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Integrated Modelling of Autonomous Electric Vehicle Diffusion: From Review to Conceptual Design

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Abstract

The future Autonomous Vehicles (AVs) are likely to be electric. We started with a review of the adoption of AVs, Electric Vehicles (EVs) and Autonomous Electric Vehicles (AEVs), as well as the six associated urban sub-systems, namely transportation, land use, environment, energy, economy, and population systems, in order to find evidence about the linkages and interactions between the diffusion of AEVs and the six sub-systems. Based on the review, we argued that an integrated urban model, which takes the linkages and interactions into account, was needed to fully understand the adoption and impacts of AEVs. Furthermore, we conducted a conceptual design of an integrated model for AEVs (without explicit modelling), and demonstrated how to update an existing agent-based Land Use and Transport Interaction (LUTI) model by incorporating AEV components. The resulting integrated model of AEVs would help different AEV-related stakeholders (e.g., local authorities) in their decision-making.

Keywords: Autonomous Vehicle; Electric Vehicle; Innovation Diffusion; Integrated Modelling; Impact Assessment; Agent-based Modelling

1 Introduction

1.1 The Introduction to Autonomous Electric Vehicle

Electric Vehicles (EVs), which run on electricity, have received increasing attention across the globe. The recent report of "Global EV Outlook 2019" by the International Energy Agency indicated that the electric car fleet exceeded 5.1 million in 2018 at the global level and was projected to reach 130 million in 2030 (IEA, 2019). EVs have several advantages over Conventional Vehicles (CVs), such as environmental benefits (e.g., the potential reductions in GHG emissions, air pollution, and noise pollution) and energy efficiency (Zhuge et al., 2020a).

As another disruptive innovation in the transport sector, Autonomous Vehicles (AVs) may be introduced into the vehicle market in the near future (e.g., 10 years), as mentioned in several recent studies (Duarte and Ratti, 2018; González-González et al., 2019; Papa and Ferreira, 2018). According to the definition by the SAE International, fully AVs (with the Level 5 of automation) can move without drivers and thus allow passengers to perform in-vehicle activities (e.g., work and sleeping) (Bahamonde-Birke et al., 2018; Fleetwood, 2017).

In most countries, the development of EVs still stays at an early stage. It has been argued that AVs would be introduced in the market when the EV market share is high. Therefore, future AVs are likely to be electric (Lam et al., 2017). Furthermore, some recent studies also suggested that those EV adopters were also interested in AVs (Berliner et al., 2019; Hardman et al., 2019). As a combination of AV and EV, Autonomous Electric Vehicles (AEVs) would be more promising, as they will take the advantages of both AVs and EVs which can complement each other. For example, range anxiety is one of the main barriers to the diffusion of EVs (Bonges III and Lusk, 2016; Zhuge and Shao, 2018a). AEVs could address this issue by searching for charging facilities automatically when the Stage of Charge (SOC) is running low. Besides, AEVs would become a key element of smart cities and are associated with the development of smart mobility, smart environment and smart gird (Yigitcanlar et al., 2019).

1.2 Interactions between the AEV Market and those Associated Urban Sub-systems

It has been increasingly recognized that the diffusion of AVs and EVs would potentially impact those connected urban-systems (Duarte and Ratti, 2018; González-González et al., 2019; Milakis et al., 2018), including transportation (e.g., parking spaces and accessibility), land use (e.g., residential location choice), economy (e.g., employment), energy (e.g., energy saving), environment (e.g., vehicular emissions) and population systems (e.g., identity) (Zhuge et al., 2019). In return, the uptake of AVs and EVs could be influenced by various factors, including sociodemographic factors, psychological factors, purchase-related factors, usage-related factors, and social influence (Zhuge and Shao, 2019b), which are connected to these urban sub-systems. For example, sociodemographic factors, such as income and age, are connected to the population system. Therefore, the potential diffusion of AEVs would interact heavily with the six connected urban sub-systems.

Since strong interactions between the AEV market and the six connected urban sub-systems exist, there is an increasing need to investigate the diffusion of AEVs from a systematic and dynamic perspective, taking the interactions into account (Hawkins and Nurul Habib, 2019; van Arem et al., 2019). In response, some researchers have proposed to explore the diffusion of AVs or EVs using integrated urban models, such as land use and transport interaction models (Hawkins and Nurul Habib, 2019; Moreno, 2017; Zhuge et al., 2019). Such models would help to gain a full understanding of the diffusion, and the results would be more useful for different stakeholders involved, including local authorities, vehicle manufacturers, fuel suppliers, and urban planners (Zhuge et al., 2019; Zhuge et al., 2020b).

1.3 Research Gaps and Aims

Previous papers on EVs have reviewed the adoption behaviour of EVs (e.g., the factors influencing the adoption) (Al-Alawi and Bradley, 2013; Coffman et al., 2017; Li et al., 2017; Rezvani et al., 2015), policies (Kester et al., 2018; Zhang et al., 2017) (e.g., economic incentives (Hardman et al., 2017; Meisel and Merfeld, 2018)), charging infrastructures (Hardman et al., 2018; Rahman et al., 2016), integration of EVs into power grid (or Vehicle-to-Grid) (Habib et al., 2015; Hu et al., 2016; Mahmud and Town, 2016; Mwasilu et al., 2014; Tan et al., 2016; Yilmaz and Krein, 2012) and integration of EVs and the renewable system (Bhatti et al., 2016; Liu et al., 2015; Mwasilu et al., 2014).

For AVs, most of the review papers were focused on the potential impacts of the AV adoption (Bagloee et al., 2016; Beza and Zefreh, 2019; Duarte and Ratti, 2018; Engholm et al., 2018; Faisal et al., 2019; González-González et al., 2019; Hörl et al., 2016; Milakis et al., 2017; Sousa et al., 2017; Stead and Vaddadi, 2019; Taiebat et al., 2018; Yigitcanlar et al., 2019). For example, according to the ripple effect concept, Milakis et al. (2017) grouped the impacts of AV diffusion into three orders: the first-order was focused on travel (e.g., travel costs and choices); the second-order was on land use and transport (e.g., vehicle ownership and transport infrastructure); the third-order was on broader impacts on the energy (e.g., energy consumption), environment (e.g., air pollution), economy and societies (e.g., social equity). Some of the review papers on AVs also looked at the modelling of AVs (Berrada and Leurent, 2017; Hawkins and Nurul Habib, 2019; Soteropoulos et al., 2019) and adoption behavior of AVs (Gkartzonikas and Gkritza, 2019). For example, Hawkins and Nurul Habib (2019) reviewed the existing Land Use and Transport Interaction (LUTI) models for AVs.

This paper will start with a review, which differs from previous studies in the following two aspects:

- First, we will look at the adoption of both AVs and EVs, because the market share of EVs is on the rise globally, and AVs are predicted to happen soon and are likely to be introduced into the vehicle market when EVs are dominant. Therefore, simultaneously investigating the adoption behaviors of AVs and EVs (or AEVs) would help to better understand the diffusion of these two disruptive innovations in the transport sector. The research outcomes would be more useful for relevant stakeholders to shape their policies and invest in infrastructures and technologies for both AVs and EVs (or AEVs);
- Second, we will review both the influential factors to the adoption of AEVs and the impacts of the AEV adoption, with a focus on connecting the influential factors and impacts to the six associated urban sub-systems, i.e., transportation, land use, economy, energy, environment and population systems (Zhuge et al., 2019). A better understanding of the connections is expected to help stakeholders from different sectors to put joint efforts into the sustainable development of AEVs. It is worth noting that we will derive the influential factors to the AEV adoption and the impacts of AEV adoption, mainly through the interpretation of empirical findings from those studies investigating AVs and EVs, separately, as there are only a few studies focusing on AEV adoption and impacts. This indicates that more investigation into the adoption of AEVs is needed.

The review will help to find evidence about the linkages and interactions between the adoption of AEVs and the six connected urban systems, based on which this paper will further propose a conceptual agent-based spatial urban model (without explicit modelling) to simulate the diffusion of AEVs at the individual level over time and across space, considering the interactions between the AEV market and the six connected urban sub-systems. Using SelfSim (an existing agent-based land use and transport interaction model) (Zhuge et al., 2016; Zhuge et al., 2019) as an example, this paper will demonstrate how to update such integrated urban models for the diffusion of AEVs. The demonstration would help transport/urban modelers to develop similar frameworks with other existing integrated urban models, such as ILUTE (Salvini and Miller, 2005), UrbanSim (Waddell, 2002), and SILO (Ziemke et al., 2016).

In particular, AVs have received increasing attention from both academia and the industry. For example, a recent special issue on “automated/connected vehicles and environment” in the journal of Transportation Research Part D: Transport and Environment, argued that “more knowledge was needed in order for a sustainable future of AVs, considering the interactions between AVs, the built environment, and sustainability”. This paper will be focused on AEVs, which would be a promising type of future AVs. Specifically, it aims to find evidence about the interactions between AEVs and those associated urban systems (including transportation system and the environment system), and also identify the key elements needed to be included in an integrated model for investigating the diffusion and impacts of AEVs. With the integrated model, we could explore the future of AEVs within various “what-if” scenarios, which would help to figure out optimal solutions to a sustainable future with AEVs.

The rest of the paper is organized as follows: Section 2 will present the review protocol and theoretical base to identify evidence about the interactions between AEVs and the six associated urban systems. Section 3 will review the factors influencing the adoption of EVs and AVs; Section 4 will review the impacts of AV and EV adoption on the connected urban sub-systems, including transportation, land use, energy, environment, economy, and population systems; Based on the evidence from the review, Section 5 will develop a conceptual integrated urban micro-simulation model for investigating the diffusion and impacts of AEVs using agent-based modelling. Section 6 draws conclusions.

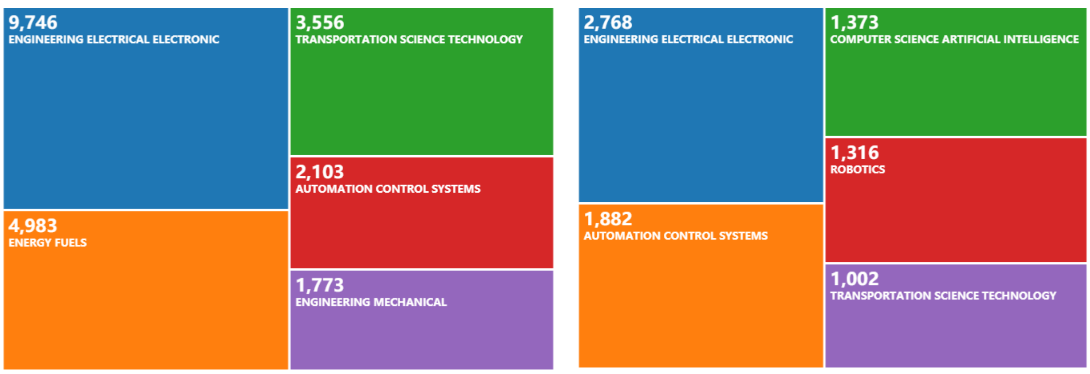
2 Review Protocol and Theoretical Base

2.1 Theoretical Base of the Review

Complexity theory presents a promising way of exploring complex systems, such as cities (Batty, 2007). In general, a complex system is composed of many interacting components that co-evolve over time. As a combination of two disruptive innovations (i.e., AVs and EVs) in cities, AEVs are likely connected to several urban sub-systems, and the diffusion of AEVs would likely interact with those connected systems over time, from a complex system perspective (Batty, 2009). The Land Use and Transport Interaction (LUTI) model is a typical and systematic approach to investigating transport and/or land use issues, considering interactions and dynamics found in a complex urban system (Martínez, 1995). Therefore, the LUTI model has been considered as an appropriate approach to investigating the diffusion of AVs (Hawkins and Nurul Habib, 2019) and EVs (Zhuge et al., 2019). LUTI is focused on transportation and land-use systems, but also involves other associated urban sub-models, including the environment (Salvini and Miller, 2005), energy (Chingcuanco and Miller, 2012), economy (Echenique, 2011), and population (Chingcuanco and Miller, 2018) systems. Therefore, this paper first reviewed the evidence about the connections between the diffusion of AEVs and the six connected systems, namely transportation, land use, environment, energy, economy, and population systems, and then developed a conceptual AEV model considering the connections based on a LUTI model (i.e., SelfSim).

2.2 Review Protocol

As aforementioned, the review in this paper aims to find evidence about the interactions between AEVs and the six associated urban sub-systems, based on which we could figure out whether an integrated model is needed and if yes, what elements (or modules) should be included in such an integrated model. In principle, a systematic review would help to collect evidence and further develop a conceptual integrated model of AEVs. However, both AVs and EVs have received substantial attention from academia, resulting in so much relevant literature falling in this review's scope. For example, we found 19,527 and 7,693 published papers in the database of Web of Science Core Collection on 19 August 2020, with the search terms of “electric vehicle” and “autonomous vehicle” used in paper titles, respectively. These papers were from different subjects, as shown in Figure 1. For both EVs and AVs, the subject of Engineering Electrical Electronic ranked first, with 9,746 and 2,768 papers found, respectively. The subject of Transportation Science Technology ranked third and fifth, with 3,556 and 1,002 papers found for EVs and AVs, respectively.



(a) Papers with Titles Containing “Electric Vehicle” (Top 5 Subjects)

(b) Papers with Titles Containing “Autonomous Vehicle” (Top 5 Subjects)

Figure 1 Search Results with Terms of “Electric Vehicle” and “Autonomous Vehicle” Used in Paper Titles (Database: Web of Science Core Collection; Search Date: 19 August 2020; the figures were produced through the Web of Science)

Given the huge amount of literature on AVs and EVs, we adopted a two-stage review strategy to simplify our review work. At the first stage, we identified the keywords which we could use to search literature related to AVs and EVs (i.e., the objects of this study) and also the six connected sub-systems. At the second stage, we conducted a systematic search in three typical databases, i.e., Web of Science, SCOPUS, and Google Scholar (Wee and Banister, 2016). For each search, we selected one object of study (which can take different forms) and one specific term from Table 1. For example, we searched with a combination of Autonomous Vehicle and Travel Demand, which were one object of study and a key element in the transportation system, respectively. For those papers found in a search, we first went through their titles and abstracts to check the extent to which these papers were relevant to the topic. Since this study was to find evidence (rather than to review and discuss all relevant studies), we only selected and discussed a few of them in this study, according to the three selection criteria, namely relevance (i.e., the extent to which the paper is relevant to our topic), the impact factor of the journal where the paper was published, and the citation of the paper (Wee and Banister, 2016). Furthermore, the snowballing method was also applied in literature search just in case that the search terms used could not cover all relevant literature. Specifically, both forward and backward snowballing methods were used to find relevant published work that cited or was cited by a paper (Wee and Banister, 2016).

Table 1 Keywords for Searching Literature

Object of Study	**Connected Sub-Systems**	**Specific Terms Used for Literature Search**
• *Autonomous/Self-driving/Automated/ Driverless* Vehicle/Car • *Electric* Vehicle/Car • *Autonomous/Self-driving/Automated/ Driverless Electric* Vehicle/Car	Transportation	Transportation/Transport; Travel Behavior; Travel Demand; Infrastructure/Facility; Dedicated Lane/Zone; Transport Modes (e.g., Public Transit and Walking); Accessibility; In-Vehicle Activity; Traffic Condition/State/Flow/Accident; Parking; Charging/Refueling Station/Post/Infrastructure; Vehicle Price/Cost; Driving Experience (e.g., Range Anxiety); Operating Cost (e.g., Energy/Travel Cost); Privacy; Safety; New Car Traveler (e.g., Older People)
	Land Use	Land Use; Urban Form; Urban Sprawl; Residential Location
	Environment	Environment; Environmental Impact/Benefit; GHG/CO_2 Emissions; Noise; Vehicular Emission; Air Quality/Pollution

	Energy	Energy; Energy/Fuel/Electricity Consumption; Energy Efficiency; Vehicle-to-Grid, Renewable Energy
	Economy	Economy; Real Estate Price; Employment; Financial Incentive/Subsidy/Tax
	Population	Population; Sociodemographic Characteristic (e.g., Gender, Age, Income and Education); Social Influence/Network (e.g., Neighbor Effect); Environmental Awareness; Technological Motivation; Identity; Norms

3 The Diffusion of AEVs: Influential factors

Since there are only a few studies focusing on AEVs, we will also review those influential factors to the adoption of AVs and EVs separately and then derive the influential factors to the AEV adoption. According to the classification by Zhuge and Shao (2019b), this paper groups the potentially influential factors into five categories, namely Sociodemographic Factors, Psychological Factors, Purchase-related Factors, Usage-related Factors, and Social Influence, which will be reviewed separately in the sub-sections below.

3.1 Sociodemographic Factors

Sociodemographic characteristics, such as age and income, were identified as influential to the uptake of EVs and AVs. For example, the work by Chen et al. (2020) suggested that those younger males with higher income and more children were more likely to adopt EVs. However, there were some exceptional cases. For example, Sierzchula et al. (2014) found that income and education level were not influential to the adoption of EVs. For AVs, the influential sociodemographic factors included gender, age, income, education level, and employment status (Bonnefon et al., 2016; Haboucha et al., 2017; Hardman et al., 2019; Hohenberger et al., 2016; Nair et al., 2018; Wang and Zhao, 2019). For example, Wang and Zhao (2019) suggested that older and unemployed females with lower income tended to be less likely to purchase AVs.

3.2 Psychological Factors

Psychological factors, such as environmental awareness, technological motivation, identity, and norms, were influential to the uptake of EVs and AVs (Buckley et al., 2018; Liu et al., 2019a; Peters et al., 2018). In terms of environmental awareness, both EVs and AVs tended to be more energy-efficient and could also be more environment-friendly. Therefore, environmental awareness could play an important role in diffusing AVs and EVs, especially at an early stage (Haboucha et al., 2017; Wu et al., 2019). A recent study by Zhuge and Shao (2019b) suggested that environmental awareness accounted for 9.6% of the total importance of adopting EVs in Beijing, among the six typical factors (e.g., vehicle price and usage). Also, green self-identity or pro-environmental self-identity could influence people's willingness to adopt EVs (Schuitema et al., 2013). For example, Barbarossa et al. (2015) found that EV adoption in Denmark was mainly influenced by green self-identity. In addition, technological motivation (e.g., not being behind on the latest technological developments and being interested in EVs equipped with the latest technologies) could also exert an influence on the adoption of EVs (Peters et al., 2018). In terms of norms, there are two typical types, namely personal norms and social norms, which are correlated. It was argued that personal norms tended to be more influential to individual behavior (e.g., adoption behavior of EVs) than social norms (Jansson et al., 2017).

3.3 Purchase-related Factors

The high vehicle sale price is one of the most influential factors to the uptake of AVs and EVs (Zhuge and Shao, 2019b). It is particularly true for AVs (Bösch et al., 2018; Hörl et al., 2016; Shabanpour et al., 2018). The high cost of AVs is largely attributed to the additional high-tech products for automation, such as Light Detection and Ranging (LIDAR) (Fagnant and Kockelman, 2015); while additional on-board batteries mainly cause the high cost of EVs. It remains unsure what the exact sale price of an AV might be in the future. For example, Bansal et al. (2016) suggested that the price might be $23,950 in 2025; however, another study by the Boston Consulting Group estimated that the price would be $9,800 in 2025 (Berrada and Leurent, 2017). Besides, it has also been argued that the AV price relative to CV price was more influential to the adoption of AVs than the absolute AV price (Haboucha et al., 2017).

In response to the high upfront cost, financial incentives, such as subsidies and tax exemption, are general approaches to promoting the development of AVs (Chen et al., 2019) and EVs (Hao et al., 2014). For example, due to the uncertainty in the AV price, Chen et al. (2019) proposed an AV incentive program for a local government to promote the adoption of AVs, considering AV lanes, AV prices, and traffic conditions. Sheldon and Dua (2020) found that the EV subsidies in China had played a very important role in the development of EVs: the EV market share could decrease by 21% given that the subsidy had been halved. However, it has also been argued that financial incentives might not be effective or only be effective in the short term. For example, Nieuwenhuijsen et al. (2018) developed a system dynamics model to analyze the long-term diffusion of AVs in the Netherlands within different scenarios. The results suggested that the AV subsidy could give rise to a sudden increase in penetration rate, but could not give a sustainable boost to market penetration. In an EV study by Bakker and Trip (2013), it was argued that the subsidized EVs could still be too expensive for private consumers. As a result, EV subsidies would not effectively promote the adoption of EVs.

3.4 Usage-related Factors

To customers, vehicle usage is one of the most important selection criteria. The potential vehicle purchasers may consider various usage-related factors, including driving experiences, the operating cost, and privacy and safety issues (Zhuge and Shao, 2019b). In terms of driving experiences, the so-called range anxiety may lead to a bad driving experience for EV users; AV drivers may have a good experience because they do not need to control vehicles and can perform in-vehicle activities (e.g., leisure and work). Furthermore, AEVs could make charging more convenient and controllable, and would potentially mitigate or event address the range anxiety (Chen et al., 2016a), which was commonly considered as one of the main barriers to the adoption of EVs (Xu et al., 2020). For the operating cost, both EVs and AVs tend to be more energy-efficient and could save energy costs. Furthermore, EVs run on electricity instead of petrol, which could further reduce energy costs. On the other hand, EV drivers have raised concerns about battery degradation, which would increase the operating cost of EVs (Yang et al., 2018). Measures might be taken to reduce the cost, for example, through intelligent charging strategies (Lunz et al., 2012). AV users might also be concerned about privacy, because they would be extensively tracked and their private information might be misused (Collingwood, 2017). However, some empirical findings suggested that privacy might not be an important concern (Gurumurthy and Kockelman, 2020). Safety is another key concern, particularly for AV purchasers (Hollström, 2019; Kaur and Rampersad, 2018; Liljamo et al., 2018; Liu et al., 2019b; Motamedi et al., 2018). However, providing safety-related information could have a positive effect on the adoption (Hohenberger et al., 2016). On the one hand, AVs can potentially reduce traffic accidents, which would be a benefit to AV adopters (Bansal et al., 2016; Fagnant and Kockelman, 2015). For example, it was estimated that AVs could avoid around 90% of traffic accidents caused by human errors (Chan, 2017; Fleetwood, 2017); On the other hand, safety issues, such as hacking, have been barriers to the uptake of AVs (Fagnant and Kockelman, 2015; Kyriakidis et al., 2015). To encourage people to use AVs and EVs, usage-related policies, such as road toll (Mersky et al., 2016) and parking fee exemption (Hackbarth and Madlener, 2013) could be useful.

3.5 Social Influence

Social influence is commonly viewed as an important factor to the diffusion of new technologies, including EVs (Axsen et al., 2013; Pettifor et al., 2017) and AVs (Anania et al., 2018; Bazilinskyy et al., 2019; Panagiotopoulos and Dimitrakopoulos, 2018; Talebian and Mishra, 2018). Essentially, there are three typical social influence types, namely global influence, neighbor effect, and friendship effect. It has been argued that whether a potential consumer would adopt a new technology could be influenced by digital information (e.g., news, advertisements, and social media), the neighbors living nearby, and those friends who have adopted the new technology. For example, the empirical findings from a questionnaire survey in Beijing suggested that the three typical types of social influence accounted for 2.8%, 2.0%, and 5.0% of the total importance in the adoption of EVs, among six typical influential factors (e.g., vehicle usage and vehicle price) (Zhuge and Shao, 2019b). Anania et al. (2018) suggested that people would become more willing to purchase AVs after receiving positive information about AVs. This was also found in the work by Talebian and Mishra (2018); Liu et al. (2017) found there were significant neighbor effects in the adoption of hybrid EVs based on spatial analyses. Zhang et al. (2020) found that social influence and initial trust were the most influential factors for adopting AVs in China.

3.6 Linking Influential Factors to Urban Sub-systems

The potential influential factors reviewed above are connected to the six urban sub-systems (see Figure 2):

- **Transportation System:** may influence sociodemographic factors (e.g., employment status), usage-related factors (e.g., the availability of transport facilities, traffic states, and traffic restrictions), and social influence. In terms of social influence, the transportation system is indirectly connected with the social network of each individual and neighbor effects, through joint activities (Axhausen and Kowald, 2015) and residential location choices, respectively.

- **Land Use System:** is connected to both usage-related factors and social influence, as land use patterns and residential location choice of households would influence neighbor effects (Axsen et al., 2009), travel behaviour, and travel costs, through accessibility. Also, land use may be associated with some of the sociodemographic factors, such as employment. For example, workplaces could be influential to employment status and type.

- **Environment System:** AEVs are expected to benefit the environment system at both local and global levels (Fagnant and Kockelman, 2014; Lave et al., 1995), and the potential environmental benefits may encourage potential purchasers to try AEVs (Haboucha et al., 2017; Wu et al., 2019).

- **Energy System:** AEVs could be more energy-efficient and thus can save energy costs for adopters, which would be one of the positive usage-related factors.

- **Economy System:** is associated with both purchase- and usage-rated factors, as financial incentives (e.g., subsidies and parking fee exemption) are commonly used to reduce the upfront and usage costs, making AEVs competitive; Furthermore, the economic system is also connected to some of the sociodemographic factors that are influential to the adoption, such as income.

- **Population System:** is connected to all the five types of influential factor, namely sociodemographic factors (e.g., age and education level), psychological factors (e.g., identity), purchase-related factors (e.g., affordability), usage-related factors (e.g., safety and privacy) and social influence (e.g., neighbor effects).

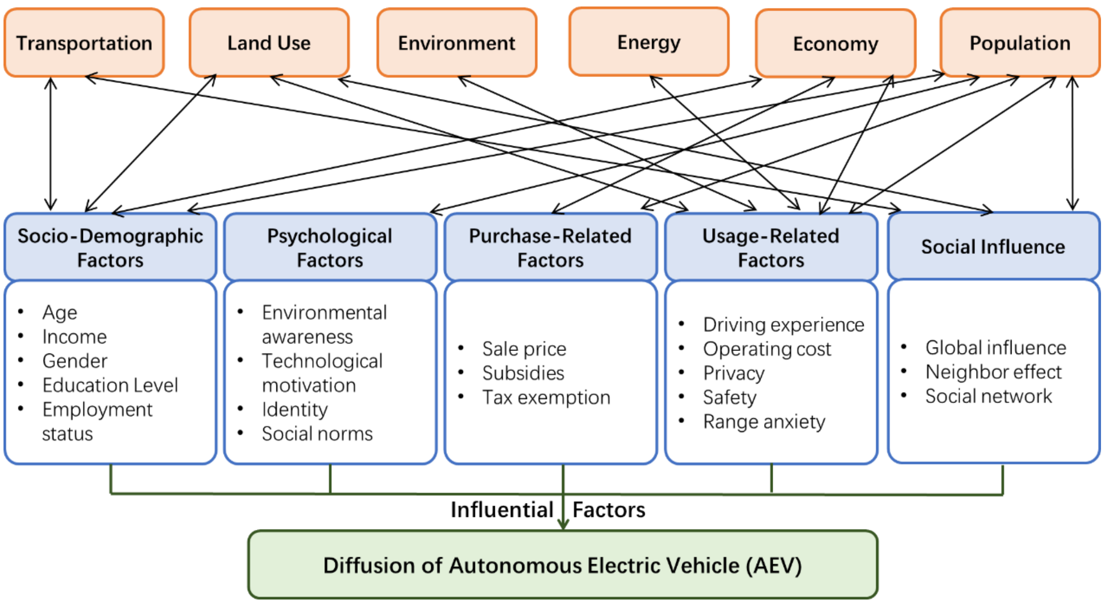


Figure 2 Linkages between the Influential Factors and those Associated Urban Sub-systems

4 Impacts of the AEV Diffusion

4.1 Overview of Impacts of the AEV Diffusion

As an element of the future transportation system, the AEV market would influence not only the other associated elements in the transportation system, but also those urban sub-systems connecting to the transportation system, including land use, energy, environment, population, and economy systems. The potential impacts of AEV adoption on these urban sub-systems are summarized as follows:

- **Impacts on Transportation System (see Section 4.2):** the widespread adoption of AEVs would potentially impact the transportation system from both supply and demand sides. For example, it would influence the quantity and layout of AEV-related transport infrastructures (e.g., parking lots and charging posts), travel behavior and demand, and accessibility;
- **Impacts on Land Use System (see Section 4.3):** the introduction of AEVs would potentially improve accessibility, which gives rise to changes in the layout of activity facilities (e.g., residential and office buildings) and further urban form (e.g., urban sprawl);
- **Impacts on Energy System (see Section 4.4):** AEVs would be more energy-efficient and also potentially promote the development of smart grid (through the Vehicle-to-Grid technology) and renewable energy system (through the use of solar and wind energy);
- **Impacts on Environment System (see Section 4.5):** AEVs have the great potential to benefit the environmental system at both global and local levels, for example, through energy efficiency and the use of renewable energy;
- **Impacts on Economy System (see Section 4.6):** The uptake of AEVs would influence real estate prices through the changes in urban form and residential relocation of households;
- **Impacts on Population System (see Section 4.7):** AEVs are unlikely to be affordable to the lower-income group, which would lead to transportation inequities; In addition, the diffusion of AEVs will also influence individual friendships indirectly. For example, in-vehicle activities (e.g., work) would result in AEV owners having more time to perform joint activities with their friends, which would help to maintain friendships.

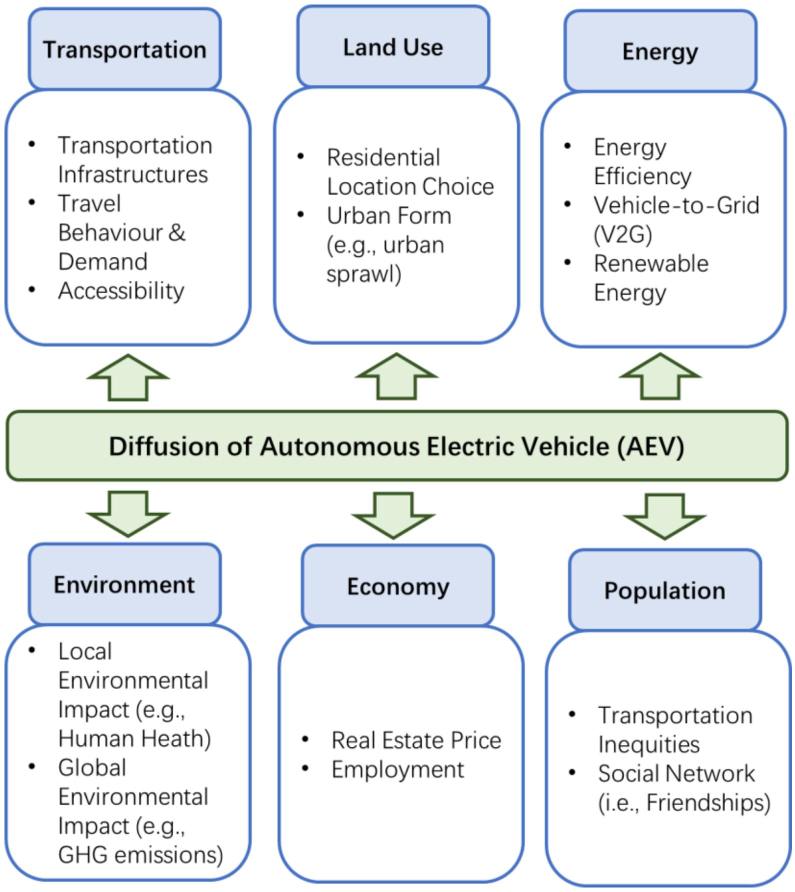


Figure 3 The Impacts of the AEV Diffusion on those Associated Urban Sub-systems

4.2 Impacts of the AEV Adoption on Transportation System

4.2.1 Impacts on Transportation Infrastructures

a) Parking Spaces and Charging Posts

Due to the limited number of parking spaces, especially in city centers, parking has been a critical urban issue to many megacities, such as Beijing and London. AVs present a promising approach to dealing with those parking-related problems (e.g., cruising to park) (Kondor et al., 2018), as AVs can drop off passengers at trip destinations and then get themselves parked at those places where parking spaces are available (Liu, 2018). These parking lots in general charge a lower parking fee (de Almeida Correia and van Arem, 2016; Fagnant and Kockelman, 2015). As a result, the city center's parking demand would decrease, and many parking spaces may be removed. This would help to reduce the cost of managing a city: for example, the annualized cost of a parking space at the Central Business District (CBD) was around $2000 (Fagnant and Kockelman, 2015).

Furthermore, the layout of parking spaces for AVs can be optimized by using multiple rows of vehicles stacked, which could save around 62% of parking spaces, on average (Nourinejad et al., 2018).

On the other hand, parking lots are the base for deploying charging posts at trip destinations (Zhuge and Shao, 2018a). EV drivers can get their vehicles recharged through these charging posts when parked, for example, at workplaces. With the widespread adoption of EVs, the demand for parking-based charging posts would be on the rise.

b) Refuelling and Charging Stations

When people choose EVs instead of CVs, charging demand is likely to increase, but refuelling demand would decrease (Zhuge and Shao, 2018a). This could lead to the removal of refuelling stations. Some of them may be replaced with enroute fast-charging stations, where EV drivers can get their vehicles recharged within a short time (e.g., 30-min charging for a stage of charge of 80%), so as to accommodate the increasing charging demand on their journeys. Therefore, fast-charging stations are particularly useful for long-distance travel, such as inter-city travel (Guo et al., 2016; Wang et al., 2018; Zhang et al., 2015). For example, Ghamami et al. (2016) used a general corridor model to optimize charging infrastructures in support of long-distance intercity travel. Battey swap station is another type of enroute fast-charging infrastructure. EV users can get their vehicles fully recharged within a short time (e.g., 3 minutes) at a battery swap station, by replacing their used on-board batteries with fully charged ones. However, economic feasibility (i.e., viable business model) and battery standardization are two main barriers to the deployment of battery swap stations. As another type of fast-charging infrastructure, wireless charging lanes (Ngo et al., 2020; Riemann et al., 2015) allow EVs to get charged when moving. However, the high investment cost (i.e., cost per mile) is one of the main barriers. Therefore, from an economic perspective, fast-charging stations present a more promising approach to accommodating enroute charging demand of EVs than battery swap stations and wireless charging lanes.

c) AV Lanes & Zones

Dedicated lanes or zones for AVs would help to promote the purchase and use of AVs, especially at an early stage of AV development when the penetration rate is relatively low. AVs can move on the dedicated lanes or in the dedicated zones, reducing the interactions with CVs. However, allocating dedicated lanes or zones to AVs would reduce the number of lanes for the other vehicles, and thus may influence traffic conditions (Ye and Yamamoto, 2018). Therefore, the lanes or zones should be deployed carefully (Chen et al., 2019; Chen et al., 2017; Chen et al., 2016b; Ghiasi et al., 2017), to maximize the overall utility of all drivers involved.

4.2.2 Impacts on Travel Behaviour and Demand

a) Interactions with other Transport Modes

AVs may interact with other transport modes, including public transport (Zakharenko, 2016) and walking (Meeder et al., 2017). Specifically, on the one hand, AVs may make public transport less attractive, due to potential competition (Davidson and Spinoulas, 2015; Meyer et al., 2017); on the other hand, AVs would also work cooperatively with public transit for the last mile trips (Bahamonde-Birke et al., 2018). In terms of the interaction with pedestrians, walking would become more preferable, as the uptake of AVs may result in the removal of on-street parking spaces and also easily crossing streets (Meeder et al., 2017); However, pedestrians are very vulnerable road users (Millard-Ball, 2018). It would be technically difficult for AVs to exactly predict the movement of every pedestrian each time when moving on a transport network (Rasouli and Tsotsos, 2019).

b) New Car Travelers

AVs could allow non-drivers and those drivers with medical conditions to travel independently by car (Harper et al., 2016; Moreno, 2017). The potential beneficiaries include older people, children, and the disabled (Bahamonde-Birke et al., 2018; Fagnant and Kockelman, 2015). However, the additional travel demand from these people would influence the transportation system (Bahamonde-Birke et al., 2018). For example, Harper et al. (2016) found that vehicle miles traveled could increase by 9% and 2.6% for non-drivers and those drivers with medical conditions, respectively. Truong et al. (2017) found that the number of daily trips would increase by 4.14% because of the introduction of AVs. Furthermore, the increase tended to be more significant to those people aged 76 above, with an increasing rate of 18.5%.

c) In-Vehicle Activities

Fully AVs can move without the control of drivers, allowing people to perform daily activities in their vehicles, such as work, leisure, and sleeping (Malokin et al., 2019; Moreno, 2017). This may lead to a reduction in perceived negative travel time or a reduction in the so-called value of travel time savings (Bahamonde-Birke et al., 2018; Correia et al., 2019; van den Berg and Verhoef, 2016). However, the extent to which AVs could reduce the value of travel time remains unclear

(Bahamonde-Birke et al., 2018; Singleton, 2019). Due to in-vehicle activities, people may also adjust their activity locations, durations, and types (Pudāne et al., 2019).

d) Traffic Conditions

It remains unclear how the adoption of AEVs would influence traffic conditions (Metz, 2018; Puylaert et al., 2018): On the one hand, the diffusion of AEVs would result in fewer traffic accidents, a reduction in vehicle ownership per household, and smaller headways (Bonnefon et al., 2016; Davidson and Spinoulas, 2015; Fagnant and Kockelman, 2015; Moreno, 2017; Simoni et al., 2019; Zhang et al., 2018), which could improve traffic conditions; On the other hand, AEVs could allow more non-drivers (e.g., older people) to travel by car and also induce more car-based trips and long-distance trips (Cohen and Cavoli, 2019; Davidson and Spinoulas, 2015; de Almeida Correia and van Arem, 2016; González-González et al., 2019; Harb et al., 2018; Kloostra and Roorda, 2019; Simoni et al., 2019). All of these would likely lead to heavier traffic congestion. Furthermore, empty AEVs or unoccupied travel would make traffic conditions worse (de Almeida Correia and van Arem, 2016; Metz, 2018; Zhang et al., 2018).

e) Travel Demand

As discussed above, AEVs could influence individual travel behavior through mode choices, in-vehicle activities, and traffic conditions. It has been argued that the adoption of AEVs would give rise to an increase in travel demand, mainly because 1) travelers can perform in-vehicle activities, making travel more comfortable and reducing the value of travel time savings, 2) travel costs would decrease due to energy efficiency, running on electricity instead of petrol and integrating renewable energy (e.g., solar energy), 3) additional travel demand from new car travelers (e.g., older people) would increase the total travel demand, 4) and AEVs might lead to urban sprawl, which could increase travel distance (e.g., commuting distance). However, the extent to which AEVs would impact travel demand varies on a case by case basis. For example, Childress et al. (2015) explored the potential impacts of AVs on travel demand within several scenarios in Seattle, Washington, using an activity-based model. The results suggested the travel demand could increase by 20% in the scenario where all vehicles were autonomous. In the US and Germany, Kröger et al. (2019) found that travel demand could be increased by 8.6% due to the adoption of AVs. Meyer et al. (2017) found that travel demand could be increased by 16% due to those new car travelers with AVs.

4.2.3 Impacts on Accessibility

As reviewed above, the introduction of AVs would heavily influence travel behaviour and further travel demand. As a result, accessibility would also be heavily influenced (Meyer et al., 2017). According to the definition by Geurs and Van Wee (2004), accessibility should take four components into account, namely land-use component, transportation component, temporal component, and individual component. Milakis et al. (2018) argued that AVs would impact all the four accessibility components based on the viewpoints of seventeen international accessibility experts. However, improved accessibility would be more likely to benefit those wealthier people, as AVs would not be affordable to those low-income households due to the high upfront cost (Cohen and Cavoli, 2019). Furthermore, the potential urban sprawl may make walking and cycling inconvenient and further reduce the accessibility of those people who rely on these two transport modes (Cohen and Cavoli, 2019). Therefore, stakeholders are suggested to take social equality into account when shaping policies and planning infrastructures for AEVs.

4.3 Impacts of the AEV Adoption on Land Use System

The interaction between land use and transport systems has been commonly recognized (Wegener, 2004; Zhuge and Shao, 2019a): the improvements in transport system could increase accessibility and further influence land-use patterns; in return, the changes in land use could influence travel demand and further the transport system. AEV is a disruptive innovation in the transport sector and thus is likely to impact the land-use system as well (Gavanas, 2019).

4.3.1 Impacts on Residential Location Choice

Residential location choice is a traditional topic in the studies of the Land Use and Transport Interaction (LUTI) (Zhuge et al., 2016). The introduction of AEVs may influence the residential location choice of households (Milakis et al., 2018). The reasons are twofold: on the one hand, people can perform daily activities (e.g., work and leisure) in their vehicles during journeys, which is associated with the value of travel time savings (Carrese et al., 2019; Krueger et al., 2019); on the other hand, travel costs would decrease due to energy efficiency and using electricity instead of petrol. For example, Zhang and Guhathakurta (2018) suggested that people might want to move to those places with better public facilities due to the reduction in commuting costs.

4.3.2 Impacts on Urban Form

It has been commonly recognized that the introduction of AEVs would potentially change urban form. However, it remains unclear how the changes would happen. First, the diffusion of AVs would likely reduce parking demand, especially in the city center (see Section 4.2.1). This would relieve downtown land for other activity facilities (Zakharenko, 2016); Second, with the widespread adoption of EVs, the total refueling demand would likely decrease, which may result in the removal of refuelling stations. Instead, some fast charging stations may be developed in order to accommodate the rising enroute charging demand (Zhuge and Shao, 2018a), as discussed in Section 4.2.1. Third, the introduction of AVs may lead to urban sprawl (Meyer et al., 2017; Soteropoulos et al., 2019; Stead and Vaddadi, 2019; Yigitcanlar et al., 2019), as AV owners may move to suburban areas due to the advantages of AVs, such as in-vehicle activities and the reduction in travel costs (see Section 4.3.1).

4.4 Impacts of the AEV Adoption on Energy System

4.4.1 Energy Efficiency

AEVs could be more energy efficient: First, with the equipped sensors, AVs would be able to predict braking and acceleration decisions of the vehicle ahead. The following vehicles can adjust their moving speeds accordingly and precisely, which can help to save energy. Furthermore, AVs can also choose those more energy-efficient routes with their onboard high-tech products, such as GPS devices (Fagnant and Kockelman, 2015); Second, EVs are generally more energy-efficient than CVs, as EVs can achieve the same performance with less energy consumed (Chau and Chan, 2007). Therefore, as a combination of AV and EV, AEVs are generally expected to have much higher energy efficiency.

4.4.2 Vehicle-to-Grid (V2G)

EVs can benefit the energy system through the Vehicle-to-Grid (V2G) technology (Guille and Gross, 2009), which is a key element of the smart grid. In the context of V2G, EV drivers can sell electricity back to the grid when EVs are connected to the grid. This could make the grid system more stable, efficient, and reliable (Lam et al., 2017; Yilmaz and Krein, 2012). Furthermore, AEVs are expected to promote the development of V2G, as they can monitor the State of Charge (SOC), and thus can automatically search for charging facilities and get themselves charged when needed

(Iacobucci et al., 2019).

4.4.3 Renewable Energy

Coupling EVs with renewable energy would be promising, as this could benefit both the transport and energy sectors (Bellekom et al., 2012). Specifically, 1) whether EVs could really benefit the environmental system through the reduction of GHG emissions depends on the energy source used for the generation of electricity. For example, the net reduction in GHG emission would be limited when electricity is generated through conventional power plants (e.g., coal-fired electric power plants) (Bellekom et al., 2012). Therefore, using renewable energy (e.g., wind energy) instead to generate electricity for EVs would significantly reduce GHG emissions (Bellekom et al., 2012); 2) renewable energy, such as wind and solar energy, is generally difficult to be integrated into the existing grid system, as they do not produce a constant amount of electricity (Bellekom et al., 2012). EVs (specifically, their on-board batteries) can be used as storage devices to deal with surplus electricity; 3) Integrating a large number of EVs would put pressure on the grid system, due to the additional electricity demand from EVs; Furthermore, the charging demand of EVs mostly occurs during the night time when electricity demand in a day peaks. Renewable energy can be used to accommodate the additional charging demand from EVs.

4.5 Impacts of the AEV Adoption on the Environment System

The potential environmental impacts of AEV adoption can be assessed at both global and local levels. Specifically, the local environmental impact assessment is focused on air and noise pollutions in cities and further human health effects, while the global environmental impact assessment generally looks at GHG emissions and further climate change.

At the local level, the environmental benefits of AEVs seem obvious. For those AEVs running on electricity only, they do not release any vehicular emissions when moving around the city. Therefore, citizens would not be exposed to any vehicular air pollutions (e.g., NOx) and thus gain health benefits (Pettigrew et al., 2018b). Furthermore, because of the quiet electric engine of AEVs, noise pollution could be reduced. For example, it was estimated that the introduction of EVs in an urban area of Elche (Spain) could reduce the sound pressure level by 2 dB, which would benefit 10% of citizens (Campello-Vicente et al., 2017).

At the global level, it remains unclear whether introducing AEVs could reduce GHG emissions. For those conventional AVs, Wadud et al. (2016) suggested that they would potentially reduce GHG emissions in the road transport sector by almost half. Also, the construction of fewer parking lots would bring considerable environmental benefits (Taiebat et al., 2018). However, AVs would potentially increase travel demand (see Section 4.2.2), which would give rise to increases in both energy consumption and GHG emissions. For EVs, it is of great importance to take electricity mixes into account when conducting a global environmental impact assessment (Choi et al., 2018), as energy sources used for electricity generation could heavily influence the net reduction in GHG emissions (Zhuge et al., 2019). Many studies have suggested that EVs could potentially reduce GHG emissions and thus benefit the environment at the global level (Hawkins et al., 2012). For example, the assessment conducted by Girardi et al. (2015) suggested that in Italy, electricity for EVs was mainly produced at fossil fuel power plants, but using EVs instead of CVs could still reduce GHG emissions. However, some studies suggested that EVs might bring limited global environmental benefits. For example, Wang et al. (2013) conducted an impact assessment using Life Cycle Analysis (LCA). The results suggested that EVs were not suitable for the electricity mix at that moment in China, and the electricity mix needed to be 90% clean for EVs. Optimizing the electricity mix would help to reduce GHG emissions. For example, Wu et al. (2018) found that the optimized electricity mix and advanced electricity generation technologies could reduce GHG emissions of Battery Electric Vehicle (BEV) in China by 13.4% in 2020. Furthermore, coupling renewable energy with EVs would also be promising. For example, Choi et al. (2018) quantified the potential of a renewable-oriented mix, and found that the reduction in GHG emissions could be up to 5% by 2026.

4.6 Impacts of the AEV Adoption on Economy System

4.6.1 Impacts on Real Estate Prices

In general, residential location choice and real estate price are highly correlated (Ettema, 2011; Zhuge et al., 2016): sellers/landlords would increase real estate prices of their properties when people show great interest in them; in return, an increase in real estate price would influence the decision-making of households on renting or purchasing properties (Zhuge and Shao, 2018b). As aforementioned, the introduction of AEVs would influence the residential location choice of households (see Section 4.3.1). Therefore, real estate prices are likely to be affected as well. For example, people may move outside of the city center due to the adoption of AEVs, which may give rise to a decrease in real estate prices of those properties in the city center.

4.6.2 Impacts on Employment

Introducing AVs into the vehicle market would potentially influence the labor market, especially in the transport sector (Heard et al., 2018). It was estimated that in the USA, 15.5 million workers might be affected due to the introduction of AVs (Taiebat et al., 2018). Among them, drivers for freight transport, public transit, and taxis tend to be more heavily influenced (Davidson and Spinoulas, 2015; Hörl et al., 2016; Pettigrew et al., 2018a; Taiebat et al., 2018). Furthermore, auto repair and car insurance can also be influenced due to the reduction in traffic accidents (Clements and Kockelman, 2017; Davidson and Spinoulas, 2015). However, the widespread adoption of AVs can increase job opportunities related to automation, such as various sensors' production. Besides, the introduction of AEVs could influence accessibility (see Section 4.2.3) and further employment opportunities, as accessibility and employment opportunities were closely associated, as evident from several studies (Cervero et al., 1999; Gao et al., 2008).

4.7 Impacts of the AEV Adoption on Population System

As aforementioned, AEVs would potentially improve accessibility, but likely only to those upper-income groups, as the AEV sale prices could be quite high, especially when AEVs are just introduced. This would lead to transportation inequities (Cohen and Cavoli, 2019; Cohn et al., 2019; Moreno, 2017). Besides, the widespread adoption of AEVs would influence social networks (i.e., friendships). On the one hand, due to in-vehicle activities (e.g., work), AEV owners could have more time available to perform joint activities with their friends. Therefore, it would become easier for them to maintain their friendships or build new friendships; On the other hand, the potential urban sprawl caused by the introduction of AEVs would result in a longer travel distance between a pair of friends, which may make it difficult for AEV owners to meet up and maintain their friendships. Therefore, it remains unclear how the diffusion of AEVs would potentially influence social networks.

5 A Conceptual Agent-based Integrated Urban Model for AEVs: SelfSim-AEV

5.1 Modeling Approaches

Since both AVs and EVs are emerging technologies in the transport sector, the modelling approaches used to investigate the adoption behaviour are quite similar. The typical approaches used include discrete choice models, system dynamics models, and agent-based modeling, as reviewed in (Al-Alawi and Bradley, 2013; Zhuge et al., 2019). Some other approaches have also been used, including the structural equation model (Lavieri et al., 2017; Zhang et al., 2019), Theory of Planned Behavior (TPB) (Buckley et al., 2018), factor analysis (Haboucha et al., 2017; Kaur and Rampersad, 2018), and Technology Acceptance Model (TAM) (Buckley et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Zhang et al., 2019).

Discrete choice models are a typical approach to predicting individual choice in transport studies (Ben-Akiva and Lerman, 1985). The models have been widely used to predict AV and EV adoption rates, using the influential factors that were reviewed in Section 3 as independent variables. Several types of discrete choice model have been used, including binary logit model (Chen et al., 2019; Hollström, 2019), multinomial logit model (Bansal and Kockelman, 2017; Shabanpour et al., 2018), mixed logit model (Daziano et al., 2017), ordinal logit model (Berliner et al., 2019) and conditional logit model (Daziano et al., 2017). However, the discrete choice model is a static model, and can not simulate the decision-making of consumers over time. In order words, the model cannot simulate the diffusion of AEVs over time, but it can be coupled with other dynamic approaches, such as the agent-based model, to deal with the dynamics (Brown, 2013).

Both system dynamics models and agent-based models are typical dynamic approaches to investigating complex adaptive systems at the macro-and micro-levels, respectively. In the studies of EV or AV adoption, the system dynamics model in general looks at those system-level outcomes, such as vehicle market share (Nieuwenhuijsen et al., 2018; Puylaert et al., 2018; Zhuge et al., 2019); while the agent-based model looks at individual vehicle choices, which can be aggregated at multiple resolutions (e.g., zone-, district- and city- levels) (Eppstein et al., 2011; Miller and Heard, 2016; Talebian and Mishra, 2018; Zhuge et al., 2019). System dynamics models and agent-based models have their advantages and disadvantages: agent-based modelling can easily and explicitly consider heterogeneity and social influence at the individual level, and can also be coupled with Geographical Information System (GIS). However, it is not easy to apply agent-based models into real-world scenarios due to the long computing time and disaggregate input data. Furthermore, in the studies of technology diffusion, the political economy aspect of new technologies plays an important role in the diffusion (Comin and Mestieri, 2014; Torvanger and Meadowcroft, 2011), but it cannot be easily considered in an agent-based simulation, mainly because it is difficult to properly define the behaviors of agents involved (e.g., government agent). For the system dynamics model, it simulates dynamic complex systems at the macro level, and thus can be easily applied into real-world scenarios in terms of input data preparation and computing time. However, heterogeneous behaviors (e.g., purchase and travel behaviors) and the interactions between consumers through their friendships and neighbors, which are important to the diffusion of AEVs, cannot be explicitly considered. Therefore, in this study, we adopted agent-based modelling in the conceptual design of an integrated urban model for the diffusion of AEVs (see Section 5.3), mainly because heterogeneity, social influence and geographical factors are of great importance to the investigation of the diffusion of AEVs. In response to the disadvantages of agent-based modelling, emerging urban big data, such as vehicle trajectory data, social media data and mobile phone data, present a promising approach to preparing to disaggregate input data for agent-based models. Furthermore, High-Performance Computing (HPC) machines would help to dramatically reduce the computing time of large-scale agent-based models. Although agent-based models of technology diffusion, in general, are not able to explicitly consider the broader landscape of social, political, and economic contexts, these factors can be treated as exogenous and be explored within "what-if" scenarios. A hybrid model, which couples agent-based model with system dynamics model, should better deal with this problem. However, combing agent-based models and system dynamics models would increase the complexity of the model design. As identified by Swinerd and McNaught (2012), there were three classes of design for the integration of agent-based models and system dynamics models. Although the integration appears to be promising, little is known about the real benefits of such integration (Swinerd and McNaught, 2012). Furthermore, the resulting hybrid model would be more difficult to apply in real-world scenarios, for example, due to more input data needed. Therefore, this paper used agent-based modelling as a primary approach to developing an integrated framework for the diffusion of AEVs.

5.2 Agent-based Land Use and Transport Interaction (LUTI) Model

As reviewed in Section 3, there are various factors influencing the adoption of AEVs, which are associated with the six urban sub-systems, namely transportation, land use, energy, environment, economy, and population systems; In return, the adoption of AEVs would potentially impact these six connected urban sub-systems, as reviewed in Section 4. In order to fully understand the diffusion of AEVs and its impacts on the connected systems through time, an integrated model incorporating the interactions between the diffusion of AEVs and the connected systems is needed.

The Land Use and Transport Interaction (LUTI) model (Iacono et al., 2008), which is a typical approach to systematically investigating land use or/and transport issues, would be a good base for integrated modelling of the AEV diffusion. This is because a typical LUTI model, such as UrbanSim (Waddell, 2002), generally involves several urban sub-systems, including transportation, land use, economy, and population systems. Some of the LUTI models, such as ILUTE (Salvini and Miller,

2005) and ILUMASS (Strauch et al., 2005), additionally consider the environment and energy systems.

Recently, agent-based modelling has become a typical approach to modelling the interactions between land use and transport systems, and has been applied in several typical LUTI models, including ILUTE (Chingcuanco and Miller, 2018), PUMA (Ettema et al., 2007), and SelfSim (Zhuge et al., 2016). Furthermore, agent-based modelling is a typical approach to exploring complex dynamic systems at the micro-scale, and has been used to simulate the six connected urban sub-systems (Batty, 2007), i.e., transportation (Bazzan and Klügl, 2014), land use (Verburg et al., 2019), economy (Farmer and Foley, 2009), energy (Rai and Henry, 2016), environment (Hare and Deadman, 2004) and population (Billari and Prskawetz, 2012) systems. Also, agent-based modelling has been widely applied to the simulations of technology diffusion (Bonabeau, 2002), including the diffusion of EVs and AVs (see Section 5.1). Therefore, an agent-based LUTI model would be theoretically feasible for developing an integrated urban model of AEVs, which needs to consider the linkages and interactions between the diffusion of AEVs and the six connected urban sub-systems.

In the conceptual design, SelfSim will be chosen as an example to demonstrate how to develop such an agent-based integrated urban model to investigate the expansion and impacts of the AEV market. Compared to other agent-based LUTI models (e.g., ILUTE and PUMA), SelfSim has an EV version (i.e., SelfSim-EV), which has been applied to simulate the EV adoption in Beijing, as detailed in (Zhuge et al., 2019). Therefore, SelfSim-EV can be more easily extended by only incorporating AV components, resulting in an AEV version of SelfSim (i.e., SelfSim-AEV).

5.3 Conceptual Design of SelfSim-AEV

5.3.1 Model Framework

As aforementioned, SelfSim-EV (Zhuge et al., 2019), which is an agent-based integrated urban model for EVs, can be updated to SelfSim-AEV, by incorporating AV-related modules. Essentially, SelfSim-AEV is composed of initialization and simulation modules. The former is used to generate an agent- and GIS-based virtual city as model inputs through a virtual city creator, as introduced in (Zhuge et al., 2018a; Zhuge et al., 2018b). A virtual city contains agents, facilities, and relationships, as well as their attributes and relationships. Here, an agent can be a person or household; Facilities include transport infrastructures (e.g., parking lots) and activity facilities (e.g., residential buildings). Agents and facilities are connected through various linkages, such as friendships and daily plans.

All the agents, facilities, and relationships can be spatially explicit with geographical information attached. The Simulation module comprises several spatial urban models, which are used to simulate urban evolution at the micro-scale, with a focus on the interactions between the diffusion of AEVs and the six connected urban sub-systems. Each of the SelfSim-AEV components will be briefly introduced based on the previous work on SelfSim and SelfSim-EV (Zhuge and Shao, 2018a; Zhuge and Shao, 2018b; Zhuge and Shao, 2019a; Zhuge et al., 2018a; Zhuge et al., 2019), with a focus on the updating work needed for the diffusion of AEVs (see Figure 4).

- **Demographic Evolution Model (connecting to Population and Economy Systems):** simulates the changes in those typical sociodemographic attributes and transitions of a person, such as age, income, employment status, and education level, as detailed in (Zhuge and Shao, 2018b). This is important, as various decision-makings of agents (for example, in the AEV adoption and travel-activity scheduling) are associated with their sociodemographic attributes and transitions. For the economic system, it connects to the demographic evolution model through the employment and income modules (Zhuge and Shao, 2018b).
- **Joint Model of Residential Location Choice and Real Estate Price (RLC-REP, connecting to Economy and Land Use Systems):** simulates the interactions and negotiations between several typical agent types in a dynamic housing market, which are grouped into seeker (i.e., buyer and renter) and offeror (e.g., investor, seller, and landlord) agents: see (Zhuge and Shao, 2018b) for model specification. The joint model is used to find new locations for household agents and also to update real estate prices. Thus, it is connected to both land use and economic systems. Essentially, the model can help to understand how AEVs would diffuse across space. Furthermore, the household residential location could influence the purchase behaviour of AEVs, for example, through the so-called neighborhood effect and travel behaviour/demand. In return, the adoption of AEVs could give rise to household residential relocation and further the change in real estate prices.
- **Social Network Evolution Model (connecting to Population System):** is used to simulate the evolving linkages between agents through the building and dissolving friendships for each individual (Zhuge et al., 2018b; Zhuge et al., 2019). The social network is a key part of the population system, and the model can help to understand how AEVs would diffuse across individuals through their social networks (i.e., friendships). Here, social influence is quantified with the number of AEV owners in their social networks, which is considered as a variable of the utility function for the decision-making of consumer agents on vehicle purchases. Therefore, people with a higher number of AEV owners in their social networks would be more likely to

choose AEVs. In return, the diffusion of AEVs might influence social networks, for example, through household residential relocation.

- **Vehicle Market Model (connecting to Transportation System):** The original EV market model (Zhuge et al., 2019) needs to be extended by additionally simulating the adoption of AVs and AEVs. In the simulation, consumer agents can choose among a set of vehicle types, including Conventional Vehicles (CVs), Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs), Autonomous Vehicles (AVs), and Autonomous BEVs. Here, consumer agents are assumed to always choose the vehicle type which can maximize their utilities. The utility function uses those influential factors as model variables, including vehicle price, vehicle usage, social influence, and environmental awareness, as reviewed in Section 3 (Zhuge et al., 2019).

- **Activity-based Travel Demand Model (connecting to Transportation, Energy and Environment Systems):** simulates individual travel behaviour with different transport modes, including CVs, EVs, AVs, and AEVs. This can be based on MATSim (Multi-Agent Transport Simulation, https://www.matsim.org/), which is a typical activity-based travel demand model with many extensions, such as EV, AV, and parking extensions (Horni et al., 2016). Essentially, the model outputs can be used to calculate accessibility, which can be further used as an input of several models, including the Transport Infrastructure Development Model, Activity Facility Development Model, RLC-REP model, and Vehicle Market Model. In addition, MATSim can trace moving trajectories of each agent throughout a whole day, so that the spatiotemporal distributions of vehicular emissions and energy consumption can be obtained based on the simulation. Such fine-grained spatially explicit outputs would be particularly useful for assessing the impacts of the AEV diffusion on the environmental and energy systems at multiple resolutions (ranging from the link- to the city- levels) (Zhuge et al., 2019).

- **Transport Infrastructure Development Model (connecting to Transportation and Land Use Systems):** is used to simulate the evolution of transport facilities and transport networks, considering the influence of the adoption of AEVs. These transport facilities include parking lots, charging posts at parking lots, refueling stations, and enroute fast charging infrastructures (e.g., battery swap stations). The road network may also be influenced by the introduction of AVs, due to the development of AV-related infrastructures, such as AV lanes. Therefore, the transport infrastructure development model would help to understand how the diffusion of AEVs may impact both the quantity and layout of AEV-related transport infrastructures over time. In response, the original model in SelfSim-EV (Zhuge and Shao, 2018a) needs to be updated by incorporating AV zones or lanes.

- **Activity Facility Development Model (connecting to Land Use System):** simulates the changes in land use patterns over time at the facility level. This involves several facility types, including residential buildings, office buildings, and leisure facilities (Zhuge and Shao, 2019a; Zhuge et al., 2019). The model would help to examine whether the introduction of AEVs would impact urban forms (e.g., urban sprawl).

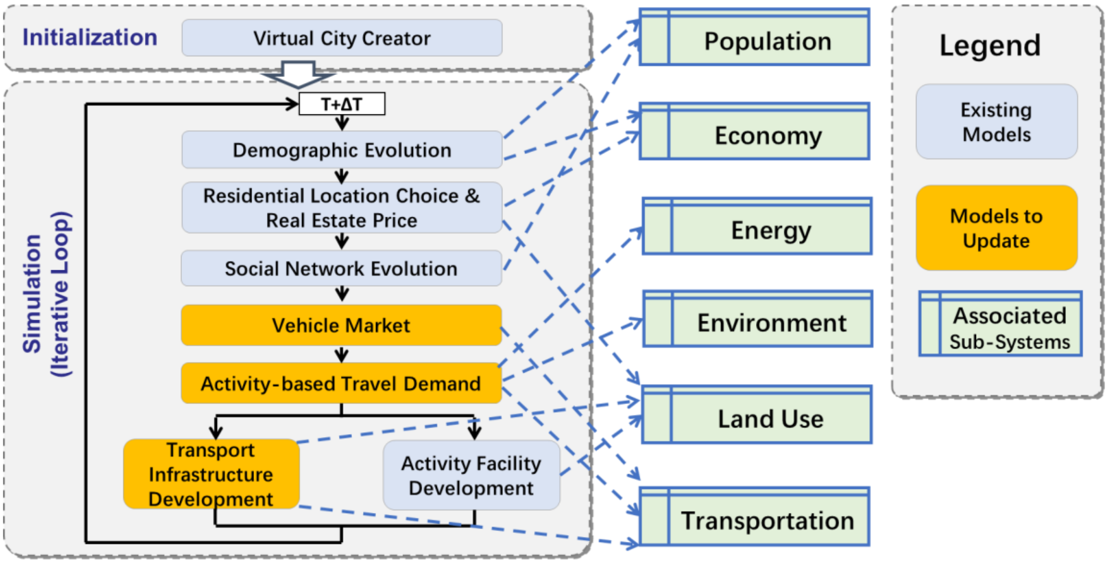


Figure 4 Framework of SelfSim-AEV (Source: Adapted from (Zhuge et al., 2019))

5.3.2 Model Inputs

General inputs of SelfSim-AEV include household travel survey data, transport networks and facilities (e.g., road networks and parking spaces), land use data (e.g., points of interest), traffic flow data, and macro-level data from relevant statistics (e.g., statistical yearbooks). Apart from these, empirical findings from relevant survey data would be essential for model calibration. Specifically, SelfSim-AEV contains various behavioural rules (e.g., decision-making) of agents in several different sub-models. In general, these behavioural rules need to be properly set or calibrated using empirical findings from survey data, in order to be behaviourally sound (or realistic). However, it would be costly and time-consuming to collect all the data needed for model calibration through general questionnaire surveys. Emerging urban big data (e.g., vehicle trajectory data, social media data, and mobile phone data) would be promising alternative data sources: on the one hand, such big data are generally collected automatically at little cost; on the other hand, the sample size could be much larger than that of a traditional questionnaire survey. Thus, the samples would be more representative.

5.3.3 Model Outputs

A SelfSim-AEV simulation can output spatially and temporally explicit results about the diffusion of AEVs and the evolution of the six connected urban sub-systems, namely, transportation (e.g., parking spaces and the traffic flow), land use (e.g., residential locations), energy (e.g., electricity and petrol consumptions), environment (e.g., vehicular emissions), economy (e.g., real estate prices) and population (e.g., sociodemographic changes). These results will help to understand the AEV diffusion path at the micro-level. Furthermore, the potential impacts of the diffusion on the associated urban elements, such as urban forms, transportation infrastructures, the environment, and the power grid system, can be assessed at multiple resolutions (e.g., facility-, traffic zone- and city-levels).

6 Conclusions

In order to find evidence about the linkages and interactions between the diffusion of AEVs and the six connected urban sub-systems (i.e., transportation, land use, economy, energy, environment, and population systems), this paper reviewed the adoption of AVs, EVs, and AEVs and their impacts on the connected urban sub-systems, mainly through the interpretation of empirical findings from those studies investigating AVs and EVs, separately. Specifically, the six connected systems could influence the adoption of AEVs through those influential factors, including sociodemographic factors (e.g., gender), psychological factors (e.g., environmental awareness), purchase-related factors (e.g., vehicle prices), usage-related factors (e.g., range anxiety) and social influence (e.g., neighbor effect); In return, the diffusion of AEVs could also influence the six connected systems, namely transportation (e.g., transportation infrastructures), land use (e.g., urban forms), economy (e.g., employment), energy (e.g., vehicle-to-grid), environment (e.g., air pollution) and population (e.g., transportation inequities) systems. Based on the evidence, we argued that an integrated urban model, which takes the linkages and interactions into account, is needed. Such an integrated urban model would be a useful tool for investigating the diffusion and impacts of AEVs from a systematic and dynamic perspective. To this end, we further conducted a conceptual design of the integrated urban model using agent-based modelling. Specifically, we used an agent-based Land Use and Transport Interaction (LUTI) model (i..e, SelfSim-EV) as a base to demonstrate how to extend existing LUTI models to incorporate AEV components. It is hoped that such a demonstration would help modelers to update the other LUTI models, such as ILUTE (Salvini and Miller, 2005) and SILO

(Ziemke et al., 2016), for the studies of AEVs when needed.

The proposed urban integrated model, SelfSim-AEV, can output lots of fine-grained results about the diffusion of AEVs and the six associated urban sub-systems, and thus can provide AEV-related stakeholders with more useful information for their decision-making. For example, urban planners would be interested in the simulation results about the impacts of the diffusion of AEVs on urban forms; For local authorities, they may be interested in the potential environmental benefits of the AEV adoption, which can be quantified based on the SelfSim-AEV simulation. Furthermore, the AEV-related stakeholders can set up various “what-if” scenarios with SelfSim-AEV to explore the future of AEVs and its impacts on the six connected urban systems. For example, these scenarios could help to understand how different policies (e.g., subsidies), technologies (e.g., vehicle-to-grid) and infrastructures (e.g., battery swap stations) would influence the diffusion of AEVs and further the six connected urban systems. The scenario results would inform the stakeholders' decision-making, for example, on investment in infrastructures and technologies.

To provide insights into the adoption and use of AEVs and support the development of SelfSim-AEV, more empirical findings of AEVs are needed. Previous studies tended to investigate the adoption and use of EVs and AVs separately. AEVs take advantages of both AVs and EVs which can complement each other. Therefore, people’s willingness to purchase and use AEVs might be different from that of EVs or AVs, indicating that more empirical findings of the adoption and use of AEVs are needed. At an early stage of the AEV development, the empirical findings can be extracted from traditional questionnaire survey data, so as to identify the early AEV adopters and their key travel and sociodemographic characteristics. Furthermore, the purchase and use behaviors of the early AEV adopters in those AEV demonstration projects could also help to understand the potential diffusion of AEVs.

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