Vienna Area remain stable. In fact, by the time SAEVs will be introduced in the future, also other changes along these dimensions will likely have taken place. Especially given the pronounced shift towards e-mobility in the past few years, our estimates of CO₂ savings that can be achieved when introducing SAEVs are likely to be overstated. Despite these shortcomings, we have chosen not to make any specific assumptions on these other dimensions (besides fixing them to the status-quo) in order to have a clearly identifiable baseline.

In addition to tackling the above limitations, some of the other aspects of the simulation model might be refined in future research. This includes taking into account the charging of SAEVs (the importance of which has recently been pointed out by [Grahn et al. \(2023\)](#)), and a dynamic interaction between demand (mode choice) and supply (SAEV fleet size and pricing). Testing different algorithms for ride-sharing and re-balancing of fleets, different fare systems, different SAEV capacities, as well as introducing pick-up and drop-off points rather than offering pick-up and drop-off at the door are further interesting extensions for future work. Also the analysis of socio-economic impacts could be refined, especially if more disaggregate data (for instance from travel diaries) become available. Especially in the context of an SAEV introduction, it might be interesting to account for heterogeneity in terms of how individuals choose between different transport modes (habitual vs. trip-based; low vs. high acceptance of SAEVs; etc.). Finally, future research might focus on the determinants of spatial heterogeneity (e.g., the proximity to specific types of public transport infrastructure), hereby extending the illustrative analysis included in the appendix of this paper.

CRediT authorship contribution statement

Stefanie Peer: Conceptualization, Methodology, Writing – original draft, Funding acquisition. **Johannes Müller:** Conceptualization, Methodology, Software, Validation, Investigation, Writing – review & editing, Visualization. **Asjad Naqvi:** Methodology, Software, Validation, Visualization, Formal analysis. **Markus Straub:** Conceptualization, Methodology, Software.

Declaration of competing interest

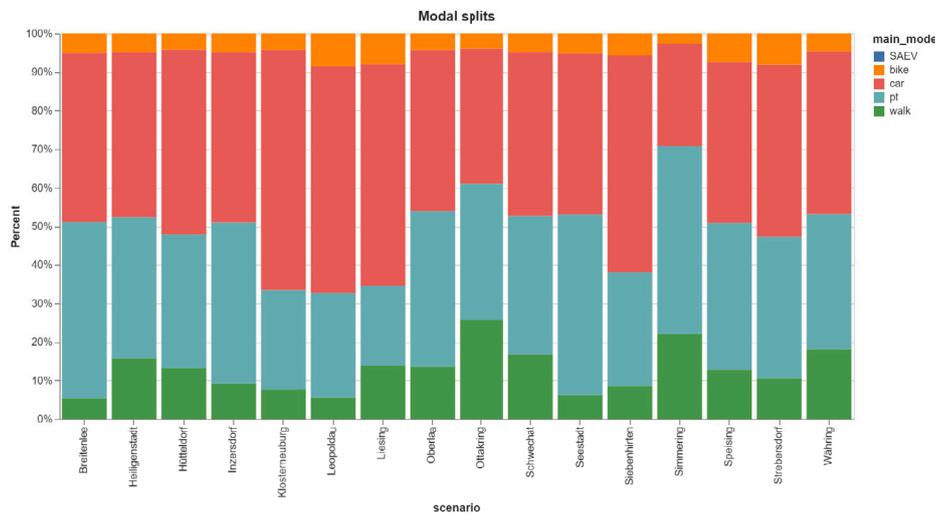
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

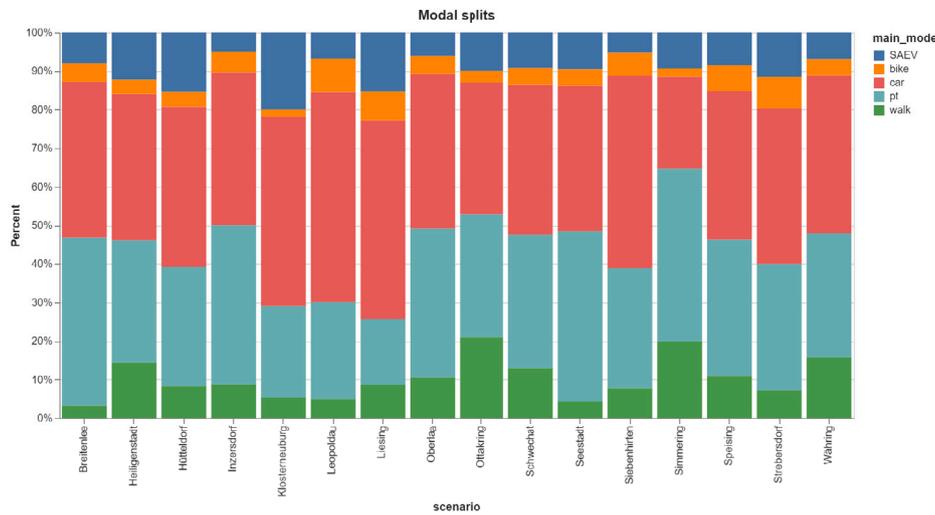
Data will be made available on request.

Appendix. Analysis disaggregated by SAEV-zones

Please note that the geographical location of the SAEV-zones as well as their size can be inferred from [Fig. 3.2](#).



(a) Baseline scenario



(b) 12 SAEVs per 1000 facilities at 30 cents per minute

Fig. A.1. Modal split in the individual SAEV zones.

References

Adler, M.W., Peer, S., Sinozic, T., 2019. Autonomous, connected, electric shared vehicles (ACES) and public finance: An explorative analysis. *Transp. Res. Interdiscipl. Perspect.* 2, 100038.

Ambühl, L., Ciari, F., Menendez, M., 2016. What about space?: A simulation based assessment of AVs impact on road space in urban areas. In: 16th Swiss Transport Research Conference. STRC 2016.

André, M., Rapone, M., 2009. Analysis and modelling of the pollutant emissions from European cars regarding the driving characteristics and test cycles. *Atmos. Environ.* 43, 986–995.

Axhausen, K., Horni, A., Nagel, K., 2016. *The Multi-Agent Transport Simulation MATSim*. Ubiquity Press.

Becker, H., et al., 2020. Impact of vehicle automation and electric propulsion on production costs for mobility services worldwide. *Transp. Res. A* 138, 105–126.

Bischoff, J., Maciejewski, M., 2020. Proactive empty vehicle rebalancing for demand responsive transport services. *Procedia Comput. Sci.* 170, 739–744.

Bösch, P. M., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. *Transp. Policy* 64, 76–91.

Chee, P.N.E., Susilo, Y.O., Wong, Y.D., 2020. Determinants of intention-to-use first-/last-mile automated bus service. *Transp. Res. A* 139, 350–375.

Chen, T.D., Kockelman, K.M., Hanna, J.P., 2016. Operations of a shared, autonomous, electric vehicle fleet: implications of vehicle & charging infrastructure decisions. *Transp. Res. A* 94, 243–254.

Chen, P.W., Nie, Y.M., 2017. Connecting e-hailing to mass transit platform: Analysis of relative spatial position. *Transp. Res. C* 77, 444–461.

Compostella, J., Fulton, L.M., D. Kleine, R., Kim, H.C., Wallington, T.J., 2020. Near-(2020) and long-term (2030–2035) costs of automated, electrified, and shared mobility in the United States. *Transp. Policy* 85, 54–66.

Cygancki, R., Heinrichs, M., Schmidt, A.von., Krajzewicz, D., 2018. Simulation of automated transport offers for the city of Brunswick. *Procedia Comput. Sci.* 130, 872–879.

Duarte, F., Ratti, C., 2018. The impact of autonomous vehicles on cities: A review. *J. Urban Technol.* 25, 3–18.

Eurostat, 2019. *Population distribution/demography*. <https://ec.europa.eu/eurostat/de/web/gisco/geodata/reference-data/population-distribution-demography/geostat>. Retrieved on 24. July 2020.

Fagnant, D.J., 2015. Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles. In: *Proceedings of the 94th Annual Meeting of the Transportation Research Board in Washington DC*.

Fielbaum, A., 2020. Strategic public transport design using autonomous vehicles and other new technologies. *Int. J. Intell. Transp. Syst. Res.* 18, 183–191.

Fosgerau, M., 2019. Automation and the value of time in passenger transport. In: *International Transport Forum Discussion Papers*, No. 2019/10. OECD Publishing, Paris.

Gawron, J.H., Keoleian, G.A., De Kleine, R.D., Wallington, T.J., Kim, H.C., 2018. Life cycle assessment of connected and automated vehicles: Sensing and computing subsystem and vehicle level effects. *Environ. Sci. Technol.* 52, 3249–3256.

Grahn, R., Qian, S., Hendrickson, C., 2023. Environmental impacts of first-mile-last-mile systems with shared autonomous electric vehicles and ridehailing. *Transp. Res. D* 118, 103677.

Grigoratos, T., Martini, G., 2015. Brake wear particle emissions: A review. *Environ. Sci. Pollut. Res.* 22, 2491–2504.

- Guan, J., Zhang, K., Zhang, S., Chen, Y., 2020. How is public transit in the megacity peripheral relocates' area in China? Captive transit rider and dynamic modal accessibility gap analytics in a peripheral large-scale residential area in Shanghai, China. *J. Transp. Land Use* 13, 1–21.
- Ho, C.Q., Mulley, C., Shiftan, Y., Hensher, D.A., 2015. Value of travel time savings for multiple occupant car: Evidence from a group-based modelling approach. In: *Australasian Transport Research Forum 2015 Proceedings*.
- Hörl, S., Balač, M., Axhausen, K., 2019. Pairing discrete mode choice models and agent-based transport simulation with MATSim. In: *2019 TRB Annual Meeting Online*. Transportation Research Board., pp. 19–2409.
- Hössinger, R., Aschauer, F., Jara-Diaz, S., Jokubauskaite, S., Schmid, B., Peer, S., Axhausen, K., Gerike, R., 2020. A joint time-assignment and expenditure-allocation model: Value of leisure and value of time assigned to travel for specific population segments. *Transportation* 47, 1439–1475.
- Hülsmann, F., Gerike, R., Kickhöfer, B., Nagel, K., Luz, R., 2011. Towards a multi-agent based modeling approach for air pollutants in urban regions. In: *Conference on "Luftqualität und Straßen"*. FGSV-Verlag, pp. 144–166.
- Jokubauskaite, S., Hössinger, R., Aschauer, F., Gerike, R., Jara-Diaz, S., Peer, S., Schmid, B., Axhausen, K., Leisch, F., 2019. Advanced continuous-discrete model for joint time-use expenditure and mode choice estimation. *Transp. Res. B* 129, 397–421.
- Kaddoura, I., Bischoff, J., Nagel, K., 2020a. Towards welfare optimal operation of innovative mobility concepts: External cost pricing in a world of shared autonomous vehicles. *Transp. Res. A* 136, 48–63.
- Kaddoura, I., Leich, G., Nagel, K., 2020b. The impact of pricing and service area design on the modal shift towards demand responsive transit. *Procedia Computer Science* 170, 807–812.
- Kassens-Noor, E., Kotval-Karamchandani, Z., Cai, M., 2020. Willingness to ride and perceptions of autonomous public transit. *Transp. Res. A* 138, 92–104.
- Kickhöfer, B., 2014. *Economic Policy Appraisal and Heterogeneous Users* (Ph.D. thesis). Technische Universität Berlin.
- Kickhöfer, B., Hülsmann, F., Gerike, R., Nagel, K., 2013. *Rising Car User Costs: Comparing Aggregated and Geo-Spatial Impacts on Travel Demand and Air Pollutant Emissions*. In: *Smart Transport Networks*, Edward Elgar Publishing.
- Kluge, J., Kocher, M.G., Müller, W., Zenz, H., 2020. *Empfehlungen Für Die Gestaltung Eines Tarifs Für Die Neue Konzessionsart Personenbeförderungsgewerbe Mit Pkw-Taxi Im Bundesland Wien*. IHS Research Reports.
- Kopelias, P., Demiridi, E., Vogiatzis, K., Skabardonis, A., Zafropoulou, V., 2020. Connected & autonomous vehicles – environmental impacts – A review. *Sci. Total Environ.* 712, 135237.
- Larson, W., Zhao, W., 2020. Self-driving cars and the city: Effects on sprawl, energy consumption, and housing affordability. *Reg. Sci. Urban Econ.* 81, 103484.
- Leich, G., Bischoff, J., 2019. Should autonomous shared taxis replace buses? A simulation study. *Transp. Res. Procedia* 41, 450–460.
- Lin, Y., Zhang, K., Shen, Z.-J.M., Miao, L., 2019. Charging Network Planning for Electric Bus Cities: A Case Study of Shenzhen, China. *Sustainability* 11, 4713.
- Liu, J., Kockelman, K.M., Boesch, P.M., Ciari, F., 2017. Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. *Transportation* 44, 1261–1278.
- Loeb, B., Kockelman, K.M., 2019. Fleet performance and cost evaluation of a shared autonomous electric vehicle (SAEV) fleet: A case study for Austin, Texas. *Transp. Res. A* 121, 374–385.
- Maciejewski, M., Bischoff, J., Hörl, S., Nagel, K., 2017. Towards a testbed for dynamic vehicle routing algorithms. In: *International Conference on Practical Applications of Agents and Multi-Agent Systems*. Springer, pp. 69–79.
- Maciejewski, M., Nagel, K., 2013. A microscopic simulation approach for optimization of taxi services. In: *3rd International Conference on Models and Technologies for Intelligent Transportation Systems 2013*. TUDpress, pp. 1–10.
- Malokin, A., Circella, G., Mokhtarian, P.L., 2019. How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios. *Transp. Res. A* 124, 82–114.
- Meyer, J., Becker, H., Bösch, P.M., Axhausen, K.W., 2017. Autonomous vehicles: The next jump in accessibilities? *Res. Transp. Econ.* 62, 80–91.
- Militão, A.M., Tirachini, A., 2021. Optimal fleet size for a shared demand-responsive transport system with human-driven vs automated vehicles: A total cost minimization approach. *Transp. Res. A* 151, 52–80.
- Millard-Ball, A., 2019. The autonomous vehicle parking problem. *Transp. Policy* 75, 99–108.
- Molin, E., Adjenughwure, K., Bruyn, M., Cats, O., Warffemius, P., 2020. Does conducting activities while traveling reduce the value of time? Evidence from a within-subjects choice experiment. *Transp. Res. A* 132, 18–29.
- Moreno, A.T., Michalski, A., Llorca, C., Moeckel, R., 2018. Shared autonomous vehicles effect on vehicle-km traveled and average trip duration. *J. Adv. Transp.* 2018.
- Müller, J., Straub, M., Naqvi, A., Richter, G., Peer, S., Rudloff, C., 2021. MATSim model Vienna: Analyzing the socioeconomic impacts for different fleet sizes and pricing schemes of shared autonomous electric vehicles. URL <https://pure.iiasa.ac.at/id/eprint/17037/>.
- Müller, J., Straub, M., Richter, G., Rudloff, C., 2022. Integration of Different Mobility Behaviors and Intermodal Trips in MATSim. *Sustainability* 14, 428.
- Nguyen-Phuoc, D.Q., Zhou, M., Chua, M.H., Alho, A.R., Oh, S., Seshadri, R., Le, D.-T., 2023. Examining the effects of automated mobility-on-demand services on public transport systems using an agent-based simulation approach. *Transp. Res. A* 169, 103583.
- Notter, B., Keller, M., Althaus, H.-J., Cox, B., Knörr, W., Heidt, C., Biemann, K., Räder, D., Jamet, M., 2019. *HBEFA 4.1*. Technical Report Bundesamt Für Umwelt BAFU, Umweltbundesamt.
- Nunes, A., Hernandez, K.D., 2020. Autonomous taxis & public health: High cost or high opportunity cost? *Transp. Res. A* 138, 28–36.
- Ongel, A., Loewer, E., Roemer, F., Sethuraman, G., Chang, F., Lienkamp, M., 2019. Economic assessment of autonomous electric microtransit vehicles. *Sustainability* 11, 648.
- Pernestål, A., Kristoffersson, I., 2019. Effects of driverless vehicles-comparing simulations to get a broader picture. *Eur. J. Transp. Infrastruct. Res.* 19.
- Prandstetter, M., Straub, M., Puchinger, J., 2013. On the way to a multi-modal energy-efficient route. In: *IECON 2013-39th Annual Conference of the IEEE Industrial Electronics Society*. IEEE, pp. 4779–4784.
- Rafael, S., Correia, L.P., Lopes, D., Bandeira, J., Coelho, M.C., Andrade, M., Borrego, C., Miranda, A.I., 2020. Autonomous vehicles opportunities for cities air quality. *Sci. Total Environ.* 712, 136546.
- Rennert, K., Erickson, F., Prest, B.C., Rennels, L., Newell, R.G., Pizer, W., Kingdon, C., Wingenroth, J., Cooke, R., Parthum, B., et al., 2022. Comprehensive evidence implies a higher social cost of CO2. *Nature* 610, 687–692.
- Schmid, B., Jokubauskaite, S., Aschauer, F., Peer, S., Hössinger, R., Gerike, R., Jara-Diaz, S.R., Axhausen, K., 2019. A pooled RP/SP mode, route and destination choice model to investigate mode and user-type effects in the value of travel time savings. *Transp. Res. A* 124, 262–294.
- Shaheen, S., Bouzaghrane, M.A., 2019. Mobility and energy impacts of shared automated vehicles: A review of recent literature. *Current Sustain./Renew. Energy Rep.* 6, 193–200.
- Shen, Y., Zhang, H., Zhao, J., 2018. Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore. *Transp. Res. A* 113, 125–136.
- Stark, K., Gade, K., Heinrichs, D., 2019. What does the future of automated driving mean for public transportation? *Transp. Res. Rec.* 2673, 85–93.
- Taiebat, M., Stolper, S., Xu, M., 2019. Forecasting the impact of connected and automated vehicles on energy use: A microeconomic study of induced travel and energy rebound. *Appl. Energy* 247, 297–308.
- Thao, V.T., Imhof, S., von Arx, W., 2023. Demand responsive transport: New insights from peri-urban experiences. *Travel Behav. Soc.* 31, 141–150.
- Tirachini, A., 2020. Ride-hailing, travel behaviour and sustainable mobility: An international review. *Transportation* 47, 2011–2047.
- Tirachini, A., Gomez-Lobo, A., 2020. Does ride-hailing increase or decrease vehicle kilometers traveled (VKT)? A simulation approach for Santiago de Chile. *Int. J. Sustain. Transp.* 14, 187–204.
- Tomschy, R., Herry, M., Sammer, G., Klementsitz, R., Riegler, S., Follmer, R., Gruschwitz, D., Josef, F., Gensasz, S., Kirnbauer, R., Spiegel, T., 2016. *Österreich Unterwegs 2013–2014: Ergebnisbericht Zur Österreichweiten Mobilitätshebung*. Technical Report.
- Viergutz, K., Schmidt, C., 2019. Demand responsive v. conventional public transportation: A MATSim study about the rural town of Colditz, Germany. *Procedia Comput. Sci.* 151, 69–76.
- Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transp. Res. Part A: Policy Pract.* 86, 1–18.
- Wang, B., Medina, S.A.O., Fourie, P., 2018. Simulation of autonomous transit on demand for fleet size and deployment strategy optimization. *Procedia Comput. Sci.* 130, 797–802.
- Warach, R.A., Galus, M.D., Dobler, C., Balmer, M., Andersson, G., Axhausen, K.W., 2013. Plug-in hybrid electric vehicles and smart grids: Investigations based on a microsimulation. *Transp. Res. C* 28, 74–86.
- Weilenmann, M., Favez, J.-Y., Alvarez, R., 2009. Cold-start emissions of modern passenger cars at different low ambient temperatures and their evolution over vehicle legislation categories. *Atmos. Environ.* 43, 2419–2429.
- Weiss, J., Hledik, R., Lueken, R., Lee, T., Gorman, W., 2017. The electrification accelerator: Understanding the implications of autonomous vehicles for electric utilities. *Electricity J.* 30, 50–57.
- Whitmore, A., Samaras, C., Hendrickson, C.T., Matthews, H.S., Wong-Parodi, G., 2022. Integrating public transportation and shared autonomous mobility for equitable transit coverage: A cost-efficiency analysis. *Transp. Res. Interdiscipl. Perspect.* 14, 100571.
- Wiener Linien, 2023. *Die Wiener Öffis in Zahlen*. <https://www.wienerlinien.at/die-wiener-offis-in-zahlen>. (Accessed 25 July 2023).
- Wirtschaftskammer Österreichs, 2019. *Beschäftigungsstruktur Österreich 2019*. <http://wko.at/statistik/eu/europa-beschaeftigungsstruktur.pdf>.
- Zhang, W., Guhathakurta, S., Fang, J., Zhang, G., 2015. The performance and benefits of a shared autonomous vehicles based dynamic ridesharing system: An agent-based simulation approach. In: *Proceedings of the 94th Annual Meeting of the Transportation Research Board*.
- Zhang, W., Wang, K., 2020. Parking futures: Shared automated vehicles and parking demand reduction trajectories in Atlanta. *Land Use Policy* 91, 103963.