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Flying to transportation electrification: The role of ride-hailing services#

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ABSTRACT

Transportation electrification can reduce dependence on fossil fuels and promote energy transition. In the literature, numerous research efforts have been dedicated to investigating the influence of diverse energy and climate policies on EV penetration. However, limited attention has been given to the specific effects of ride-hailing services on EV penetration and the broader sustainable energy transition. In this study, we combine a Stated Preference (SP) survey with a bottom-up transportation model to examine the role of ride-hailing services on EV penetration and energy transition. Our method provides the benefit of analyzing how individuals opt for ride-hailing services over other transportation modes for different trips, while also endogenously determining the technology mix. The results reveal that ride-hailing services have the potential to increase EV penetration by 2.46%, or by 2.89% if the ride is shared, thereby contributing to the transition towards clean energy. Policy interventions such as the implementation of carbon pricing and the promotion of public transport can further drive transportation electrification, showcasing a synergistic effect with ride-hailing services.

Keywords: transportation electrification, ride-hailing services, energy transition, electric vehicle, ride-sharing services

NONMENCLATURE

Abbreviations	
EV	Electric Vehicle
Symbols	
$Smode_{y,r,i}$	Probability of travel mode choice
$x_{r,i}$	Explanatory variable of transport mode
β	Coefficient for the explanatory variable
$\Omega_{y,i}$	Fixed effect for each transport mode
$\tilde{x}_{r,j}$	Control variable for each travel mode
s_n	Socioeconomic variable for individual n
A_j	Impact of unobserved characteristics
$\varepsilon_{n,r,j}$	Unobserved part of utility
α	Coefficient for socioeconomic variables
β	Coefficient for control variables
$y_{n,r,i}$	Binary variable for travel mode choice
$\pi_{y,r}$	Probability of the occurrence of travel combination r
D_r	The distance of trip
P_r	Binary variable for the origin of travel
D_r	Binary variable for the start time
$QD_{y,i}$	Travel demand of specific travel mode
QT_y	Total travel demand
δ	Travel parameter
$Pmode_{y,i}$	Travel cost of each travel mode
$Ptec_{y,i,t}$	Travel cost of technology t
$Stec_{y,i,t}$	Share of technology t
$Ptime_{y,i,t}$	Time cost
AWH_t	Annual working hours
$ATS_{y,i}$	Average travel speed
$Pfuel_{y,i,t,f}$	Cost of fuel f
$Pghg_{y,i,t,f}$	Carbon emission cost
$Pdevice_{y,i,t}$	Annualized purchase cost
TC_y	Total annual cost
$PTdevice_{y,i,t}$	Purchase cost
$OMT_{y,i,t}$	Annual maintenance cost
$PTfuel_{y,i,t}$	Annual fuel cost
$PTghg_{y,i,t,f}$	Carbon emission cost
$IC_{y,i,t}$	Acquisition cost
$T_{i,t}$	Lifecycle of each transportation mode
$Punitf_{y,i,t,f}$	Unit fuel price
$AFC_{y,i,t,f}$	Annual fuel consumption
δ_y	Carbon tax
$ef_{y,f}$	Emission factor
$XT_{y,i,t}$	Annual mileage traveled of vehicle
$CO_{y,i,t}$	Load factor of vehicle
$O_{y,i,t}$	The number of vehicles in operation
$ST_{y,i,t}$	Stock of vehicles

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$rc_{y,i,t}$	The number of newly added vehicles
$rt_{y,i,t}$	The number of retired vehicles
$rt_{y,i,t}$	The number of retired vehicles

1. INTRODUCTION

With the increasing global awareness of climate change and global warming, decarbonization has become a critical focus for future development. The transportation sector, which ranks as the second-largest energy consumer after industry, has seen a continuous rise in total carbon emissions [1-2]. According to the International Energy Agency (IEA), in 2022, carbon emissions from China's transportation sector accounted for approximately 10.4% of the nation's total carbon emissions [3-4].

How the transportation sector reduces emissions is crucial to achieving climate goals. Transportation electrification can reduce reliance on fossil fuels, facilitate energy transitions, generate health co-benefits, and is regarded as essential for most future scenarios that align with the 2℃ target [5]. To encourage the widespread adoption of electric vehicles (EVs), various energy and climate policies have been implemented in countries such as the United States, Switzerland, Canada, Germany, and China [6-8]. While assessing the impacts of these policies on EV penetration, significant attention has been given to consumer behavior. The research efforts are usually put on improving the realistic representation of consumers' behaviors, by for example introducing time costs, non-financial preferences, and consumer heterogeneity into vehicle choice models [9-10], endogenously determining the mode splits based on discrete choice experiment [11], or introducing the latest available technologies for vehicle choice adoption [12]. Findings suggest that consumer behavior plays a crucial role in the energy transition and transportation decarbonization, as it interacts with policy measures. However, the potential impact of travelers' choice of ride-hailing services on the transport energy system has often been overlooked.

As a new form of service emerging from the sharing economy revolution, ride-hailing services have become an innovative and promising strategy for meeting travel demand, particularly in countries like China and the United States, where commercial ride-hailing companies such as Didi Chuxing, Uber, and Lyft have been successfully established and operate on a large scale [13-14]. Ride-hailing vehicles can be powered by either fossil fuels or electricity and may be used either individually or in a shared capacity. These services compete with other modes of transportation, potentially altering the modal split and influencing the technological landscape by affecting the balance between fuel-based and electric vehicles. Consequently, the penetration and utilization of ride-hailing vehicles have the potential to reshape the energy mix and the adoption of transportation technologies [15].

This paper investigates the role of ride-hailing services in transportation electrification. By exploring the differences in the impact of ride-hailing services under various policy scenarios, we examine how ride-hailing electrification policies influence the overall system's electrification. We also assess the effects of different ride-hailing behaviors and fuel technologies on the adoption rate of electric vehicles. This paper develops a discrete choice model that considers travelers' preferences and behaviors, treating ride-hailing services as a distinct mode of transportation. After obtaining the market shares of various transportation modes, these are incorporated into a travel demand forecasting model. The travel demand is then integrated into an urban passenger transport energy system optimization model to derive trends in urban transport electrification and carbon emissions. To explore the differences in the role of ride-hailing services under various scenarios, several policy scenarios are designed.

2. METHODOLOGY

This paper develops an integrated model to predict the transport electrification and energy consumption. We first conduct a Stated Preference (SP) survey to predict the choice probabilities for various modes of transportation. We then input the mode shares to a recursive model to forecast the travel demand of different mode. An energy system optimization model is finally applied to investigate the role of ride-hailing services in the transport electrification and energy consumption. The overall structure of the travel model is depicted in Fig. 1.

2.1 Discrete choice model

The discrete choice model has been widely used for investigating transport mode choice. The estimation cases of mode choice models for urban travel in Chinese cities mostly rely on the MNL model [16-17]. This section explains the stated preference survey method and discrete choice model modeling.

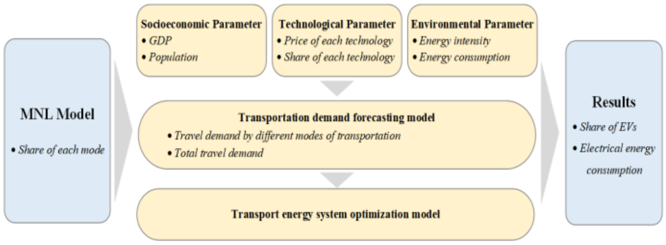

Fig. 1 Model framework

We select Nanjing as a case study to estimate the individual preference parameters. The data on the mode choice were gathered through an online survey which was disseminated in April 2023 via the Wenjuanxing platform, a Chinese company specialized in market research. A total of 530 survey responses were collected. We consider three attributes including travel distance, travel time, and the origin of travel to design synthetic trip scenarios. The survey comprises two sections. In the first section, the respondents are required to provide socioeconomic data, such as age, gender, occupation, income. They also indicated whether the residence is urban or suburban, preferred transport mode, which help us get their traveling habits. In the second section, respondents are asked to make choices between ride-hailing services and other conventional modes of transport within hypothetical scenarios.

We use the following formula to estimate the probability that a traveler chooses transport mode *i* in year *y* for synthetic trip *r*.

$$Smode_{y,r,i} = \frac{\exp\left(\Omega_{y,i} + x_{r,i}^{T}\hat{\beta}_i\right)}{\sum_m \left(\exp(\Omega_{y,m} + x_{r,m}^{T}\hat{\beta}_m\right)} \tag{1}$$

$$U_{n,r,j} = \underbrace{A_j + x_{r,j}^{\mathrm{T}}\beta_j + s_n^{\mathrm{T}}\alpha_j}_{systematic\ utility} + \underbrace{\varepsilon_{n,r,j}}_{random\ utility} \tag{2}$$

$$L(\alpha,\beta,A) = \sum_n\left(\sum_r\left(\sum_i\left(y_{n,r,i}\log\left(P_{n,r,i}\left(\chi_r, s_n \mid \alpha,\beta,A\right)\right)\right)\right)\right) \tag{3}$$

The parameters α , β , and A in the equation can be estimated using Maximum Likelihood Estimation, as provided in equation (3).

$$\pi_{y,r} = p\left(D_r\right)\times p\left(S_r\right)\times p\left(P_r\right) \tag{4}$$

$$Smode_{y,i} = \sum_r \pi_{y,r}\times Smode_{y,r,i} \tag{5}$$

In equation (4), the probability of the occurrence of a specific combination *r*, denoted as $\pi_{y,r}$, can be determined. Since the travel combination *r* is uniquely determined by (D_r, S_r, P_r), $\pi_{y,r}$ can also be regarded as the joint probability of travel distance, location, and time. Combining equation (1) with equation (4), we can obtain the choosing probability $Smode_{y,i}$ of mode *i* in year *y* as illustrated in equation (5).

2.2 Travel demand forecast model

The travel demand model serves to anticipate the travel requirements across various modes of transportation. In this model, the total demand for travel is forecasted through the adjustment of socioeconomic, environmental, technological, and other pertinent factors. Furthermore, through the integration of the probability prediction model derived from equation (1), the demand for each specific travel mode is precisely determined.

$$QD_{y,i} = QT_y \times Smode_{y,i} \tag{6}$$

$$QT_y = \delta\times\left(\frac{GDP_y}{POP_y}\right)^{\alpha}\times\left(PT_y\right)^{\beta}\times POP_y \tag{7}$$

$$TC_y = \sum_i Pmode_{y,i}\times Smode_{y,i} \tag{8}$$

As shown in equation (7) - (8), the total travel demand for a specific year is jointly determined by socioeconomic factors and the overall travel cost. The total travel cost for year *y* is the sum of the costs for each travel mode in that year.

$$Pmode_{y,i} = \sum_t Ptec_{y,i,t}\times Stec_{y,i,t} + Ptime_{y,i} \tag{9}$$

$$Ptime_{y,i} = \frac{GDP_t}{POP_t\times AWH_t\times ATS_{y,i}} \tag{10}$$

$$Ptec_{r,y,m,t} = \sum_{f\in FC}\left(Pfuel_{y,i,t,f} + Pghg_{y,i,t,f}\right) + Pdevice_{y,i,t} \tag{11}$$

Equations (9) - (11) present the derivation process of $Pmode_{y,i}$, the travel cost is obtained by summing the travel cost of each technology under each travel mode with the time cost of each travel mode.

2.3 Transport energy system optimization model

2.3.1 Objective function

This paper establishes a bottom-up energy system optimization model with cost minimization as the optimization objective. It considers factors such as future population, residential travel intensity, average travel distance, etc. Detailed categorizations of fuel types and energy efficiency levels for different vehicle technologies in urban passenger transportation are provided. The optimization model delineates the competition between different modes of transportation and the competition among different fuel types for the same mode.

$$\min TC_y = \sum_i \left[\sum_t \left(PTdevice_{y,i,t} + OMT_{y,i,t} + PTfuel_{y,i,t} \right) \right] + \sum_i \sum_t \sum_f PTghg_{y,i,t,f} \quad (12)$$

$$PTdevice_{y,i,t} = IC_{y,i,t} \times \frac{\alpha_{i,t}}{1-\left(1+\alpha_{i,t}\right)^{-T_{i,t}}} \quad (13)$$

$$PTfuel_{y,i,t} = \sum_f Punitf_{y,i,t,f} \times AFC_{y,i,t,f} \quad (14)$$

$$Pghg_{y,i,t,f} = \delta_y \times ef_{y,f} \times AFC_{y,i,t,f} \quad (15)$$

The objective function of the model is to minimize the total annual cost as shown in equation (12). The total annual cost TC_y includes the purchase cost $PTdevice_{y,i,t}$, the annualized maintenance cost $OMT_{y,i,t}$, the annual fuel cost $PTfuel_{y,i,t}$, and the carbon emission cost $PTghg_{y,i,t,f}$. *y* denotes the year, *i* denotes the mode of travel, *f* denotes the different fuel types for a certain mode of travel, *t* denotes vehicle technology category.

2.3.2 Constraints

The model considers future development requirements, applies multiple constraints, and chooses a combination of technologies that minimizes the cost of the objective function.

$$QD_{y,i} \le \sum_t XT_{y,i,t} \times CO_{y,i,t} \times O_{y,i,t} \quad (16)$$

$$QD_{y,i} = QT_y \times Smode_{y,i} \quad (17)$$

$$ST_{y,i,t} = \overline{ST}_{y-1,i,t} \times \left(1-T_{i,t}^{-1}\right) + rc_{y,i,t} - rt_{y,i,t} \quad (18)$$

$$p_{y,i,t} \times \sum_t x_{y,i,t} \le x_{t,i,t} \quad (19)$$

Equations (16) – (17) represent the constraints on travel demand, stating that the total carrying capacity provided by all technologies in each mode must be no less than the total travel demand for the year. Equation (18) shows the constraint on the vehicle stock, $ST_{y,i,t}$ represents the stock of vehicles for travel mode *i* and technology *t* in year *y*. Equation (19) represent the constraints on the penetration rate of electric vehicles in the update or addition of vehicles.

3. SCENARIO DESIGN

This part discusses the strategies for implementing a low-carbon urban transportation system in Nanjing. We predict the energy structure and transportation electrification to analyze the role of ride-hailing services. We establish a Business As Usual scenario (BAU), in which the original economic and social development patterns remain unchanged from 2020 to 2050. To capture the policy effects, we introduce scenarios involving the imposition of a carbon tax (TAX) and the promotion of public transportation (TRANSIT). The Nanjing government proposed a plan requiring all newly added ride-hailing vehicles to be electric starting from 2020 [18]. This study further constructs a scenario (UNRESTRIVTED) in which the EV mandate is absent from the ride-hailing fleet, aiming to uncover the impact of this policy.

To reveal the role of ride-hailing services, we introduce a Counterfactual scenario (COUN) where ride-hailing services is not considered as an existing or future mode of transportation in Nanjing. This scenario is combined with the reference scenario and policy scenarios, allowing us to reveal the heterogeneity of the ride-hailing service under different circumstances. To capture the behavior effect, we further introduce a scenario where ride-sharing services are expanded in the presence of ride-hailing services. We assume that ride-hailing services become more prevalent over time. The scenario settings and naming conventions follow Table 1. The study covers the period from 2015 to 2050, parameters are calibrated using data from 2015 to 2019.

Table. 1 Scenario Setting and Naming.

Scenario	BAU	TAX	TRANSIT
Ride-hailing Scenario	BAU	TAX	TRANSI-NT
Counterfactual Scenario	BAU_COUN	TAX_COUN	TRANSIT _COUN
Ride-sharing Scenario	BAU_RS	BAU_RS	BAU_RS
No EV mandate Scenario	UNRESTRIV TED	/	/

4. RESULTS AND DISCUSSION

4.1 The role of ride-hailing services in EV penetration

Fig. 2 illustrates the technological composition of new vehicles for taxis, buses, and private cars under the counterfactual scenario. As shown in Fig. 2(a) and Fig. 2(b), by 2050, all new taxis and buses will be EVs under the BAU scenario. This shift is primarily driven by Nanjing's policy, which mandates that all new vehicles must be pure electric starting in 2030 [18]. For private cars, the penetration rate of pure electric vehicles is projected to increase to 69.58%, with plug-in hybrid electric vehicles reaching 5.60%. Overall, the EV penetration rate among passenger vehicles is expected to reach 75.89%. Furthermore, the findings suggest that the implementation of carbon taxes and the promotion of public transportation policies can significantly accelerate EV adoption. Carbon taxes increase the cost of operating gasoline and diesel vehicles, encouraging consumers and businesses to transition to electric alternatives. Meanwhile, investments in public transportation infrastructure reduce the dependency on private vehicles, further driving the shift toward electric mobility.

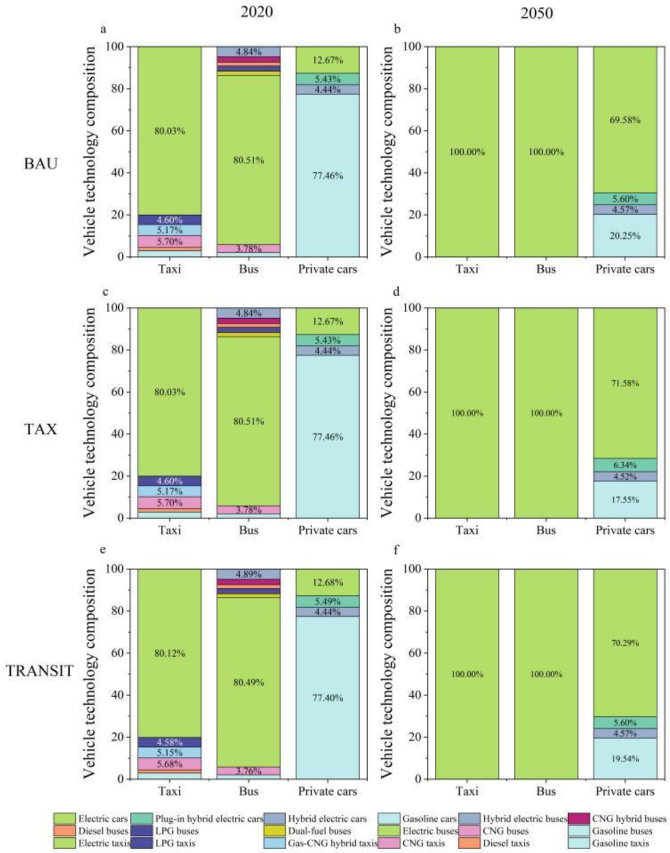

Fig. 2 Technology composition of new vehicles

Fig. 3(a) shows the change in the number of new EVs relative to the counterfactual scenario when ride-hailing services are introduced. The figure shows that the expansion of ride-hailing services contributes to an increase in the EV fleet, and this effect is further amplified by the introduction of carbon taxes and the promotion of public transportation. Fig. 3(b) depicts the change in EV penetration in the presence of ride-hailing services. Under the BAU scenario, the development of ride-hailing services increases EV penetration by 2.46%. The promotion of public transportation and the implementation of carbon taxes further enhance EV penetration, increasing it by 2.92% to 3.68%.

It can be seen that ride-hailing services have created a competitive relationship with other modes of transportation, encroaching on their market share. Moreover, since all new ride-hailing vehicles are composed entirely of EVs, they not only meet travel demand but also further expand the penetration of EVs and promote the development of transportation electrification. In conclusion, the data clearly show that ride-hailing services are not only a complementary component of urban mobility but also a powerful catalyst for advancing the electrification of transportation. By strategically integrating these services with supportive policies, cities like Nanjing can significantly accelerate their progress toward carbon neutrality and energy sustainability.

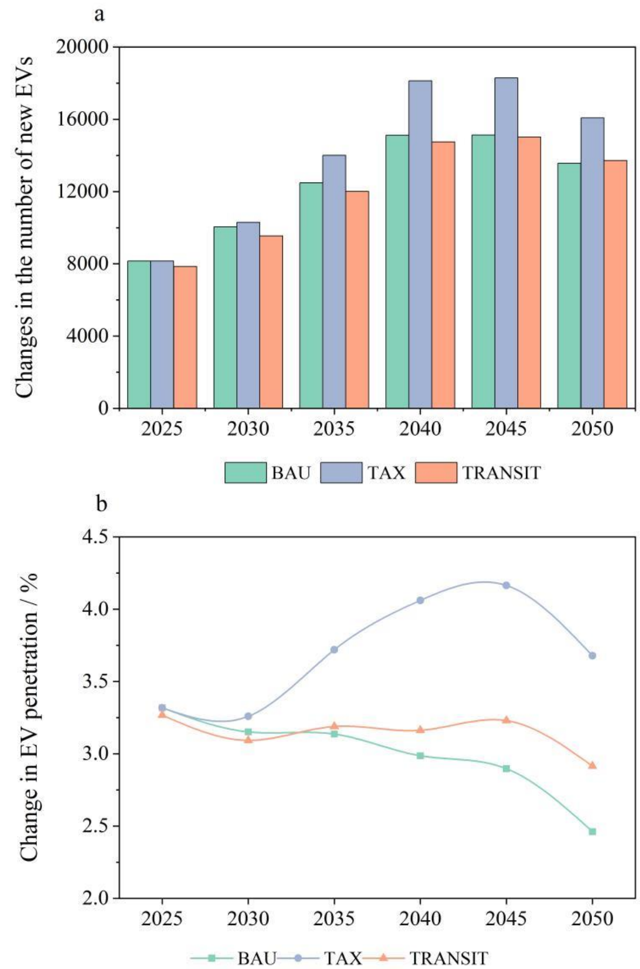

Fig. 3 Change in EVs compared to corresponding counterfactual scenario

4.2 The role of ride-hailing services in energy structures

As illustrated in Fig. 4(a) and Fig. 4(b), under the counterfactual scenario, the share of electricity in the energy mix increases from 1.77% in 2020 to 37.79% in 2050. Compared Fig. 4(a) and Fig. 4(b) with other figures, we can observe that implementing carbon taxes and promoting public transportation can further encourage the growth of electricity's share in the total energy mix.

By comparing the scenario with ride-hailing services to the counterfactual scenario, it is evident that ride-hailing services can facilitate the transition to a cleaner energy mix. Implementing ride-hailing services can increase the share of electricity consumption by 4.66%. This indicates that the presence of ride-hailing services plays a positive role in advancing the transition to a cleaner energy structure. Additionally, policy measures will promote the share of clean energy. In summary, we observe synergies between the development of ride-hailing services and the implementation of the policy. Ride-hailing services and public transportation all compete with private cars, and the imposition of a carbon tax has raised the costs associated with fuel-powered private cars, which together have contributed to the electrification of transportation.

Furthermore, the positive feedback loops generated by these interventions highlight the potential for greater gains in transportation electrification. For instance, ride-hailing services not only reduce the number of gasoline-powered private cars on the road but also increase the demand for electric vehicles, further reinforcing the shift toward clean energy. The cumulative effect of these measures is a gradual yet significant reduction in reliance on fossil fuels, paving the way for the long-term sustainability of the transportation sector.

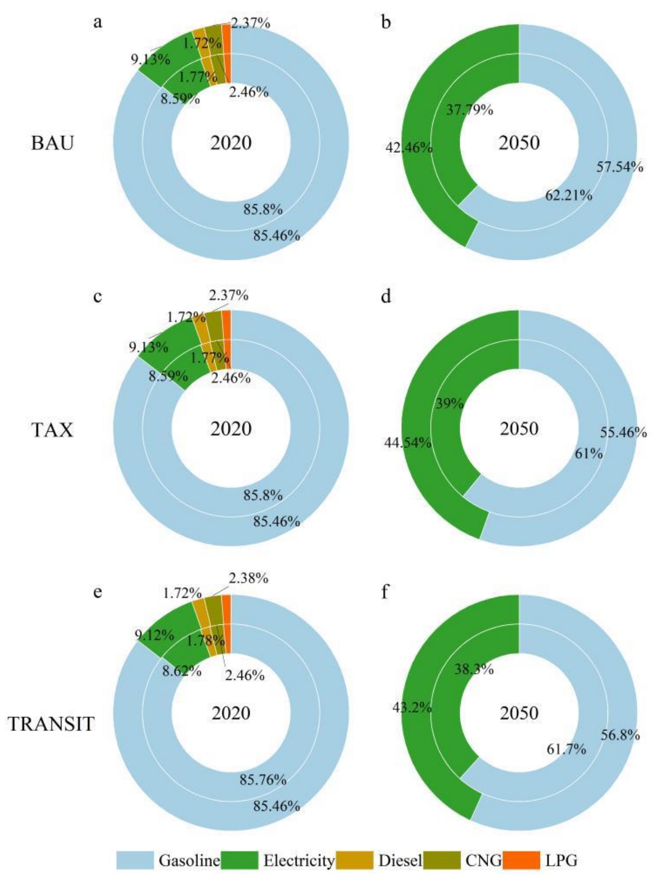

Fig. 4 Energy mix (inner ring: counterfactual scenario under policies; outer ring: corresponding scenario with ride-hailing services)

4.3 The role of ride-sharing services

Fig. 5 depicts the impact of developing ride-sharing services on electricity consumption and EV penetration. As illustrated in Fig. 5(a), EV penetration initially falls below the BAU scenario but surpasses it after 2030. Fig. 5(b) elucidates that in the ride-sharing scenario, the share of electricity consumption surpasses that of the BAU scenario after 2035. By 2050, compared to the BAU scenario, the development of ride-sharing services will lead to an additional 3404 EVs being used for ride-hailing services. Ride-sharing services reduce electricity consumption by encouraging shared travel, which decreases the demand for ride-hailing vehicles. However, as ride-sharing services grow, the proportion of trips made via ride-hailing gradually increases, driving up demand. This leads to an increased need for vehicles, further boosting EV penetration and the share of electricity consumption. It is evident that with the emergence of ride-sharing service, which influences traveler behavior, the impact of ride-hailing services on transportation electrification is further amplified.

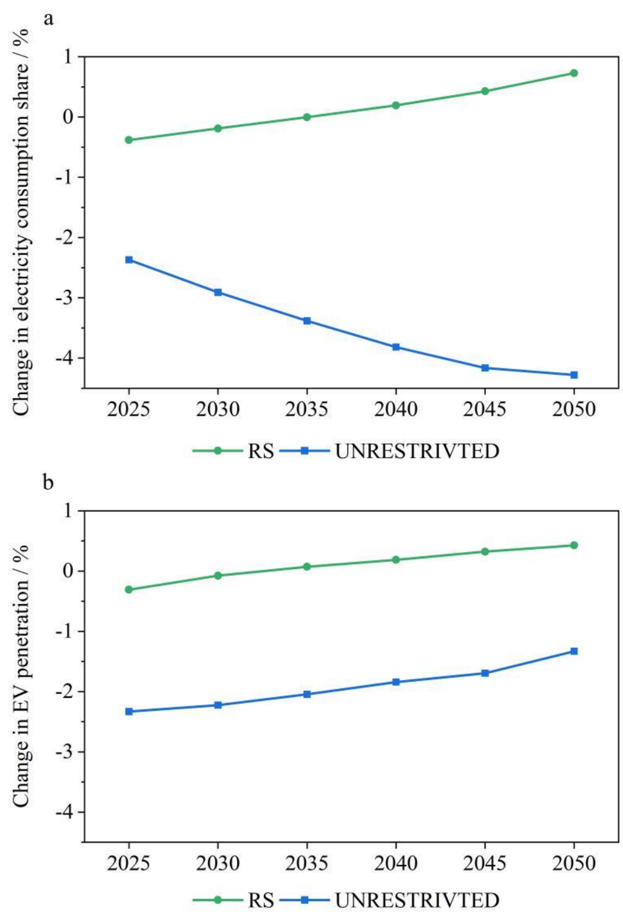

Fig. 5 The changes in the share of electricity consumption and EV penetration

4.4 *The role of EV mandate*

Fig. 5 also presents a comparison between the UNRESTRIVTED scenario and the BAU scenario. By implementing EV mandate policies, EV penetration increases by 1.33% by 2050, and the share of electricity consumption expands by 4.28%. It is worth noting that compared to the UNRESTRICTED scenario, the BAU scenario reduces energy consumption by 5.27%. This is because EVs have higher energy efficiency and lower energy consumption compared to gasoline vehicles. We can conclude that enforcing technology proportion restrictions in ride-hailing services can promote EV penetration and accelerate the transition of the energy mix. By mandating that all new ride-hailing vehicles be electric, policymakers can significantly accelerate the transition towards a more sustainable and cleaner energy mix. Such policies not only benefit the environment by reducing greenhouse gas emissions but also support energy security by decreasing dependence on fossil fuels. In addition, the successful enforcement of these mandates could set a precedent for other sectors of the transportation industry, encouraging a faster transition to electrification across personal vehicles, public transportation, and even commercial fleets.

5. CONCLUSION

Understanding the impact of Nanjing's policies on the electrification of passenger transportation systems is crucial for ensuring a sustainable energy transition and effectively responding to carbon peaking and carbon neutrality targets. This paper develops a travel probability prediction model using discrete choice methods to forecast travel demand, which is then integrated with an energy system optimization model. Additionally, counterfactual scenarios were introduced to assess the impact of the absence of ride-hailing services and evaluate the effects of various travel-related policies. The role of ride-sharing services was also examined from the perspective of traveler behavior.

Electric vehicles demonstrate higher energy utilization efficiency compared to traditional fuel vehicles, and ride-hailing services have promoted the development of transportation electrification, increasing the penetration of EVs and the share of electricity in total energy consumption. This contributes to the transition of road transportation towards cleaner energy sources. The implementation of carbon tax policies and the development of public transportation are proactive measures for promoting transportation electrification, complementing the role of ride-hailing services. Moreover, carbon tax policies have proven to be more effective than policies focused on developing public transportation.

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DECLARATION OF INTEREST STATEMENT

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

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