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Smart cities, urban mobility and autonomous vehicles: How different cities needs different sustainable investment strategies

Maximilian A. Richter [a,*], Markus Hagenmaier [b], Oliver Bandte [c], Vinit Parida [d,e], Joakim Wincent [f,g]

[a] University of St. Gallen, Institute for Mobility, Bahnhofstrasse 8, CH-9000 St. Gallen, Switzerland
[b] BCG's Vienna office, The Boston Consulting Group GmbH, Am Hof 8, AUT-1010 Vienna, Austria
[c] BCG's Boston office, Boston Consulting Group, 200 Pier Four Blvd, MA 02210, Boston, United States of America
[d] Luleå University of Technology, Entrepreneurship and Innovation, SE-97187 Luleå, Sweden
[e] University of Vaasa, School of Management, Vaasa, Finland / University of South-Eastern Norway, USN Business School, Vestfold, Norway
[f] University of St. Gallen, Global Center for Entrepreneurship & Innovation, Dufourstrasse 40a, 9000 St. Gallen, Switzerland
[g] Hanken School of Economics, Arkadiankatu 22, 00100 Helsinki, Finland

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ABSTRACT

The Smart city is important for sustainability. Governments engaged in developing urban mobility in the smart city need to invest their limited financial resources wisely to realize sustainability goals. A key area for such sustainability investment is how to implement and invest in emerging technologies for urban mobility solutions. However, current frameworks on how to understand the impact of emerging technologies aligned with long-term sustainability strategies are understudied. This article develops a simulation-based comparison between different cities and autonomous vehicle (AV) adoption scenarios to understand which aspects of cities lead to positive AV implementation outcomes. As urban mobility and cities will become smart, the analysis represents a first attempt to explore the impact of AVs on a large scale across different cities around the world. Archetypes are formed and account for most, if not all, world cities. For three of our archetypes (car-centric giants, prosperous innovation centers, and high-density megacities), promoting AV-shuttle use would deliver the greatest advantage as measured by improvements in the model's KPIs. To develop urban powerhouses, however, micromobility would deliver greater benefits. For highly compact middleweights, a shift from private cars to other non-AV modes of transportation would be the smartest choice.

1. Introduction

Smart city policies hold out the promise of improving the quality of life for citizens. A key strategic area for such sustainability investment focuses on the introduction of smart urban mobility solutions. The motivation for this focus is quite clear because more than 90 % of the world's population live in locations where air pollution fails to meet the agency's guidelines (WHO, 2018). Hence, governments are forced to make their cities more environmentally friendly by using innovative technologies (Wang et al., 2019). To achieve long-term sustainability benefits for society, a focus on urban mobility solutions has become a critical element in the long-term strategy of governments' smart city agendas (Gonzalez et al., 2019).

Transportation accounts for nearly one-quarter of all greenhouse gases (Conibear et al., 2020). Investing in smart mobility helps to further the goals of a smart city strategy by presenting environmentally friendly transportation (Zawieska and Pieriegud, 2018). New emerging smart mobility technologies are thought to have a significant impact on social change as well as on people's lives in the cities of the future (Marletto, 2019; Gurumurthy and Kockelman, 2020). Autonomous vehicles (AVs) are regarded as one possible technology that may prove to be part of a multi-faceted approach to support the achievement of smart city goals (Woo et al., 2021). However, current understanding of how future cities should approach the introduction and implementation of AV solutions is largely unclear.

Looking at the limited literature on this topic, most studies provide a

* Corresponding author.
E-mail addresses: maximilianalexander.richter@unisg.ch (M.A. Richter), hagenmaier.markus@bcg.com (M. Hagenmaier), bandte.oliver@bcg.com (O. Bandte), vinit.parida@ltu.se, vinit.parida@uwasa.fi (V. Parida), joakim.wincent@hanken.fi, joakim.wincent@hanken.fi (J. Wincent).

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descriptive view of the potential positive effects of AVs (Anderson et al., 2014; Fagnant et al., 2015). By replacing traditional cars, AVs could reduce pollution in urban areas (Brown et al., 2018), lower the demand for parking spaces (Yi et al., 2018), and reduce transport costs (Boesch et al., 2018). Introducing AVs could significantly decrease road fatalities and accidents, which will lead to a reduction in human suffering and in expenses for medical treatment (MacKenzie et al., 2014; Clements and Kockelman, 2017). AVs also improve transportation access for disadvantaged social groups (Fagnant and Kockelman, 2015). However, this potential of autonomous driving can only be unlocked if the effects of AVs on cities and their populations are understood. If, however, AVs are deployed merely as upgraded human-driven vehicles, the optimal benefits of this new technology may not be achieved, especially in large metropolitan areas with high population densities and limited road resources (Shen et al., 2018). Rather, an uncontrolled introduction of AVs may have significant deleterious effects on traffic conditions and, even more seriously, on social conditions within cities (Milakis et al., 2017).

The deployment and positive impact of AVs is based on different ownership models (Haboucha et al., 2017). As shown in Fig. 1, a range of options for deploying AVs is possible, from privately-owned AVs (PAV) to shared autonomous vehicles (SAV). PAVs are comparable to the current ownership of a vehicle. Passengers continue to commute using an AV that they have in their ownership. Except that the owners of the vehicles are no longer the drivers. Instead, owners become passengers and will be able to pursue activities such as reading, working, and sleeping, while travelling in their cars (Le Vine et al., 2015). Furthermore, technology development facilitates the emergence of new ownership-shared autonomous vehicles (SAV). In this use case, the passenger does not own the vehicle but rents an AV for a one-way trip (Krueger et al., 2016). New technologies provide solutions where passengers can order a vehicle via mobile phone applications. A distinction must be made with regard to SAVs. The vehicle is used for an own ride with no other passenger joining the trip. Pooling is also a use case (Haboucha et al., 2017). Here, passengers are matched via websites and mobile apps to travel a similar route. In this way, journeys are combined, and trips are shared.

How different types of AV perform in practice will depend on each city's particular characteristics. Cities differ in factors such as population density, land concentration, infrastructure, and urban development, so it may be challenging to implement AV in some cities. Amsterdam, for example, is a very active city, with about 60 % of people using active forms of transportation, such as biking and walking (EPOMM, 2019). In Los Angeles, in contrast, more than 80 % of people drive their own cars, and the city is a rather new city built for vehicle use (EPOMM, 2019). Although AVs will emerge to some extent in every archetype, other forms of transportation, such as micromobility, could deliver greater benefits for city dwellers in some circumstances. Thus, matching the existing and emerging needs of the smart city with appropriate urban mobility solution types is imperative, given that previous studies have found evidence that the introduction of AVs can lead to undesirable side effects including an eventual worsening of the city-level metric (MacKenzie et al., 2014; Bischoff et al., 2018). In this scenario, the government of a smart city would invest in a technology that brings no added value to citizens. Accordingly, it is important for governments to critically evaluate the opportunities and risks of investing in urban mobility and AV solutions.

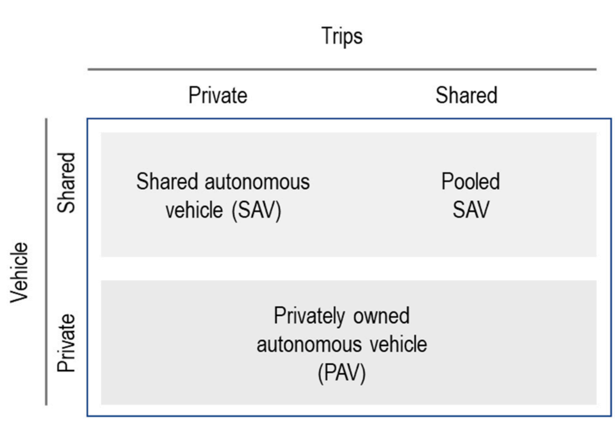

Fig. 1. Autonomous vehicle implementation scenarios based on ownership model.

This leads to our research question, "What are the potential long-term benefits and drawbacks from the introduction of AV in various smart city archetypes?" This question is particularly important since many cities do not have a clearly defined smart city agenda (Haarstad and Wathne, 2019; Tang et al., 2019; Yigitcanlar, 2018). Rather, a government tends to focus on a set of topics when developing a smart city (Clement and Crutzen, 2021). Furthermore, sustainable reform in urban mobility, which ensures that new technologies deliver their benefits, has become one of the key challenges that policy makers and urban planners around the world are facing (Dia and Javanshour, 2017).

Representing the environment in a real-life model through simulations can help to explain the impact of new technologies on future smart city initiatives (Lovas, 1994). Based on the simulation results, policy makers and urban planners can adapt their long-term strategies for urban mobility. Nevertheless, prior research by Wadud et al. (2016) and Kroeger et al. (2018) has shown substantial uncertainty over the potential impact of the new technology – autonomous vehicles. The uncertainties are attributable to the fact that most studies i) are spatially limited to specific cities (Soteropoulos et al., 2018), and ii) focus on the impact of AVs with respect to one parameter, such as emissions, parking area, and vehicle miles traveled (Mounce and Nelson, 2019).

By using different future urban mobility scenarios to assess the impact on cities, we contribute to the urban mobility literature (Barba-Sánchez et al., 2019; Caragliu and Del Bo, 2019), especially in relation to AVs (Merfeld et al., 2019; Gurumurthy and Kockelman, 2020; Woo et al., 2021) and big data (Del Vecchio et al., 2019). Through the different simulation scenarios regarding the success of investments in AV technologies, we can also reference the results to the smart city literature (Clement and Crutzen, 2021; Ruhlandt, 2018), especially since Lombardi et al. (2012) have shown that urban mobility is a feature of smart city strategies. Finally, we address the foresight methodology by modelling future urban mobility scenarios through our simulation approach with an emerging technology (Liebl and Schwarz, 2010; Vecchiato and Roveda, 2010; Gordon et al., 2020).

The remainder of the paper is organized as follows. Section 2 provides a review of the literature on smart city investment and the uncertainty of the impact of AVs on cities. Section 3 details the methodology and the data used in the analysis. Section 4 presents the results and findings. In Section 5, sustainable investment strategies for urban mobility are derived, followed by a conclusion.

2. Literature background

2.1. Emergence of smart cities

Research on smart cities was first conducted in the 1970s (Los Angeles Community Analysis Bureau, 1974). In the following decades, research stagnated with few articles on smart city concepts (Gibson et al., 1992). Smart city research gained momentum in the 2000s when smart cities were considered a winning urban strategy using technology to increase the quality of life in urban areas (Hall, 2000). After the first smart city expo world congress in 2011, barriers were broken, and the smart city literature noticed an exponential growth with about 200,000 publications per year (Stuebinger and Schneider, 2020). Although smart cities are the growing global phenomenon of the 21st century (Lim et al., 2021; Yeh, 2017), there is no universal definition of 'smart cities' (Allwinkle and Cruickshank, 2011; De Jong et al., 2015; Gupta et al., 2020).

Nevertheless, the smart city concept has come to the limelight as a way for government to address increasing demands from diverse stakeholders related to climate change, urbanization, and larger populations (Bibri and Krogstie, 2017; Estevez et al., 2016).

The smart city concept should undoubtedly improve the quality of life of citizens while simultaneously simplifying city management (Lombardi et al., 2012) and prompting metropolises struggling with similar problems to align their responses. However, there is no one-size-fits-all smart city strategy (Clement and Crutzen, 2021). The reason is that each city has unique needs and resources that may require different and inimitable solutions (Siokas et al., 2021). Beyond this, policy makers must consider that cities have different visions and priorities for achieving their objectives (Glasmeier and Christopherson, 2015). Furthermore, the concept of the smart city is not limited to the application of technologies. In fact, technologies available to solve problems are infinite (Albino et al., 2015). Today, modern cities devote various technological, financial, and human resources to complete their digital transformation (Siokas et al., 2021). Shamsuzzoha et al. (2021) show that the strategies depend on from where the smart city offensive starts. As an example, the smart city agendas in Singapore and London are set top-down, whereas the strategy in Helsinki is a bottom-up process.

Nevertheless, government officials are responsible for the day-to-day functioning of larger cities. In response, governments around the world are trying to foster innovation and provide favorable urban solutions by focusing on investing in emerging technological advances (Siokas et al., 2021). To foster innovation, most smart cities have freed up budgets to invest in new technologies (Barba-Sánchez et al., 2019; Ullah et al., 2021). Grand View Research (2018) placed the global market size of smart cities at USD 550 billion in 2016 and predicted an increase to USD 2.57 trillion by 2025. Much of this money is invested in new technologies to drive digitalization and improve the prosperity of a city. However, a key question remains on what is the most impactful strategy for smart city investment.

As the smart city concept matures, relevant initiatives are growing in number in many cities across the world. The budget for such investments is limited, and financial resources must, therefore, be directed at the most promising technologies. Since most city governments focus on a set of topics when developing a smart city rather than having a smart city agenda (Clement and Crutzen, 2021), it is important to understand the potential of individual technologies as well as their "fit" for the specific conditions of each city. Examples from past smart city initiatives show that projects where the technology and its added value for society are not fully understood have failed. For instance, the Google company, Sidewalk Labs, planned the construction of a radical new city district in Canada. To implement new technologies in the city, USD 980 million were invested to realize the vision of a high-tech city in Toronto. However, the project failed because experts overestimated the technological benefits (Wong and Jagdev, 2019). To solve pollution problems in their cities, India has launched a Smart City Mission. One hundred cities were identified to promote digitalization and were supported with financial resources. Each smart city was expected to complete its project within five years. However, approximately 49 % of the 5196 projects were not completed because the technological possibilities were over-embellished (CFA, 2021).

It became clear that cities needed to look at innovative technologies carefully and decide, based on the city's character, whether investment in new technologies was worthwhile. Urban mobility is a major lever for smart cities (Lombardi et al., 2012). The biggest revolution since the invention of cars could well be autonomous driving. We contribute to the ability of cities to better assess the success of AVs. This technology can be included in the strategies of smart cities so that misplaced investments can be avoided.

2.2. Urban mobility and autonomous vehicle solutions for smart cities

Lombardi et al. (2012) have identified urban mobility as one initiative suitable to a smart city agenda. Docherty et al. (2018) stated that technological changes were outpacing the capacity of systems and structures of governance to respond to the challenges already apparent. One of these new urban mobility technologies is autonomous driving. Many studies conclude the success of AVs is principally down to the influence of policy makers who are well placed to play a significant role in shaping the impact on urban mobility (Anderson et al., 2014; Clark et al., 2016; Enoch, 2015; Fox, 2016). To unleash the potential of AVs, a strategic action plan on the part of urban decision makers is required (Giduthuri, 2015). Moreover, Perra et al. (2017) argued that the configuration of urban transportation is one of the key planning functions of policy makers developing the smart city concept. They also affirmed that an integrated and sustainable approach demands proactive involvement on the part of policy makers. Since there is no general plan, it is important to understand which cities are best suited to different autonomous urban mobility scenarios.

In this regard, service research gaps remain. First, to the best of our knowledge, there have been only a few studies conducted (Fagnant et al., 2015; Ye and Yamamoto, 2018) that have analyzed the impact of autonomous vehicles on a large scale across different countries and have drawn up long-term recommendations for action. Fagnant et al. (2015) stated that policy makers should begin supporting research into how AVs could affect transportation and land-use patterns, and how best to alter urban mobility to maximize the benefits while minimizing any negative consequences of the transition to a largely autonomous fleet. According to Gavanas (2019), the international literature is not yet sufficiently engaged in addressing the challenges that come with planning the appropriate implementation of AVs.

Second, there is substantial uncertainty in the literature on the potential impact of AVs on urban mobility. In this study, we measure the impact using key performance indicators – KPIs. As seen in Fig. 2, the vehicle miles traveled due to the introduction of AVs depends on the study and ranges from a decrease of 35 % (Childress et al., 2015) to an increase of 341 % (Harb et al., 2018). Similarly, the cost per mile of AV usage, the number of traffic collisions, and emissions differ between studies. These differing model projections from different studies indicate that there is great variability in the potential outcomes from introducing AVs to enhance urban mobility.

Third, previous studies have focused on the impact of AVs with respect to one KPI, such as emissions, parking areas, or vehicle miles traveled. Only a few studies have considered multiple KPIs based on simulation results. For example, Harper et al. (2018) investigated the parameter of vehicle miles traveled, environmental issues, and needed infrastructure. Fagnant and Kockelman (2014) and Liu et al. (2017) also analyzed multiple parameters. However, each of these studies considered only a single city, Seattle, Singapore, and Austin, respectively.

Finally, there is a need for studies to provide a comprehensive strategic plan on how smart cities should orientate themselves in terms of their urban mobility concept. Since many studies have focused on specific aspects of AV deployments, the resulting recommendations provide only a limited set of suggestions for policy makers without delivering a holistic understanding of how AVs will influence urban mobility in different cities. Jones and Leibowicz (2019), for example, limited their policy recommendations to realizing a sustainable charging infrastructure, whereas the work of Zhang et al. (2015) proposed only measures to limit the vehicle miles traveled. While each of these studies has provided valuable insights into the specific aspect addressed, a comprehensive overview is needed to provide holistic guidance on how to invest in an autonomous future in smart cities.

Since it is assumed that cities on an international level differ significantly in terms of their characteristics, such as infrastructure design and vehicle-based travel patterns, knowledge transfer between studies is only possible to a limited extent. This work addresses that literature gap and provides a comprehensive simulation-based study to examine the impact of AVs on multiple key performance indicators (KPIs) for a range of cities. Since smart city initiatives have attracted funding over recent

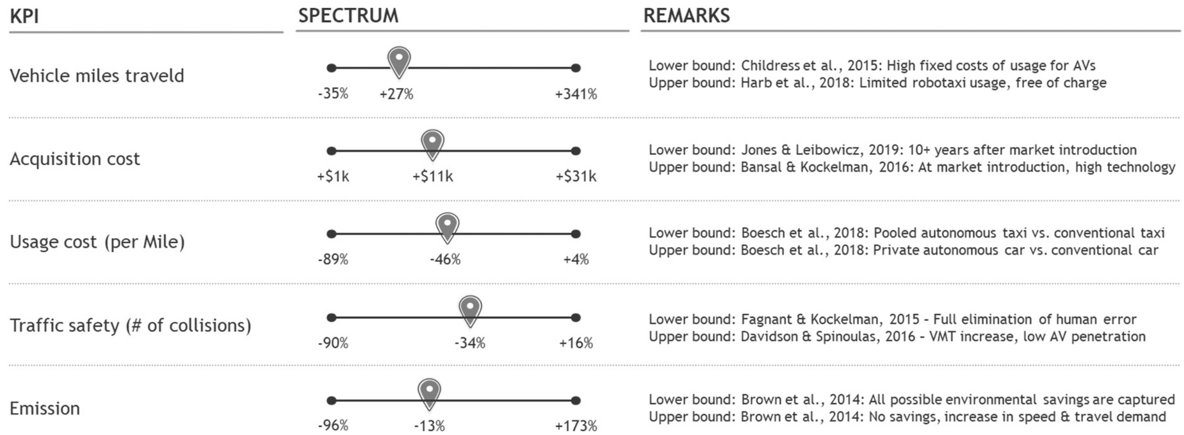

Fig. 2. Uncertainty in the literature – high variability in simulations for the KPIs considered due to different parameters, cities, and scenarios.

years (Caragliu and Del Bo, 2019), this study helps to allocate these funds in a more efficient way in terms of urban mobility.

3. Methodological approach

This study applies a traffic simulation approach in the form of a space continuous modelling tool to evaluate the effects of introducing AV on a global scale. There is no "one size fits all" AV implementation strategy. Each smart city has unique needs and resources, which will likely require diverse and unique implementation scenarios. Although every city is unique in its history, size, and population, a strategy tailored to the city's characteristics is essential (Albino et al., 2015). Hence, we have divided the cities into clusters with similar characteristics. For each of these generated clusters, we simulated the effects of AVs in four different scenarios. We used six key performance indicators (KPIs) to measure the impact of AV introduction: traffic volume, which is represented by vehicle miles traveled; safety, measured by annual fatalities; environmental effects, measured by energy consumption; land use, measured in total parking area; transportation costs; and average journey time. For the selection of parameters, we relied on studies that compare multiple KPIs. The study by Fagnant et al. (2015) aimed to explore the feasibility aspects of AVs and discuss their potential impact on the transportation system. Their study is one of the most comprehensive in terms of the number of KPIs chosen. It employed the six parameters that we selected for our study. Other studies exploring the multiple KPIs that we followed are Milakis et al. (2017), Davidson and Spinoulas (2016), and Clements and Kockelman (2017). Milakis et al. (2017) identified plausible future development paths for automated vehicles in the Netherlands and estimated the likely implications for traffic volume, safety, and energy consumption. Davidson and Spinoulas (2016) explored what the introduction of AVs could mean for the future of transport and included traffic volume, safety, and journey time. Clements and Kockelman (2017) studied traffic volume, safety, used space, and cost. In our study, all parameters are weighted equally.

The scenarios applied represent future scenarios on how cities could develop. Based on the results along the cluster, we derived statements on which scenario would be the most advantageous for cities. Furthermore, recommendations for action on how to implement AVs successfully are given by cluster, resulting in long-term strategic policy planning.

3.1. Archetype creation

It is difficult to simulate all cities. For this reason, archetypes were created that identify city types and combine them into archetypes. In past studies, clusters and archetypes have been formed at the level of smart cities. Tang et al. (2019) presented a comparative analysis of 60 municipal smart city plans. The cluster analysis used identified four different models. Furthermore, McIntosh et al. (2014) tried to understand how factors such as transit service levels and urban density help to explain vehicle miles traveled. Gisbert et al. (2017) clustered cities in Spain using urban metrics analysis. However, these studies did not refer to the level of traffic analysis and, therefore, cannot be used in our study. Nevertheless, we have adopted the cluster analysis approach. Clustering methods were used to investigate different patterns between cities. In our study, we used a k-mean method, which has already been used in comparable studies (Li et al., 2018; Ke et al., 2016). Li et al. (2018) used a k-mean method to identify archetypes representative of heating and cooling energy demand in Chongqing. Similar clustering methods were used to subdivide the study area based on land surface features, such as land use change (Ke et al., 2016). However, studies have used non-transport-related data. Moreover, cities have not been compared globally but have often been confined to one country or continent.

We selected 40 cities worldwide with varied geographic distribution, heterogeneity of environment, dominant type of transport, and level of innovativeness. To identify the 40 cities, a long list of several hundred metropolitan cities across the world was compiled. Then, we removed cities that had a similar characteristic to other prioritized cities, cities with limited data availability, and cities with fewer than 500,000 inhabitants. We then defined eight quantitative input criteria that are used for city clustering. When selecting the input criteria, we used criteria that were relevant for the simulation. As shown in Table 1, we adopted parameters that were used in traffic simulations as input criteria in other studies. The listed studies used congestion time, route time, population density, modal mix, and urban development patterns to simulate traffic flow. Furthermore, we added two characteristics: land use concentration, and city age. Land use describes what the corresponding cell is used for. Examples of cells are residential areas, employment, and shopping areas. We also added city age to our input parameter given that modern cities have a better transport network and are more advantageous for autonomous driving (Southworth and Ben-Joseph, 2003).

Hence, the clustering criteria included congestion time (Inrix, 2019), route time (different sources, such as Moovit (2019) and Eurostat (2016)), modal mix (EPOMM, 2019), population density (Demographia, 2016), land use concentration, urban development pattern (extracted from Google Maps), and city age [different sources such as the World Factbook (Central Intelligence Agency, 2019), and city specific information from, for example, Berlin.de, 2019]. Based on clustering method of MacQueen (1967) and Hartigan and Wong (1979), we were able to identify that a class of five shows the best match for clustering. Using the attributes for the global cities, we applied this unsupervised machine learning approach to group similar cities that have the characteristics that differ the most between groups. To make the clusters even more detailed, a manually adjusted positioning of cities was executed based on descriptive criteria, such as topography, population size, public

Table 1
Input parameter used for traffic simulation, which we use for archetype creation.

Input criteria	Zhang et al. (2015)	Fagnant et al. (2015)	Bischoff and Maciejewski (2016)	Simoni et al. (2019)	Zwick et al. (2021)
Congestion time	X	X	X	X	X
Route time	X	X	X	X	X
Population density	X	X	X	X	X
Modal mix	X	X	X	X	X
Urban development patterns	X	X	X	X	X
Land use concentration					
City age					

transportation costs, and public transportation coverage. As a result, the 40 cities were divided into five clusters, which we call archetypes. High-compact middleweight represents cities in which most of the population live within a well-defined central area. Population density is above average, and inhabitants use a broad range of transport modes, with demand evenly distributed across options. The car-centric giant represents an automobile-dependent archetype, which generally has a large population but very low population density. It is defined by a large geographic area, dispersed population, and underdeveloped public transit network. It has a densely populated center as well as smaller low- and medium-density satellite hubs. The prosperous innovation center represents established cities that have developed over an extended period, with low population growth and average density. Several medium-density hubs are contained within the city boundaries. The street pattern is irregular, and thoroughfares are often narrow. Inhabitants use a range of transport modes equally. Developing urban powerhouses are modern metropolises that are growing rapidly and have a high population density. This archetype consists of multiple distinct hubs, which are clustered along a coastline or river. Most inhabitants currently use public transportation. A high-density megacity is a relatively modern city that has grown strongly over the past century. It has a large population, with a high-density hub at its center surrounded by densely populated satellite hubs. The archetype is typically located on a coastline. Its streets are generally configured in a grid pattern. Inhabitants use a range of transport options at present. Table 2 shows the results and details of the archetypes.

3.2. (Space-) continuous modelling

The purpose of a simulation is to represent the environment in an appropriate way. It is intended to model a real-life or hypothetical situation on a computer so that it can be studied (Lovas, 1994). By changing variables and implementing different scenarios in the simulation, conclusions can be drawn from their impact on the initial situation. However, the aim is to produce a sufficiently accurate representation of the traffic situation under changed framework conditions (Bando et al., 1995). To reflect the impact of AVs on cities, the BCG Gamma travel demand simulation model was used. Gamma is a subsidiary of the Boston Consulting Group, which focuses on applying data science, analytics, and artificial intelligence. The model is mostly based on the NHCRP report 716 on travel demand forecasting (Bhat, 2012) and comprises five technical steps (Fig. 3). These five steps are performed individually for each archetype. The synthetic simulation depicts a typical day within each cluster.

In step 1, which is the region grid, the entire area of each modeled cluster is separated into equal tiles, 1 km^2 each. This region grid creates a representative virtual city for each archetype based on the data from the cities in the cluster. Second, thirteen land-use types are created to model different city layouts and their underlying characteristics, such as residential, employment, and shopping (Fig. 4). For each of the land-use types, several underlying characteristics are defined that influence mobility behavior. Here, employment rates, school enrollment, household income, and household size are used as characteristics. Step 3 assigns land-use types to each of the tiles based on preferential urban design. These three steps result in an individual archetype design for each cluster (Fig. 4). This design is averaged from the data of the cities located in the cluster. For example, in high-compact middleweights, people live within a well-defined central area, making this archetype compact whereas developing urban powerhouses have high population density and are located in multiple distinct hubs.

In step 4, a travel demand model takes the land-use type allocation as an input to calculate transit volume per traffic mode, which is represented in number of trips. The method applied in this report follows the conventional sequential process for estimating transportation demand. This is often called the "four-step" process: trip generation, trip distribution, mode choice, and assignment.

- Trip Generation: Based on the defined land-use type inputs (Steps 1 to 3), we can assign the number of *productions* and *attractions* for each tile of the grid. Productions initiate trips, which originate at this tile and attractions, which are destinations for trips ending at this tile. Information from land use, population, and economic forecasts are used to estimate how many trips are made to and from each zone. Trips can be home based, or non-home based, as illustrated in Fig. 5.

- Trip Distribution: Depending on the allocation of land-use types across the grid, we can simulate the distribution of trips within and across all tiles. It is the step that links the trip productions and trip attractions for each zonal pair. Three steps are necessary to calculate the trip distribution:

Table 2
Presentation of the cluster analysis results – archetypes and their characteristics.

	High-compact middleweights	Car-centric giants	Prosperous innovation centers	Developing urban powerhouses	High-density megacities
City examples	Berlin, Vienna	Detroit, Toronto	London, San Francisco	Bangkok, Buenos Aires	New York City, Shanghai
Size[a] [km^2]	2300	8500	5000	4000	10,800
Population	8,300,000	4,800,000	5,600,000	9,500,000	24,300,000
Centralization	Very compact city	Strong decentralization	Mixed types	Decentralized cities	Mixed types
Modes	Distributed mix, with focus on public transit	Car-centric cities	Distributed mix	Public transit focused	Evenly distributed mix
City age	Mixed types	Mid-aged cities	Old, established cities	Newer cities	Mixed types

[a] Includes urban area and periphery.

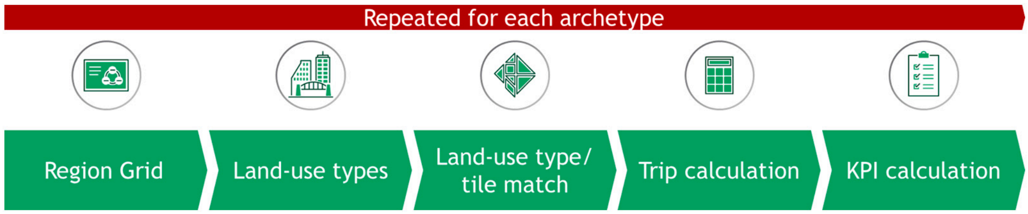

Fig. 3. Five-step modelling process to generate key performance indicators based on the region grid, which is separately applied to all five archetypes.

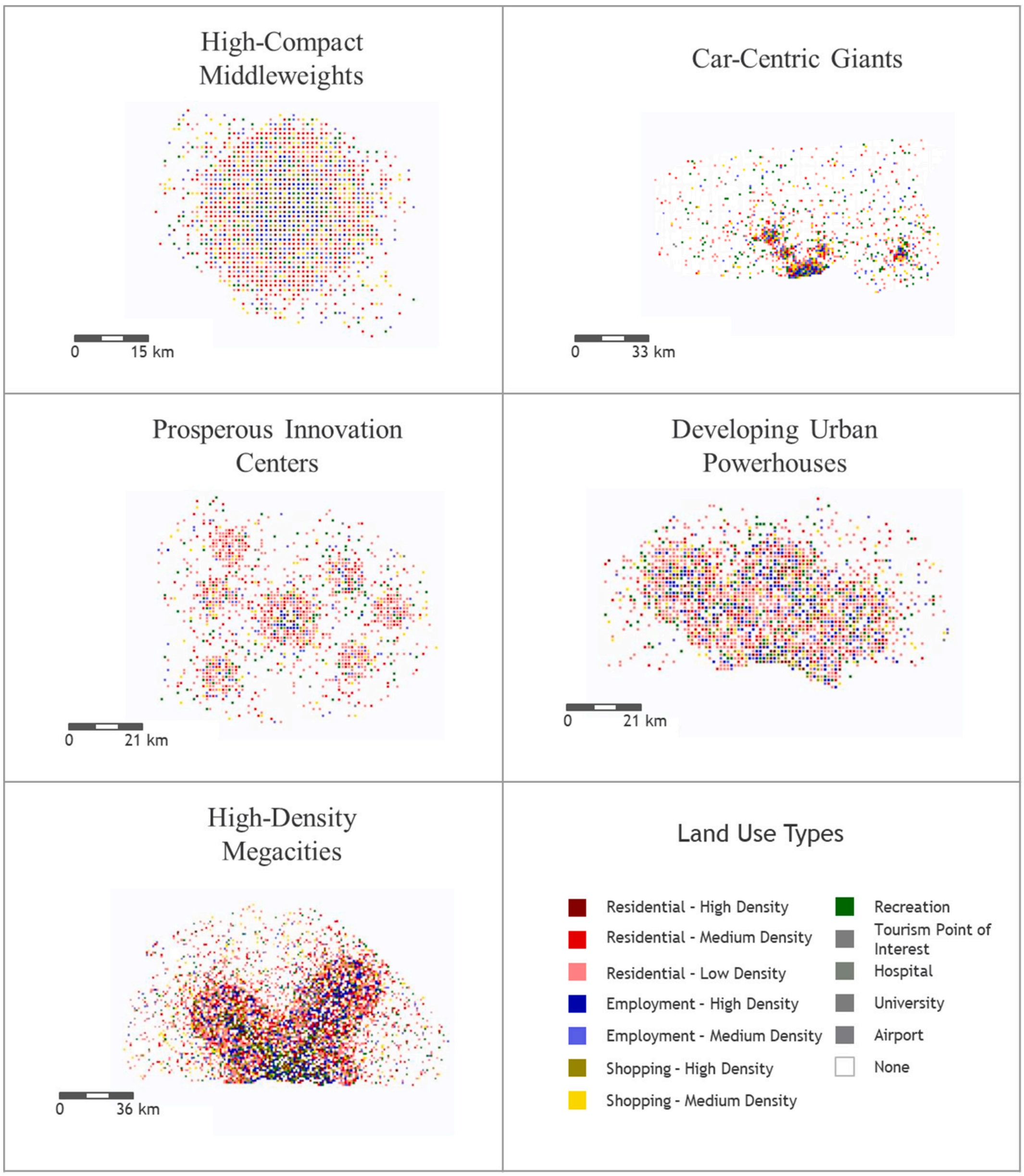

Fig. 4. Depiction of archetype region grid including land-use types, which are based on the clustering of 40 cities.

1) Estimate the distance between the tiles' centroids based on the assumption of the traditional grid network. Friction factors are inversely related to spatial separation of zones. It decreases with the increase in travel times.
2) Calculate the denominator of the gravity model for each production:

$$T_{ij} = P_i{}^*\left[A_j{}^*\frac{F_{ij}}{\Sigma A_k F_{jk}}\right]$$

where, T_{ij} = the number of trips from zone i to zone j
P_i = the number of trip productions in zone i
$A_{j,k}$ = the number of trip attractions in zone j, any other zone k
$F_{i,j,k}$ = the friction factor relating the spatial separation between

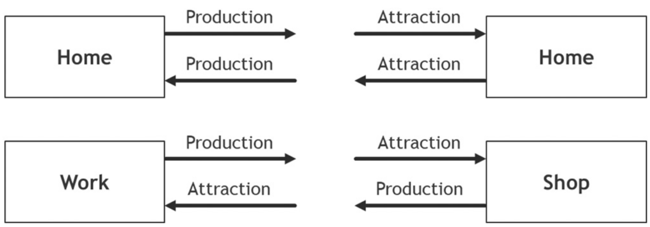

Fig. 5. Travel demand forecasting and techniques (Bhat, 2012) used to generate predicted demand for simulation.

zone *i*, zone *j*, any other zone *k*.

3) Estimate the distance between the tiles' centroids based on the assumption of the traditional grid network (only north-south and west-east connections).

- Mode Choice: Modal split is a fixed, distanced-based assumption for all tile connections for each scenario. Hence, the mode choice differs between scenarios – explicitly described in the section, Modal mix.
- Trip Assignment: Route assignment allocates trips between an origin and destination by a mode to a route. This step is covered in the mobility tool as a detail on a tile. This means there is no reallocation of traffic routes because the trip is assumed to take place on straight lines between neighboring tiles.

Based on the number of generated trips due to the demand model, the transit volume for each transport mode is derived. Based on the transit volume, the following KPIs are derived for each cluster in step 5: annual fatalities, energy consumption, total parking area, transportation cost, and average journey time. The input parameter from Table 3 has been used for the simulation and the derivation of the KPIs. These parameters were calculated as an average across the values of different countries to reflect a global value. For example, handbooks for technical data were used to calculate energy consumption and average costs. For public transport, data from MVG Munich (MVG, 2019) were used and, for AV shuttles, technical data from the manufacturer Navya (2019). The number of average deaths refers to how many deaths are caused by the specific means of transport. The numbers are based on published data by the government of each city or country. We used data from Transport Accident Commission (TAC, 2019) for Australian cities and data from Transport for London (2019). The occupancy rate is derived from different sources across the world, such as the National Household Travel Survey (NHTS, 2018) by the Federal Highway Administration, and the European Environment Agency (2016).

3.3. Urban mobility scenarios

In this paper, scenarios are defined as different images of the future.

3.3.1. Shift from private cars to non-AV transport modes

Although the private vehicle defined the past century to a large extent, and a world without cars is hard to imagine, metropolitan authorities have introduced policies to curb private car trips and encourage other forms of transport. Several major cities, including Amsterdam, Hamburg, Helsinki, Madrid, and Oslo, have begun to restrict the use of cars. Other cities such as Bogota, Brussels, Chengdu, Copenhagen, Dublin, Hyderabad, Milan, and Paris employ various measures that aim to reduce motorized traffic including introducing car-free days (Carthkart-Keays, 2015).

3.3.2. Dominance of micromobility

Micromobility is a term used to describe a novel category of transportation using non-conventional battery-powered vehicles – standing scooters, also known as electric scooters or e-scooters (SAE International, 2019) – designed for travel over distances that are too short to drive or utilize public transportation, yet too far to walk (Krizek and McGucking, 2019). Micromobility solutions are not a fad because they have rapidly expanded across the world and are present in 350 cities currently (Rose et al., 2020).

3.3.3. Strong push for AV shuttles

We identified several companies that manufacture AV shuttles, such as Navya and Easymile. At least 34 other companies, such as Bosch, ZF Friedrichshafen, Continental, and Daimler, are working on this technology. Furthermore, these vehicle types are already used in pilot projects in about 20 countries. This scenario suggests that, in the future, autonomous vehicles will be used in a pooled way and not as personal transport possessed by individuals.

3.3.4. Strong uptake of AV pods

These are smaller autonomous vehicles that require a little less space and are used by only one to two people. The occupancy is much lower because, in this scenario, the vehicle is not shared with someone else. There will be routes that are not worth driving with shared vehicles or people will simply not want to share vehicles. For example, Tesla is gradually introducing technology that will allow the vehicle to drive completely autonomously. This would lead to a scenario that is mainly characterized by autonomous individual traffic.

3.4. Transportation modes

To make the simulation as realistic as possible, single mode trips as well as multi-modal trips were considered. In the simulation of the base case, only non-AV trips were considered whereas, in the future scenario, the transport modes were supplemented by AV modes. Multi-modal trips represent the fact that people do not restrict their use to only one mode of transport. They are much more intermodal, and the travel chain contains several transport modes. The used transport modes and multi-modal trips are shown in Fig. 6.

3.5. Modal mix

With each virtual archetype, we used publicly available data from our city sample to model the modal split today. For the current modal split, we included five transport modes (private car, public transport, taxi/ride hailing, micromobility, and walking). This information formed the starting point for our simulation. For this, we used the findings of a joint study by BCG and the World Economic Forum (Moavenzadeh and Lang, 2018), which asked 5500 inhabitants across multiple types of city what transport mode they would select given eight choices. The study analyzed the behavior of people when autonomous vehicles are implemented in their cities. Employing conjoint analysis, it was determined

Table 3
Simulation input parameter as the average across different cities.

Modes	Walking	Micro-mobility	Private car	Public transit	Taxi	AV pod	AV taxi	AV shuttle
Average speed [km/h]	5	15	25	15	25	25	20	15
Average energy consumption [kwh/km]	0	0.02	0.36	14.3	0.36	0.18	0.33	0.68
Average deaths [deaths/billion km]	0	1.3	6.3	33.9	6.3	1.3	1.3	1.3
Average occupancy [pax]	1	1	1.5	81	1.4	1.2	1.6	5
Average cost [$/passenger km]	0	0.29	0.55	0.25	1.34	0.5	0.51	0.37

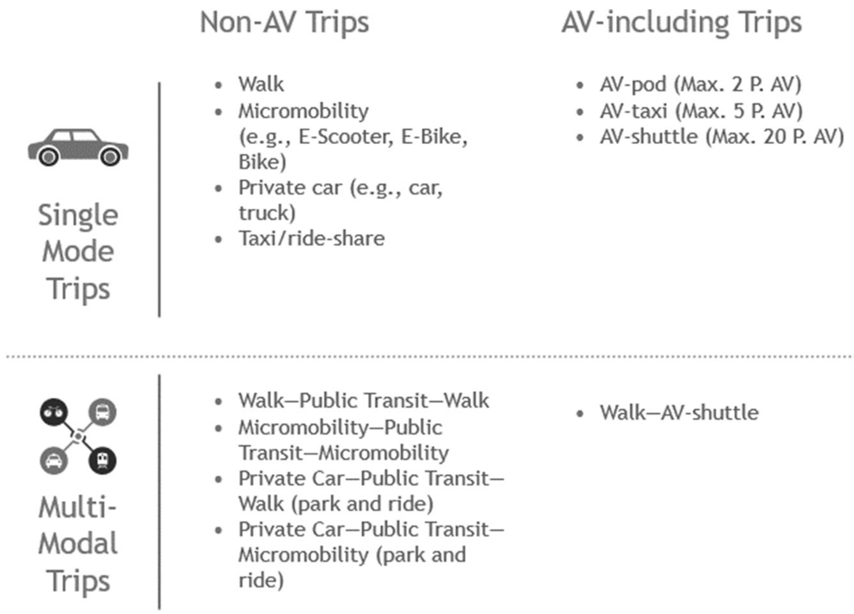

Fig. 6. Both single mode trips and multi-modal trips are considered in the simulation. The graphic represents the used transport modes and multi-modal transport chains.

how many people use the autonomous vehicle instead of a traditional means of transport daily. The findings of this study offer insights and guidance to help both government and mobility providers reshape urban mobility systems into new versions that are safer, cleaner, and more inclusive. To the five existing options, we added three AV modes: AV pods (which seat up to two passengers), AV taxis (up to five passengers), and AV shuttles (up to 15 passengers). The resulting future modal split was our base case scenario. For the actual simulation, we considered the distribution of mobility options across short-, medium-, and long-distance trips using current data and the results of the BCG/WEF survey (Moavenzadeh and Lang, 2018). Since the study considered only three archetypes and not all the transport modes that we deliberated on, modal mixes had to be adopted. Here, a reclassification of the BCG/WEF mode was applied to incorporate modal mix into our transport mode logic. The modal mix used for the base case 2018 and the future base case 2035 in our study is shown in Table 4. The numbers indicate how the distribution of the means of transport is divided. To create the respective modal mix for each scenario, the modal mix was adjusted based on the future modal mix base case. For this purpose, the corresponding means of transport that experience an uptake were significantly increased. The modal mix distribution for each archetype and scenario is depicted in Fig. 7.

There are differing opinions on when autonomous vehicles will penetrate our roads. The fact is, in recent years, autonomous driving has become a reality. Companies such as Waymo and NuTonomy had launched self-driving-car services as early as 2016. According to Bloomberg (2019), there are 24 AV pilot projects in the US and 50 other pilot projects across the world. If such companies expand their services from suburban pilot projects to area-wide operations in cities around the world, a fundamental revolution in mobility is likely to occur, as well as a dramatic change in traffic, urban form, and travel behavior. Optimists predict that shared autonomous taxis will soon displace most private vehicles (ITF, 2018; Keeney, 2017). Nevertheless, current projects are only pilots. Since we assume the widespread use of autonomous vehicles in this study, we tend to follow conservative studies, such as Arbib and Seba (2017), who predicted that, by 2030, autonomous vehicles will serve 95 % of all U.S. passenger miles. Furthermore, studies on autonomous cars (Compostella et al., 2020; Pakusch et al., 2018) use the conservative time frame of 2030–2035 for area-wide distribution. Consequently, we decided to base our study on the year 2035.

Table 4
Modal mix derived from Moavenzadeh and Lang (2018) for the current and future share of transportation.

Archetypes	High-compact middleweights	Car-centric giants	Prosperous innovation centers	Developing urban powerhouses	High-density megacities
Current modal mix					
Public transit	23	12	19	29	21
Private car	31	58	33	22	25
Taxi/ride hailing	4	6	9	22	22
Micromobility	15	11	9	6	6
Walking	26	13	30	32	26
Future modal mix base case					
Public transit	14	10	15	20	16
Private car	18	31	15	10	12
Taxi/ride hailing	1	4	4	3	10
AV pod	3	11	9	2	8
AV taxi	9	11	11	9	10
AV shuttle	12	8	8	12	9
Micromobility	18	10	12	14	11
Walking	25	12	27	30	24

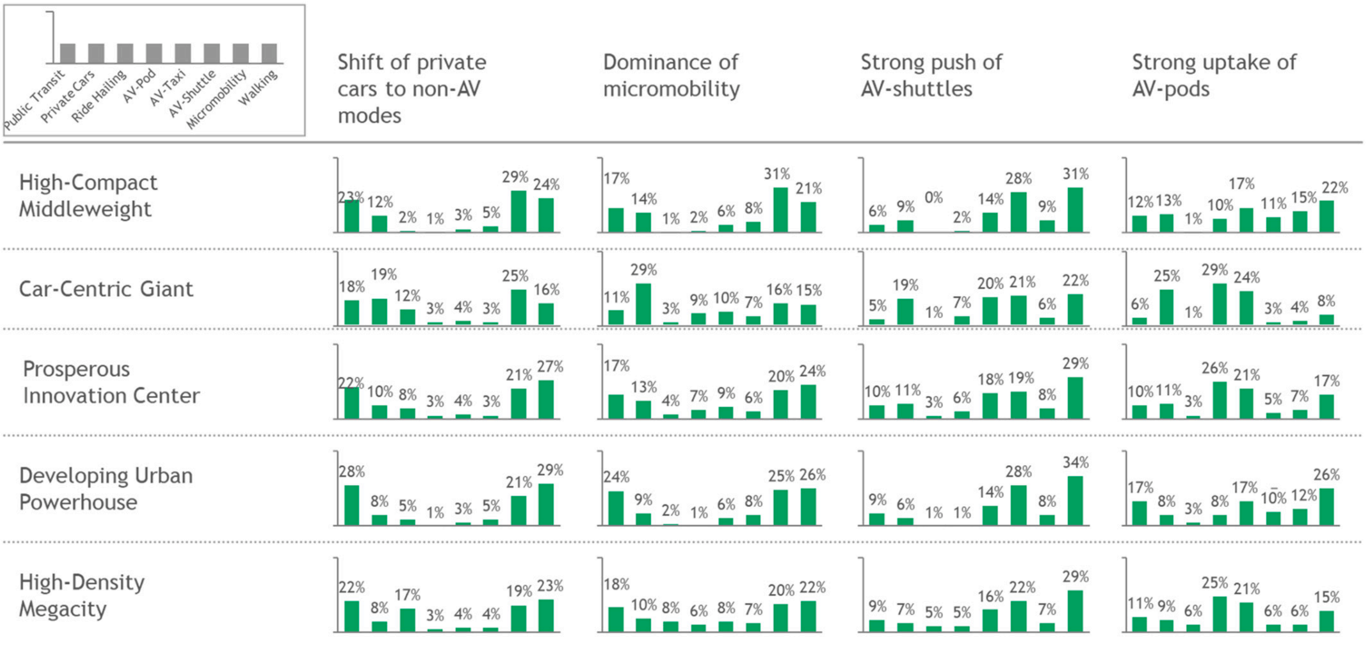

Fig. 7. Future modal mix per archetype and scenario aligned with the determined future modal mix, which is derived from Moavenzadeh and Lang (2018).

4. Model results

In this section, the results of the quantitative model are presented. First, the results are discussed in general terms, followed by the results of the individual archetypes.

The changes in KPIs are presented in Fig. 8. These allow a comparison of the performance of the KPIs for the different scenarios. For each KPI, we show the performance change to the base case scenario, which represents the traffic condition in 2019.

The most significant result from the set is the improvement in the KPIs practically across all archetypes and scenarios. Overall, these results indicate an improvement in traffic conditions (in terms of the KPIs considered) from implementing AVs independent of the scenario compared to the non-integration of AVs. Transferred to the scenarios with the most significant changes, this amounts to a reduction of up to 22 % in traffic volume, 60 % in fatalities, 21 % in energy consumption, 58 % in parking area, 27 % in transportation costs, and 8 % in journey time across different archetypes. Only in the strong uptake of the AV-pods scenario is an increase in traffic volume (up to 19 %) observed. This scenario, therefore, has the least positive influence. This is due to the low occupancy rate and the persistently high level of individual traffic. In relation to our hypotheses, this means that cities benefit differently from AVs depending on their unique traits. Thus, for certain city types, there are scenarios that have a better impact on the city of the

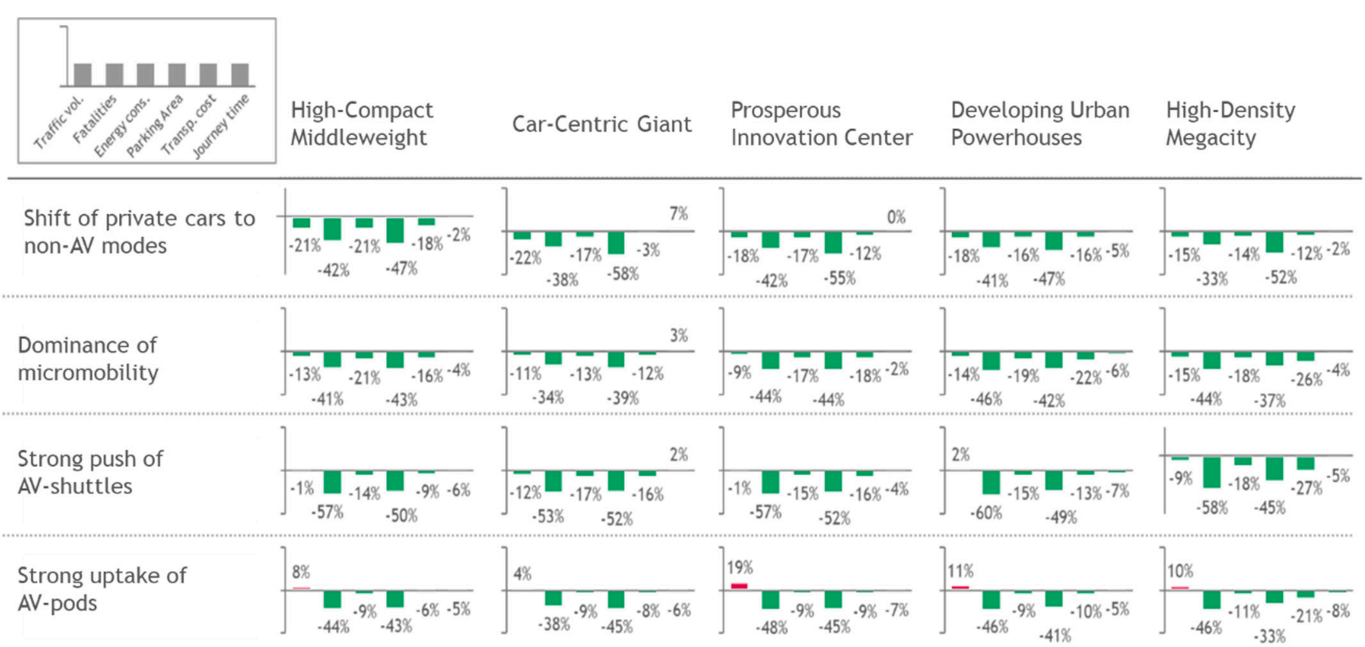

Fig. 8. Simulation results showing change in traffic volume, fatalities, energy consumption, needed parking area, transportation costs, and journey time for each of the four scenarios applied to each of the five city archetypes.

future than an AV spread. Since politicians today can wield an important influence on the strategy of their city, they are well placed to exert an impact on the success of AVs. Furthermore, the introduction of AVs must be controlled by politicians. If they are introduced as AV pods, the situation will not improve as much as if AV shuttles are introduced into cities. This statement applies to all archetypes.

Results per smart city archetype significantly vary by urban mobility scenario.

High-Compact Middleweights (HCM) profit the least from the introduction of AVs, for both scenarios of the strong push for AV shuttles and the strong uptake of AV pods. The relatively low improvement when pushing for AV vehicles is due to the characteristic in this archetype of many short trips, a dense city center, and good access to public transit. However, AV shuttles and AV taxis cannibalize public transportation, which leads to relatively poor improvement in traffic volume: −1 % for the strong push of the AV-shuttle scenario and 8 % + for the strong uptake of the AV-pod scenario. The best suited scenario for HCMs is regulating private cars. This scenario performs best for this archetype because the traffic volume experiences a significant drop of 21 % due to the existing infrastructure, which is able to absorb the change from private cars. The substantial reduction in transportation costs comes from people changing from more expensive private transport to cheaper public transport.

Car Centric Giants (CCG) profit only moderately from the introduction of AVs. Although AV pods offer a convenient and fast replacement for private cars that is greener, cheaper, safer, and reduces journey time, transportation remains mainly individual, weakening improvement compared to other scenarios and even leading to increased traffic volume due to the cannibalization of pedestrian and public transit. However, as public transit access is poor, many people in a scenario without autonomous cars switch to taxi/ride hailing, which weakens the positive effect and keeps transportation cost reduction low. Nevertheless, the best scenario for CCGs is a strong push of AV shuttles since missing alternatives in the widely distributed urban pattern can be compensated for by these new emerging vehicles. Given this scenario, a disproportionately large reduction in parking space (52 %) and in fatalities (53 %) leads to the best positive changes compared to the base case scenario.

While AV shuttles deliver the greatest positive impact on Prosperous Innovation Centers (PIC), they also benefit significantly from curbing private cars and encouraging other non-AV transport modes, including micromobility. The advantages result from the large reduction in the area given over to parking (up to 55 %) and the decrease in parking spaces (up to 57 %). In addition, the traffic volume is greatly reduced (−18 %) in the scenario shift of private cars to non-AV. The scenario of a strong uptake of AV pods has the worst effect with a 19 % increase in traffic volume. In addition, the 9 % reduction in transport costs and 9 % in energy consumption in this scenario is below the improvement seen in other scenarios.

Developing Urban Powerhouses (DUP) benefit greatly from a strong push of AV shuttles, but the scenario dominance of micromobility is more advantageous. In the strong push of AV-shuttles scenario, the change in fatalities (−57 %) and required parking spaces (−52 %) is substantial. In the dominance of micromobility scenario, all KPIs perform consistently well, which means that this scenario delivers strong added value. This is because good access to public transit is very well complemented by micromobility and replaces private cars. Furthermore, the large share of short trips allows micromobility to offer a faster journey. Even though a strong uptake of AV pods leads to a fast journey time because streets dominated by AVs allow for smoother traffic flow, the shift from today's shared transportation to individual transportation increases traffic volume (+2 %) and weakens the positive effect of energy consumption, required parking areas, and transportation costs.

High-Density Megacities (HDM) profit most from the introduction of AV shuttles, which offer an excellent option for evenly distributed short-, medium-, and long-distance journeys. Significant improvement is observed since shared autonomous mobility replaces private cars and taxi/ride hailing and simultaneously fosters walking. This eliminates the high costs of individual transport, which is replaced by the lower costs of AV-shuttle use. Moreover, private cars become nearly extinct, with only 10 % of trips being undertaken in such vehicles. The large share of AV shuttles and AV taxis means that charging spaces are needed, which slightly lowers the effect of the reduction in the parking needed compared to the dominance of the micromobility scenario.

5. Sustainable investment strategies for urban mobility and AV

Spickermann et al. (2014) found that high investments are needed to deal with urban mobility challenges. Hence, a sustainable investment strategy for urban mobility is necessary. Based on our results, we see that, for three of our archetypes (Car-Centric Giants, Prosperous Innovation Centers, and High-Density Megacities), promoting AV shuttles delivers the greatest advantage as measured by improvements in the model's KPIs (Table 5). For Developing Urban Powerhouses, however, micromobility would deliver greater benefits; and for High-Compact Middleweights, a shift from private cars to other non-AV modes of transportation would be the smartest investment choice. Still, promoting an uptake of privately owned AV would not be beneficial across all archetypes.

For High-Compact Middleweights, a shift from private cars to other non-AV forms of transport creates the best overall outcome based on the KPIs considered in this study. As seen in the simulation, cities benefit the most if planners prioritize measures that reduce car volume in urban cities. Since mass-transit networks will pick up the slack by carrying more passengers, it is not prioritized when introducing AVs. AVs should be used in a much more regulated way, where the public transportation network ends or where access to public transport is limited. To do so, planners could introduce measures that define regulatory levers (such as congestion pricing, road closures during peak times, and high parking fees), which will strongly reduce individual motorized vehicle traffic. But, to avoid public transit becoming overcrowded, planners will need to invest in additional routes and new “hybrid” public transport, such as on-demand public buses. Furthermore, it may be advantageous to provide last mile options for large numbers of short trips. For example, agencies could partner with leading last mile providers to set up a sustainable urban mobility plan that includes micromobility as the main mode of transport.

Promoting AV shuttles is the best choice for Car-Centric Giants. Public transit networks are often poorly developed in CCGs and cannot absorb additional traffic. According to our simulation, KPIs improve the most when politicians adapt their strategy to accommodate a rapid spread of AV shuttles. In this case, journeys are bundled, with a consequent reduction in traffic volume on roads. In addition, the use of AV shuttles increases access to the public transport network by offering flexible routes, leading to increased use of public transport. Hence, it is quite important to prevent an overload of public transit that would result from extending the existing public transit network (higher frequency, modernization of means of transport, higher accessibility) before shared autonomous vehicles are ready. Furthermore, micromobility should be implemented only as a niche solution. Micromobility has the lowest benefits for this archetype because of the large number of medium and long-distance trips in CCGs. City decision makers should limit the application of micromobility to the first/last mile option in city centers to increase the attractiveness of public transit.

While AV shuttles deliver the greatest positive impact for Prosperous Innovation Cities according to our KPIs, they also benefit significantly from curbing private cars and encouraging other non-AV transport modes, including micromobility. Planners should adopt a balanced approach that promotes all three. As seen in our data, PICs, such as London and San Francisco, have narrow streets and ageing architecture. Planners should consider curbing private cars in urban centers and creating car-free central zones that favor AVs. They can also build AV-

Table 5
Sustainable investment strategy per archetype derived from urban mobility scenario performance.

	High-compact middleweight	Car-centric giant	Prosperous innovation center	Developing urban powerhouses	High-density megacity
Shift of private cars to non-AV modes	High positive impact	High positive impact	High positive impact	Low positive impact	Low positive impact
Dominance of micromobility	Highest positive impact	Lowest positive impact	Low positive impact	Highest positive impact	High positive impact
Strong push of AV-shuttles	Low positive impact	Highest positive impact	Highest positive impact	High positive impact	Highest positive impact
Strong uptake of AV-pods	Lowest positive impact	Low positive impact	Lowest positive impact	Lowest positive impact	Lowest positive impact

friendly infrastructure, such as dedicated lanes and sensors, to help this new technology succeed. They should run pilot AV projects in zones with simple street patterns before venturing into areas with more complex configurations.

For Developing Urban Powerhouses, micromobility promises the greatest benefits. Cities in these archetypes offer good access to public transportation as well as dense city hubs surrounded by satellites. Facilitating an uptake in micromobility will improve affordability and access. Hence, micromobility can play a key part in urban transport. Building docking bays and parking areas close to mass transit stations and creating attractive subscription models combining micromobility with public transport (such as free last-mile trips for annual mass-transit pass holders) are two ways to achieve this. Developing a single booking platform and end-user interface will further encourage use of these modes. Furthermore, planners can reduce collision rates by creating exclusive micromobility lanes. Many DUPs, such as Bangkok, suffer from disorganized transport systems, underinvestment, and low-tech mobility equipment. In this situation, AV shuttles should be treated as a long-term goal to be realized once these deficiencies have been addressed.

Since High-Density Megacities derive the maximum benefit from AV shuttles, they should start to introduce them early on. Planners can run pilots to promote consumer acceptance and introduce trial incentives that encourage switching, thereby solving problems that could delay a wider rollout. Because small AVs will deliver far fewer benefits, it is imperative that policy makers encourage AV shuttles and AV taxis over AV pods. HDM city dwellers take a relatively high proportion of long-distance trips, so planners should create dedicated AV-shuttle lanes that facilitate these longer journeys and ensure that other vehicles are not hampered by slower-moving, shared AVs. We expect AVs to replace conventional taxis and ride-hailing services in HDMs, so city authorities need to prepare for this transition and the consequent impact on the taxi industry.

6. Conclusion

6.1. Discussion

The question underpinning this research was: "What are the potential long-term benefits and drawbacks from the introduction of AVs in various smart city archetypes?" The answer is that not all cities benefit equally from AV implementation. Accordingly, it is not worthwhile for all cities to include the technology of autonomous driving in the smart city agenda or to give high priority to AV implementation. Whether investments in new greener ways of smart mobility are worthwhile for cities depends on their structure and characteristics. By carrying out a continuous space modelling approach, this form of simulation provides an overview of the city types where AVs can work. Our analysis includes data from 40 cities with eight different characteristics, such as urban settings, population density, and model mix. Based on these data, five city archetypes are identified, to which each city is assigned via clustering. For each archetype, four simulation scenarios are performed to determine which scenario is best suited. Our findings lead us to argue that not every smart city government needs to invest in AV. By following the strategies, we have outlined for cities, governments can use their financial resources more sustainably.

The key findings highlight that AVs do not deliver the same benefits to every smart city concept. City types with well-developed public transport systems and small travel routes benefit little from the spread of autonomous vehicles. For such city types, a reduction in individual traffic, such as traditional cars, leads to the greatest improvement in the traffic situation because the public transport network can absorb the additional transport users. Cities with poorly developed public transport systems benefit most from the spread of AV shuttles because these extend access to the existing public transport network and, thus, take pressure off the roads. Densely populated cities with a sizeable number of inhabitants and large areas also benefit from AV-shuttle expansion. AV pods are not advantageous in any of the archetypes. The low occupancy of AV pods leads to an increased load on the transport network.

6.2. Theoretical implications

Our research contributes to the extant literature in three ways. First, in line with Del Vecchio et al. (2019), this study highlights the importance of data-driven policy development due to traffic simulations. We live in an increasingly complex world with rising demand for mobility, which poses a challenge for policy makers to define long-term policies and strategies (Macal and North, 2009). Data-driven tools help to deal with increasing complexity of transportation, which arises from modern life and new means of transportation, such as autonomous driving (Bazzan and Klügl, 2014; Spickermann et al., 2014; Moradi and Vagnoni, 2018). Nevertheless, as shown above, prior research has mostly employed simulation focused on single cities or KPIs to evaluate the impact of AVs on smart cities. We provided an approach across multiple cities and KPIs to evaluate the impact of AV deployment. By analyzing cities through archetypes, we provide a way to make strategic investment recommendations for different types of city. This approach eliminates uncertainties in simulation across cities due to different input variables. Thus, we deliver a relevant approach for optimizing decision making in urban mobility and smart cities.

Second, this study contributes to the emerging smart city research committed to the idea that there is no "one-size-fits-all" smart policy (Clement and Crutzen, 2021). Moreover, Ruhlandt (2018) argued that policy makers need to develop a smart city strategy that is tailor-made. Desdemoustier et al. (2019) provide further insights into the smart city as a local phenomenon rather than adopting a nationwide approach. They show that cities have different strategies. Our approach echoes this argument in affirming that different cities must adopt discrete strategies to optimize their urban mobility needs. Our findings demonstrate that the different characteristics of cities mean that not all cities benefit from the same urban mobility strategy. AVs are beneficial in three archetypes, yet two archetypes benefit more from non-AV scenarios. Accordingly, investment in these technologies would not necessarily provide added value.

Finally, up to now, research has used traffic simulations to predict the impact of AVs (Jing et al., 2020). Nevertheless, the impact of AVs is uncertain as shown in the literature review. Hence, the future of urban mobility remains unclear, and inferring the value of any smart city strategy is limited. We present a first attempt to use the same variables across several cities from around the world. This creates transparency and allows a comparison between different cities and their possible strategies. Accordingly, we provide a foresight methodology based on our tool, which contributes to the quality of long-term decision making and its literature (Liebl and Schwarz, 2010; Vecchiato and Roveda, 2010; Gordon et al., 2020).

6.3. Managerial implications

New emerging technologies require contextual analysis. Our results demonstrate that policy makers and companies who are investing in AVs should not ignore knowledge on the individual attributes of cities. There is concern that this knowledge will be ignored, with consequences that will prove costly. The fact that cities have different characteristics is important to consider when implementing disruptive innovations, such as new autonomous driving technologies. Policy makers should not consider the technology in isolation. They must consider the specific urban environment. This holds certain practical implications for driver stakeholders.

6.3.1. Policy makers

This paper presents results on archetypes to help policy makers better align their long-term mobility strategies for smart cities. Policy makers on a national and regional level are urged to revise and adjust their transport strategies to avoid detrimental effects. However, most public officials have not yet shown a preparedness to react appropriately (Thomopoulos and Givoni, 2015; Faisal et al., 2019). Based on our results, public transportation will likely continue to be the backbone of urban mobility in most archetypes. In line with Spickermann et al. (2014), we argue that policy makers need to convey a seamless, multimodal travel experience for citizens. Hence, when new transportation options emerge, policy makers should ensure that traditional public transport players collaborate with AV solution providers. Policy makers should include these new providers when planning long-term infrastructure investments and should work with them to improve network access. Furthermore, effective rules are a prerequisite for successful AV introduction. For archetypes that will benefit the most from non-AV scenarios, it is particularly important to establish regulatory frameworks at an early stage to avoid AVs disrupting the existing and well-functioning public infrastructure. Policy makers need to actively drive the introduction of new technologies on a holistic level rather than AV solution providers driving the dissemination. By shaping the physical environment in which AVs operate, policy makers can exert a significant impact on the success of AVs. For policy makers, it is also essential to recognize that the implementation scenario of private autonomous vehicles is not beneficial for any archetype. Accordingly, policy makers need to ensure that autonomous driving adds value to the entire population and does not favor individuals.

6.3.2. AV solution providers

As demonstrated, cities are different, so the different disruptions introduced by different types of AV do not provide the same added value for every city. Based on our analysis, it is important for AV solution providers to acknowledge that the most beneficial scenarios will be different for different cities and that a one-size-fits-all scenario is unlikely to materialize. For example, a strong push of AV shuttles is likely to be the best scenario for High-Density Megacities, such as New York City and Shanghai. In cities such as Berlin or Vienna, city planners and policy makers should not risk large amounts of money on AVs because their public transportation systems are well developed, and the benefits from this new transport mode are rather small. AVs are not just about new transportation modes. They will fundamentally change cities and force city planners and policy makers to rethink how their transportation should be reorganized to unleash the highest benefits from autonomous driving. Consequently, companies must ensure that autonomous vehicles represent added value for cities and their citizens. If there is no added value for cities, the technology will not be accepted by customers, or it will be restricted by policy makers and mean that the high investment costs will not yield a return on investment.

6.4. Limitation and future research

As with most research, this study has certain limitations that should be considered. First, we limited the simulation to traffic-related parameters. Even though indirect psychological factors, such as lack of acceptance, are already well researched (Merfeld et al., 2019; Lindgren et al., 2021), these were not considered in the study. Therefore, in future research, the model could be parametrized and developed further to examine the specific psychological aspects. Second, to predict the impact of AVs on urban mobility, the modal mix is important. Since the modal mix is not known for the future, we had to predict it. There is a corresponding uncertainty in the prediction, which affects the result. However, we have tried to make predictions as accurately as possible based on various studies. Nevertheless, future studies examining how fast different AV implementation scenarios will spread would be helpful for further simulations. Third, to facilitate comparison with different types of cities, we had to create archetypes. These archetypes lead to a certain degree of simplification. Future research could address this limitation by operating more detail simulations across different cities with the same input variables, such as agent-based modelling and sensitivity analyses with various input parameters, so that several scenarios can be run. Finally, in deriving smart city strategies, we have not considered the absolute costs of implementing autonomous vehicles because the costs for business models in the future will likely not only be covered by cities but by AV service providers as well. However, future research could address the actual costs incurred by cities to implement the new technologies.

Data availability

Data will be made available on request.

References

Albino, V., Berardi, U., Dangelico, R.M., 2015. Smart cities: definitions, dimensions, performance, and initiatives. J. Urban Technol. 22, 3–21. https://doi.org/10.1080/10630732.2014.942092.

Allwinkle, S., Cruickshank, P., 2011. Creating smarter cities: an overview. J. Urban Technol. 18 (2), 1–16. https://doi.org/10.1080/10630732.2011.601103.

Anderson, J.M., Kalra, N., Stanley, K.D., Sorensen, P., Samaras, C., Oluwatola, T.A., 2014. Autonomous Vehicle Technology: A Guide for Policymakers, 2016. RAND Corporation, Santa Monica, CA. https://www.rand.org/pubs/research_reports/RR443-2.html.

Arbib, J., Seba, T., 2017. Rethinking Transportation 2020-2030: The Disruption of Transportation and the Collapse of the Internal-Combustion Vehicle and Oil IndustriesRethinking transportation 2020–2030: the disruption of transportation and the collapse of the internal-combustion vehicle and oil industries. RethinkX (www.rethinkx.com). https://www.wsdot.wa.gov/publications/fulltext/ProjectDev/PSEProgram/Disruption-of-Transportation.pdf.

Bando, M., Hasebe, K., Nakayama, A., Shibata, A., Sugiyama, Y., 1995. Dynamical model of traffic congestion and numerical simulation. Phys. Rev. 51 (2) https://doi.org/10.1103/PhysRevE.51.1035.

Barba-Sánchez, V., Arias-Antúnez, E., Orozco-Barbosa, L., 2019. Smart cities as a source for entrepreneurial opportunities: evidence for Spain. Technol. Forecast. Soc. Chang. 148 (Nov. 2019), 119713. ISSN 0040-1625. https://doi.org/10.1016/j.techfore.2019.119713.

Bazzan, A.L., Klügl, F., 2014. A review on agent-based technology for traffic and transportation. Knowl. Eng. Rev. 29 (3), 375–403. https://doi.org/10.1017/S0269888913000118.

Berlin.de, 2019. Geschichte. Retrieved from. https://www.berlin.de/berlin-im-ueberblick/geschichte/.

Bhat, C.R., 2012. Travel demand forecasting: parameters and techniques. In: National Cooperative Highway Research Program (NCHRP) Report 716. Retrieved from. https://ntrl.ntis.gov/NTRL/dashboard/searchResults/titleDetail/PB2012108697.xhtml.

Bibri, S.E., Krogstie, J., 2017. Smart sustainable cities of the future: an extensive interdisciplinary literature review. Sustain. Cities Soc. 31, 183–212.

Bischoff, J., Maciejewski, M., 2016. Simulation of city-wide replacement of private cars with autonomous taxis in Berlin. Procedia Comput. Sci. 83, 237–244.
Bischoff, J., Maciejewski, M., Schlenther, T., Nagel, K., 2018. Autonomous vehicles and their impact on parking search. IEEE Intell. Transp. Syst. Mag. 11 (4), 19–27. https://doi.org/10.1109/mits.2018.2876566v.
Bloomberg Philanthropies, 2019. Autonomous Vehicle in Cities. Retrieved from. https://www.bloomberg.org/program/government-innovation/bloomberg-aspeninitiative-cities-autonomous-vehicles/.
Boesch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. Transp. Policy 64, 76–91. https://doi.org/10.1016/j.tranpol.2017.09.005.
Brown, A., Gonder, J., Repac, B., 2018. Erratum to: An Analysis of Possible Energy Impacts of Automated Vehicles. https://link.springer.com/chapter/10.1007/978-3-319-05990-7_22.
Caragliu, A., Del Bo, C.F., 2019. Smart innovative cities: the impact of smart city policies on urban innovation. Technol. Forecast. Soc. Chang. 142, 373–383. https://doi.org/10.1016/j.techfore.2018.07.022.
Carthkart-Keays, 2015. Will we ever get a truly car-free city? Retrieved from, The Guardian. https://www.theguardian.com/cities/2015/dec/09/car-free-city-oslo-helsinki-copenhagen.
Central Intelligence Agency, 2019. The World Factbook. Retrieved from. cia.gov/library/publications/the-world-factbook/.
CFA – Center for Financial Accountability, 2021. Smart City Deadline Looms but Targets Remains Distant. https://www.cenfa.org/media-coverage/smart-city-deadline-looms-but-targets-remain-distant/.08.01.2022.
Childress, S., Nichols, B., Charlton, B., Coe, S., 2015. Using an activity-based model to explore the potential impacts of automated vehicles. Transp. Res. Rec. 2493 (1), 99–106. https://doi.org/10.3141/2493-11.
Clark, B., Parkhurst, G., Ricci, M., 2016. The potential impact of autonomous vehicles on transport systems and society: a review and future prospects. In: Presented at the 48th Universities' Transport Studies Group Conference, 48th Universities' Transport Studies Group Conference, Bristol, UK.
Clement, J., Crutzen, N., 2021. How local policy priorities set the Smart City agenda. Technol. Forecasting Soc. Change 171 (2021), 120985. ISSN 0040-1625. https://doi.org/10.1016/j.techfore.2021.120985.
Clements, L.M., Kockelman, K.M., 2017. Economic effects of automated vehicles. Transport. Res. Rec. J. Transport. Res. Board 2606 (1), 106–114. https://doi.org/10.3141/2606-14.
Compostella, J., Fulton, L., De Kleine, R., Kim, H., Wallington, T., 2020. Near- (2020) and long-term (2030–2035) costs of automated, electrified, and shared mobility in the United States. Transport Policy 85 (2020), 54–66. ISSN 0967-070X. https://doi.org/10.1016/j.tranpol.2019.10.001.
Conibear, L., Butt, E.W., Knote, C., Lam, N.L., Arnold, S.R., Tibrewal, K., Bond, T.C., 2020. A complete transition to clean household energy can save one–quarter of the healthy life lost to particulate matter pollution exposure in India. Environ. Res. Lett. 15 (9), 094096.
Davidson, P., Spinoulas, A., 2016. Driving alone versus riding together-how shared autonomous vehicles can change the way we drive. Road Transport. Res. 25 (3), 51–66.
De Jong, M., Joss, J., Schraven, D., Zhan, C., Weijnen, M., 2015. Sustainable–smart–resilient–low carbon–eco–knowledge cities; making sense of a multitude of concepts promoting sustainable urbanization. J. Clean. Prod. 109 (2015), 25–38. https://doi.org/10.1016/j.jclepro.2015.02.004.
Del Vecchio, P., Secundo, G., Maruccia, Y., Passiante, G., 2019. A system dynamic approach for the smart mobility of people: implications in the age of big data. Technol. Forecast. Soc. Chang. 149, 119771.
Demographia, 2016. Demographia World Urban Areas, , 12th Annual edition2016, p. 04. Retrieved from. https://cdn.plataformaurbana.cl/wp-content/uploads/2016/05/demographia-world-urban-areas.pdf.
Desdemoustier, J., Crutzen, N., Giffinger, R., 2019. Municipalities' understanding of the smart city concept: an exploratory analysis in Belgium. Technol. Forecast. Soc. Chang. 142, 129–141.
Dia, H., Javanshour, F., 2017. Autonomous shared mobility-on-demand: Melbourne pilot simulation study. Transport. Res. Proc. 22, 285–296. https://doi.org/10.1016/j.trpro.2017.03.035.
Docherty, I., Marsden, G., Anable, J., 2018. The governance of smart mobility. Transp. Res. A Policy Pract. 115, 114–125. https://doi.org/10.1016/j.tra.2017.09.012.
Enoch, M., 2015. How a rapid modal convergence into a universal automated taxi service could be the future for local passenger transport. Tech. Anal. Strat. Manag. 27 (8), 910–924. https://doi.org/10.1080/09537325.2015.1024646.
EPOMM, 2019. TEMS - The EPOMM Modal Split Tool. Retrieved from. http://www.epomm.eu/tems/.
Estevez, E., Lopes, N., Janowski, T., 2016. Smart Sustainable Cities: Reconnaissance Study.
European Environment Agency, 2016. Occupancy rates. Retrieved from. https://www.eea.europa.eu/publications/ENVISSUENo12/page029.html.
Eurostat, 2016. Statistics on commuting patterns at regional level. Retrieved from. https://datastudio2019.datatherapy.org/index.html%3Fp=101.html.
Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transport. Res. C Emerg. Technol. 40, 1–13. https://doi.org/10.1016/j.trc.2013.12.001.
Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp. Res. A Policy Pract. 77, 167–181. https://doi.org/10.1016/j.tra.2015.04.003.
Fagnant, D.J., Kockelman, K.M., Bansal, P., 2015. Operations of shared autonomous vehicle fleet for Austin, Texas, market. Transport. Res. Rec. J. Transport. Res. Board 2536, 98–106. https://doi.org/10.3141/2536-12.
Faisal, A., Yigitcanlar, T., Kamruzzaman, M., Currie, G., 2019. Understanding autonomous vehicles: A systematic literature review on capability, impact, planning and policy. J. Transport Land Use 12 (1), 45–72. https://doi.org/10.5198/jtlu.2019.1405.
Fox, S.J., 2016. Planning for Density in a Driverless World. Georgetown University Law Center, Georgetown. Retrieved from. https://scholarship.law.georgetown.edu/cgi/viewcontent.cgi?article=1000&context=ipr_papers.
Gavanas, N., 2019. Autonomous road vehicles: challenges for urban planning in European cities. Urban Sci. 3 (2), 61. https://doi.org/10.3390/urbansci3020061.
Gibson, D., Kozmetsky, G., Smilor, R., 1992. The Technopolis Phenomenon: Smart Cities, Fast Systems, Global Networks. Rown & Littlefield.
Giduthuri, V.K., 2015. Sustainable urban mobility: challenges, initiatives and planning. Curr. Urban Stud. 3, 261–265. https://doi.org/10.4236/cus.2015.33022.
Gisbert, F., Martí, I., Gielen, E., 2017. Clustering cities through urban metrics analysis. J. Urban Des. 22 (5), 689–708. https://doi.org/10.1080/13574809.2017.1305882.
Glasmeier, A., Christopherson, S., 2015. Thinking about smart cities. Camb. J. Reg. Econ. Soc. 8 (1), 3–12.
Gonzalez, R.A., Ferro, R.E., Liberona, D., 2019. Government and governance in intelligent cities, smart transportation study case in Bogot1á Colombia. Ain Shams Eng. J. 11, 25–34. https://doi.org/10.1016/j.asej.2019.05.002.
Gordon, A.V., Ramic, M., Rohrbeck, R., Spaniol, M.J., 2020. 50 Years of corporate and organizational foresight: looking back and going forward. Technol. Forecast. Soc. Chang. 154, 119966.
Grand View Research, 2018. Smart Cities Market Size, Share & Trends Analysis Report By Application, By Smart Governance, By Smart Utilities, By Smart Transportation, By Region, And Segment Forecasts, 2022 - 2030. https://www.grandviewresearch.com/industry-analysis/smart-cities-market?utm_source=pressrelease&utm_medium=referral&utm_campaign=PRN_Mar6_SmartCitiesrd2&utm_content=Content.
Gupta, A., Panagiotopoulos, P., Bowen, F., 2020. An orchestration approach to smart city data ecosystems. Technol. Forecast. Soc. Chang. 153, 119929.
Gurumurthy, K.M., Kockelman, K.M., 2020. Modeling Americans' autonomous vehicle preferences: a focus on dynamic ride-sharing, privacy & long-distance mode choices. Technol. Forecast. Soc. Chang. 150, 119792.
Haarstad, H., Wathne, M.W., 2019. Are smart city projects catalyzing urban energy sustainability? Energy Policy 129, 918–925. https://doi.org/10.1016/j.enpol.2019.03.001.
Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transport. Res. C Emerg. Technol. 78, 37–49. https://doi.org/10.1016/j.trc.2017.01.010.
Hall, P., 2000. Creative cities and economic development. Urban Stud. 37 (4), 639–649. https://doi.org/10.1080/00420980050003946.
Harb, M., Xiao, Y., Circella, G., Mokhtarian, P.L., Walker, J.L., 2018. Projecting travelers into a world of self-driving vehicles: estimating travel behavior implications via a naturalistic experiment. Transportation 45 (6), 1671–1685. https://doi.org/10.1007/s11116-018-9937-9.
Harper, C., Hendrickson, C., Samaras, C., 2018. Exploring the economic, environmental, and travel implications of changes in parking choices due to driverless vehicles. ASCE J. Urban Plan. Develop. 144 (4), 1–40.
Hartigan, J.A., Wong, M.A., 1979. Algorithm AS 136: a K-means clustering algorithm. Appl. Stat. 28, 100–108. https://doi.org/10.2307/2346830.
Inrix, 2019. Inrix Scorecard. Retrieved from. https://inrix.com/scorecard/.
ITF, 2018. Safer Roads with Automated Vehicles? International Transport Forum (www.itf-oecd.org). at. www.itf-oecd.org/sites/default/files/docs/safer-roads-automated-vehicles.pdf.
Jing, P., Hu, H., Zhan, F., Chen, Y., Shi, Y., 2020. Agent-based simulation of autonomous vehicles: a systematic literature review. IEEE Access 8, 79089–79103.
Jones, E.C., Leibowicz, B.D., 2019. Contributions of shared autonomous vehicles to climate change mitigation. Transp. Res. Part D: Transp. Environ. 72, 279–298. https://doi.org/10.1016/j.trd.2019.05.005.
Ke, X., Qi, L., Zeng, C., 2016. A partitioned and asynchronous cellular automata model for urban growth simulation. Int. J. Geogr. Inf. Sci. 30 (4), 637–659. https://doi.org/10.1080/13658816.2015.1084510.
Keeney, T., 2017. Mobility-As-A-Service: Why Self-Driving Cars Could Change Everything, ARC Investment Research (http://research.ark-invest.com). at. http://bit.ly/2xz6PNV.
Krizek, K.J., McGucking, N., 2019. Shedding NHTS light on the use of "little vehicles" in urban areas. Transport Findings. https://doi.org/10.32866/10777.
Kroeger, L., Kuhnimhof, T., Trommer, S., 2018. Does context matter? A comparative study modelling autonomous vehicle impact on travel behaviour for Germany and the USA. Transp. Res. A Policy Pract. 122, 146–161. https://doi.org/10.1016/j.tra.2018.03.033.
Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transport. Res. C Emerg. Technol. 69 (Aug. 2016), 343–355. https://doi.org/10.1016/j.trc.2016.06.015.
Le Vine, S., Zolfaghari, A., Polak, J., 2015. Autonomous cars: the tension between occupant experience and intersection capacity. Transport. Res. C Emerg. Technol. 52, 1–14. https://doi.org/10.1016/j.trc.2015.01.002.
Li, X., Yao, R., Liu, M., Vincenzo, C., Yu, W., Wang, W., Alan, S., Li, B., 2018. Developing urban residential reference buildings using clustering analysis of satellite images. Energy Build. 169, 417–429.
Liebl, F., Schwarz, J.O., 2010. Normality of the future: trend diagnosis for strategic foresight. Futures 42 (4), 313–327.

Lim, C., Cho, G., H., & Kim, J., 2021. Understanding the linkages of smart-city technologies and applications: key lessons from a text mining approach and a call for future research. Technol. Forecast. Soc. Change 170. https://doi.org/10.1016/j.techfore.2021.120893.

Lindgren, T., Pink, S., Fors, V., 2021. Fore-sighting autonomous driving – an ethnographic approach. Technol. Forecast. Soc. Change 173 (2021), 121105. ISSN 0040-1625. https://doi.org/10.1016/j.techfore.2021.121105.

Liu, J., Kockelman, K.M., Boesch, P.M., Ciari, F., 2017. Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. Transportation 44 (6), 1261–1278. https://doi.org/10.1007/s11116-017-9811-1.

Lombardi, P., Giordano, S., Farouh, H., Yousef, W., 2012. Modelling the smart city performance. Innovation Eur. J. Soc. Sci. Res. 25 (2), 137–149. https://doi.org/10.1080/13511610.2012.660325.

Los Angeles Community Analysis Bureau, 1974. The State of the City: The Cluster Analysis of Los Angeles. Community Analysis Bureau, Los Angeles, CA, USA.

Lovas, G., 1994. Modeling and simulating of pedestrian traffic flow. Transport. Res. B Method. 28 (6), 429–443. https://doi.org/10.1016/0191-2615(94)90013-2.

Macal, C.M., North, M.J., 2009, December. Agent-based modeling and simulation. In: Proceedings of the 2009 winter simulation conference (WSC). IEEE, pp. 86–98. https://doi.org/10.1109/WSC.2009.5429318.

MacKenzie, D., Wadud, Z., Leiby, P.N., 2014. A first order estimate of energy impacts of automated vehicles in the United States. In: Transportation Research Board Annual Meeting, vol. 93rd. The National Academies, Washington, DC.

MacQueen, J., 1967. Some methods for classification and analysis of multivariate observations. In: Le Cam, L.M., Neyman, J. (Eds.), Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, vol. 1. University of California Press, Berkeley, CA, pp. 281–297.

Marletto, G., 2019. Who will drive the transition to self-driving? A socio-technical analysis of the future impact of automated vehicles. Technol. Forecast. Soc. Chang. 139 (2019), 221–234. https://doi.org/10.1016/j.techfore.2018.10.023.

McIntosh, J., Trubka, R., Kenworthy, J., Newman, P., 2014. The role of urban form and transit in city car dependence: analysis of 26 global cities from 1960 to 2000. Transport. Res. D Transport Environ. 33 (2014), 95–110. ISSN 1361-9209. https://doi.org/10.1016/j.trd.2014.08.013.

Merfeld, K., Wilhelms, M., Kreutzer, K., Sven, H., 2019. Carsharing with shared autonomous vehicles: uncovering drivers, barriers and future developments – a four-stage Delphi study. Technol. Forecast. Soc. Change 144, 66–81. https://doi.org/10.1016/j.techfore.2019.03.012.

Milakis, D., Snelder, M., van Arem, B., van Wee, G., Correia, G., 2017. Development and transport implications of automated vehicles in the Netherlands: scenarios for 2030 and 2050. Eur. J. Transp. Infrastruct. Res. 17 (1), 63–85.

Moavenzadeh, J., Lang, N.S., 2018. Reshaping Urban Mobility With Autonomous Vehicles. Retrieved from. http://www3.weforum.org/docs/WEF_Reshaping_Urban_Mobility_with_Autonomous_Vehicles_2018.pdf.

Moovit, 2019. Moovit Public Transit Insights. Retrieved from. https://datastudio2019.datatherapy.org/index.html%3Fp=101.html.

Moradi, A., Vagnoni, E., 2018. A multi-level perspective analysis of urban mobility system dynamics: what are the future transition pathways? Technol. Forecast. Soc. Chang. 126, 231–243.

Mounce, R., Nelson, J.D., 2019. On the potential for one-way electric vehicle carsharing in future mobility systems. Transp. Res. A Policy Pract. 120, 17–30. https://doi.org/10.1016/j.tra.2018.12.003.

MVG, 2019. Unsere Fahrzeuge. Retrieved from. https://www.mvg.de/ueber/das-unternehmen/fahrzeuge.html.

Navya, 2019. Autonom Shuttle for More Fluid Mobility. Retrieved from. https://navya.tech/wp-content/uploads/documents/Brochure_Shuttle_EN.pdf.

NHTS, 2018. 2017 NHTS Data User Guide. Retrieved from. https://nhts.ornl.gov/assets/NHTS2017_UsersGuide_04232019_1.pdf.

Pakusch, C., Stevens, G., Boden, A., Bossauer, P., 2018. Unintended effects of autonomous driving: a study on mobility preferences in the future. Sustainability 10 (2018), 2404. https://doi.org/10.3390/su10072404.

Perra, V.-M., Sdoukopoulos, A., Pitsiava-Latinopoulou, M., 2017. Evaluation of sustainable urban mobility in the city of Thessaloniki. Transport. Res. Proc. 24, 329–336. https://doi.org/10.1016/j.trpro.2017.05.103.

Rose, J., Schellong, D., Schaetzberger, C., Hill, J., 2020. How E-Scooter Can Win a Place in Urban Transport. Retrieved from. https://www.bcg.com/publications/2020/e-scooters-can-win-place-in-urban-transport.aspx.

Ruhlandt, R.W.S., 2018. The governance of smart cities: a systematic literature review. Cities 81, 1–23. https://doi.org/10.1016/j.cities.2018.02.014.

SAE International, . J3194: Taxonomy and Classification of Powered Micromobility Vehicles. Retrieved from. https://www.sae.org/standards/content/j3194201911/, 2019.

Shamsuzzoha, A., Nieminen, J., Piya, S., Rutledge, K., 2021. Smart city for sustainable environment: a comparison of participatory strategies from Helsinki, Singapore and London. Cities 114, 103194. https://doi.org/10.1016/j.cities.2021.103194.

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.

Simoni, M.D., Kockelman, K.M., Gurumurthy, K.M., Bischoff, J., 2019. Congestion pricing in a world of self-driving vehicles: an analysis of different strategies in alternative future scenarios. Transport. Res. C Emerg. Technol. 98, 167–185. https://doi.org/10.1016/j.trc.2018.11.002.

Siokas, G., Tsakanikas, A., Siokas, E., 2021. Implementing smart city strategies in Greece: appetite for success. Cities 108 (2021), 102938. ISSN 0264-2751. https://doi.org/10.1016/j.cities.2020.102938.

Soteropoulos, A., Berger, M., Ciari, F., 2018. Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. Transp. Rev. 39 (1), 29–49. https://doi.org/10.1080/01441647.2018.1523253.

Southworth, M., Ben-Joseph, E., 2003. Streets and the Shaping of Towns and Cities. Island Press, Washington.

Spickermann, A., Grienitz, V., Heiko, A., 2014. Heading towards a multimodal city of the future?: multi-stakeholder scenarios for urban mobility. Technol. Forecast. Soc. Chang. 89, 201–221.

Stuebinger, J., Schneider, L., 2020. Understanding smart city—a data-driven literature review. Sustainability 12 (20), 8460. https://doi.org/10.3390/su12208460.

TAC, 2019. Lives Lost – Year to Date. Retrieved from. http://www.tac.vic.gov.au/road-safety/statistics/lives-lost-year-to-date.

Tang, Z., Jayakar, K., Feng, X., Zhang, H., Peng, R.X., 2019. Identifying smart city archetypes from the bottom up: a content analysis of municipal plans. Telecomm Policy. https://doi.org/10.1016/j.telpol.2019.101834.

Thomopoulos, N., Givoni, M., 2015. The autonomous car – a blessing or a curse for the future of low carbon mobility? An exploration of likely vs. desirable outcomes. Eur. J. Futures Res. 3 (1) https://doi.org/10.1007/s40309-015-0071-z.

Transport from London, 2019. Casualties in Greater London. Retrieved from. http://content.tfl.gov.uk/casualties-in-greater-london-2017.pdf.

Ullah, F., Qayyum, S., Jamaluddin, M., Al-Turjman, T., Sepasgozar, S., 2021. Risk management in sustainable smart cities governance: a TOE framework. Technol. Forecast. Soc. Change 167 (2021), 120743. ISSN 0040-1625. https://doi.org/10.1016/j.techfore.2021.120743.

Vecchiato, R., Roveda, C., 2010. Strategic foresight in corporate organizations: handling the effect and response uncertainty of technology and social drivers of change. Technol. Forecast. Soc. Chang. 77 (9), 1527–1539.

Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transp. Res. A Policy Pract. 86, 1–18. https://doi.org/10.1016/j.tra.2015.12.001.

Wang, Y., Ren, H., Dong, L., Park, H., Zhang, Y., Xu, Y., 2019. Smart solutions shape for sustainable low-carbon future: a review on smart cities and industrial parks in China. Technol. Forecast. Soc. Chang. 144, 103–117. https://doi.org/10.1016/j.techfore.2019.04.014.

WHO, 2018. Ambient (outdoor) air pollution, WHO. https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-qualityand-health.

Wong, N., Jagdev, S., 2019. Sidewalk Labs Announces $1.3B Investment in Toronto Development. Bloomberg News. https://www.bnnbloomberg.ca/sidewalk-labs-announces-us-980m-investment-in-toronto-development-1.1277757. Retrieved 08.01.2022.

Woo, S., Youtie, J., Ott, I., Scheu, F., 2021. Understanding the long-term emergence of autonomous vehicles technologies. Technol. Forecast. Soc. Change volume 170 (2021), 120852. ISSN 0040–1625. https://doi.org/10.1016/j.techfore.2021.120852.

Ye, L., Yamamoto, T., 2018. Impact of dedicated lanes for connected and autonomous vehicle on traffic flow throughput. Phys. A Stat. Mechanics Appl. 512 https://doi.org/10.1016/j.physa.2018.08.083.

Yeh, H., 2017. The effects of successful ICT-based smart city services: from citizens' perspectives. Gov. Inf. Q. 34 (3), 556–565. https://doi.org/10.1016/j.giq.2017.05.001.

Yi, Z., Smart, J., Shirk, M., 2018. Energy impact evaluation for eco-routing and charging of autonomous electric vehicle fleet: ambient temperature consideration. Transport. Res. C Emerg. Technol. 89, 344–363. https://doi.org/10.1016/j.trc.2018.02.018.

Yigitcanlar, T., 2018. Smart City policies revisited: considerations for a truly smart and sustainable urbanism practice. World Technopolis Rev. 7, 97–112. http://web.2ver.com/HOME/data/download/soitmc/Reading1.pdf.

Zawieska, J., Pieriegud, J., 2018. Smart city as a tool for sustainable mobility and transport decarbonisation. Transp. Policy 63, 39–50.

Zhang, W., Guhathakurta, S., Fang, J., Zhang, G., 2015. Exploring the impact of shared autonomous vehicles on urban parking demand: an agent-based simulation approach. Sustain. Cities Soc. 19, 34–45. https://doi.org/10.1016/j.scs.2015.07.006.

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.