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Are shared automated vehicles good for public- or private-transport-oriented cities (or neither)?

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A R T I C L E I N F O

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A B S T R A C T

Simulation studies suggest that Shared Automated Vehicles (SAVs) could reduce the total vehicle kilometres travelled (VKT) thanks to efficiently pooling multiple users in one vehicle. However, mode choice studies indicate that SAVs would attract mostly public transport users, leading to an increase in VKT. This paper is among the first to combine these operational and behavioural expectations and the first to do so analytically. In our theoretical set-up, travellers choose between car, public transport, and SAVs, depending on their individual valuation of private travel and other attributes of each mode. We find that the introduction of SAVs lead to a VKT change in public-transport-oriented cities ranging from a small decrease to a large increase, where the latter is true for plausible parameter settings and hence is a cautionary point for SAV-introduction policies. Conversely, SAVs would attract only few travellers in private-transport-oriented cities and therefore would not significantly impact VKT.

1. Introduction

The expected emergence of automated vehicles, together with the already achieved ability to connect vehicles and users online, has triggered the conception of *Shared Autonomous Vehicles* (SAVs).[1] For over a decade, studies have explored the potential of a mobility system that consists of a centrally-coordinated fleet of SAVs, which are used by passengers or groups travelling together or shared among travellers connected via an online platform. Many have indicated that automated vehicles (AVs) could reduce road accidents, make travel more pleasant and reliable, and allow the travellers to reclaim the 'lost' time spent travelling. Furthermore, providing the AVs as a shared service – 'the SAV', is claimed to prevent a drastic increase in vehicle kilometres that may arise with an introduction of privately used AVs. The reasoning here is the following: if travel with an AV is overall more attractive (due to, e.g., lower stress levels) than driving a car, then current car users would travel more for various purposes when getting access to an AV. Facilitating or mandating that previously unconnected travellers (or their groups) share a vehicle for their trip, is expected to counter the increase of vehicle travel. This expectation is crucial, because, notwithstanding the other potential benefits of vehicle automation and SAVs, policy makers and academics agree that their impact on the amount of vehicle travel, and consequently on congestion, environment and accessibility, is at the core of what would make them 'good or bad' for future cities (e.g., Cohen & Cavoli, 2019).

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[1] Note that the term 'shared automated vehicle' (SAV) is variably used in literature to represent different systems (Narayan et al. 2020), including car sharing (the vehicle is used by a single traveller or group at any time, similarly to a car rental or ride-hailing service) and ride sharing (the vehicle is simultaneously used by multiple travellers or groups). In this paper, we adopt the latter definition of an SAV.

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However, assessing the impact of SAVs on congestion, expressed in vehicle kilometres travelled (VKT), is a complex task, as it entails both behavioural aspects (crucially which modes will lose the passengers to SAVs) and also operational ones (what is the overall effect of users travelling together with vehicles that need to constantly rebalance), a challenge that is further discussed in section 1.1. While studies are increasingly investigating the relationship between SAVs and congestion, this emerging field has two limitations. First, the findings from travel behaviour studies are not well integrated into the simulation frameworks that look at the operational impacts on the VKT. Specifically, the behavioural studies highlight the role of preferences for sharing either directly (e.g., Lavieri and Bhat, 2019) or implicitly by current mode use (e.g., Krueger et al., 2016). The operational decisions (such as how to match the users or route the vehicles) do not have an impact on those studies. The simulation studies, on the other hand, largely analyse 'mode replacement' scenarios – e.g., if all travellers / all car users / all taxi users used SAVs (such as Lokhandwala & Cai, 2018) – in order to investigate operational decisions. Second, the outcomes from simulation studies are necessarily confined to the study case. Given that many elements – such as land-use, infrastructure networks, characteristics of public transport services – are often considered in the simulation, it is not a priori clear how generalisable they are to other locations. In addition, a detailed depiction of simulated environments necessarily becomes outdated. In this case, that may happen even before a wide-spread adoption of SAVs. Clearly, however, it is crucial for long-term (S)AV policies that the VKT predictions are robust against case-specific details that may not translate well to other locations and future time moments.

This study addresses the above-discussed limitations by proposing a general model for mode shifts with an adoption of SAVs, which is combined with an analytical derivation of VKT impacts. We thereby provide a theoretical and transparent basis for expectations about the impact of SAVs on VKT and transport systems, with a focus on private- and public-transport-oriented cities. Such a basis is crucial for policy that aims to devise long-term strategies for (S)AV implementation in areas that often transcend a specific simulated area. The analytical expressions can furthermore serve as a tool to gauge VKT impacts of SAVs in various locations (characterised, in particular, by the public- or private-transport orientation of those locations) and as a benchmark for detailed simulated applications in various geographic and time contexts.

1.1. Four factors determining the VKT impact of SAVs

This section provides a more detailed overview of the behavioural and operational factors that determine the VKT impact of SAVs. We identify four main factors illustrated in Fig. 1. The following paragraphs describe each of them and assess the sign of VKT change compared to the current system without any AVs or SAVs.

First, an advantage of SAV introduction is that a centrally controlled fleet can be operated efficiently, both regarding the decisions about vehicle routing, and the assignment of users to vehicles. In particular, online coordination can be very effective to match users with compatible origins and destinations, reducing the need for long detours, especially if the total number of users in the system is large (Fielbaum et al., 2023, Lehe et al., 2021).

The second factor is the potentially induced demand. Given that SAVs are expected to provide a more pleasant travel experience and non-driving activities on board than current travel modes, numerous studies have argued that this would lower the generalised transport costs and thereby increase personal travel (e.g., Auld et al., 2017; Olsen & Sweet, 2019). However, other studies (e.g., Kim et al.; 2020, and Pudāne et al., 2019) suggest that induced demand would primarily affect non-daily travel – such as more frequent or longer holiday trips. In daily travel, travellers may otherwise adjust their daily schedules and routines with or without additional travel. Independently of whether current travellers would increase their kilometres when switching to SAVs, induced demand may result from a new population of SAV users – that is, such that at present do not have a driving licence and/or access to other transport modes (Cohen & Cavoli, 2019).

The third factor that may affect VKT is empty travel: in order to serve consecutive groups of passengers, vehicles sometimes would

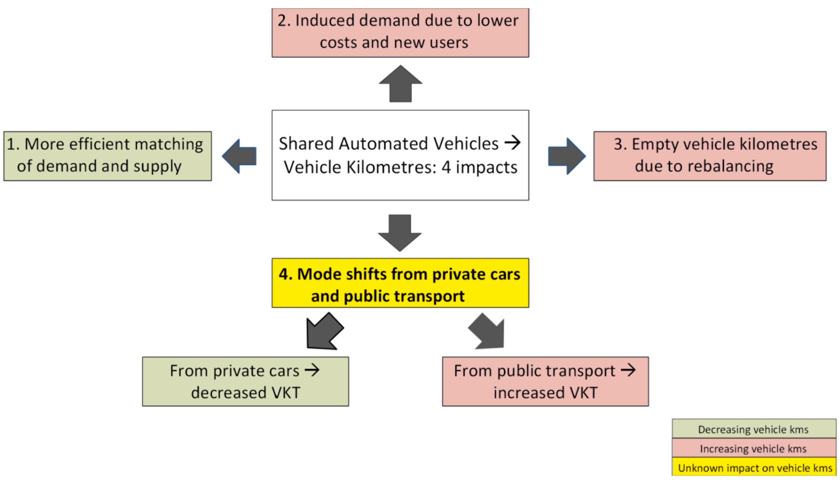

Fig. 1. Four impacts of SAV on VKT.

need to travel empty from one place to another, a process called rebalancing. Rebalancing increases VKT, especially if active anticipatory techniques are utilised; such empty VKT can be compensated by the gains of pooling *if users come from private modes* (Alonso-Mora et al., 2017), which leads us to the fourth factor and the main subject of this study.

The fourth and likely crucial factor that may impact VKT is mode shifts. Clearly, a shift from a private car to an SAV for a given trip would reduce the VKT, given that the trip is shared with another travel party. Conversely, shifts from public transport would generally increase the VKT, since the same demand would be served with a larger number of smaller vehicles. Hence, the question of 'which passengers would the SAV attract?' becomes crucial. As discussed in-depth in section 2, the literature presents mixed evidence on this question, although a shift from current public transport to SAVs seems to be dominant.

The four factors mentioned above are clearly intertwined. For instance, the number and precedence of SAV users will be affected by operational decisions, such as the quality of service offered by the system. The number of SAV users in turn will impact the operational decisions. For example, the operators could try to attract more car users by offering low waiting times and detours, but this would reduce the opportunities for user pooling or would require more or longer rebalancing trips which would in turn increase VKT. These interdependencies reinforce the need for theoretical and simulation models that jointly address multiple (if not all) of the behavioural and operational factors that drive the VKT changes with SAVs. This paper aims to do exactly that – to combine the mode shift and several operational aspects to derive VKT impact of SAVs in a theoretical setting.

The rest of the paper is organised as follows. In section 2, we review empirical studies into mode choice with SAVs and simulation studies reporting VKT with SAVs or existing ride-sharing systems. In section 3, we formulate the mode choice model including the SAV and use it for first analyses. In section 4, we set up the model of a stylised city. In section 5, we analyse the impacts of transport system characteristics on the VKT change with SAVs. In section 6, we discuss the results in light of the model assumptions. In section 7, we conclude and discuss implications for research and policy.

2. Literature review

The literature about the challenges and potential benefits of SAVs has grown rapidly in the last few years. In this survey and our models, we are considering vehicles that are dedicated to the commercial transport of passengers, and in which different users can share the vehicle simultaneously. In what follows, we review the studies revealing the expected mode shifts to SAVs and the VKT impacts of SAVs, respectively. We draw literature lists from the reviews by Narayanan et al. (2020) and Harb et al. (2021), and use snowballing to find additional sources. This review contains literature until mid-2022.

2.1. Mode shifts with SAVs

In this review, we only present empirical studies (e.g, surveys, discrete choice experiments) that report a conclusion regarding mode shifts to SAVs with ridesharing. Note that a significantly larger body of literature focus on other determinants of mode shifts to SAVs or on mode shifts to other automated modes (private AVs, SAVs that are only shared sequentially, large-capacity automated public transport). Table 1 shows the studies that fulfil these criteria.

Most studies in Table 1 indicate that current public transport users are more open to SAVs with ridesharing than private car users. However, there is also some conflicting evidence by Al Maghraoui et al. (2020) and diverging effects found in some European countries by Polydoropoulou et al. (2021). Lavieri and Bhat (2019) show that current commute mode, with the exception of sharing a car with family or acquaintances, does not have a significant impact on SAV use for work or leisure. Note, however, that only 3.5 % of their sample were non-car users, which include but are not limited to public transport users. Moreover, privacy-sensitivity (as a factor of several statements) had a large and negative impact on SAV use, which resonates with the underlying reason for mode shifts (i.e., public transport to SAVs) found in other studies.

Several other studies do not directly report that public transport passengers would be more willing to use SAVs, but point to characteristics that are shared by both transport modes and could imply such a mode shift. Nazari et al. (2018) found that respondents without a driving licence would prefer to share AVs with other travellers during their commutes. It is conceivable that a share of these respondents use public transport for their daily trips. Stoiber et al. (2019) found that pooled (i.e., simultaneously shared) AVs were popular in Switzerland: 61 % of respondents chose pooled rather than privately-used AVs. Although they do not specify the current travel modes by the interested users, they acknowledge that the country has strong public transport and carsharing systems and travellers may have a pro-sharing mindset.

The preceding analysis points to the idea that similar travel modes are more likely to substitute each other, as also proposed by van Wee et al. (2019). We illustrate that idea in Fig. 2 (adapted from Singleton et al., 2020). This figure indicates that current private cars and future private AVs, and public transport and shared AVs are expected to be similar in terms of travel time (e.g., due to detours), costs, availability (the ability to use the vehicle at any time and without much prior planning), door-to-door service, the sustainability image of the mode and the areas they serve. Importantly, we also identify several aspects that relate to the private / shared travel experience in these modes: the available activities during travel, the comfort (including the amount of personal space and availability

Table 1
Empirical studies reporting mode shifts to SAVs.

Study	Method	Study area	Mode shifts
Al Maghraoui et al. (2020)	Survey question asking to replace current mode with AV / simulated SAV option	France	60 % car users, 58 % public transport users would use an AV. 27 % car users, 17 % public transport users would use a SAV.
Asgari et al. (2018)	Stated choice experiment	The United States	Car drivers and passengers prefer single rides to shared rides in AVs. Public transport users prefer shared rides to single rides.
Clayton et al. (2020)	Descriptive statistics, stated choice experiment	The United Kingdom	49.3 % bus users would use a SAV. 40 % car users would use a SAV.
Gkartzonikas et al. (2022)	Stated choice experiment	The United States	Respondents whose primary mode of travel for social/recreational trips is bus were more likely to choose SAV.
Krueger et al. (2016)	Stated choice experiment	Australia	Multimodal, carsharing users and car passengers were more likely to shift to SAVs.
Lavieri & Bhat (2019)	Stated choice experiment	The United States	Not-alone car commuters (who share trip with family/acquaintances) would be less likely to use SAVs for work and leisure than drive-alone commuters. Non-car commuters (including public transport users) do not differ from drive-alone commuters in likelihood of using SAVs. Privacy-sensitivity reduces SAV use.
Polydoropoulou et al. (2021)	Stated choice experiment	Cyprus, Finland, Greece, Iceland, Israel, Hungary, United Kingdom	Car users would shift to private AVs (Cyprus, Hungary, Israel, Iceland, Finland), PT users would shift to SAVs (Greece, Israel, Iceland) or AVs (Israel, Finland).

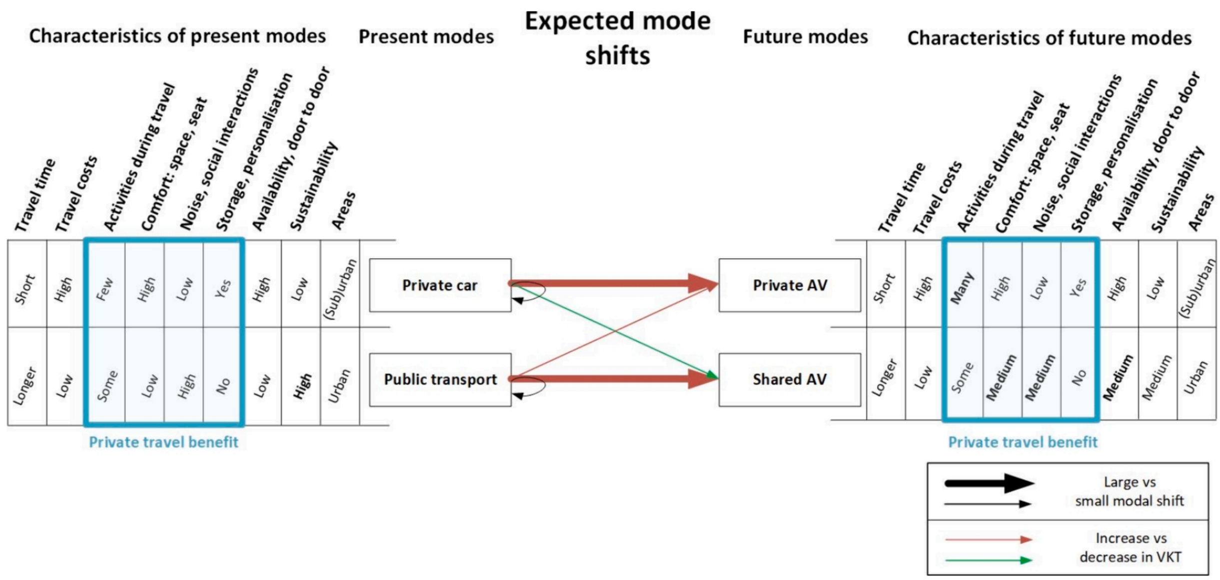

Fig. 2. Possible impacts of automated vehicles on VKT.
Adapted from Singleton et al. (2020).

of a seat), noise levels and the exposure to social situations, and finally, the ability to store items and personalise the vehicle. Although there are some differences (highlighted in bold in the figure), we overall assess the similarity between the two private modes and between the two shared modes to be high. Therefore, given that a traveller maintains their preferences for the mentioned travel aspects, we would expect strong shifts from private cars to private AVs and from public transport to SAVs (with ridesharing).[2]

Note that our analysis of potential mode shifts relates also to the growing body of literature on current non-automated ridesharing. For example, Alonso-González et al. (2021) report that individuals who cycle and use public transport more often are more inclined to use pooled on-demand service for commute or leisure trip. Moody et al. (2021) reports substitution patterns away from public

[2] Note that Fig. 2 also illustrates our approach for modelling mode choices in section 3. The utility function there consists of travel time, travel costs and what we have named 'private travel benefit'. We approximate this multi-dimensional benefit with a single parameter that becomes lower as the capacity of the vehicle increases. We partially incorporate the availability aspects by modelling waiting and access times that emerge endogenously from SAV and public transport operations.

transport to simultaneously and sequentially shared rides. However, and as indicated by Lavieri and Bhat (2019); there are also notable differences between the current ridesharing and future SAV services. Passengers may be more apprehensive in sharing the vehicle with strangers in absence of the operator (Merat et al., 2017), which may intensify the concerns of security and privacy (Sanguinetti et al., 2019). In addition, the fares will likely be reduced due to saved driver costs (Bösch et al., 2018). Our analysis does not further address shifts between other travel modes, such as ridesharing with a driver, taxis, sequentially shared AVs and active modes. Some of those are discussed in Singleton et al. (2020) following the same principle of comparison by aspects.

We expect that the hypothesised mode shifts in Fig. 2 (represented by the thick arrows) are detrimental or at least not beneficial for both private- and public-transport-oriented cities. Cities with strong large-capacity public transport systems may experience loss of ridership with the introduction of SAVs and following drop in service levels. Cities with a majority of private car users would not benefit from the introduction of a shared mobility, because likely the new mode would not be attractive to the travellers.

2.2. VKT impact of SAVs

We now review the studies that have directly analysed whether the introduction of a SAV system increases or decreases VKT. Note that, unlike in section 2.1, we report studies of both SAVs and non-automated ride-pooling. This is because, from the supply modelling viewpoint, these systems are equivalent, as long as they assume centralised guidance in terms of routing and assignment of vehicles and passengers.[3] Furthermore, Table 2 shows that the demand modelling is also equivalent for SAVs and non-automated pooling for the vast majority of our found studies that assume certain mode replacement patterns. That is, SAVs and non-automated ride pooling would be represented similarly in both streams of literature. For simplicity, we refer to vehicles in all of these studies as SAVs. A summary of the studies is provided in Table 2, where we take note of the studied SAV capacities, type of service (if it is restricted to, for example, first- or last-mile), study area, and the set-up for demand modelling (in terms of mode replacement or mode choice assumptions).

Several observations stand out from Table 2. First, VKT changes range from −45 % VKT reduction for taxi fleet to +146 % car-VKT increase. However, findings of decreasing or moderately increasing VKT are more common than large increases. Namely, four studies report increases above 20 % of car VKT, and these findings are largely due to unique scenarios or algorithms adopted in these papers. Here, Levin et al. (2017) adopted a simple assignment algorithm (largely based on first-come-first-serve principle). Masoud & Jayakrishnan (2017) test scenarios where vehicle-sharing and ride-sharing are only available within clusters of households. This arguably results in much higher VKT when moving from owned vehicles to AVs without ride-sharing, and limited opportunities to reduce VKT with ride-sharing. Jäger et al. (2018) and Martinez & Crist (2015) report scenarios where SAVs replace a large-capacity public transport service. Setting aside these four more extreme points, the overview nevertheless reveals large differences in VKT impacts.

Second, we note that the differences in VKT changes are not primarily due to SAV capacities (i.e., the maximum number of users that can simultaneously share the vehicle) or the characteristics of geographical locations − case study characteristics that we chose to report in Table 2. With regard to the capacities, capacity of 2 is associated with changes in taxi/ride-hailing VKT from –33 % (Cai et al., 2019) to −8% (Zhu & Mo, 2022). Capacity of 4 is associated with changes from −45 % (Lokhandwala & Cai, 2018) to + 5 % (Fagnant & Kockelman, 2018). Capacity of 6 is associated with changes from −54 % to + 8 % (Zwick et al., 2021). With regard to locations, studies in Europe report VKT changes of −54 %, −20 %, +6% and + 8 % (from, respectively, Munich − Zwick et al., 2021; Stuttgart − Heilig et al. 2017; Lisbon − Martinez & Crist, 2015; Munich − Zwick et al., 2021). Studies in the US report values from 45 % reduction in VKT by taxi-fleet (New York, Lokhandwala and Cai, 2018) to 16 % increase in total VKT (Boston, WEF, 2018). Studies in China report ride-hailing/taxi VKT changes from –33 % (Cai et al., 2019) to −8% (Zhu and Mo, 2022). We conclude that the VKT differences are largely due to the model assumptions and the types of SAV services that are modelled. Both are discussed next.

Third, most papers have assumed that SAVs replace privately-used cars or taxis. Also within these studies, some predict a decrease in VKT (e.g. Alonso Mora et al., 2017; Heilig et al., 2017; Tsao et al., 2019; Liu et al., 2022) while others − an increase (Masoud & Jayakrishnan, 2017; Levin et al., 2017; Fagnant and Kockelman, 2018). This contrast can be explained by the competing effects of reduced VKT due to sharing the car and increased VKT due to the need for rebalancing (which is relevant in comparison to private cars that do not need to rebalance). Here, newer papers (e.g. Alonso-Mora et al., 2017; Tsao et al., 2019; Liu et al., 2022) tend to be more optimistic about the potential reduction of VKT, suggesting that the state-of-the-art algorithms to route the vehicles and assign them to users are more efficient. Additionally, new research shows that VKT and congestion can be reduced by congestion-aware routing and assignment (Correa et al., 2019; Levin, 2017; Zhou & Roncoli, 2022) and by requiring passengers to walk towards the vehicle (Fielbaum et al., 2021; Gurumurthy & Kockelman, 2022). For surveys on state-of-the-art algorithms, see Danassis et al. (2022), Mourad et al. (2019) and Zardini et al. (2022).

Fourth, the studies that consider public transport report mixed VKT results, depending on the assumed relationships between SAVs and public transport. First, some studies explore the possibilities to replace (high-capacity) public transport with SAVs (Martinez and Crist, 2015; Jäger et al., 2018), resulting in substantially increased VKT. Second, few studies consider SAVs as a first- or last-mile service to public transport, directly replacing low-occupancy buses or taxis (Chen et al., 2020; Shen et al., 2018). These studies report VKT savings. Third, we found three studies considering mode choice between private cars, SAVs and public transport (Lau & Susilawati, 2021; WEF, 2018; Zwick et al., 2021). Here, the findings are mixed from small VKT savings (−6% by Lau & Susilawati,

[3] Operators' costs might also be different as drivers' salary constitutes a large portion thereof. However, the operational decisions that command the resulting VKT (assignment and routing) do not depend on whether the vehicle is automated or not.

Table 2
Previous studies reporting changes on VKT due to SAVs.

Study	SAV capacity / type of service	Study area	Demand modelling	VKT impact of SAVs
Alonso-Mora et al. (2017)	Max 2–10 users per SAV	Manhattan, New York	SAVs replace taxis	−5% to −32 % by taxi fleet
Bischoff et al. (2017)	Max 2–4 users per SAV	Berlin, Germany	SAVs replace taxis	−15 % to −20 % by taxi fleet
Cai et al. (2019)	Max 2 users per SAV	Shanghai, China	SAVs replace taxis	−33 % by taxi fleet
Chen et al. (2017)	Max 3 users per SAV	San Francisco, New York and Los Angeles, US	SAVs replace non-pooled ride-hailing	−11 % to −19 % by ride-hailing fleet
Chen et al. (2020)	SAVs as first-mile service, max 4 users per SAV	Sembawang Town, Singapore	SAVs replace taxis	−25 % to −35 % by taxi fleet
Fagnant & Kockelman (2018)	Max 4 users per SAV	Austin, Texas	SAV replace < 11.1 % of car trips	−0.2 % to + 4.9 %
Heilig et al. (2017)	Max 4 users per SAV	Stuttgart, Germany	SAVs and other modes (PT, walk, cycle) replace cars	−20 %
Jäger et al. (2018)	Max 6 users per SAV	Singapore	SAVs replace buses	10 times more than with bus fleet
Lau & Susilawati (2021)	First-last-mile service, max 2 users per SAV	Kuala Lumpur, Malaysia	Multinomial logit between car, public transport, and SAV	−6% by cars
Levin et al. (2017)	Max 4 users per SAV.	Austin, US	SAVs replace cars	+0% to + 116 % by cars
Liu et al. (2022)	Max 2 users per SAV	Langfang, China	SAVs replace cars	−15 % by cars
Lokhandwala & Cai (2018)	Max 4 users per SAV	New York, US	SAVs replace taxis	−45 % by taxi fleet
Martinez & Crist (2015)	Three SAV types: for max 2, 5, 8 users	Lisbon, Portugal	SAVs replace cars and buses (1) or cars, buses and high-capacity PT (2)	+6% (1), +22 % (2)
Masoud & Jayakrishnan (2017)	A set of households share the ownership and utilisation of a fleet of automated vehicles, max 4 users per SAV	San Diego, US	All motorised trips replaced by SAVs	+119 % to + 146 % by cars, or equivalently + 4 % to + 17 % by cars compared to AVs
Shen et al. (2018)	First-mile service, max 4 users per SAV	Singapore	SAVs replace 10 % of buses, which have lowest demand	0 % to −~50 % less passenger car unit kilometres than with buses
Tsao et al. (2019)	Max 2 users per SAV	San Francisco, US	Compares with non-shared AV	−18 % to −23 %
World Economic Forum (2018)	Two SAV types: shared taxi with capacity 4 and shared minibus with capacities 12–16	Boston, US	Conjoint analysis with a large number of conventional and automated modes	+16 %
Zhang et al. (2015)	Max 2 trip-requests per SAV	Artificial 10x10 mile city	Compares with non-shared AV	−4.74 %
Zhu & Mo (2022)	Max 2 trip-requests per SAV (assuming multiple travellers per request)	Haikou, China	SAVs replace non-shared ride hailing trips	−8% of ride hailing VKT
Zwick et al. (2021)	Max 6 users per SAV	Munich, Germany	SAVs replace private cars (1) or incremental logit between car, car passenger, public transport, bicycle, walking (2)	−33 % to −54 % (1), +3% to + 8 % (2)

2021) to small and medium increases (WEF, 2018; Zwick et al. 2021). It is noteworthy that, among these three studies, VKT savings are reported in a car-oriented city (Kuala Lumpur, Malaysia), whereas VKT increases are reported in cities with sizable public transport shares (Munich, Germany and Boston, US).[4] That is, we find (as we will also explore later) that particularly public-transport-oriented cities may 'suffer' (in terms of increased VKT) from SAV introduction due to modal shift away from public transport. This conclusion is also echoed by Tikoudis et al. (2021) who modelled the CO2 emissions due to ridesharing in 247 cities. They report that emissions will increase in cities where public transport has high occupancy rates (in particular, in Europe and Japan) due to shift away from public transport to ridesharing. This effect may be exacerbated, according to Mo et al. (2021), if for-profit ridesharing companies prefer to serve the typically more profitable solo rides.

Two studies are worth mentioning although they do not exactly analyse the impact of SAVs on VKT. First, Tirachini et al. (2020) study the operations of a real-life company that resembles SAV in Mexico but where routes are fixed in advance (i.e., the system is not fully on-demand), finding that it can reduce VKT only under very favourable scenarios in terms of vehicle sizes and mode shifts. Second, this review has concentrated on the operational and mode-choice aspects of VKT development with SAVs. Note that, as shown in Fig. 1, there are also other reasons for changing VKT, such as induced travel. An example of a study that has explored this direction is Zhang & Guhathakurta (2021), who found increasing VKT due to residential relocations in Atlanta, US.

[4] This conclusion contrasts the discussion on the impact of geographical locations two paragraphs higher. This is because most studies do not consider the impacts of mode shift on VKT (but are instead based on assumptions of 'mode replacements').

2.3. Contribution of our study

From the review, we conclude that most of the literature analysing VKT impacts of SAVs (as reviewed in section 2.2) assume that they will replace privately-used cars, taxis or ride-hailing services. This is despite the fact that mode choice studies (as revealed in 2.1) repeatedly have highlighted the strong substitution effects between public transport and SAVs. The few studies that integrate mode choice into simulations support the proposition that VKT impacts of SAVs will depend on the current public transport ridership in the area. However, the review also has highlighted that studies are difficult to compare due to the varying assumptions, algorithms and specifications for the SAV service. This highlights the need for systematic cross-country comparisons, such as those performed by Tikoudis et al. (2021); as well as theoretical treatments (such as this paper) that explicitly consider location characteristics and current modal split in an area.

Our work builds on the stream of literature that utilises simplified models in order to obtain strategic insights. These models, sometimes referred to as strategic or *macroscopic*, have a long history in transport modelling and analysis, and still play a crucial role today. Some seminal examples are the papers by Alonso (1964) and Mohring (1972); which were instrumental to develop the first ideas on the relation between transport and land use, and on optimal bus frequencies, respectively. Small (2015) reviews the field of bottleneck models (pioneered by Vickrey (1969); and Arnott et al., 1990; Arnott et al., 1993), which has yielded numerous insights into traffic congestion. This type of approach has continued contributing to our knowledge about transport systems and in many different areas, with recent papers analysing public transport (Jara-Diaz et al. 2024), hypercongestion (Lehe and Pandey, 2024), or the potential impact of tradable credit schemes (Candia and Verhoef, 2022), among many others. In the context of AVs, van den Berg & Verhoef (2016) used a simplified setting to analyse congestion effects and optimal provision regimes; Pudāne (2020) and Yu et al. (2022) analysed the congestion impacts of various activities performed on board AVs. What all these papers have in common is that they do not expect to produce specific and accurate predictions, as they are not based on data but on simplified representation of reality; on the other hand, their discoveries are expected to be more general, and the role played by the different components of the system can often be made clear through closed-form expressions.

Our contribution lies in using the described strategic approach to analyse the expected changes on VKT when SAVs are introduced. Concretely, we set up a general mode choice model (in section 3), from which we are able to obtain some general theorems, and we then pair that mode choice model with models of transport operations in a stylised city (in sections 4 and 5). This allows us to analytically identify the main factors that could make VKT increase or decrease, in what we will define as public- or private-transport-oriented city.

3. Analysis based on a general mode choice model

Recalling that the objective of this paper is to theoretically derive the VKT impact of SAVs in public- and private-transport-oriented cities, this section provides a general abstract formulation of the problem. We focus here on the demand aspects – in particular, the travellers' sharing preferences – that determine (as shown below) whether a city develops to be private- or public-transport oriented. Only a small number of parameters summarise the SAVs and other travel mode characteristics. In other words, our insights at this stage do not depend on the specific characteristics of the SAV system and other modes, such as fares, assignment decisions, or capacities. Section 4 introduces some of these operational aspects to more concretely illustrate possible SAV application cases and derive additional insights. Note that we do not account for the induced demand in our models – the total number of passengers and their travel demand remains the same. This is in line with the discussion in section 1.1 suggesting more complex schedule changes in response to the introduction of (S)AVs instead of 'just' increasing person kilometres. Several further assumptions and their impact on the results is discussed in section 6.

We start by describing our general mode choice model. Following that, we compare mode shares and VKT in scenarios when the choice set does not (the *before* situation) and does (the *after* situation) include SAVs. The list of all variables is provided in the Appendix A.

3.1. The general mode choice model

Let us consider that travellers choose between public transport (indexed *PT*), private automobile (*A*), and shared automated vehicles (*SAV*) for their commute or another regular trip. We assume that the three modes are available for everybody, that they operate 'in parallel', and that travellers cannot use combinations of modes. We define Γ_{PT}, Γ_A, and Γ_{SAV} as the generalised travel costs of using these modes. These costs will constitute a part of the travellers' modal utilities, therefore we define them as negative (i.e., $\Gamma < 0$ for all modes). These parameters Γ encompass monetary costs and quality of service (such as walking, waiting, and in-vehicle times), but exclude one aspect that will play a crucial role: the benefit of travelling privately. It is evident that such a benefit exists, because travellers that choose to drive their cars do not only consider the monetary costs and the times involved, but also many other factors (Beirão & Sarsfield Cabral, 2007, Soza-Parra et al., 2019), such as the inconvenience of travelling with strangers. We capture all these not time- or monetary-cost-related differences between private cars and public transport by means of a function B_i^A, which we call 'Private travel benefit' for traveller i (A stands for private automobile) – see Fig. 2 for possible components of this benefit. The private travel benefit is heterogeneously distributed, and we assume its distribution to be uniform between zero and a maximum value in the population, which we denote simply B. In other words, $B_i^A = \theta_i B$, where $\theta_i \in [0,1]$ is a uniformly distributed variable (similar to the approach by Basso & Jara-Díaz, 2012). The maximum private travel benefit B represents the private travel benefit for those passengers that value travelling privately the most, and can also be interpreted as a parameter that reveals if a city is more private-transport oriented: if B is large, it means that travellers generally have a strong preference towards private modes. Theorem 1 and the following Remark, see below, proves that this parameter necessarily relates to the public transport mode share in the 'before SAV' scenario – it determines whether the city develops to be private- or public-transport oriented.

The private travel benefit applies to the three travel modes as follows. We denote by K_{PT} and K_{SAV} the capacity of public transport and shared automated vehicles, respectively. We assume that given typical public transport capacities (e.g., $K_{PT} = 50$ passengers), the associated private travel benefit is zero. In the context of our study, an important question is – would travellers experience any privacy benefit when travelling in SAVs that are considerably smaller and more comfortable than public transport (e.g., $K_{SAV} = 5$), but where the vehicle is still shared with strangers? We suggest that the answer is 'yes', although the benefit would be substantially smaller than in a private vehicle. In other words, our assumption is that the private travel benefit increases from public transport to SAVs to private AVs. This assumption has mixed support from literature: the study by Steck et al. (2018) supports it, finding the alternative specific constants[5] to be increasing in the mentioned order. However, Krauss et al. (2022) obtained that the alternative specific constant is the lowest for non-automated ridepooling, followed by public transport and private car.[6] Further, we assume that the larger the capacity of the vehicle K_{SAV}, the lower the experienced private-travel benefit in an SAV. This decrease may relate to, for example, the increasing noise, number of co-travellers, and generally decreasing comfort levels in larger vehicles.[7] Hence, we model that relationship as $B_i^{SAV} = f(K_{SAV})B_i^A$, where $f(K_{SAV})$ is a decreasing function taking values in $(0,1)$. To simplify the notation, in the rest of this section we will omit the reference to K_{SAV} and will use f instead of $f(K_{SAV})$, as well as θ instead of θ_i. We can now write the utility that would be experienced by travellers using each of the three modes:

$$U_A(\theta) = \Gamma_A + \theta B, \tag{1}$$

$$U_{PT}(\theta) = \Gamma_{PT}, \tag{2}$$

$$U_{SAV}(\theta) = \Gamma_{SAV} + \theta f B. \tag{3}$$

Let us illustrate the role of the Γ s, f, and B through an example. Commuters X, Y and Z choose their travel mode. X has a strong sharing mindset, hence $\theta_X = 0$; Y strongly value private travel with $\theta_Y = 1$; and Z assigns some value to private travel, say, $\theta_Z = 0.5$. The generalised costs of travelling by public transport are €15, including fare and the monetary equivalent of travel time components, whereas the generalised costs of travelling by car are €20. The maximum private travel benefit (i.e., the one experienced by Y) is B = €7. Therefore, in the pre-SAV scenario, X and Z would choose public transport as it maximises their utility. For X, $U_A(0) = -20 < -15 = U_{PT}(0)$, and for Z, $U_A(0.5) = -16.5 < -15 = U_{PT}(0.5)$. On the other hand, Y would travel by car as $U_A(1) = -13 > -15 = U_{PT}(1)$. When SAVs become available, they present a generalised cost of €16 and keep a third of the private travel benefit, hence $f = 1/3$. Commuters X and Y will not change their mode choices, while Z will shift from public transport to SAV: $U_{PT}(0.5) = -15 < -14.83 = U_{SAV}(0.5)$.

Note few assumptions inherent in the specification Eqs. (1)-(3). First, the additive contribution θB implies that the private travel benefit does not depend on the journey duration or other characteristics of the transport system. Alternatively, one could model this factor similarly to how crowding in public transport is often modelled – as a multiplier for the sensitivity to in-vehicle time (Jara-Díaz & Gschwender, 2003) – which would also align with the literature on value-of-travel-time impacts of (S)AVs (e.g., Steck et al., 2018). This extension would, however, mean that the general analysis (presented in this section) cannot, to any extent, be separated from the more detailed introduction of the operational aspects that endogenously determine the travel times with all modes (as introduced in the following sections). Further assumptions embedded in our mode choice model is that only θB differentiates the travellers in their mode choice, that θ is uniformly distributed and that f is constant in the population. These assumptions are discussed in section 6. Note also that the dependency between f and K_{SAV} is generally unknown. Below, we derive some theoretical results that are valid regardless of this functional form, as long as some conditions (listed below) hold. In section 5, we explore different functions f in order to obtain numerical results.

Finally, note that the mode choice in Eqs. (1)-(3) can be interpreted either as a short-term or long-term decision. A short-term trip decision implies that the user has the three alternatives available for every trip, and chooses the one that yields the maximum utility. A long-term interpretation means that the user is deciding which of the three modes to commit to, e.g., by deciding whether to acquire a car or register in an SAV program. Correspondingly, the following VKT analysis can also be seen as a result of daily or long-term mode decisions. The different short-term and long-term costs of travel modes would be reflected in what is included in the respective Γ parameters.

[5] Note that in a discrete choice framework, the private travel benefit could be interpreted as the alternative specific constant of the concerned travel mode.

[6] Despite the vast literature on SAVs, there seem to be only few empirical studies that include all three modes of interest and also disentangle baseline preferences from quality of service aspects. Therefore, it is unclear to what extent this assumption is supported empirically.

[7] Recent research has suggested that sharing with very few people might actually be worse than sharing with many due to safety concerns (Meshram et al., 2020). Our assumptions, however, require that private travel benefit is greater in SAVs than in public transport and hence do not allow to model such a scenario. We discuss the role of this assumption in section 6.

3.2. Mode shares before and after SAV introduction

Let us now derive the market share of each mode, prior and after the introduction of SAVs. As usual in mode choice models, the absolute values of the utilities (U_A, U_{PT}, U_{SAV}) do not matter, but only the differences between them. For convenience, let us denote $c = \Gamma_{PT} - \Gamma_{SAV}$, and $d = \Gamma_{SAV} - \Gamma_A$. We consider the cases where the set of parameters fulfils the following three conditions, represented in Fig. 3. These conditions jointly imply that we are interested in the cases where, after the introduction of SAVs, each of the three modes has some passengers.

1. $U_A(0) < U_{SAV}(0) < U_{PT}(0)$. This inequality means that a traveller who attaches a zero value to private travel would prefer an SAV to a private car and public transport to an SAV. If the first inequality was not true, we would have that for $\forall\theta$, $U_A(\theta) > U_{SAV}(\theta)$, and therefore the mode SAV would not have any passengers. Similarly, if the second inequality was not true, public transport would have no passengers. This condition implies that both c and d are positive (as seen by inserting $\theta = 0$ in the Eqs. (1)-(3)).
2. $U_A(1) > U_{SAV}(1) > U_{PT}(1)$. This inequality expresses that a traveller who attaches the most value to private travel would prefer a private car to an SAV and SAV to public transport. The reasoning is analogous as above: if the first inequality was not true, private cars would have no users, whereas not fulfilling the second inequality would imply that SAVs have zero passengers. This condition is equivalent to assuming that $\frac{c}{B} < f < 1 - \frac{d}{B}$ (as seen by inserting $\theta = 1$ in the Eqs. (1)-(3)).
3. Let θ_1 be such that $U_{SAV}(\theta_1) = U_{PT}(\theta_1)$ (note that this θ_1 exists because the utility graphs of SAV and PT cross in the interval$\theta \in [0,1]$ according to the previous two conditions). From Eqs. (2)-(3), this means that $\theta_1 B = \frac{c}{f}$. The third condition is that $U_A(\theta_1) < U_{SAV}(\theta_1)$, or equivalently $\Gamma_A + \frac{c}{f} < \Gamma_{SAV} + c$. If this condition was not true, then SAVs would have no passengers, as it would hold that $U_{PT}(\theta) > U_{SAV}(\theta)\,\forall\theta < \theta_1$, and $U_A(\theta) > U_{SAV}(\theta)\,\forall\theta > \theta_1$. This condition is equivalent to assuming that $f > \frac{c}{d+c}$.

We now prove some general results based on this formulation. We remark that such results are valid regardless of the specific operational characteristics of the three modes (captured by the parameters c and d), as long as the three conditions above hold, i.e., as long as the three modes have a positive market share after the introduction of SAVs. Our results eventually lead to Theorem 2 and the subsequent corollary that address the main question of this paper: under what conditions is VKT expected to increase due to the introduction of SAVs?

Theorem 1. The relative decrease in the public transport share does not depend on the maximum private travel benefit B. The relative decrease in the private vehicles share decreases with B. The number of SAV users decreases with B.

Proof of Theorem 1:. Let us denote by $P_{PT,1}$, $P_{A,1}$ the share of users of the respective modes before the introduction of SAVs, and utilise the analogous notation for the after-SAV scenario $P_{PT,2}$, $P_{A,2}$, $P_{SAV,2}$. Due to the uniformly-distributed θ, the parameter $P_{PT,1}$ corresponds to the point θ_0 where the PT and A curves intersect in Fig. 3, i.e., $\Gamma_{PT} = \Gamma_A + \theta_0 B$, implying that.

$$P_{PT,1} = \theta_0 = \frac{c+d}{B} \tag{4}$$

and

$$P_{A,1} = \frac{B-c-d}{B}. \tag{5}$$

As expected, Eqs. (4)-(5) indicate that a better public transport system (with larger c) results in a larger public transport mode share. By the same principle, after the introduction of SAV, the PT and SAV curves intersect in the point θ_1, which corresponds to $P_{PT,2}$, i.e. $\Gamma_{PT} = \Gamma_{SAV} + \theta_1 fB$, implying that

$$P_{PT,2} = \theta_1 = \frac{c}{fB}. \tag{6}$$

On the other hand, the point $\theta_2 = 1 - P_{A,2}$ where the SAV and A curves intersect is given by $\Gamma_{SAV} + \theta_2 fB = \Gamma_A + \theta_2 B$, implying that $\theta_2 = \frac{d}{B(1-f)}$ and therefore

$$P_{A,2} = \frac{B(1-f)-d}{B(1-f)} \tag{7}$$

To prove the theorem, we compute the market shares after the SAV introduction. The relative decrease in public transport share indeed does not depend on B:

$$\frac{P_{PT,2}}{P_{PT,1}} = \frac{c}{f(c+d)}. \tag{8}$$

It is noteworthy that with larger f values more PT users are lost with the introduction of the SAV, because SAVs are relatively more attractive. On the other hand, the reduction in private car share depends on B:

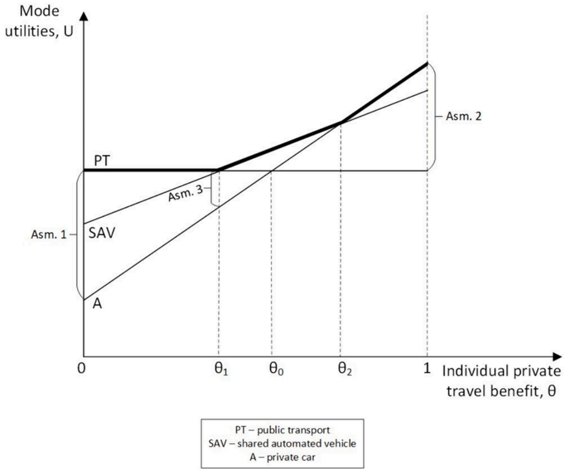

Fig. 3. The utility curves of the three modes involved as a function of θ. The bolded curve shows the maximum utility between the three modes.

$$\frac{P_{A,2}}{P_{A,1}} = \frac{B(1-f)-d}{B(1-f)-(1-f)(c+d)} \tag{9}$$

The condition (3) above is equivalent to $d > (1-f)(c+d)$. Therefore, the numerator in Eq. (9) is smaller than its denominator, and the fraction increases (becomes closer to 1) with increasing B. [8] Finally, the portion of SAV users is given by

$$P_{SAV,2} = 1 - P_{PT,2} - P_{A,2} = 1 - \frac{c}{fB} - \left(1 - \frac{d}{(1-f)B}\right) = \frac{df - c(1-f)}{f(1-f)B}. \tag{10}$$

The numerator of the last expression is positive thanks to condition (3). Therefore, $P_{SAV,2}$ is inversely proportional to B, and the proof is concluded.

Remark: As expected, the parameter B plays a crucial role in determining the mode share before and after the introduction of SAVs. In particular, the larger the B, the more private transport users at present (without SAVs). **Therefore, we say from here on that a city is *public-transport oriented* when B is small, and *private-transport oriented* when B is large.**

Theorem 1 describes how the modal split will change with the introduction of SAVs in private- and public-transport-oriented cities. To summarise, the relative change in public transport ridership is not affected by the private travel benefit B. This means that public-transport-oriented cities will lose more public transport passengers to SAVs, because they have more public transport users before SAV introduction. In private-transport-oriented cities, the percentage of users leaving the private car to start utilising SAVs will be lower, but that percentage comes from a larger number, therefore the comparison between the absolute decrease in private car users is inconclusive. This suggests, first, that private-transport-oriented cities will likely retain a large share of private car users after the introduction of SAVs. Second, public-transport-oriented cities are more attractive for SAV operators as the expected ridership is larger.

Given the terms public- and private-transport-oriented cities, as introduced in the remark above, the reader may observe that such cities (especially at the extremes) have a non-negligible share of captive public- or private-transport users, respectively. These are, for example, the travellers without a drivers' licence or residents in areas with no public transport coverage. Our response to this observation is the following. While our model formally assumes availability of both public transport and private car for all users, this does not completely exclude the so-called captive users. That is because perceived mode unavailability can be re-interpreted (especially in the long term) as endogenous to travellers' preferences. Individuals who strongly dislike travelling with strangers may not place any value in living in the vicinity of public transport services. Similarly, individuals who do not place any value on private travel may not be motivated to obtain a drivers' licence and/or purchase a car. Thereby, these travellers can actually be seen as located at the extreme ends of the private-travel-benefit θ distribution, and in that manner are captured by the model.

3.3. VKT before and after SAV introduction

Moving forward, it is relevant to explore not only the mode changes (as per Theorem 1) but also VKT changes after the introduction of SAVs. To study this, let us use $VKT^{PP}{}_{PT}$, $VKT^{PP}{}_{A}$, and $VKT^{PP}{}_{SAV}$ to denote the contribution of each person (PP – per person) to the total VKT depending on their used mode. We assume, for the time being, that $VKT^{PP}{}_{PT} < VKT^{PP}{}_{SAV} < VKT^{PP}{}_{A}$. These parameters contain the information about how efficiently each mode serves a given demand. For example, the fact that SAVs can match users efficiently but need to rebalance (i.e., sometimes it is necessary to move empty vehicles back to the high-demand areas in the city) is

[8] A function g(x)=(x-a)/(x-b), with a>b>0 is increasing, which can be seen directly by taking the derivative.

captured by $VKT^{PP}{}_{SAV}$, so that the following results do not depend on specific assumptions about such operational aspects. The following section 4 extends our model to include operational characteristics. Note that, we do not update the value of $VKT^{PP}{}_{PT}$ after the introduction of SAVs. This decision is discussed in section 6.

Theorem 2. Whether VKT increases or decreases does not depend on the maximum private travel benefit B. However, the magnitude of the VKT change is larger when B is lower.

Proof of Theorem 2. Let us calculate the average VKT per person before (with subscript 1) and after (with subscript 2) the introduction of SAV. We obtain that

$$VKT^{PP}{}_{1} = \frac{c+d}{B}VKT^{PP}{}_{PT} + \left(1 - \frac{c+d}{B}\right)VKT^{PP}{}_{A} \tag{11}$$

and

$$VKT^{PP}{}_{2} = \frac{c}{fB}VKT^{PP}{}_{PT} + VKT^{PP}{}_{A}\left(1 - \frac{d}{B(1-f)}\right) + VKT^{PP}{}_{SAV}\left(\frac{d}{B(1-f)} - \frac{c}{fB}\right). \tag{12}$$

Denoting by Z the change in VKT, we have that

$$\begin{aligned} &Z(c, d, B, f, VKT^{PP}{}_{A}, VKT^{PP}{}_{PT}, VKT^{PP}{}_{SAV}) = VKT^{PP}{}_{2} - VKT^{PP}{}_{1} = \\ &\frac{c}{B}\left[VKT^{PP}{}_{PT}\left(\frac{1}{f} - 1\right) + VKT^{PP}{}_{A} - \frac{VKT^{PP}{}_{SAV}}{f}\right] + \frac{d}{B}\left[\frac{VKT^{PP}{}_{SAV}}{1-f} - \frac{VKT^{PP}{}_{A}}{1-f} - VKT^{PP}{}_{PT} + VKT^{PP}{}_{A}\right]. \end{aligned} \tag{13}$$

Eq. (13) shows that the sign of the VKT difference does not, in general, depend on B. However, since the resulting expression is divided by B, this makes Z larger with small B values, which completes the proof.

Corollary: Z increases with $VKT^{PP}{}_{SAV}$. If $VKT^{PP}{}_{SAV} \approx VKT^{PP}{}_{PT}$, then $Z < 0$, whereas if $VKT^{PP}{}_{SAV} \approx VKT^{PP}{}_{A}$, then $Z > 0$. The threshold where the introduction of SAVs reduces VKT is given by $VKT^{PP}{}_{SAV,*} = \left(c\left[VKT^{PP}{}_{PT}(\frac{1}{f} - 1) + VKT^{PP}{}_{A}\right] - d\left[VKT^{PP}{}_{A}(\frac{1}{f} - 1) + VKT^{PP}{}_{PT}\right]\right) / \left(c - \frac{d}{1-f}\right)$.

Proof of the Corollary: First, Z increases with $VKT^{PP}{}_{SAV}$ because $VKT^{PP}{}_{2}$ does, and $VKT^{PP}{}_{1}$ is not affected by it. The other results follow from Eq. (13). If $VKT^{PP}{}_{SAV} \approx VKT^{PP}{}_{A}$, then $VKT_2 - VKT_1$ can be rewritten as $\frac{VKT^{PP}{}_{A} - VKT^{PP}{}_{PT}}{B}(d + c - \frac{c}{f})$, with both terms being positive. (Note that the second represents exactly the reduction in the public transport share.) On the other hand, if $VKT_{SAV} \approx VKT_{PT}$, Z can be rewritten as $\frac{VKT^{PP}{}_{A} - VKT^{PP}{}_{PT}}{B}(c + d - \frac{d}{1-f})$, where the second term is negative. (It represents the reduction in the private car share.) The computation of $VKT^{PP}{}_{SAV,*}$ follows directly from the inequality $Z(c, d, B, f, V^{PP}{}_{A}, V^{PP}{}_{PT}, V^{PP}{}_{SAV}) > 0$.

Theorem 2 has demonstrated how VKT changes in public- and private-transport-oriented cities. To summarise, we find that the VKT may increase or decrease in both types of cities. However, the change (whether positive or negative) would be larger in public-transport-oriented cities. In authors' opinion, this result can be regarded as bad news: if the introduction of SAVs reduces VKT, this will benefit mostly cities where the problem is more controlled (i.e., public-transport-oriented cities with a low B). In other words, SAVs will not provide a solution for car-dependent congested cities. Conversely, if SAVs increase VKT, then the cities that currently provide sustainable transportation would be strongly challenged. This is a cautionary point for transport policy, since public-transport-oriented cities are often not well-equipped to deal with a large increase in vehicle traffic.

The obtained results are schematically represented in Fig. 4, where we illustrate that only the magnitude, and not the sign, of the VKT change depends on the public- or private-transport-orientation. Furthermore, from the corollary, we have obtained that the VKT increases linearly with $VKT^{PP}{}_{SAV}$, where the slope is the mode share of SAVs.

4. Application over a simplified city representation

The previous section provides general insights about the VKT developments in different types of cities (public- or private-transport-oriented), which depend on the operational performance and the generalised user costs of the three involved travel modes. In this section, we further specify the defined key variables as functions of physical variables in the transport system (such as vehicle capacities, speed, and travel distances), and we also formalise the operational performance as an endogenous function of the number of users. This allows us to quantify the total change in VKT due to the introduction of SAVs (variable Z above). Section 5 analyses the impact of the characteristics of the city and the three involved transport modes on the mode shifts and VKT change. The MATLAB code used to create figures can be found in Fielbaum and Pudane (2024); https://doi.org/10.4121/777220e4-9a78-4653-8780-89c2572f6c81.

Note that our analysis in these two sections is a simplification, since we abstract the city[9] with a minimalistic graph (see section 4.1)

[9] The model can also be interpreted as a single corridor between two zones in a city. The conclusions and analysis remain the same under this interpretation.

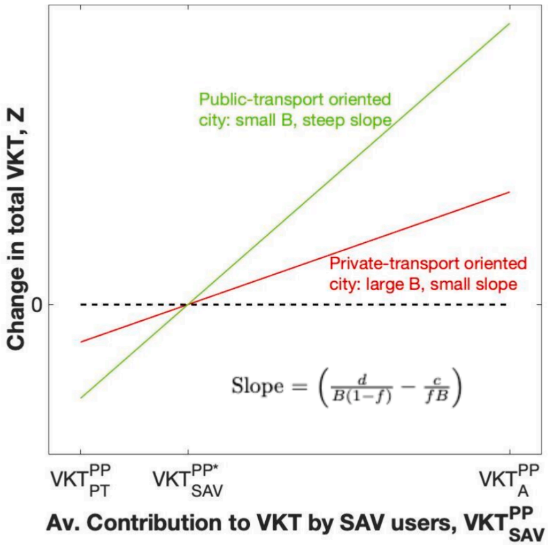

Fig. 4. A stylised representation of the change in total VKT as a function of $VKT^{PP}{}_{SAV}$. We show the results for a public-transport (green) and a private-transport (red) oriented city. The sign of Z is always the same for the two curve but the green curve is always larger in magnitude (Theorem 2). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and simplify the operation of travel modes and demand structure. As such, this section relates to the stream of literature that studies the design of mobility systems leveraging simplified representations of cities to obtain closed-form mathematical expressions, such as Badia & Jenelius (2020), Calabrò et al., (2023), Daganzo (2010), and Fielbaum et al. (2016). We remark that, like all of these papers, this minimalistic representation is accompanied by a small set of representative parameters describing the city (e.g., its size), the demand (e.g., its total level), and the costs (e.g., the running costs of a vehicle). The sources for these numeric values are provided in Table A1 in the Appendix A. Thanks to these simplifications, the computations are performed in milliseconds allowing for the comparison of numerous scenarios (as in section 5).

4.1. The city model and the operation of the three transport modes

We assume that origins and destinations of travellers are uniformly distributed in equally-sized origin and destination squares – as represented in Fig. 5. In our idealised city model, travellers only move in one direction. This is a common representation of peak travel in related literature (e.g., Basso et al., 2021; Jara-Díaz et al., 2024), where travellers commute, e.g., from the peripheries to CBD or vice versa.[10] The size of the squares' sides is denoted by L. While travelling within the squares, the SAVs pick up and drop off passengers at their origins and destinations. The number of passengers determines the detour times Det and waiting times for SAVs. Considering the operation of public transport, we assume that passengers walk from any point in the square to the public transport stop in its middle and that they also walk to their final destination after the ride. We further assume that both the SAVs and public transport operators adjust their fleets to travel at capacity at every cycle. Finally, the private car users travel door-to-door from their origin to the destination. The distance between the centres of the two squares is denoted by A. As detailed below, we denote by q the average distance between any point in a unitary square and its centre (making average walking distance in public transport equal to 2qL), and we assume that private cars need to travel on average $A + \delta L$ to connect their origins and destinations, with $0 \leq \delta \leq 2q$ (in the worst case, the vehicles also need to travel between the squares' centres). In this model, the quality of service of every mode is characterised by their waiting, walking, and in-vehicle times, when they exist (e.g., walking only takes place in public transport). This approach is standard in related literature (Jara-Diaz & Gschwender, 2003; Basso & Jara-Diaz, 2012; Calabro et al., 2023; Fielbaum, 2024). The more subjective aspects, such as comfort and privacy, are captured by the private travel benefit. We now explain the equations governing the operation and costs of each of the three modes. Unless explicitly stated, all the equations provided below are ours.

4.2. Modelling SAVs

Let us consider a service offering SAVs in the city described above. The company decides how many vehicles to offer Q_{SAV}. The number of vehicles affects the quality of service, because more vehicles imply shorter waiting times. Therefore, a reactive demand will

[10] If a small number of passengers were travelling in the opposite direction, the VKT would still be mostly explained by the main direction. This is because the larger demand would mostly determine the fleet size for public transport and SAVs and the longest detours for SAVs. Therefore, considering the assumption, we believe that it does not significantly affect the comparison between the different modes.

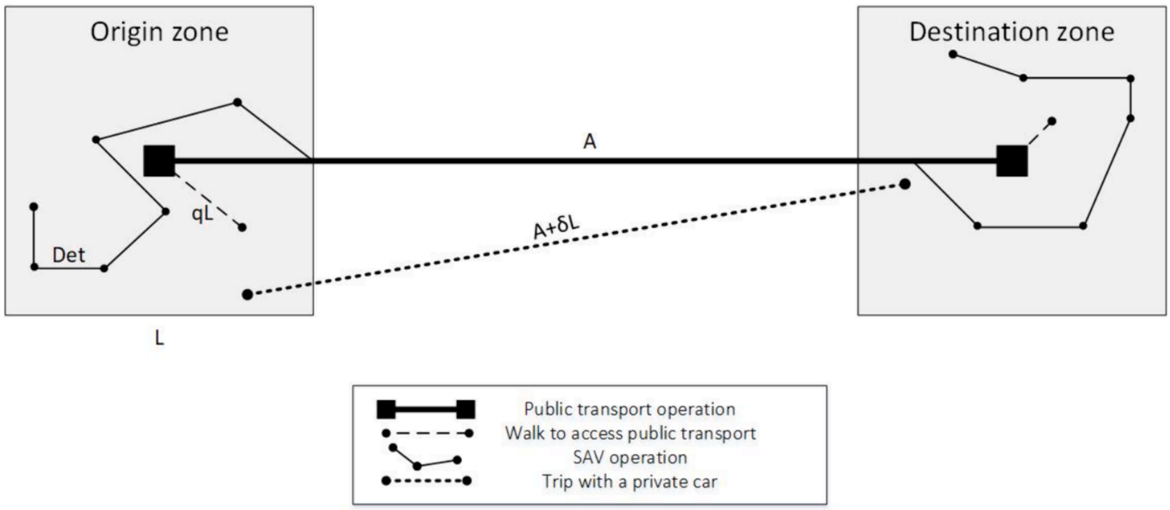

Fig. 5. Representation of the stylised city and the three involved transport mode: public transport, private vehicles, and SAVs.

increase with Q_{SAV} and decrease with the fare F_{SAV}. Let us denote by N_{SAV} the number of users per time unit and by K_{SAV} the capacity of the vehicles. We now explain in detail the operation of the fleet of SAVs, after which we compute the resulting fleet size Q_{SAV} and fare F_{SAV}.

4.2.1. Pooling – detours and sharing

Up to K_{SAV} passengers can travel together in an SAV. Considering their contribution to the VKT, an SAV has the advantage over a private car, because it uses one instead of K_{SAV} vehicles. On the other hand, the route of each vehicle is longer than that of a private car due to the detours to pick up and drop off every user. Let us denote by $\mathrm{Det}(K_{SAV})$ the average detour when serving K_{SAV} users. The total length toured by a vehicle in order to serve all the users is

$$\mathrm{Len}_{SAV} = A + 2\mathrm{Det}(K_{SAV}). \tag{14}$$

Eq. (14) includes A, the time needed to connect the two squares, and two times the average detour $\mathrm{Det}(K_{SAV})$, since there is a detour at the origin and another at the destination. As we assume that origins and destinations are randomly located within the squares with a side length of L, the average length of the detour corresponds to the expected length of the solution to the well-known *travelling-salesman-problem* (TSP); hence, following Fielbaum et al. (2024) and Valenzuela & Jones (1997), we can approximate it as

$$\mathrm{Det}(K_{SAV}) = \gamma L\sqrt{K_{SAV}}, \text{ with } \gamma \approx 0.71 \tag{15}$$

4.2.2. Rebalancing

After dropping the passengers off, the vehicles need to return empty to the origin square. This need for rebalancing induces extra VKT that is not relevant for private (non-automated) car users. Note that, in reality, the SAVs would probably transport some travellers in the opposite direction and thus may incur small detours on the way back as well. However, this fact does not significantly affect our derivations, since the demand in the main direction would still be the main determinant of the fleet size and travel times for SAVs. We simplify our derivations by assuming that the empty travel simply connects the two zones; thus, it has the length A.

4.2.3. Resulting fleet size

Putting everything together, and denoting by v_c the velocity of the motorised vehicles,[11] the total time needed by a SAV to tour a whole cycle is

$$t_{c,SAV} = \frac{1}{v_c}\left(2A + 2\gamma L\sqrt{K_{SAV}}\right). \tag{16}$$

One SAV performs $\frac{1}{t_{c,SAV}}$ cycles per time unit and transports $\frac{K_{SAV}}{t_{c,SAV}}$ users in that time. As N_{SAV} passengers are utilising the system, we conclude that the system needs a number of vehicles given by

[11] We assume that all the motorised vehicles (SAV, private vehicles, and public transport) have the same speed. This is done because which mode is faster depends on the specific infrastructure that is different for every city. Therefore, a neutral assumption as we do here is the best way to avoid any bias.

$$Q_{SAV} = \frac{2N_{SAV}(A + \gamma L\sqrt{K_{SAV}})}{v_c K_{SAV}}. \tag{17}$$

Eq. (16) assumes the system is at steady state, so that when the vehicle arrives to the origin square, K_{SAV} passengers have already emerged. We can show that this assumption holds as follows. The average headway between two consecutive vehicles is $t_{c,SAV}/Q_{SAV}$, so $N_{SAV}t_{c,SAV}/Q_{SAV}$ users emerge in that time lapse. Therefore, we need that $K_{SAV} \le N_{SAV}t_{c,SAV}/Q_{SAV}$ so that K_{SAV} passengers have arrived before the departure of each vehicle. This inequality is actually an equality due to Eqs. (16)-(17).

4.2.4. *Quality of service*

The two features that define the quality of service for SAVs are the waiting and in-vehicle times. Regarding the former, we assume that the vehicle departs from the square's centre immediately after the K_{SAV} passengers have emerged, whereby the average waiting time for the SAV passengers is

$$t_{w,SAV} = \frac{K_{SAV}}{2N_{SAV}} + \frac{L}{2v_c}\gamma\sqrt{K_{SAV}}. \tag{18}$$

The average waiting time defined in Eq. (18) is a sum of two terms. The first term represents the time waiting for the users to emerge: it takes $1/N_{SAV}$ for one user to emerge, thus K_{SAV}/N_{SAV} for all the users to arrive, and this is divided by two because we calculate the average. The second term in Eq. (18) represents the time that passengers spend waiting while the vehicle travels from the square's centre to their location. This term is based on the average detour $Det(K_{SAV})$ obtained in Eq. (15), and it is also divided by two to calculate the average.

The in-vehicle time is

$$t_{v,SAV} = \frac{A}{v_c} + \frac{L}{v_c}\gamma\sqrt{K_{SAV}}. \tag{19}$$

The average in-vehicle time defined in Eq. (19) is a sum of two terms. The first one represents the time spent travelling from the origin square to the destination one. The second term is the detour time: it is divided by two to obtain the average travel time and multiplied by two to capture detours both at the origin and destination squares as per Eq. (15).

4.2.5. *Pricing*

We assume a regulated competitive market, meaning that average users' costs should be equal to the systems' marginal costs, and an optimal subsidy might be allocated if this is efficient from a microeconomic perspective (Jara-Díaz and Gschwender, 2009).[12] We follow the method proposed by Jansson (1984) and Jara-Díaz & Gschwender (2009) for the case of public transport, where the main aspect is acknowledging that users' time must be included in the total costs when following the principle "price = marginal costs". Crucially, users' costs UC_{SAV} can be calculated as the sum of the fare F_{SAV}, their time-related costs, minus the private travel benefit: $UC_{SAV} = F_{SAV} + \alpha_v t_{v,SAV} + \alpha_w t_{w,SAV} - \frac{1}{2}fB$, where the last term is divided by 2 because it represents the average benefit.

As this is a competitive market, each user's cost UC_{SAV} has to be equal to the total marginal costs of the system. In the previous paragraph, we calculated UC_{SAV}, so let us now compute the total costs of the system. Denoting by c_{SAV} the hourly cost of operating one vehicle, which encompasses capital costs, fuel or electricity, maintenance, etc., total operators costs' are given by $c_{SAV}Q_{SAV}$. Total users' costs are $N_{SAV}(\alpha_v t_{v,SAV} + \alpha_w t_{w,SAV} - \frac{1}{2}fB)$, where we exclude the fare as it is a transfer between two agents (in other words, in the total costs of the system the fare would appear with a negative sign for the operators and with a positive sign for the users). Putting everything together, we obtain that

$$F_{SAV} + \alpha_v t_{v,SAV} + \alpha_w t_{w,SAV} - \frac{1}{2}fB = \frac{d}{dN_{SAV}}\left(c_{SAV}Q_{SAV} + N_{SAV}\left[\alpha_v t_{v,SAV} + \alpha_w t_{w,SAV} - \frac{1}{2}fB\right]\right). \tag{20}$$

where the left side is the average user cost and the right side is the derivative of the total costs, i.e., the marginal costs. Combining Eqs. (17)-(20) and eliminating the terms that cancel out we obtain the following:

$$F_{SAV} = \frac{2(A + \gamma L\sqrt{K_{SAV}})c_{SAV}}{v_c K_{SAV}} - \frac{\alpha_w K_{SAV}}{2N_{SAV}}. \tag{21}$$

The negative term appears because there are scale economies: more users reduce waiting times for everybody through a larger fleet. This phenomenon has been described as the SAV-version of the *Mohring Effect* by Fielbaum et al. (2023).

4.3. *Public transport model*

We assume a public transport system that accounts for users' and operators' costs. For an exogenous capacity K_{PT}, it must hold that

[12] Further research should investigate the sensitivity of the results to different market configurations: e.g., a monopoly or oligopoly able to set the fares at different levels.

$$N_{PT} = \rho K_{PT}. \tag{22}$$

Here, ρ is the public transport frequency. Eq. (22) implies that frequencies are set such that buses run full, thus the number of users travelling by public transport N_{PT} is equal to the total capacity offered by the system ρK_{PT}. Similar to the SAV case above, and following Jara-Díaz and Gschwender (2009); the public transport fare F_{PT} should be computed as the total marginal costs of the system minus what users pay through their time. To compute the fare, let us begin by noting that the total cycle time is

$$t_{c,PT} = \frac{2A}{v_c}. \tag{23}$$

Here, the multiplication with two happens because buses have to go back and forth in a complete cycle. This implies that the total number of buses $Q_{PT} = \rho t_c$ is equal to

$$Q_{PT} = \frac{2AN_{PT}}{v_c K_{PT}}. \tag{24}$$

Users' costs are defined via the unitary value of one time unit walking (to access the vehicle) α_a, waiting α_w, and in-vehicle α_v:

$$UC_{PT} = N_{PT}(\alpha_a t_a + \alpha_w t_w + \alpha_v t_v). \tag{25}$$

Walk time is a fixed quantity that does not depend on the number of buses nor the frequencies. Recall that q denotes the average distance between a point and the centre of a square with unitary edge.[13] Hence, the walk time is

$$t_{a,PT} = \frac{2qL}{v_a}. \tag{26}$$

Here, v_a is the walking speed, and the multiplication with two happens because users need to walk at the origin and at the destination. Regarding waiting time, as users arrive uniformly and we assume the headway $\frac{1}{\rho}$ between consecutive buses to be constant (i.e., buses are perfectly coordinated), users wait on average half of that time:

$$t_{w,PT} = \frac{K_{PT}}{2N_{PT}}. \tag{27}$$

Eq. (27) incorporates the so-called "Mohring Effect", a source of scale economies in public transport, where more users diminish the waiting times for everybody. Finally, in-vehicle time is constant (for the sake of simplicity, we disregard the time spent at stops, see Jara-Díaz & Tirachini, 2013):

$$t_{v,PT} = \frac{A}{v_c}. \tag{28}$$

Putting Eqs. (22)-(28) together, and denoting by c_{PT} the total costs per bus, we obtain the monetary fare:

$$F_{PT} = \frac{2Ac_{PT}}{v_c K_{PT}} - \frac{\alpha_w K_{PT}}{2N_{PT}}. \tag{29}$$

Eq. (29) is obtained following the same procedure as in Eq. (20): that is, by equating average users costs to the marginal total costs of the system. The first term in Eq. (29) is exactly equal to the average operators' costs. The second term, also related to the Mohring Effect, implies that subsidies are necessary, which is a usual result in public transport due to the presence of sources of scale economies (Hörcher & Tirachini, 2021).

4.4. Private cars

Private cars are straightforward to analyse. They incur a fixed monetary cost c_A, and an average travelling time equal to $t_{v,A} = \frac{A+\delta L}{v_c}$. The parameter δ represents the movement within the squares, so it depends on the topology of the network. If all vehicles need to travel through the same arc as the public transport buses, i.e. if the only connection between the two squares is via their centres, then $\delta = 2q$. If there are plenty of connections, a reasonable assumption is that $\delta = 0$, meaning that on average users travel a quite similar distance to the one between the centres. In general, we assume $0 \le \delta \le 2q$.

4.5. Summary: Mode utilities, mode shares and VKT

In order to analyse the mode shares and VKT emerging from the setting introduced in 4.1–4.4., we insert these operational re-

[13] The parameter q is approximately 0.3, see https://math.stackexchange.com/questions/15580/what-is-average-distance-from-center-of-square-to-some-point#:~:text=The%20%5Bfinal%5D%20integral%20you%20are,1%2B%E2%88%9A2, accessed on 24/05/2022.

lationships into the parameters Γ_{PT}, Γ_A, Γ_{SAV}. Recall that these parameters (which we name generalised travel costs) represent the portion of utility without the private travel benefit. The complete expression for the parameters is as follows:

$$\Gamma_{SAV} = -(F_{SAV} + \alpha_w t_{w,SAV} + \alpha_v t_{v,SAV}) = -\frac{1}{v_c}\left[\frac{2Ac_{SAV} + 2\gamma L\sqrt{K_{SAV}}\,c_{SAV}}{K_{SAV}} + \alpha_v A + \alpha_v L\gamma\sqrt{K_{SAV}} + \alpha_w \frac{L\gamma\sqrt{K_{SAV}}}{2}\right], \tag{30}$$

$$\Gamma_{PT} = -(F_{PT} + \alpha_w t_{w,PT} + \alpha_v t_{v,PT} + \alpha_a t_{a,PT}) = -\frac{2Ac_{PT}}{v_c K_{PT}} - \frac{\alpha_v A}{v_c} - \frac{\alpha_a qL}{v_a}, \tag{31}$$

$$\Gamma_A = -c_A - \alpha_v \frac{A + \delta L}{v_c}. \tag{32}$$

Note further that the three key conditions discussed in section 3 are not guaranteed to hold, as they depend on all of the parameters. We make sure that the conditions are fulfilled in the numerical illustrations following in section 5.

Using the expressions of Γ_{SAV}, Γ_{PT} and Γ_A above, we further analyse the impact of transport system variables on the mode shares and VKT. As a reminder, the mode shares before (index 1) and after (index 2) the introduction of SAVs are as follows (obtained in section 3):

$$P_{PT,1} = \frac{\Gamma_{PT} - \Gamma_A}{B}, \tag{33}$$

$$P_{A,1} = \frac{B - \Gamma_{PT} + \Gamma_A}{B} \tag{34}$$

$$P_{PT,2} = \frac{\Gamma_{PT} - \Gamma_{SAV}}{fB} \tag{35}$$

$$P_{A,2} = \frac{B(1-f) - \Gamma_{SAV} + \Gamma_A}{B(1-f)} \tag{36}$$

$$P_{SAV,2} = \frac{(\Gamma_{SAV} - \Gamma_A)f - (\Gamma_{PT} - \Gamma_{SAV})(1-f)}{f(1-f)B} \tag{37}$$

These mode shares determine the VKT impact of the SAV:

$$VKT_2 - VKT_1 = N[(P_{PT,2} - P_{PT,1})VKT^{PP}{}_{PT} + (P_{A,2} - P_{A,1})VKT^{PP}{}_{A} + P_{SAV,2}VKT^{PP}{}_{SAV}] \tag{38}$$

Here, N is the total number of travellers in the system (recall that we do not consider any new demand induced by the introduction of the SAV system). The equation requires input about the VKT generated by serving one passenger with each of the three modes. The preceding setup allows us to specify these VKT contributions:

$$VKT^{PP}{}_{SAV} = \frac{1}{K_{SAV}} t_{c,SAV} v_c = \frac{2A + 2\gamma L\sqrt{K_{SAV}}}{K_{SAV}}, \tag{39}$$

$$VKT^{PP}{}_{A} = A, \tag{40}$$

$$VKT^{PP}{}_{PT} = \frac{1}{K_{PT}} t_{c,PT} v_c = \frac{2A}{K_{PT}}. \tag{41}$$

Eq. (39) can be interpreted as follows: the VKT per passenger in SAVs are equal to the kilometres travelled in one cycle, divided by the number of users transported in that cycle. The same analysis holds for public transport (Eq. (41)). The case of cars is straightforward. These equations are sufficient to analyse the role of various system characteristics in the following section.

5. Role of system characteristics in mode shifts and VKT

The previous section has set up the dependencies between system characteristics and the modal shares and VKT impacts of SAVs. Many characteristics have an impact there, including distances between the destinations, vehicle speeds, costs and fares. In this section, we select three characteristics that are especially important either because they can be relatively easily controlled by the operator or because they describe policy-relevant SAV implementation scenarios. First, we expect that the mode choice is strongly influenced by the parameter B, i.e., the public- versus private-transport orientation of the city. This result was already analysed in section 3. The current section allows us to demonstrate this impact in the stylised city, introduced in section 4. The second characteristic is the capacity of SAVs, which is decided by the operator. As discussed above, larger vehicles will face longer detours, but induce less VKT and require lower fares, becoming more different to private vehicles and more similar to public transport. Finally, we analyse the impact of the shape of the function $f(K_{SAV})$. As introduced earlier, this function characterises the private travel benefit that travellers experience in an SAV. Clearly, the link between the capacity K_{SAV} and this subjective experience is unknown at present.

Hence, we analyse three possible specifications in this regard. In this section, we discuss the role of these three characteristics and provide numerical illustrations.

To do so, we combine the analysis of the relevant equations with representative illustrations of them. The parameter values that are used in these illustrations are shown in Table A1 in the Appendix A. The base values for the three characteristics are $B = 10€$, $K_{SAV} = 4$, $f(K_{SAV}) = f_{min} + (f_{max} - f_{min})\frac{K_{max} - K_{SAV}}{K_{range}}$. We specify the upper and lower bounds for function $f(K_{SAV})$ as $f_{max} = 0.5$ and $f_{min} = 0.25$. This setting means that the privacy aspect is lost ($f_{max} < 1$) whenever the vehicle is shared. However, the SAV users still benefit slightly from the private travel even with larger capacities due to the more private environment or simply higher comfort of the smaller vehicle (compared to public transport; $f_{min} > 0$). We consider capacities $K_{SAV} = \{2, ..., 12\}$, thus $K_{range} = 10$. This large variation is supported by literature: at least values from 2 (Tsao et al., 2019) to 10 (Alonso-Mora et al., 2017) have been considered. The default capacity $K_{SAV} = 4$ is a frequently-assumed value, as shown in Table 2.. When we analyse one of the characteristics (e.g. K_{SAV}), we use the base definition for the other variables.

5.1. Role of B: Private- versus public-transport orientation of a city

We first study the effect of B – the indicator capturing the maximum private travel benefit gained by car users. To do so, we show in Fig. 6 the mode shares before and after the introduction of SAV (left) and the resulting changes in VKT (right). Note that Eqs. (33)-(37), (39)-(41) do not depend on the total number of users in the system, so we show the average VKT per person.

Let us first focus on the left side of Fig. 6. Before SAV introduction (solid lines), the public transport share is larger when B is small. This confirms that B is indeed a fitting indicator for the public- vs private-transport orientation of the city, as stated in the Remark following Theorem 1. Following are the observations from the figures that align with the theoretical results in section 3:

1. SAVs attract more passengers in public-transport-oriented cities. In this example, the difference is significant: the SAV mode shares are 12 % and 58 % in the most private- and public-transport-oriented cities, respectively.
2. SAVs become the dominant transport mode replacing public transport when B is small.
3. Relative reduction in the public transport share is constant, as also predicted by Theorem 1.
4. The reduction in the private transport share decreases with B. In this case, the difference is large: 33 % of private car users shift to SAVs in public-transport-oriented cities and 7 % do so in private-transport oriented cities.

Taken together, these observations point towards a crucial finding of this paper: **although public-transport-oriented cities may be more attractive for SAV operators (it would attract a large ridership), their introduction in such locations would likely work against the sustainability goals of the cities**. This is evident from the discussed modal shifts and further corroborated by the following VKT analysis.

Let us now analyse the right side of Fig. 6. As stated in Theorem 2, the sign of the change does not depend on B (i.e., the curves do not intersect), and in this case we obtain that VKT increases. As also predicted by Theorem 2, public-transport-oriented cities are more heavily affected, meaning that the absolute distance between the two curves in Fig. 6 (right) is greater towards the left of the image. This **poses a strong warning on the potential negative consequences of SAVs in public-transport-oriented cities**. In section 5.2 we show that with larger K_{SAV} values (e.g., $K_{SAV} = 9$, see Fig. 8 below) a reduction in VKT is attainable. According to Theorem 2, the reduction would also be more pronounced in public-transport-oriented cities. However, in our examples (section 5.2) this reduction is small, and the risk of increased VKT is more policy relevant.

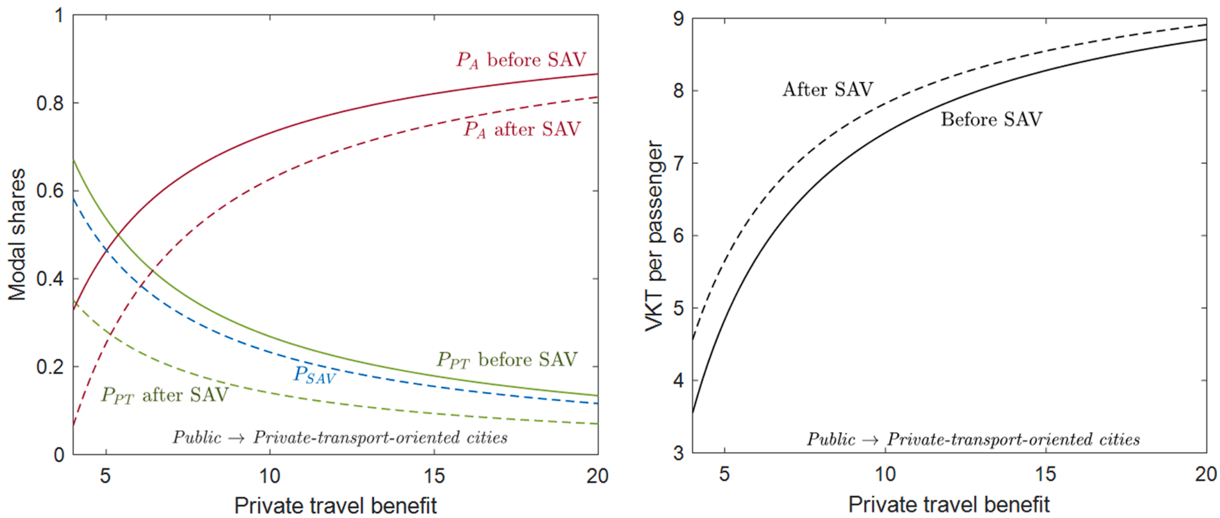

Fig. 6. Changes in the modal shares (left) and in VKT (right) when SAVs are introduced, for public- and private-transport-oriented cities.

Conversely, **SAV introduction in private-transport-oriented cities is likely unattractive for both operators and policy makers.** For operators, this location is unattractive, because they would capture only a small market share. For policy makers, more important than the small VKT increase or decrease would likely be the shift away from public transport, which would undermine the efforts to improve transport sustainability in the private-transport-oriented city.

5.2. Role of K_{SAV}*: Capacity of the SAVs*

As stated earlier, K_{SAV} is a relevant characteristic, because it can be easily controlled by the SAV operator or policy and because it can have a significant impact on the mode shifts and VKT. We first analyse two extremes − very small and large vehicles.

Small K_{SAV}. Comparing Eqs. (39) and (40) reveals that SAVs with $K_{SAV} = 2$ are less sustainable than private vehicles in terms of per-person VKT contribution (whereas SAVs with $K_{SAV} = 3$ are more sustainable). Although the sign of the VKT change here is largely due to the set-up of empty travel-back (see section 4.2),[14] the qualitative result is general: **introducing a SAV system in which only few passengers share the vehicle has lower potential of decreasing VKT regardless of which users shift to SAVs. This is because a large VKT share comes from the empty rebalancing trips and they simultaneously have a lower VKT benefit from pooling.** It is noteworthy that as private vehicles do not rebalance, they need parking space, which is a negative externality not considered in our model.

Large K_{SAV}**.** It is reasonable to assume that for larger values of K_{SAV}, SAVs are more sustainable than private cars in terms of per-person VKT contribution (in our numerical results, this is already true for $K_{SAV} = 3$). From Eqs. (39)-(40) it can be seen that this holds when A is considerably larger than L, and this difference becomes more significant with larger K_{SAV}. This conveys that the VKT savings due to sharing outweigh the empty rebalancing and detours.

Hence, especially for large K_{SAV}, the modal shifts to SAVs are critical for determining the VKT impact of SAVs. On the one hand, the corresponding small $f(K_{SAV})$ means that SAVs are less attractive for travellers who value private travel benefit (see Eq.3). This can be seen as the slow increase of the SAV utility in Fig. 7, which means that it resembles public transport. On the other hand, a large K_{SAV} means that users face longer detours and waiting times but pay lower fares (this last aspect is partially compensated because c_{SAV} increases with K_{SAV}.), thus Γ_{SAV} might increase or decrease. If Γ_{SAV} decreases it is likely that large SAVs would have zero or negligible market share (because both components of $U_{SAV} = \Gamma_{SAV} + f(K_{SAV})B$ would decrease). Let us study the case in which Γ_{SAV} increases. Eqs. (5)-(7) imply that

$$P_{A,1} - P_{A,2} = -\frac{c+d}{B} + \frac{d}{B(1-f)} = -\frac{\Gamma_{PT} - \Gamma_A}{B} + \frac{\Gamma_{SAV} - \Gamma_A}{B(1-f)}. \tag{42}$$

In the case of public transport, we obtain that

$$P_{PT,1} - P_{PT,2} = \frac{\Gamma_{PT} - \Gamma_A}{B} + \frac{\Gamma_{SAV} - \Gamma_{PT}}{fB} \tag{43}$$

Eqs. (42) and (43) are quite similar. In both cases, only the second term depends on K_{SAV}. Since the change in the numerator is the same in both (through Γ_{SAV}), the impact of K_{SAV} is determined by the denominators. With larger capacities K_{SAV}, the denominator increases in Eq. (42), which makes the modal shift from private cars smaller. At the same time, the denominator in Eq. (43) decreases, making the shift from public transport larger. In other words, larger SAVs attract more passengers from public transport, which leads to an unsustainable overall change. Note that this can be intuitively explained by stating that **when the SAVs are large, they become increasingly similar to public transport, so most people using SAVs would be former public transport passengers.** This is illustrated in Fig. 7, where the SAV slope is flatter than in Fig. 3, reflecting the larger shift from public transport.

The above arguments imply the following corollary.

Corollary: Operating SAVs with either very small or very large vehicles is more likely to increase VKT, and for different reasons. When vehicles are too small it is due to operational reasons (pooling may not compensate for rebalancing), and when they are too large for demand-related reasons (SAVs would induce a modal shift from public transport**).**

Given this result, a reasonable question is whether there exists a 'sweet spot' where SAVs with intermediate capacities lower the VKT. This is studied in Fig. 8, where the x-axis represents the capacity of SAVs; we leave the case of $K_{SAV} = 2$ out of the picture, because SAV share results to be negligible in that case. Several aspects are worth highlighting:

1. A small K_{SAV} indeed leads to an increase in VKT. Note that this occurs even when SAVs attract a similar number of users from PT and from private vehicles. Hence, the reason behind this VKT increase is that SAVs are not sustainable (at least in our model).
2. The largest mode share of SAVs is reached with $K_{SAV} = 5$. While for low values of K_{SAV} the SAV users come from both public transport (52.5 % with $K_{SAV} = 3$) and private cars (47.5 % with $K_{SAV} = 3$), when K_{SAV} becomes large most users come from public transport (75 % with $K_{SAV} = 12$).
3. When K_{SAV} increases, VKT first decreases and then increases, matching the discussion above. At the largest considered K_{SAV} values almost nobody shifts from private vehicles.

[14] The literature review in section 2 revealed that VKT decrease with small SAVs (with capacity 2) is certainly attainable given advanced assignment and routing algorithms.

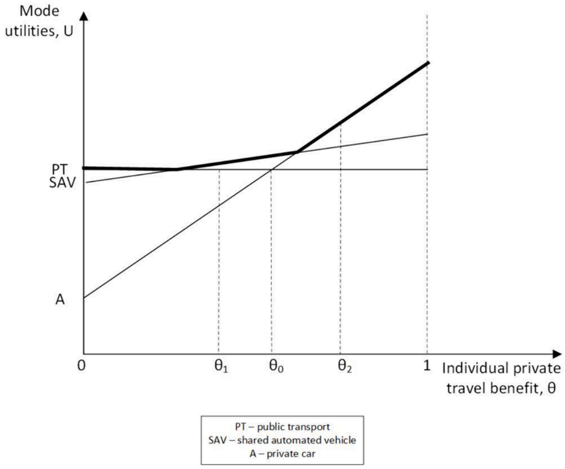

Fig. 7. Utilities of the three modes, and the resulting mode shares, when K_{SAV} is large.

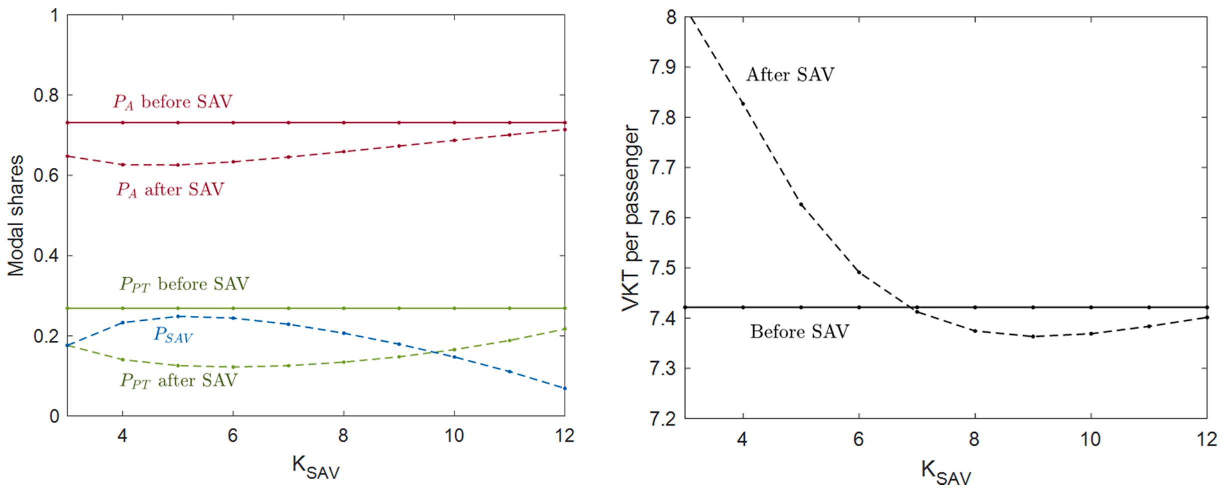

Fig. 8. Changes in the modal shares (left) and in VKT (right) when SAVs are introduced, as a function of their capacity.

4. In our numerical experiments, **we obtain a small reduction in VKT for intermediate values of** K_{SAV}. Hence, it is possible for SAVs to slightly reduce the negative externalities associated with transport. However, this possibility is very sensitive toward the type of city and operational decisions.
5. The capacity that minimises VKT ($K_{SAV} = 9$) differs from the capacity that maximises SAV usage ($K_{SAV} = 5$). This means **that there is a mismatch between SAV operators' interests and cities' sustainability goals**, so that regulation is needed.

The impact of SAV capacities was also theoretically analysed by Bahamonde-Birke (2022). Although the paper utilises a different model set-up, its conclusion of beneficial intermediate capacities aligns with ours.

5.3. Role of f: Private travel experience in SAVs

The preceding results are clearly influenced by the assumed private travel experience in SAVs, which is captured by the function $f(K_{SAV})$. Specifically, recall from section 3 that $B_i^{SAV} = f(K_{SAV})B_i^A$. That is, we assume that travellers would retain exactly the share $f(K_{SAV})$ of their private travel benefit B_i^A when using a SAV compared to a private car. How this share varies with the capacity of the SAV depends on aspects such as noise levels, available space, arrangement of the seats in the vehicle, as well as the riding comfort, which is typically lower in larger vehicles. Additional factors could relate to possible security risks that may depend on vehicle capacity. All of these factors would likely influence the ability of passengers to engage in activities (e.g., working, sleeping, eating) during travel, which may be one of the main benefits of more private travel.

Given that there is reasonable uncertainty regarding how the vehicle capacity would influence the private travel experience, we test several functional forms of $f(K_{SAV})$:

1. Linear decrease (assumed so far):$f(K_{SAV}) = f_{min} + \frac{K_{max} - K_{SAV}}{K_{max} - K_{min}}(f_{max} - f_{min})$
2. Constant (private-travel experience does not depend on K_{SAV}):$f(K_{SAV}) = f_{max}$
3. Inversely proportional decrease[15]: $f(K_{SAV}) = f_{min,*} + \frac{K_{min}}{K_{SAV}}(f_{max} - f_{min,*})$, with $f_{min,*} = \frac{f_{min} - f_{max} K_{min}/K_{max}}{1 - K_{min}/K_{max}}$

We have deliberately selected the functional forms 2) and 3) as less and more rapid decrease of private travel benefit compared to the so-far assumed linear decrease 1), see Fig. 9 (right). Intuitively, a more rapid decrease of the private travel benefit means that travellers would experience the SAV journey as similar to PT at smaller capacities K_{SAV}. Vice versa, a slow (or no) decrease in the private travel benefit would signify that travellers experience the journey in SAVs as more similar to private cars even at larger capacities K_{SAV}. We can expect that more rapid decrease would therefore lead to more public transport passengers shifting to SAVs, and slower decrease may attract more private car users. Consequently, a more rapid decrease would lead to higher VKT. This expectation is generally confirmed in Fig. 9 (left). It is 'easier' to achieve a VKT reduction by selecting a larger SAV capacity, if the travellers continue to switch from private cars at the same rate (constant $f(K_{SAV})$ case). The only exception occurs when K_{SAV} is low, where a greater $f(K_{SAV})$ can yield higher VKT: this happens because – as discussed above – SAVs are less sustainable when they use small vehicles, so a larger mode share (thanks to an increased $f(K_{SAV})$) in this case increases the VKT.

In sum, this analysis suggests that **a way to make the introduction of SAVs more sustainable, is to make the on-board experience more similar to a private trip**. This argument is intuitive: if SAVs are perceived as comfortable as a private vehicle but yet are shared, then they may attract car users to a more sustainable mode. Sanguinetti et al. (2019) analyse and offer guidance for how to enhance on-board experience and minimise disruption from co-travellers in an SAV.

6. Discussion of model assumptions

In any work, and in particular studies of theoretical character, such as ours, there are a number of unavoidable assumptions. In this section, we discuss our model results from the previous sections in light of these assumptions. In particular, we aim to conclude whether any assumption, when relaxed, would change the direction of our conclusions and/or make the results more or less extreme.

Assumption 1: Only the individual private travel benefit θB differentiates travellers in their mode choice

In our model, the only source of heterogeneity among the users is the individual private travel benefit θB. This property could be relaxed by adding a random term ε (of, e.g., Gumbel distribution as is conventional in logit models) to the utility functions (1)-(3). Unfortunately, this relaxation would prevent us from obtaining the closed-form expressions for the mode shares in section 3.2. We further note that having non-random utility functions is a usual simplification in transport equilibrium models (e.g., the classical concept of Wardrop Equilibrium relies on it), and it is a set-up even in high-level mode choice models, such as the one by Mogridge et al. (1987) from which the well-known Down-Thomson paradox is derived.

We now discuss the consequences of potentially relaxing this assumption. If a random term ε is included in functions (1)-(3), the chosen travel mode would not be solely determined by a comparison of the deterministic (given θ) utility functions as shown in Fig. 3. Instead, even when a certain utility is the maximum of the three, the model would assign a positive share of travellers to the other two modes. We expect the main impact of this relaxation to be a lower share of SAV users in all scenarios. This is because SAVs are, in the present model, chosen given a lower utility margin over the other modes – such lower margin is more easily compensated by the random term. Thereby, our model results of changed VKT would become less extreme – we would likely observe smaller increases or decreases in the VKT. However, we expect that the direction of our conclusions would remain unchanged.

Assumption 2: The distribution of the private travel benefit is uniform in the population: $\theta \in \mathbf{U}(0,1)$

This assumption allows us to easily derive the mode shares (4)-(7) before and after SAV introduction from Fig. 3. Arguably, a single-peaked distribution (such as normal or log-normal distribution) may be a better fit for many phenomena, including the private travel benefit of interest here, than the uniform distribution with sharp cut-off values. Replacing the uniform distribution with such alternatives would complicate the following derivations, and likely closed-form results may no longer be attainable. If single-peaked θ distributions replaced the uniform distribution in our model, we expect that the popularity of SAVs would increase in all scenarios. That is because SAVs are generally chosen with intermediate θ values (see Fig. 3). Nevertheless, this result would depend on the exact placement of the peak in relation to the θ values that lead to SAV choice. With increasing SAV shares our obtained VKT changes (being positive or negative) would be larger. We expect that the direction of our conclusions would otherwise remain the same.

Assumption 3: Relative private travel benefit f in an SAV is the same for all travellers

The specification (1)-(3) implies that any traveller (with a given individual parameter θ) values the privacy in an SAV as inferior to the privacy offered by a private car, and the relative value of both is a constant f. A more detailed mode choice model could consider that there may be heterogeneity in the population in terms of private travel perception. For example, SAVs may offer relatively quiet rides with few other travellers, but preclude listening to loud music or freely talking by phone; for some travellers, the quiet environment may be more important, while others may place a higher value on the ability to make phone calls, making the constant f less realistic. If the constant f is replaced with an individual-specific f value, and if the distribution of f does not relate to the distribution of the private travel benefit θ, then we expect that our conclusions of mode shifts and VKT change would not be affected. This relaxation would introduce noise around the SAV utility line in Fig. 3, which, however, should not substantially affect the aggregate mode shifts.

Assumption 4: Private travel benefit is greater in SAVs than in public transport (or: $f > 0$)

[15] The inversely proportional formula is specified to maintain f(Kmin)=fmax and f(Kmax)=fmin in the same way as the linear formula.

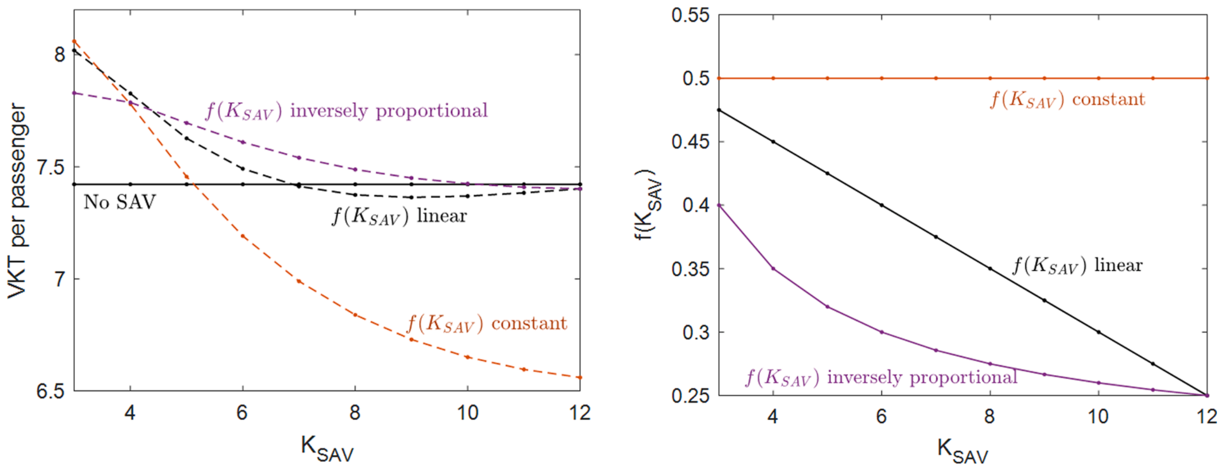

Fig. 9. Changes in VKT for different functional forms of $f(K_{SAV})$ (left), and the three functional forms (right).

Our mode choice model normalises the utility from private travel in public transport to zero, since there is little to no privacy in public transport modes. Importantly, however, it assumes that the small capacities of SAVs provide a private travel benefit to travellers: $f(K_{SAV})$ is greater than zero. While there are some aspects that justify this assumption (e.g., larger vehicles may be more noisy due to more people on board and more announcements on the speakers), one could argue that the private travel experience may be, in fact, worse in smaller vehicles. First, travelling with only a few people may pose safety issues due to the risk or fear of being assaulted or harassed. Second, travellers in larger vehicles may have more space for work and other activities than in smaller ones (e.g., it is more common to spot people working in a train or large bus than in a taxi or minibus). This disadvantage of small SAVs could be modelled by changing the private travel benefit in public transport from zero to a positive number: $B^{PT} = f_{PT}B$, with $f_{PT} > f(K_{SAV})$ when K_{SAV} is small. However, this would imply that in Fig. 3, the slope of public transport would be steeper than the one of SAV with such small K_{SAV}, which together with the first condition in section 3.2 (i.e., $U_{PT}(0) > U_{SAV}(0)$) would result in these SAV having no passengers.

While this extreme result is a consequence of our specific setting, we remark that if SAVs present no advantage in terms of private travel benefit compared to public transport, then it is reasonable to expect their mode share to be low. Therefore, it aligns with the intuition that this scenario would have little impact on the VKT.

Assumption 5: Public transport is non-reactive to the introduction of SAVs

Eqs. (1)-(3) also imply that public transport is not reactive to SAV introduction, as Γ_{PT} remains the same in both cases. The same Γ_{PT} means that the frequency has not changed when SAVs are introduced. However, the number of public transport passengers has decreased (as in Eqs. (4) and (6)), which implies that $VKT^{PP}{}_{PT}$ should be greater after the introduction of SAVs in Eqs. (11)-(13). Note, however, that we also assume in Eq. (41) that PT always travels full. This, on the other hand, implies that the frequency of PT service would have had to be adjusted in response to SAV introduction. In other words, our model assumes that PT services are reduced, while the passengers do not react to the changed PT level of service. The consequence of this model set-up is that our VKT increases are underestimated. If the PT reduced the frequency and the passenger had perceived the change (reactive demand), then that would lead to stronger shifts away from PT and a larger VKT increase. If the PT did not reduce the frequency, then $VKT^{PP}{}_{PT}$ should increase. Both cases lead to a larger total VKT after the introduction of SAVs. Intermediate options could also be considered, where the PT frequency is partially adjusted. It is not obvious which option should be taken, and any of them could bias our VKT results in an unpredictable direction. Therefore, we have decided to keep a model in which we do not change $VKT^{PP}{}_{PT}$ nor Γ_{PT} (even if this might not be realistic), because it allows us to unambiguously argue about the sign of the resulting bias – i.e., towards underestimating the VKT generated by SAVs.

In sum, whereas our work is subject to a number of assumptions, we argue that their impact is, in most cases, in the magnitude of the found effects and not in the direction of the obtained effects. Namely, relaxing one of the assumptions (no. 1) would result in a lower share of SAVs, whereas relaxing another two (no. 2 and 5) would result in a higher share of SAVs. One assumption (no. 3) has a neutral effect, as far as we see. Finally, relaxing one assumption (no. 4) would yield a scenario where SAVs do not become widespread at all. Investigating ways to relax these assumptions and accordingly updating the mode shifts and VKT remains a recommended direction for future study.

7. Synthesis, conclusions, and recommendations for further research

7.1. Synthesis and conclusions

This paper has analysed the mode shifts and VKT changes resulting from the introduction of SAVs. Unlike most studies to date, we approached this question with the goal to analytically demonstrate the relationships between mode preferences, aspects of transport systems and the expected VKT impact. To do so, we have built a simple closed-form model that includes both *operational aspects* (e.g., routing of the SAVs, setting the fares and frequencies) and *mode preferences* (determining whether SAV users shift from public or from private travel modes). Our analysis is based, at first, on a general mode choice model. This model includes what we call a 'private travel benefit', which consolidates travel experience aspects that tend to deteriorate with an increasing number of co-travellers. Examples of such aspects are the ability to perform activities during travel, the available personal space and the exposure to noise. We find that the importance of such private travel aspects in the population determines whether a city develops to be private- or public-transport oriented – that is, whether a larger share of people travels by private car or by public transport. We further implement this preference structure in a stylised city, where SAVs operate parallel to private cars and public transport. Our main conclusions follow:

1. Public transport loses the same proportion of users to SAVs in private- and public-transport-oriented cities, and a larger share of private car users switch to SAVs, if the city is public-transport oriented.
2. The VKT change in public-transport-oriented cities ranges from a small decrease to a large increase depending on the parameter settings.
3. In public transport-oriented cities, SAVs can have a large detrimental impact on VKT and congestion. This prompts a strong policy warning about the potentially harmful effects of unregulated SAVs (which compete with public transport).
4. In private-transport-oriented cities, SAVs 'stay small' and, consequently, do not significantly impact VKT and congestion.
5. SAVs with medium capacities are more likely to achieve a reduction in VKT. Smaller vehicles have lower VKT benefits from pooling. However, they maximise the SAV ridership. Larger vehicles lead to VKT increase because they do not sufficiently attract private car users. This means that the interest of SAV operators may conflict with policy goals. Therefore, in a setting where SAVs compete with public transport, the public authority can reduce the potential negative effect by imposing medium vehicle capacities.
6. Enhancing the passengers' private travel experience in SAVs (e.g., by facilitating various on-board activities) reduces the total VKT.

7.2. Policy and environmental implications

The findings summarised in section 7.1 are based on our model and hence are subject to a range of assumptions. However, the qualitative argumentation that supports them is more general. Therefore, we consider our conclusions as valid and relevant for transport and environmental policies.

The most important policy take-away from our work is that SAVs are not the key to more sustainable travel if they are allowed to compete with public transport (conclusions 1–4 above). By attracting a substantial share of public transport users, they can lead to increased VKT and congestion in both public- and private-transport-oriented cities. In particular, the concern of increasing VKT is great in public-transport-oriented cities, where more travellers are accustomed to sharing their vehicles and thereby are a target population for SAVs (conclusion 3). It can be noted that public-transport-oriented cities are also typically not designed for large car volumes (e.g., like many historical European cities with narrow roads) – hence, the potentially increasing VKT is even more alarming. Finally, if the SAVs are still introduced in a manner where they compete with public transport, then there are some policy levers that can mitigate the negative environmental impacts. Namely, requiring the SAVs to be medium sized can attract more car users while maintaining the sustainability benefits of pooling (conclusion 5). Better passenger travel experience in SAVs can make them more similar, and thus competitive, with cars (conclusion 6).

Next to considering the environmental implications of SAV with ridesharing (as done so far), transport policy is often interested in the most desirable form of (S)AV transport. While this paper did not assess such other forms – such as private AVs, sequentially-shared AVs or a joint SAV-public transport system – the general lesson to consider mode shifts is relevant. For instance, while SAVs may operationally outperform private AVs (since they facilitate trip 'pooling'), they would likely attract more public transport users than private AVs (seeing also the comparison in Fig. 2). In sum, it is not clear which of these modes would be more environmentally friendly. Several studies (Calabrò et al., 2023; Fielbaum, 2020; Pinto et al., 2020) conclude that an environmentally-oriented policy would encourage SAVs that are provided within the public transport system rather than competing with it.

The centrality of demand response is an important lesson for further work, since demand – and that is to say, human behaviour – is more difficult to predict than operational performance. In particular, studies of potentially distant futures (such as the time when fully automated vehicles are prevalent) are even more challenging, since respondents may struggle to imagine a truly different hypothetical world and also may find it difficult to stay motivated and committed to the survey task (Debbaghi et al., 2024).

7.3. Recommendations for further research

Based on our findings, we recommend further research on three levels, from modifications or extensions of our model to broader research directions. First, to extend and fine-tune our theoretical mode choice model (see section 3), we recommend testing other ways to specify the private travel benefit. To support this direction, more empirical studies should quantify travellers' perceptions and preferences for private travel in existing and new travel modes (e.g., automated shuttles with various capacities). This may lead to specifications with non-monotonous functions of vehicle capacity and even cases where public transport has a higher private-travel benefit than SAVs. In addition, the private travel conditions may modify the travel time perception resulting in a benefit that is proportional to the trip duration. Other extensions can be considered following the discussion of model assumptions in section 6.

Second, our findings highlight the challenge with unregulated SAV introduction – if allowed to compete with public transport, SAVs would likely be detrimental (or, at least, not beneficial) to both public- and private-transport-oriented cities. Further research in SAV operations should therefore focus on the ways for SAV services to complement public transport. While schemes where SAVs provide feeder services to public transport are widely studied, there are other promising strategies that would benefit from the human-free nature of the SAV services. A relevant implication from our paper is that such strategies should be analysed while accounting for demand responses (such as mode shifts), as otherwise results can be misleading.

Third, we would like to highlight the potential of theoretical research approaches as a complement to case-specific simulation studies. Especially for innovations and developments with a long time horizon – such as the introduction of (S)AVs – the detailed representation of specific transport systems may become outdated by the time that the performed analyses become relevant. In that situation, one may wonder to what extent are the obtained figures robust to changes in the public transport service levels and routes, configuration of residential zones and resulting changes in private transport flows since the time that is represented in the model? Furthermore, to what extent are the simulated services representative of a particular novel service that is eventually offered? Overall, we suggest that the level of abstraction that is inevitable in theoretical models – and that is typically seen as a limitation – may in many instances be on par with the uncertainty surrounding novel transport solutions in the future. As a benefit, the theoretical approaches are transparent in showing (in closed-form equations) the general relationships between particular service characteristics and outcomes of interest. Furthermore, even if less accurate than simulation in any particular location, they are more easily transferable to multiple locations – such as the various cities with public- or private-transport orientation in the present work.

CRediT authorship contribution statement

Andrés Fielbaum: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Baiba Pudāne:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization.

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 is available in this link: https://doi.org/10.4121/777220e4-9a78-4653-8780-89c2572f6c81.

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Appendix A

Similar to numerous papers in the field (e.g. Jara-Díaz and Gschwender, 2009; Jara-Díaz and Tirachini, 2013), operators' costs grow linearly with the capacity, i.e. $c_{PT} = c_0 + c_1 K_{PT}$, $c_{SAV} = c_0 + c_1 K_{SAV}$. The numerical values of c_0, c_1, and the rest of the parameters utilised in section 4.7 are shown in Table A1.

Table A1
Glossary and numerical values of the parameters.

Parameter	Meaning	Value	Source/Justification
Parameters with exogenous values			
α_v	Users' perceived cost of one unit of in-vehicle time.	2.9 €/h	Tirachini & Antoniou (2020)
α_w	Users' perceived cost of one unit of waiting time.	$2 \cdot \alpha_v$	Fielbaum et al. (2023)
α_a	Users' perceived cost of one unit of walking time.	$2.5 \cdot \alpha_v$	Fielbaum et al. (2023)
A	Distance between the centres of the two zones.	10 km	
L	Length of the sides of the squares.	2 km	Related to maximum walkable distances (Daniels & Mulley, 2013)
δ	Extra length of private modes.	0.3	Mean value between the minimum and maximum.
c_A	Monetary costs of the private mode.	4 €	Own estimation.
c_0	Fixed operators' costs per vehicle (shared modes).	4.02 €/h	Fielbaum (2020)
c_1	Fixed operators' costs per seat (shared modes).	0.29 €/h –seat	Fielbaum (2020)
K_{PT}	Capacity of public transport buses.	50	Usual observed value.
v_c	Vehicles' speed	25 km/h	Usual observed value.
v_a	Walking speed	4 km/h	Chang & Schonfeld (1991)
Parameters without exogenous values.			
Γ_h	Utility of modeh = PT, A, SAV, without considering private travel benefit.		
$B^A{}_{max}$	Maximum private travel benefit when travelling by car.	5€ –20€	Taken as an explanatory variable.

(continued on next page)

Table A1 (*continued*)

Parameter	Meaning	Value	Source/Justification
θ_i	Valuation of user i of private travel benefit.	$\in [0,1]$	Uniformly distributed.
f	Portion of the private travel benefit kept when using SAV.	$\in [0.25, 0.5]$,	Depends on K_{SAV}.
U_h	Utility when travelling by modeh = PT,A,SAV.		
c	$\Gamma_{PT} - \Gamma_{SAV}$		
d	$\Gamma_{SAV} - \Gamma_A$		
$VKT_1{}^{PP}$	Average VKT per person before SAV.		
$VKT_2{}^{PP}$	Average VKT per person after SAV.		
$VKT_h{}^{PP}$	Average VKT per person when travelling by mode h = PT,A,SAV.		
Z	Difference in VKT due to SAV (i.e. $VKT_2{}^{PP}$-$VKT_1{}^{PP}$)		
$P_{h,1}$	Percentage of users travelling in modeh = PT,A before SAV.		
$P_{h,2}$	Percentage of users travelling in modeh = PT,A,SAV after SAV.		
$t_{w,h}$	Av. waiting time when travelling by modeh = PT,SAV.		
$t_{v,h}$	Av. in-vehicle time when travelling by mode h = PT,A,SAV		
$t_{a,PT}$	Av. walking time when travelling by PT.		
UC_h	Av. users' costs when travelling by mode h = PT,SAV.		
F_h	Monetary fare of modeh = PT,SAV.		
K_h	Vehicles' capacity of modeh = PT,SAV.		
Q_h	Fleet's size of modeh = PT,SAV.		
c_h	Monetary cost of operating each vehicle of the modeh = PT,SAV.		
ρ	Frequency of the PT line.		

References

Al Maghraoui, O., Vosooghi, R., Mourad, A., Kamel, J., Puchinger, J., Vallet, F., Yannou, B., 2020. Shared autonomous vehicle services and user taste variations: survey and model applications. Transp. Res. Procedia 47, 3–10. https://doi.org/10.1016/j.trpro.2020.03.066.

Alonso, W., 1964. Location and land use: toward a general theory of land rent. Harvard University Press.

Alonso-González, M.J., Cats, O., van Oort, N., Hoogendoorn-Lanser, S., Hoogendoorn, S., 2021. What are the determinants of the willingness to share rides in pooled on-demand services? Transportation 48 (4), 1733–1765. https://doi.org/10.1007/s11116-020-10110-2.

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proc. Natl. Acad. Sci. 114 (3), 462–467. https://doi.org/10.1073/pnas.1611675114.

Arnott, R., De Palma, A., Lindsey, R., 1990. Economics of a bottleneck. J. Urban Econ. 27 (1), 111–130.

Arnott, R., De Palma, A., Lindsey, R., 1993. A structural model of peak-period congestion: A traffic bottleneck with elastic demand. Am. Econ. Rev. 161–179.

Asgari, H., Jin, X., Corkery, T., 2018. A Stated Preference Survey Approach to Understanding Mobility Choices in Light of Shared Mobility Services and Automated Vehicle Technologies in the U.S. Transportation Research Record, 2672(47), 12-22. doi: 10.1177/0361198118790124.

Auld, J., Sokolov, V., Stephens, T.S., 2017. Analysis of the effects of connected-automated vehicle technologies on travel demand. Transp. Res. Rec. 2625 (1), 1–8. https://doi.org/10.3141/2625-01.

Badia, H., Jenelius, E., 2020. Feeder transit services in different development stages of automated buses: comparing fixed routes versus door-to-door trips. Transp. Res. Procedia 47, 521–528.

Bahamonde-Birke, F.J., 2022. Should competition between regulated public transport and autonomous ride-sharing providers be allowed? An outlook into a possible transport paradox. J. Transp. Econ. Pol. (JTEP) 56 (1), 56–78.

Basso, L.J., Jara-Díaz, S.R., 2012. Integrating congestion pricing, transit subsidies and mode choice. Transp. Res. A Pol. Pract. 46 (6), 890–900. https://doi.org/10.1016/j.tra.2012.02.013.

Basso, L.J., Navarro, M., Silva, H.E., 2021. Public transport and urban structure. Econ. Transp. 28, 100232 https://doi.org/10.1016/j.ecotra.2021.100232.

Beirão, G., Sarsfield Cabral, J.A., 2007. Understanding attitudes towards public transport and private car: a qualitative study. Transp. Policy 14 (6), 478–489. https://doi.org/10.1016/j.tranpol.2007.04.009.

Bischoff, J., Maciejewski, M., Nagel, K., 2017. City-wide shared taxis: A simulation study in Berlin. 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), 275-280.

Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. Transp. Pol. 64, 76–91. https://doi.org/10.1016/j.tranpol.2017.09.005.

Cai, H., Wang, X., Adriaens, P., Xu, M., 2019. Environmental benefits of taxi ride sharing in Beijing. Energy 174, 503–508. https://doi.org/10.1016/j.energy.2019.02.166.

Calabrò, G., Araldo, A., Oh, S., Seshadri, R., Inturri, G., Ben-Akiva, M., 2023. Adaptive transit design: Optimizing fixed and demand responsive multi-modal transportation via continuous approximation. Transp. Res. A Policy Pract. 171, 103643.

Candia, D., Verhoef, E.T., 2022. Tradable mobility permits in a monocentric city with pre-existing labor taxation: A general equilibrium perspective. Transp. Res. B Methodol. 163, 145–165.

Chang, S.K., Schonfeld, P.M., 1991. Multiple period optimization of bus transit systems. Transp. Res. B Methodol. 25 (6), 453–478. https://doi.org/10.1016/0191-2615(91)90038-K.

Chen, M. H., Jauhri, A., Shen, J.P., 2017. Data Driven Analysis of the Potentials of Dynamic Ride Pooling. In: Proceedings of the 10th ACM SIGSPATIAL Workshop on Computational Transportation Science, 7-12. doi: 10.1145/3151547.3151549.

Chen, S., Wang, H., Meng, Q., 2020. Solving the first-mile ridesharing problem using autonomous vehicles. Computer-Aided Civil Infrastruct. Eng., 35(1), Article 1.

Clayton, W., Paddeu, D., Parkhurst, G., Parkin, J., 2020. Autonomous vehicles: Who will use them, and will they share? Transp. Plan. Technol. 43 (4), 343–364. https://doi.org/10.1080/03081060.2020.1747200.

Cohen, T., Cavoli, C., 2019. Automated vehicles: exploring possible consequences of government (non)intervention for congestion and accessibility. Transp. Rev. 39 (1), 129–151. https://doi.org/10.1080/01441647.2018.1524401.

Correa, O., Khan, A. K. M. M. R., Tanin, E., Kulik, L., Ramamohanarao, K., 2019. Congestion-Aware Ride-Sharing. ACM Trans. Spat. Algorith. Syst. 5(1), 5:1-5:33. doi: 10.1145/3317639.

Daganzo, C.F., 2010. Structure of competitive transit networks. Transp. Res. B Methodol. 44 (4), 434–446. https://doi.org/10.1016/j.trb.2009.11.001.

Danassis, P., Sakota, M., Filos-Ratsikas, A., Faltings, B., 2022. Putting ridesharing to the test: efficient and scalable solutions and the power of dynamic vehicle relocation. Artif. Intell. Rev. https://doi.org/10.1007/s10462-022-10145-0.

Daniels, R., Mulley, C., 2013. Explaining walking distance to public transport: the dominance of public transport supply. J. Transp. Land Use 6 (2), 5–20.

Debbaghi, F. Z., Kroesen, M., De Vries, G., Pudāne, B., 2024. Daily schedule changes in the automated vehicle era: Uncovering the heterogeneity behind the veil of low survey commitment. Transport. Res. Part A: Pol. Pract.

Fagnant, D.J., Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation 45 (1), 143–158. https://doi.org/10.1007/s11116-016-9729-z.

Fielbaum, A., 2020. Strategic public transport design using autonomous vehicles and other new technologies. Int. J. Intell. Transp. Syst. Res. 18 (2). https://trid.trb.org/view/1720905.

Fielbaum, A., 2024. On the relationship between free public transport, stop spacing, and optimal frequencies. Transp. Res. B Methodol. 183, 102924.

Fielbaum, A., Pudane, B., 2024. Modal Shares and Vehicle Kilometres Travelled with Shared Automated Vehicles: MATLAB Codes. 4TU.ResearchData. doi: 10.4121/777220e4-9a78-4653-8780-89c2572f6c81.

Fielbaum, A., Bai, X., Alonso-Mora, J., 2021. On-demand ridesharing with optimized pick-up and drop-off walking locations. Transport. Res. Part C: Emerging Technol. 103061.

Fielbaum, A., Jara-Diaz, S., Gschwender, A., 2016. Optimal public transport networks for a general urban structure. Transp. Res. B Methodol. 94, 298–313. https://doi.org/10.1016/j.trb.2016.10.003.

Fielbaum, A., Jara-Diaz, S., Alonso-Mora, J., 2024. Beyond the last mile: different spatial strategies to integrate on-demand services into public transport in a simplified city. Public Transport. https://doi.org/10.1007/s12469-023-00348-1.

Fielbaum, A., Tirachini, A., Alonso-Mora, J., 2023. Economies and diseconomies of scale in on-demand ridepooling systems. Econ. Transp. 34, 100313.

Gkartzonikas, C., Ke, Y., Gkritza, K., 2022. A tale of two modes: Who will use single user and shared autonomous vehicles. Case Stud. Transp. Pol. 10 (3), 1566–1580. https://doi.org/10.1016/j.cstp.2022.05.015.

Gurumurthy, K.M., Kockelman, K.M., 2022. Dynamic ride-sharing impacts of greater trip demand and aggregation at stops in shared autonomous vehicle systems. Transp. Res. A Policy Pract. 160, 114–125. https://doi.org/10.1016/j.tra.2022.03.032.

Harb, M., Stathopoulos, A., Shiftan, Y., Walker, J.L., 2021. What do we (Not) know about our future with automated vehicles? Transport. Res. Part C: Emerg. Technol. 123, 102948 https://doi.org/10.1016/j.trc.2020.102948.

Heilig, M., Hilgert, T., Mallig, N., Kagerbauer, M., Vortisch, P., 2017. Potentials of autonomous vehicles in a changing private transportation system – a case study in the Stuttgart Region. Transp. Res. Procedia 26, 13–21. https://doi.org/10.1016/j.trpro.2017.07.004.

Hörcher, D., Tirachini, A., 2021. A review of public transport economics. Econ. Transp. 25, 100196 https://doi.org/10.1016/j.ecotra.2021.100196.

Jäger, B., Brickwedde, C., Lienkamp, M., 2018. Multi-agent simulation of a demand-responsive transit system operated by autonomous vehicles. Transp. Res. Rec. 2672 (8), 764–774. https://doi.org/10.1177/0361198118786644.

Jansson, J.O., 1984. Transport System Optimization and Pricing. John Wiley & Sons.

Jara-Díaz, S., Gschwender, A., 2003. Towards a general microeconomic model for the operation of public transport. Transp. Rev. 23 (4), 453–469.

Jara-Díaz, S.R., Gschwender, A., 2009. The effect of financial constraints on the optimal design of public transport services. Transportation 36.

Jara-Díaz, S., Tirachini, A., 2013. Urban bus transport: open all doors for boarding. JTEP 47.

Jara-Díaz, S., Gschwender, A., Castro, J.C., Lepe, M., 2024. Distance traveled, transit design and optimal pricing. Transp. Res. A Policy Pract. 179, 103928 https://doi.org/10.1016/j.tra.2023.103928.

Kim, S.H., Mokhtarian, P.L., Circella, G., 2020. How, and for whom, will activity patterns be modified by self-driving cars? Expectations from the state of Georgia. Transport. Res. F: Traffic Psychol. Behav. 70, 68–80. https://doi.org/10.1016/j.trf.2020.02.012.

Krauss, K., Krail, M., Axhausen, K.W., 2022. What drives the utility of shared transport services for urban travellers? A stated preference survey in German cities. Travel Behav. Soc. 26, 206–220.

Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transport. Res. Part C: Emerging Technol. 69, 343–355. https://doi.org/10.1016/j.trc.2016.06.015.

Lau, S.T., Susilawati, S., 2021. Shared autonomous vehicles implementation for the first and last-mile services. Transport. Res. Interdiscipl. Perspect. 11, 100440 https://doi.org/10.1016/j.trip.2021.100440.

Lavieri, P.S., Bhat, C.R., 2019. Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future. Transp. Res. A Policy Pract. 124, 242–261.

Lehe, L., Gayah, V.V., Pandey, A., 2021. Increasing returns to scale in carpool matching: evidence from *Scoop*. Findings 25093. https://doi.org/10.32866/001c.25093.

Lehe, L.J., Pandey, A., 2024. A bathtub model of transit congestion. Transp. Res. B Methodol. 181, 102892.

Levin, M.W., 2017. Congestion-aware system optimal route choice for shared autonomous vehicles. Transport. Res. Part C: Emerging Technol. 82, 229–247. https://doi.org/10.1016/j.trc.2017.06.020.

Levin, M.W., Kockelman, K.M., Boyles, S.D., Li, T., 2017. A general framework for modeling shared autonomous vehicles with dynamic network-loading and dynamic ride-sharing application. Comput. Environ. Urban Syst. 64, 373–383. https://doi.org/10.1016/j.compenvurbsys.2017.04.006.

Liu, Z., Li, R., Dai, J., 2022. Effects and feasibility of shared mobility with shared autonomous vehicles: an investigation based on data-driven modeling approach. Transp. Res. A Policy Pract. 156, 206–226. https://doi.org/10.1016/j.tra.2022.01.001.

Lokhandwala, M., Cai, H., 2018. Dynamic ride sharing using traditional taxis and shared autonomous taxis: a case study of NYC. Transport. Res. Part C: Emerg. Technol. 97, 45–60. https://doi.org/10.1016/j.trc.2018.10.007.

Martinez, L., Crist, P., 2015. Urban Mobility System Upgrade: How shared self-driving cars could change city traffic. International Transport Forum.

Masoud, N., Jayakrishnan, R., 2017. Autonomous or driver-less vehicles: Implementation strategies and operational concerns. Transport. Res. Part E: Logist. Transport. Rev. 108, 179–194. https://doi.org/10.1016/j.tre.2017.10.011.

Merat, N., Madigan, R., Nordhoff, S., 2017. Human factors, user requirements, and user acceptance of ride-sharing in automated vehicles. OECD. https://doi.org/10.1787/0d3ed522-en.

Meshram, A., Choudhary, P., Velaga, N.R., 2020. Assessing and modelling perceived safety and comfort of women during ridesharing. Transp. Res. Procedia 48, 2852–2869.

Mo, B., Cao, Z., Zhang, H., Shen, Y., Zhao, J., 2021. Competition between shared autonomous vehicles and public transit: a case study in Singapore. Transport. Res. Part C: Emerging Technol. 127, 103058 https://doi.org/10.1016/j.trc.2021.103058.

Mogridge, M., Holden, D., Bird, J., Terzis, G., 1987. The Downs/Thomson paradox and the transportation planning process. Int. J. Transport Econ. 14 (3), 283–311.

Mohring, H., 1972. Optimization and scale economies in urban bus transportation. Am. Econ. Rev. 62 (4), 591–604.

Moody, J., Esparza-Villarreal, E., Keith, D., 2021. Use of exclusive and pooled ridehailing services in three mexican cities. Transp. Res. Rec. 2675 (9), 507–518. https://doi.org/10.1177/03611981211002835.

Mourad, A., Puchinger, J., Chu, C., 2019. A survey of models and algorithms for optimizing shared mobility. Transp. Res. B Methodol. 123, 323–346. https://doi.org/10.1016/j.trb.2019.02.003.

Narayanan, S., Chaniotakis, E., Antoniou, C., 2020. Shared autonomous vehicle services: a comprehensive review. Transport. Res. Part C: Emerg. Technol. 111, 255–293. https://doi.org/10.1016/j.trc.2019.12.008.

Nazari, F., Noruzoliaee, M., & Mohammadian, A. (Kouros)., 2018. Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes. Transport. Res. Part C: Emerging Technol., 97, 456-477. doi: 10.1016/j.trc.2018.11.005.

Olsen, T., Sweet, M.N., 2019. Who's driving change? Potential to commute further using automated vehicles among existing drivers in Southern Ontario, Canada. Transport. Res. Record 2673 (7), 50–61. https://doi.org/10.1177/0361198119846094.

Pinto, H.K.R.F., Hyland, M.F., Mahmassani, H.S., Verbas, I.Ö., 2020. Joint design of multimodal transit networks and shared autonomous mobility fleets. Transport. Res. Part C: Emerg. Technol. 113, 2–20. https://doi.org/10.1016/j.trc.2019.06.010.

Polydoropoulou, A., Tsouros, I., Thomopoulos, N., Pronello, C., Elvarsson, A., Sigþórsson, H., Dadashzadeh, N., Stojmenova, K., Sodnik, J., Neophytou, S., Esztergár-Kiss, D., Hamadneh, J., Parkhurst, G., Etzioni, S., Shiftan, Y., Di Ciommo, F., 2021. Who is willing to share their AV? Insights about gender differences among seven countries. Sustainability, 13(9), Article 9. doi: 10.3390/su13094769.

Pudāne, B., 2020. Departure time choice and bottleneck congestion with automated vehicles: Role of on-board activities. Eur. J. Transp. Infrastruct. Res. 20 (4), 306–334.

Pudāne, B., Rataj, M., Molin, E.J.E., Mouter, N., van Cranenburgh, S., Chorus, C.G., 2019. How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. Transp. Res. Part D: Transp. Environ. 71, 222–235. https://doi.org/10.1016/j.trd.2018.11.014.

Sanguinetti, A., Kurani, K., Ferguson, B., 2019. Is It OK to Get in a Car with a Stranger? Risks and Benefits of Ride-pooling in Shared Automated Vehicles. https://escholarship.org/uc/item/1cb6n6r9.

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 Policy Pract. 113, 125–136.

Singleton, P. A., De Vos, J., Heinen, E., & Pudāne, B. (2020). Potential health and well-being implications of autonomous vehicles. En D. Milakis, N. Thomopoulos, & B. van Wee (Eds.), Advances in Transport Policy and Planning (Vol. 5, pp. 163-190). Academic Press. doi: 10.1016/bs.atpp.2020.02.002.

Small, K.A., 2015. The bottleneck model: An assessment and interpretation. Econ. Transp. 4 (1–2), 110–117.

Soza-Parra, J., Raveau, S., Muñoz, J.C., Cats, O., 2019. The underlying effect of public transport reliability on users' satisfaction. Transp. Res. A Policy Pract. 126, 83–93.

Steck, F., Kolarova, V., Bahamonde-Birke, F., Trommer, S., Lenz, B., 2018. How autonomous driving may affect the value of travel time savings for commuting. Transp. Res. Rec. 2672 (46), 11–20. https://doi.org/10.1177/0361198118757980.

Stoiber, T., Schubert, I., Hoerler, R., Burger, P., 2019. Will consumers prefer shared and pooled-use autonomous vehicles? A stated choice experiment with Swiss households. Transp. Res. Part D: Transp. Environ. 71, 265–282. https://doi.org/10.1016/j.trd.2018.12.019.

Tikoudis, I., Martinez, L., Farrow, K., Bouyssou, C.G., Petrik, O., Oueslati, W., 2021. Ridesharing services and urban transport CO2 emissions: Simulation-based evidence from 247 cities. Transp. Res. Part D: Transp. Environ. 97, 102923.

Tirachini, A., Antoniou, C., 2020. The economics of automated public transport: effects on operator cost, travel time, fare and subsidy. Econ. Transp. 21, 100151 https://doi.org/10.1016/j.ecotra.2019.100151.

Tirachini, A., Chaniotakis, E., Abouelela, M., Antoniou, C., 2020. The sustainability of shared mobility: can a platform for shared rides reduce motorized traffic in cities? Transport. Res. Part C: Emerg. Technol. 117, 102707 https://doi.org/10.1016/j.trc.2020.102707.

Tsao, M., Milojevic, D., Ruch, C., Salazar, M., Frazzoli, E., Pavone, M., 2019. Model predictive control of ride-sharing autonomous mobility-on-demand systems. Int. Conf. Robot. Automat. (ICRA) 2019, 6665–6671. https://doi.org/10.1109/ICRA.2019.8794194.

Valenzuela, C.L., Jones, A.J., 1997. Estimating the held-karp lower bound for the geometric TSP. Eur. J. Oper. Res. 102 (1), 157–175. https://doi.org/10.1016/S0377-2217(96)00214-7.

Van den Berg, V.A., Verhoef, E.T., 2016. Autonomous cars and dynamic bottleneck congestion: the effects on capacity, value of time and preference heterogeneity. Transp. Res. B Methodol. 94, 43–60.

van Wee, B., van Cranenburgh, S., Maat, K., 2019. Substitutability as a spatial concept to evaluate travel alternatives. J. Transp. Geogr. 79, 102469 https://doi.org/10.1016/j.jtrangeo.2019.102469.

Vickrey, W.S., 1969. Congestion theory and transport investment. Am. Econ. Rev. 59 (2), 251–260.

World Economic Forum, 2018. Reshaping Urban Mobility with Autonomous Vehicles: Lessons from the City of Boston.

Yu, X., van den Berg, V.A., Verhoef, E.T., 2022. Autonomous cars and activity-based bottleneck model: how do in-vehicle activities determine aggregate travel patterns? Transport. Res. Part C: Emerg. Technol. 139, 103641.

Zardini, G., Lanzetti, N., Pavone, M., Frazzoli, E., 2022. Analysis and Control of Autonomous Mobility-on-Demand Systems. Annual Review of Control, Robotics, and Autonomous Systems, 5(1), null. doi: 10.1146/annurev-control-042920-012811.

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 (N.º 15-2919). Article 15-2919. Transportation Research Board 94th Annual MeetingTransportation Research Board. https://trid.trb.org/view/1337820.

Zhou, Z., Roncoli, C., 2022. A scalable vehicle assignment and routing strategy for real-time on-demand ridesharing considering endogenous congestion. Transport. Res. Part C: Emerging Technol. 139, 103658 https://doi.org/10.1016/j.trc.2022.103658.

Zhu, P., Mo, H., 2022. The potential of ride-pooling in VKT reduction and its environmental implications. Transp. Res. Part D: Transp. Environ. 103, 103155 https://doi.org/10.1016/j.trd.2021.103155.

Zwick, F., Kuehnel, N., Moeckel, R., Axhausen, K.W., 2021. Agent-based simulation of city-wide autonomous ride-pooling and the impact on traffic noise. Transp. Res. Part D: Transp. Environ. 90, 102673 https://doi.org/10.1016/j.trd.2020.102673.