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Energy and environmental impacts of shared autonomous vehicles under different pricing strategies

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The introduction of vehicle automation, shared mobility, and vehicle electrification will bring about changes in urban transportation, land use, energy, and the environment. The accurate estimation of these effects is therefore essential for sustainable urban development. However, existing research on estimating the energy and environmental effects of shared autonomous electric vehicles generally ignores the interaction between land-use and transportation systems. This study, therefore, analyzes the long-term effects of shared autonomous vehicles (SAVs) from the perspective of land use and transportation integration. Different SAV pricing scenarios are also developed to explore the optimal pricing strategy for low carbon–oriented SAVs. Moreover, the study has further assessed the effect of vehicle electrification on vehicle emissions and energy consumption. The results have shown a nonlinear relationship between SAV fares and their transportation, land-use, energy, and environmental effects. Under an appropriate pricing strategy, SAV deployment could reduce $PM_{2.5}$ emission and energy consumption by 56–64% and 53–61%, respectively. With the further introduction of vehicle electrification, these can rise to 76% and 74%.

npj Urban Sustainability (2023)3:8 ; https://doi.org/10.1038/s42949-023-00092-2

INTRODUCTION

Globally, the transportation sector faces enormous environmental challenges related to increases in energy consumption and greenhouse gas (GHG) emissions[1]. According to the Ministry of Ecology and Environment of the People's Republic of China, in 2019, 53.4% of Chinese cities failed to meet national air-quality standards, and the increased demand for energy and increases in vehicle exhaust emissions were the main reasons[2]. In 2019, China's transportation sector accounted for 9.0% of total energy consumption, reaching 12,868.67 PJ[3]. From a global perspective, the transportation industry is the crucial and fastest-growing sector contributing to GHG emissions, which are the main factor contributing to climate change[1]. The International Council on Clean Transportation (ICCT) estimated that global carbon dioxide emissions related to transportation will increase significantly in the future, growing more than 70% by 2050[4].

As the primary source of road traffic pollution, vehicle emissions degrade air quality and endanger human health. A new study by ICCT showed that in 2015, a total of 385,000 people died prematurely owing to vehicle exhaust emissions worldwide[5]. The transportation sector, therefore, is facing the challenge of improving energy efficiency and reducing vehicle emissions while also enhancing the performance of the urban transportation system and meeting increasing travel demand[6–9]. Shared autonomous vehicles (SAVs), which integrate automation and on-demand mobility services, could play an important role in achieving such goals[10,11]. Governments worldwide have high expectations for autonomous vehicles, which have great potential for development[12]. Meanwhile, the sharing economy is favored by young people and has tremendous market and development potential[7,13]. It is worth noting that autonomous driving technology and shared mobility have a mutually reinforcing effect. By reducing fleet size and increasing the utilization rate of autonomous vehicles[10,12], shared mobility can mitigate urban transportation problems (e.g., traffic congestion, noise, and accidents)[7,14] and reduce energy consumption and emissions[14–16]. Moreover, it is reported that autonomous vehicles may improve user satisfaction and increase the number of users by reducing the average waiting time for ride sharing[10,13]. Therefore, the transition from traditional car transportation to SAVs maybe seen as a general trend in road transportation[17].

There are still many uncertainties about the environmental and energy effects of SAVs, and some researchers and policymakers have concerns about whether SAVs are beneficial for sustainable social development[17,18]. On the one hand, SAVs can save energy and reduce emissions by, for example, promoting transportation efficiency[18], increasing road capacity[19], mitigating congestion[19], reducing accident frequency[20], matching vehicle sizes to trip requirements[12], and eco-driving[21]. On the other hand, SAVs can lower people's marginal travel costs and make the locational decisions of residents and enterprises more free, leading to urban sprawl and increased travel time, distance, and frequency[22,23]. SAVs are also likely to increase travel by specific user groups (e.g., elderly, children, the disabled) who cannot drive by themselves in daily life, thus increasing travel demand, resulting in more vehicle kilometers traveled[10,24] and significant increases in energy consumption and emissions, which will affect sustainable development. In short, SAVs seem to be a double-edged sword. This raises the question of whether, in the long-term, promoting SAVs will reduce or increase transportation-related GHG emissions and energy consumption.

Although some studies have modeled SAVs and estimated their energy and environmental effects[16,19,25,26], they only utilized

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independent transportation demand models with an externally specified travel demand. Such approaches do not account for the interaction between transportation and land-use systems, which causes these studies to ignore an essential fact—namely, that in the long-term, SAVs will not only affect the residents' travel behaviors and traffic flow[27], but also change the spatial location decisions for residents and enterprises[22,28–31], thus changing travel distribution and ultimately affecting emissions and energy consumption[32–35]. To fill this research gap, this study will assess the long-term energy and environmental effects of SAVs from the perspective of land use and transportation integration.

Different from previous studies, this study first analyzed and identified how changes in residents' travel behavior caused by SAVs affect road traffic flow. On that basis, the long-term effects of SAVs on the land-use system, transportation system, energy, and environment were investigated using an integrated land-use and transportation model and the vehicle-emission model. Furthermore, to maximize the benefits of SAVs and reduce their potential negative effects on the environment, this study determined the optimal SAV pricing strategy using a comprehensive evaluation method[8]. In addition, electrification is also an important trend in automobile development, and there is considerable synergy between SAVs and electric vehicles (EVs)[15,36,37]. Consequently, this study further examined the effect of vehicle electrification on the environmental and energy benefits of SAVs.

The results have revealed that SAV fares have a nonlinear relationship with energy consumption and regional vehicle emissions. If SAV fares are set too low, the promotion of SAVs will lead to a 6.0% and 1.1% increase in energy consumption and $PM_{2.5}$ emission, respectively. A low SAV fare is thus detrimental to reducing energy use and emissions in the transportation sector. Meanwhile, when SAV fares are set too high, it will dampen public acceptance, and SAVs will not be able to fully play their role in sustainable development. An appropriate SAV pricing strategy is needed to realize the advantages of SAVs for promoting sustainable urban transportation development, and reducing energy consumption and vehicle emissions. Moreover, technological innovations in vehicle electrification, electric power structure, and EV energy efficiency, in coordination with an appropriate pricing strategy, can enhance the environmental and energy benefits of SAVs and reduce $PM_{2.5}$ emission and energy consumption by more than 70%.

RESULTS

Land-use and transportation effects

To better assess the effect of SAVs on urban land use, transportation, energy, and the environment, this study considered two types of regional development scenarios. The first is a business-as-usual scenario (S0), in which the city maintains the existing development mode and continues to develop[6]. The other is the SAV development scenario, in which SAV is introduced as an optional travel mode[38]. To study the effect of SAV pricing strategies on the results, five different SAV pricing scenarios were designed with reference to the market prices of similar services in the study area and related research assumptions[22,25,39–41], namely, S1, S2, S3, S4, and S5. SAV fares increase sequentially in S1–S5. In this study, SAV fares have three parts: base fare, unit time fare, and unit distance fare, taking the US dollar as the unit. Table 1 summarizes the scenarios studied in this study. More detailed descriptions of these scenarios are provided in Supplementary Note 1.

By combining the integrated land-use and transportation model and the scenario planning method, the effects of different regional development scenarios on urban transportation and land-use systems were obtained. Figure 1 shows the changes in regional total flow time and the SAV mode share rate under different regional development scenarios. Supplementary Table 1 summarizes the transportation system performance under five SAV pricing scenarios. Figure 2 shows the different ratios for the land-use system between different SAV pricing scenarios and S0. To comprehensively reflect the effects of different regional development scenarios on the land-use system, four evaluation indicators were adopted based on 3Ds indicators for the urban built environment (i.e., density, diversity, design)[42–44] and data availability: accessibility, land-use diversity, population density, and job density. For a detailed introduction to these indicators, please see Supplementary Note 5.

SAV introduction will significantly affect the performance of the urban transportation system. First, SAVs can reduce the value of travel time (VOTT) for travelers and ease their travel burden, as passengers can work or have leisure time in vehicles. Such effects will stimulate travel demand, especially in the case of lower SAV fares, for which travelers' VOTT is greatly reduced. In addition, SAVs may threaten the public transportation system, as public transportation typically operates on fixed routes, while SAVs are more flexible and efficient to provide door-to-door service[41]. Under S1, for example, the induced vehicle kilometers traveled is up 101.1%, and the share of the public transportation system is reduced to 1.7% (Supplementary Table 1). Second, SAVs can promote user travel efficiency by increasing road capacity, which is achieved by improving the utilization efficiency of road sections and intersections[10,18,39]. Furthermore, SAV introduction can reduce travelers' reliance on cars and increase the share of active

Table 1. Scenario summary.

Scenarios	S0	S1	S2	S3	S4	S5
SAVs available	No	Yes	Yes	Yes	Yes	Yes
SAV base fare (USD)	/	0.08	0.16	0.24	0.40	0.56
SAV per-unit-time fare (USD per hour)	/	0.24	0.48	0.72	1.20	1.68
SAV per-unit-distance fare (USD per km)	/	0.02	0.04	0.06	0.10	0.14
Initial year	2010	2025	2025	2025	2025	2025
Final year	2040	2040	2040	2040	2040	2040

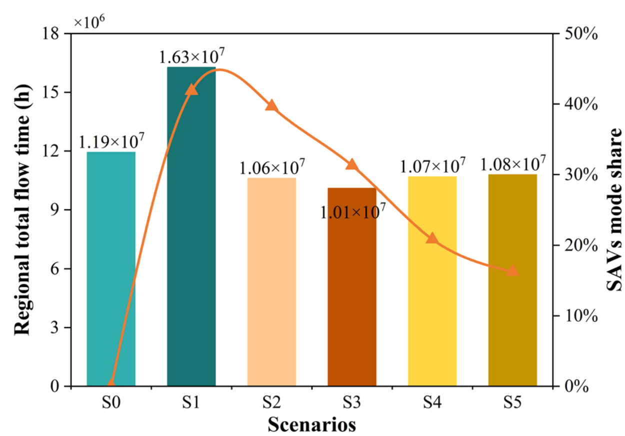

Fig. 1 The impact of different development scenarios on the transportation system. Columns represent the impact of different development scenarios on regional total flow time and different colors represent different regional development scenarios. The orange line represents SAV mode share of different development scenarios. It can be found that the low SAV pricing strategy with a higher SAV mode share is the worst scenario among all regional development scenarios in terms of regional total flow time.

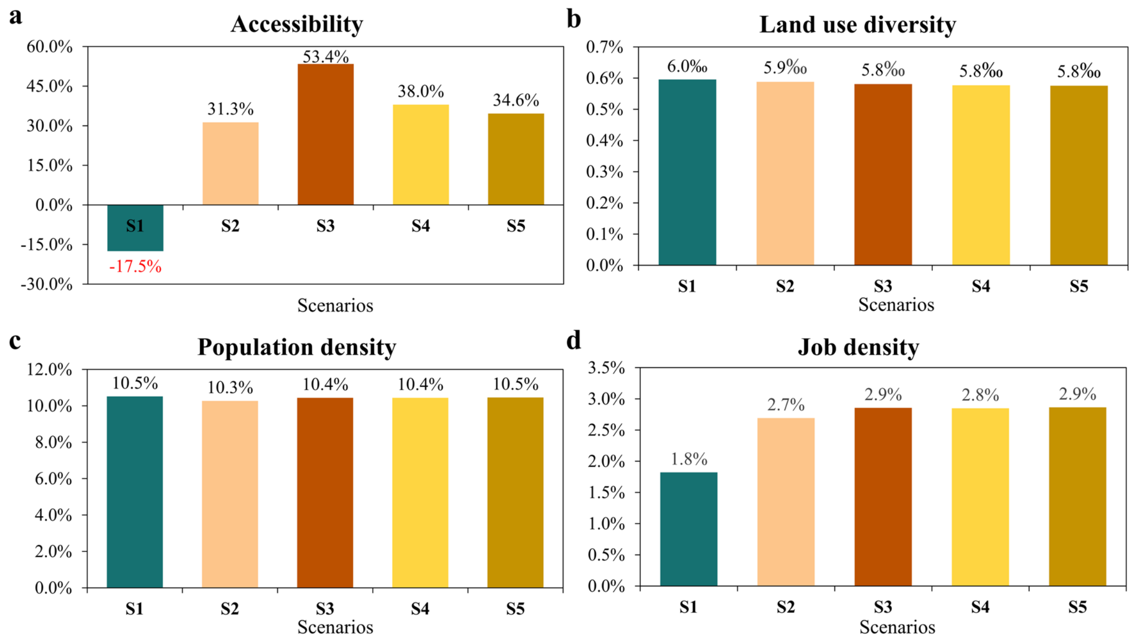

Fig. 2 The impact of SAVs on land-use system. The impact of SAVs pricing scenarios (relative to S0) on (**a**) accessibility, (**b**) land-use diversity, (**c**) population density, and (**d**) job density. Data labels show the percentage change relative to Scenario S0. Different SAVs pricing scenarios are represented in different colors.

transportation modes, shifting the trip structure for city inhabitants toward low-carbon development[17]. For example, under S3, car, walking, and bicycle modes account for 10.8%, 15.0%, and 26.1%, respectively (Supplementary Table 1). Through the above-mentioned effects, SAVs affect the transportation system, and those effects vary with changes in the SAV pricing strategy. Specifically, under a low SAV pricing strategy (S1), the travel time and cost savings brought by SAVs are offset by the induced travel demand, thus weakening transportation system performance and yielding a much longer total travel time than in S0—up to 36.3% (Fig. 1). In general, however, SAV introduction can significantly reduce regional total flow time and significantly improve transportation system performance (Fig. 1).

SAVs will promote the redistribution of population and jobs and affect regional accessibility. After SAV introduction, owing to changes in travel costs and convenience, users may reselect their work and residential locations, changing the population and job density of the study area and the urban land-use pattern[22,27–30]. Specifically, compared with S0, SAV deployment will increase job density and population density by about 2.0% and 10.0%, respectively, while having little effect on land-use diversity (about 0.6%). It is worth mentioning that the above effects do not vary significantly between different SAV pricing scenarios (S1–S5) (Fig. 2b–d). Furthermore, the redistribution of population and jobs, as well as the changes in regional total flow time, will further affect regional accessibility[45,46]. It is worth noting that, unlike land-use diversity and population and job density, SAV's effect on regional accessibility shows more variation across the scenarios. More specifically, under S1, although the magnitude of SAVs' effect on land-use diversity, job density, and population density is roughly the same as that of the other SAV pricing scenarios, the low-cost transportation system will reduce the speed, reliability, and operation efficiency of the road network (Fig. 1), reducing regional accessibility by about 17% (Fig. 2a). However, under other SAV pricing strategies, the dual improvement of transportation system performance and land-use performance will increase regional accessibility by 30%–50% (Fig. 2a).

Energy and environmental effects

Based on the above results, SAVs' effects on energy consumption and vehicle emissions can be obtained. Energy consumption under different regional development scenarios was used to analyze the energy effect of SAVs (Fig. 4). For the environmental effect of SAVs, this study adopted two different approaches: (1) mapping the spatial distribution of vehicle emissions (including $PM_{2.5}$, NOx, SO_2, CO_2, CO, and hydrocarbons) under different regional development scenarios to determine the overall environmental effect of SAVs (Fig. 3 and Supplementary Figs. 1–6) and (2) quantitative evaluation of the environmental implications of SAV pricing scenarios based on the spatial average of the study area (Fig. 4, and Supplementary Tables 2 and 3). For the environmental effect assessment of SAVs, this study modeled the emission of six types of vehicle emissions and exposure of five types of air pollutants (Supplementary Tables 2, 3). As six types of vehicle emissions follow the similar trends, $PM_{2.5}$ is used as an example to illustrate the environmental effect of SAVs.

SAV introduction can make transportation systems more environmentally friendly and energy efficient. From the quantitative results, under most SAV pricing scenarios, SAVs have a significant effect on reducing energy consumption, thus facilitating emission reduction and mitigating urban air pollution. Specifically, relative to S0, under S2, S3, S4, and S5, the environmental results of CO_2 and five air pollutants are improved with SAV introduction. For example, under S3, $PM_{2.5}$ emission and exposure are reduced by 64.2% and 63.5%, respectively, compared with S0 (Fig. 4, and Supplementary Tables 2, 3). Further, SAV deployment can achieve a 40%–60% reduction in energy consumption under the four SAV pricing scenarios (Fig. 4). Regarding spatial distribution, compared with S0, vehicle emissions in most parts of the study area show a descending trend under S2, S3, S4, and S5 (Fig. 3 and Supplementary Figs. 1–6). Under S0, vehicle emissions in the city center are significantly higher than in other areas owing to higher population density and more severe congestion, and most regions face great challenges in achieving green transportation (Supplementary Fig. 1). In S2, S3, S4, and S5, with SAV introduction, urban transportation

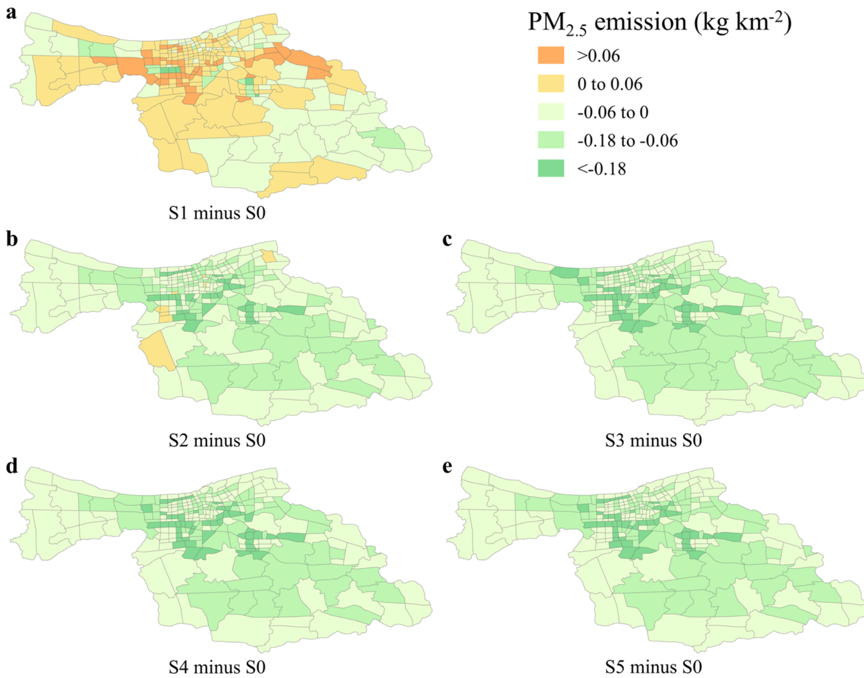

Fig. 3 The impact of SAVs on $PM_{2.5}$ emission. The spatial distribution of relative $PM_{2.5}$ emission between different SAV pricing scenarios and Scenario S0 across the study area. SAV pricing scenarios incorporate Scenario S1 (**a**), Scenario S2 (**b**), Scenario S3 (**c**), Scenario S4 (**d**), and Scenario S5 (**e**). Orange indicates increased $PM_{2.5}$ emission in SAV pricing scenarios, and green indicates reduced $PM_{2.5}$ emission in SAV pricing scenarios. Supplementary Figs. 2–6 presents the impact of SAVs on the emissions of CO_2 and other air pollutants. Jiangyin City, Jiangsu Province, China, is the background. This city, as a county-level city in Wuxi City, is one of six pilot smart cities under construction and was selected in this study to evaluate the impacts of SAVs.

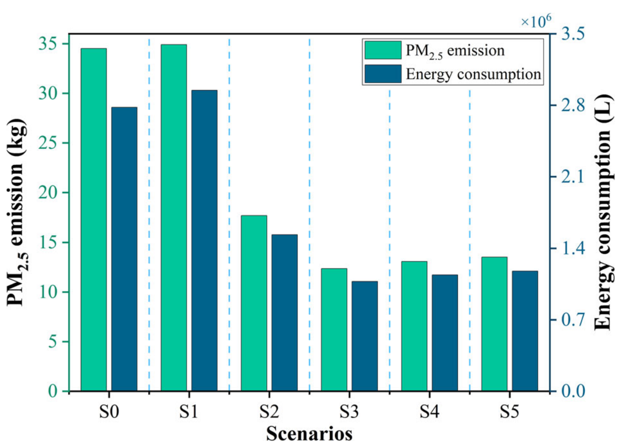

Fig. 4 The impact of different development scenarios on energy and environment. Green columns: $PM_{2.5}$ emission under different regional development scenarios across the study area. Blue columns: the impact of different development scenarios on energy consumption. It can be found that SAV fares have an important non-linear relationship with the energy and environmental impacts of SAVs.

performance and land-use patterns are improved, resulting in a significant reduction in six types of vehicle emissions in most areas.

When the SAV fare is low, however, SAV introduction will have a negative effect on energy consumption and the environment. Compared with S0, under S1, energy consumption and $PM_{2.5}$ emission increase by 6.0% and 1.1%, respectively (Fig. 4 and Supplementary Table 2), and the other five types of vehicle emissions showed similar increases (Supplementary Tables 2, 3). It should be noted, however, that owing to changes in the spatial distribution of the population under S1, $PM_{2.5}$ exposure is not higher than in S0 as expected; instead, a 5.0% reduction is achieved (Supplementary Table 3).

Optimal SAV pricing strategy

To maximize the environmental potential of SAVs, this study identified the optimal SAV pricing strategy by evaluating and comparing various regional development scenarios. The evaluation indicators were taken from the results of various models, including (1) a transportation performance indicator: regional total flow time; (2) land-use performance indicators: accessibility, land-use diversity, population density, and job density; (3) environmental performance indicators: total $PM_{2.5}$ emission and average exposure; and (4) an energy performance indicator: energy consumption. Supplementary Table 4 summarizes the distance of each regional development scenario from the optimal solution and its ranking.

Comparing different SAV pricing scenarios reveals that SAV fares have a nonlinear relationship with SAVs' effects on transportation, land use, energy use, and the environment (Figs. 1, 2a, 4). Under S1, low-cost, high-efficiency SAVs will sharply increase the time, frequency, and distance of travel and threaten the public transportation system, resulting in higher energy consumption and vehicle emissions than other development scenarios (Fig. 4). By increasing the SAV price, excessive travel demand will be curbed, thus reducing energy consumption and emissions. Moreover, this improvement effect is maximized in S3 (Fig. 4 and Supplementary Tables 2 and 3). However, a further increase in SAV fares will lead to a decrease in SAV mode share. This will decrease SAVs' effectiveness in promoting transportation efficiency and accessibility (Figs. 1 and 2a) and gradually increase energy consumption and vehicle emissions (Fig. 4), thus weakening their energy-saving and environmental improvement effects.

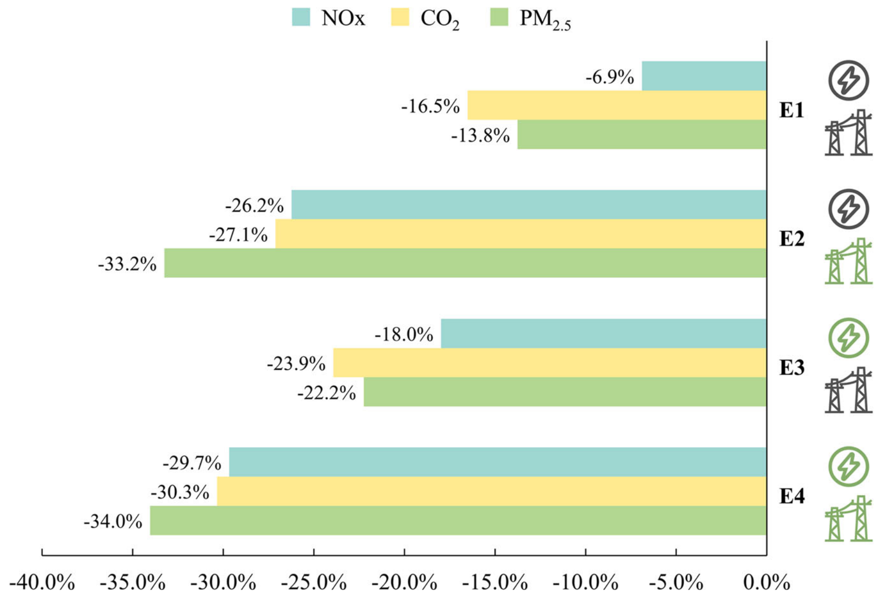

Fig. 5 Reduction ratios of NOx, CO_2, and $PM_{2.5}$ emissions under different electrification scenarios relative to Scenario S3. Scenario E1 further considers vehicle electrification based on Scenario S3, and EV energy efficiency and emission levels from electricity generation are both at the current level. Scenarios E2 and E3 build on Scenario E1 by considering a cleaner generation mix in the electric power structure and advances in EV energy efficiency, respectively. Scenario E4 takes into account three technical innovations: vehicle electrification, EV energy consumption, and electric power structure. Grey icons represent current levels, and green icons represent future levels.

In summary, S3, as the optimal SAV pricing scenario for Jiangyin City, will not only maximize the benefits of SAVs but also reduce their potential adverse effects on energy and the environment. Consequently, an appropriate SAV pricing strategy is essential for fully exploiting the potential of SAVs in promoting sustainable development[8].

Furthermore, this study tested the impact of vehicle occupancy on the optimal SAV pricing scenario (S3), shown in Supplementary Table 5. The SAV vehicle occupancy adopted in this study is 3.0, which is applicable for S1-S5. When the SAV vehicle occupancy of S3 is adjusted to the current China average level (namely 1.3) and moderate SAV vehicle occupancy (namely 2.0), the effects of SAVs in improving the total flow time and regional accessibility will be impaired, the environmental benefits of S3 are weakened, and the improvement ratio of $PM_{2.5}$ emission is reduced to 56.0% and 61.1%, respectively (Supplementary Table 5).

Environmental benefit for fleet electrification

To further assess the effect of vehicle electrification on vehicle emissions and energy consumption, four shared autonomous electric vehicle (SAEV) development scenarios were designed based on the optimal SAV pricing scenario (S3), namely, E1, E2, E3, and E4. These scenarios look at (1) the rate of vehicle electrification (both SAVs and non-automated vehicles), (2) EV energy efficiency (kWh km^{-1}), and (3) emission levels from electricity generation (g kWh^{-1})[6]. Specifically, the EV energy efficiency and emission level from electricity generation under E1 maintain the current level while E2 and E3 consider a cleaner generation mix in the electric power structure and advances in EV energy efficiency, respectively. E4 considers developments in both generation mix and energy efficiency. More detailed descriptions of vehicle electrification scenarios are provided in Supplementary Note 7 and Supplementary Table 17.

The electrification of the SAV fleet can further enhance environmental and energy benefits. Relative to S3, $PM_{2.5}$, CO_2, and NOx emissions under E1 are reduced by 13.8%, 16.5%, and 6.9%, respectively (Fig. 5). Furthermore, comparing the spatial distribution of six types of vehicle emissions under the two scenarios reveals that vehicle electrification plays a significant role in further mitigating vehicle emission problems (Supplementary Figs. 7–12). Under E2 and E3, the effects of SAEVs in terms of environmental improvement are more significant since decarbonization of the electric power sector and EV energy efficiency improvement are considered. Specifically, under E2 and E3, $PM_{2.5}$ emissions are reduced by 33.2% and 22.2%, respectively (Fig. 5). In addition, comparing E2 and E3, vehicle emissions are more sensitive to emission levels from electricity generation than to EV energy efficiency. That is, lowering the emission level from electricity generation is more effective for reducing CO_2 and air pollutants emissions than advancements in EV energy efficiency (Supplementary Tables 6–8). If technical innovations in vehicle electrification, electric power structure, and vehicle energy consumption are considered simultaneously, then the six types of vehicle emissions will be further reduced, in which the emission reductions of $PM_{2.5}$, CO_2, and NOx emissions will reach 34.0%, 30.3%, and 29.7%, respectively, under E4 (Fig. 5). In addition, compared with S0, $PM_{2.5}$ emission and energy consumption under E4 decrease substantially, up to 76.4% and 74.2%, respectively (Supplementary Tables 6–8).

DISCUSSION

This study assessed the long-term effects of a shift from conventional private vehicles to SAVs in terms of transportation, land use, energy, and the environment. Moreover, to facilitate efficient SAV introduction, the optimal SAV pricing strategy was determined based on multiple effects. This study further analyzed the benefits of vehicle electrification—another important future transportation trend[15,36,37]—to give policymakers a better understanding of future transportation. The findings can provide the following theoretical guidance for SAV development.

First, SAVs can optimize the urban transportation system and promote urban development. SAV introduction will affect accessibility and resident travel behavior. On the one hand, the change in residents' travel mode will affect the operating conditions of the road network, thereby affecting energy use and vehicle emissions[33,47]. On the other hand, the variation in accessibility will change the spatial distribution of urban land use, which will affect residents' travel demand[34,48,49], ultimately affecting vehicle emissions and energy demand[35]. Therefore, this study first analyzed SAVs' effects on urban transportation and land-use systems. The results revealed that although SAVs will increase travel demand and decrease the proportion of trips made using public transportation, SAV introduction will have more advantages than disadvantages. SAVs' effects on promoting transportation efficiency can overcome the negative effects to reduce regional total flow time and improve accessibility. Similar conclusions were drawn by Nahmias-Biran et al. [49], who found that SAV deployment could improve the performance of transportation networks and increase regional accessibility. However, Zhang and Guhathakurta[22] and Cordera et al. [28] found that SAV introduction would not improve accessibility but would lead to urban sprawl and increase travel distance for users. Those results are mainly attributable to the fact that they only considered the effect on VOTT but not the effect on increasing road capacity in modeling SAVs, which affected transportation network performance and thus led to different results. Besides, Mo et al. [50] applied an agent-based model to simulate the competition between SAVs and public transportation and found that the introduction of SAVs will enable public transportation operators to reduce the supply of low-efficiency and high-cost lines and put more resources on short and cost-effective lines. While public transportation share was preempted, passengers and transportation departments can benefit from it since SAVs will fill gaps in service areas in time, and concentrate the resources to improve the existing public transportation's level of service. Therefore, it can also be one of the positive effects of SAVs on the transportation system.

Second, regarding energy consumption and vehicle emissions, SAVs can play an important role in sustainable mobility. To help policymakers understand SAVs' long-term effects on energy consumption and emissions so they can formulate appropriate strategies, this study examined the energy and environmental effects of different SAV pricing scenarios. The results indicated that SAV promotion can decrease car-use demand, and optimize urban land-use and transportation systems, thereby significantly reducing energy consumption and emissions. Although low SAV pricing may produce the opposite results, we can nevertheless conclude that SAVs have great potential for promoting the sustainable development of urban transportation. In addition, this study shows the importance of shared mobility in improving the environmental benefits of SAVs by testing the impact of vehicle occupancy on the optimal SAV pricing scenario. Our findings are consistent with previous studies[12,15,16,24,26], as shown in Supplementary Table 9. Therefore, in general, SAV can be said to play an essential role in saving energy and reducing emissions in the transportation sector.

Third, we identified a nonlinear relationship between SAV fares and SAVs' effects on transportation, land use, energy use, and the environment. An appropriate SAV fare can play an integral part in promoting sustainable development. Pricing policy will affect public acceptance of SAVs and is also an important means of realizing effective SAV use[13]. Fare revenues can cover the operating costs of SAV fleets while boosting technological innovation. The SAV pricing strategy can also be used to manage travel demand to achieve sustainable development without inducing excessive demand[41]. We revealed that when SAV fares are low, owing to the drastic reduction in travel costs, residents' travel demand will increase significantly, leading to an increase in energy consumption and emissions, which is detrimental to saving energy and reducing emissions. In the case of high SAV fares, the SAV fleet will be small, and its mode share will only be 16%, meaning that SAVs would be unable to play their full role in sustainable urban development. An appropriate SAV fare, meanwhile, can offset the induced travel demand, give full play to SAVs' effects on saving energy and reducing emissions, and maximize sustainable urban development.

Fourth, SAEV deployment can significantly reduce emissions and save energy. This study found that technological innovations in vehicle electrification, the electric power structure, and EV energy efficiency, combined with optimal pricing strategies, can substantially reduce $PM_{2.5}$ emission and energy consumption (up to 76% and 74%, respectively). Gawron et al. [16] similarly found that SAEV introduction could reduce GHG emissions by up to 87% under scenarios of accelerated electrical grid decarbonization, dynamic ride sharing, and lower fuel consumption rates. Moreover, the environmental benefits of SAEV fleets identified in this study are similar to those found in the previous studies[10,25]. Another interesting finding in this study was that reducing emissions from electricity generation will more effectively reduce vehicle emissions than making advancements in EV energy efficiency. This indicates that simultaneously optimizing the transportation system and the power system will have great value for promoting green urban development[51].

This study has some limitations. For example, this study only focused on SAV or SAEV emissions during the operation phase, ignoring emissions produced during the production and end-of-life phases. Thus, future studies should model vehicles' life cycle emissions to gain a more comprehensive understanding of the environmental effects of SAVs and SAEVs. In addition, attention should be paid to the effects of the combination of SAVs and other transportation technologies, such as whether the combination of SAV use and road congestion pricing can play a role in mutual promotion[39,40]. This could be explored with the aid of the integrated modeling framework established in this study.

Overall, this study's findings can help transportation authorities gain a deeper understanding of future transportation trends—namely, vehicle automation, shared mobility, and vehicle electrification. This study can also help authorities formulate policies for contributing to the transportation sector pollution prevention and carbon emission reduction in the context of sustainable city development. Such policies can cover upcoming changes to existing policies before SAV deployment, as well as future policy incentives aimed at bringing the great potential of SAVs into play. For example, our fleet electrification results show that the government should formulate incentives to accelerate the transition to EVs and adopt stricter fuel economy standards to push vehicles and power grids toward cleaner, more efficient development[37].

METHODS

Study area

Jiangyin, as the forefront of innovation in autonomous driving in China, is selected as a case study to evaluate the energy and environmental impacts of SAVs. China's autonomous vehicle industry has expanded rapidly in recent years. It has received not only strong support from government policies but also a steady stream of technological and capital assistance. As one of six pilot cities focused on smart city infrastructure and intelligent connected vehicles, Wuxi which covers Jiangyin has played an important role in the autonomous driving field[52]. Considering the size of the area, this study selected a county-level city, Jiangyin, as the study area. Jiangyin is located in the south of Jiangsu Province, with a total area of 986.97 square kilometers and a permanent population of 1,779,515, as of the end of 2021.

Model framework

A sequential model was developed and applied to assess the urban development, energy, and environmental effects of different regional development scenarios (Fig. 6). First, a quasi-dynamic land use and transport integrated model (or integrated

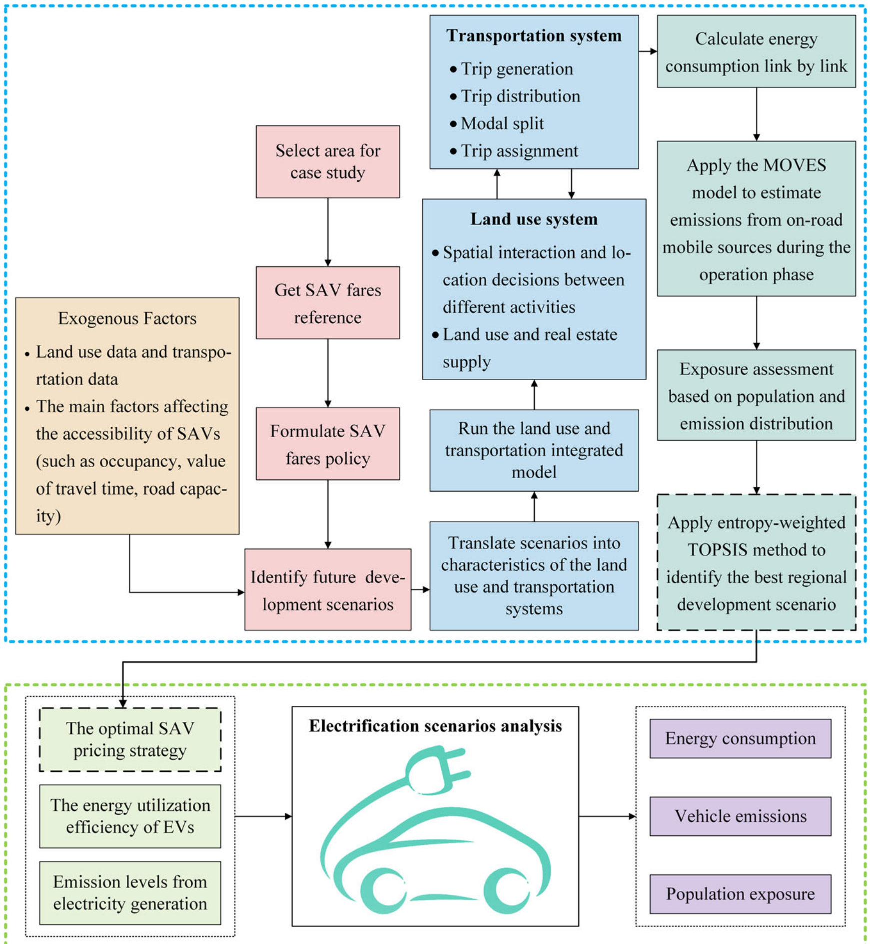

Fig. 6 A conceptual overview of the sequential modeling processes. A sequential model is applied to assess the energy and environmental impacts of different regional development scenarios quantitatively. The model incorporates the quasi-dynamic land use and transport integrated model, vehicle emission model, entropy-weighted TOPSIS method, and electrification scenarios analysis.

model) and the scenario planning method were applied to simulate the urban development of the city of Jiangyin, China, in 2040 and analyzed the effect of different regional development scenarios on land-use and transportation systems and energy. Then, the traffic flow results obtained using the integrated model became the input for the vehicle-emission model to determine vehicle emissions under different development scenarios (see Supplementary Note 4). Based on the spatial distribution of population and vehicle emissions, this study calculated average population-weighted exposure to air pollutants. Next, a comprehensive evaluation method was applied to select the optimal development scenario from different regional development scenarios (see Supplementary Note 6). Finally, based on the optimal SAV pricing scenario, this study further analyzed the effect of fleet electrification on energy consumption, vehicle emissions and population exposure and evaluated whether this effect was affected by EV energy efficiency and emission levels from electricity generation. More detailed information about methodologies used in the model framework is described in Supplementary Notes 1–7, Supplementary Fig. 13, and Supplementary Tables 10–18.

Regional development scenarios

This study considered two types of regional development scenarios for evaluating the effect of shared autonomous vehicles (SAVs) on sustainable development. One type is the business-as-usual scenario (S0) and the other type contains all scenarios that focus on SAV development. Under S0, the city maintains the existing development mode and continues to develop. The base year of S0 is 2010, with the integrated model running every five years until 2040. In the SAV development scenarios, we will introduce SAVs into the transportation system in 2025 based on S0. The SAV development scenarios can be subdivided according to different SAV pricing strategies. This study assumed that the vehicles under both the business-as-usual scenario and the SAV development scenarios are gasoline-powered. The study also designed a shared autonomous electric vehicle (SAEV) development scenario to consider the effects of vehicle electrification. Please refer to Supplementary Note 1 for the formulation process of SAV pricing strategies.

The land use and transportation integrated model

We applied the TRANUS model, a quasi-dynamic land use and transportation integrated model to analyze the impact of different development scenarios on land use and transportation system. For more details on the theoretical basis, model establishment, and model calibration for the TRANS model, please see Supplementary Notes 2 and 3. The parameters of the two types of regional development scenarios in the integrated model were set as follows:

1. Business-as-usual scenario
   The base year of the business-as-usual scenario was 2010, and the integrated model ran every 5 years until 2040. This scenario was developed according to the comprehensive plan of Jiangyin released by the Jiangsu Institute of Urban Planning and Design. The plan sets out clear requirements for Jiangyin's future economic development (e.g., per capita GDP, labor production rate), social development (e.g., resident income, labor employment level), land resource utilization (e.g., area and spatial location of different land-use types in each region), transportation service level (e.g., average wait time, average speed, road capacity), and road network planning (e.g., road network density, width). This study used this plan to determine the transportation and land-use parameters of the integrated model for future years (2015–2040).
   The land-use parameters of the base year (2010), such as the amount of employment and population in each traffic analysis zone (TAZ), were obtained from the Jiangyin statistical yearbook, while the land area and land prices of different land-use types were obtained from the Jiangyin Municipal People's Government. In terms of transportation, value of travel time (VOTT) and average wait time, among others, were derived from actual traffic surveys. The road capacity and the speed limit of each link, mode share, and average occupancy rate of each travel mode came from the Jiangyin Bureau of Transportation and the Jiangyin Public Transportation Company. Supplementary Tables 14–16 show the partial land-use and transportation data of the base year.
2. SAV development scenarios

The SAV development scenarios deploy SAVs based on the business-as-usual scenario. The base year of the scenarios was 2025, and the integrated model ran every 5 years until 2040. In the integrated model, this study mainly modeled SAVs' effects on road capacity and VOTT. Specifically, this study first determined SAV market penetration in different years based on previous studies[53]. Then, a meta-regression model was applied, combined with existing research results, to determine the relationship between VOTT and road capacity and SAV market penetration. Finally, based on the above relationship, SAVs' effect on road capacity and VOTT in different years was determined, as shown in Supplementary Table 12. For more details about the process of establishing influence relationships, please see ref. [38].

SAV mode share under different scenarios mainly depends on the SAV pricing strategies. The SAV pricing strategy changes the users' travel utility by affecting the travel cost. Users make the travel mode and route decisions according to the principle of expected utility maximization, thus affecting SAV mode share.

In addition, this study considered the average vehicle occupancy of SAVs, which was set to 3.0 based on previous studies[54,55]. Given the uncertainty of future development, this paper further tested the optimal SAV pricing scenario under the current China average vehicle occupancy (set to 1.3[56–58]) and moderate SAV vehicle occupancy base on previous studies (set to 2.0[59–61]).

Vehicle emission model and entropy-weighted TOPSIS method are described in Supplementary Note 4 and Supplementary Note 6, respectively.

Evaluation indicator selection

Four types of evaluation indicators were selected to reflect the effects of different regional development scenarios on urban transportation, land use, energy use, and the environment. For more details on the definition and calculation formula of these indicators, please see Supplementary Note 5.

(1) Transportation performance indicator. This study used regional total flow time to measure transportation system performance. Regional total flow time is defined as the sum of the flow time between different TAZs.
(2) Land-use performance indicators. Based on the 3Ds indicators of the urban built environment (i.e., density, diversity, and design)[42–44] and data availability, this study selected accessibility, land-use diversity, population density, and job density to describe the effects of different development scenarios on the land-use system.
    Accessibility indicator refers to the degree of difficulty residents face in reaching a certain activity using the transportation system, which depends on the number of activities in a given region and the difficulty of traveling between different zones[62]. Land-use diversity is defined as the abundance of land-use types in an area.
(3) Environmental performance indicator. This study selected total $PM_{2.5}$ emission and average population-weighted exposure as the environmental performance indicators to describe the environmental effects of regional development scenarios. Regional average exposure was determined based on population data and $PM_{2.5}$ emission.
(4) Energy performance indicator. Energy consumption was used as the energy performance indicator (unit: liter).

Electrification scenario

To explore the potential of vehicle electrification for reducing vehicle emissions and energy consumption, this study designed SAEV development scenarios based on the optimal SAV pricing scenario. Electric vehicles (EVs) and gasoline-driven vehicles were assumed to have the same vehicle characteristics, except in terms of energy sources. Previous studies have found that battery electric vehicles (BEVs) outperform other EV types in terms of saving energy and reducing emissions[12,63]. Therefore, SAEVs and electrified cars were modeled as BEVs in this study.

According to the differences in EV energy efficiency and emission levels from electricity generation, the SAEV development scenario was subdivided into four electrification scenarios: E1, E2, E3, and E4, as shown in Supplementary Table 17. Please refer to Supplementary Note 7 for the scenario setting and calculation process of the SAEVs development scenario.

Reporting summary

Further information on research design is available in the Nature Research Reporting Summary linked to this article.

DATA AVAILABILITY

The authors declare that all data supporting the findings of this study are available within the paper and its Supplementary Information files.

CODE AVAILABILITY

The Jiangyin integrated model and vehicle emission model are available from the corresponding authors upon request.

Received: 28 October 2022; Accepted: 8 February 2023;
Published online: 25 February 2023

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ACKNOWLEDGEMENTS

This research has been supported by the National Natural Science Foundation of China (Project No. 71971038, 52272308, 71701030, and 72025104), the Humanities and Social Sciences, and the Fundamental Research Funds for the Central Universities of China (Project No. DUT22QN253, DUT20GJ210, and JBK2103009).

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COMPETING INTERESTS

The authors declare no competing interests.

ADDITIONAL INFORMATION

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s42949-023-00092-2.

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