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Carbon emission reduction benefits of ride-hailing vehicle electrification considering energy structure

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ABSTRACT

Ride-hailing services provided by companies like Uber, Lyft, and Didi have rapidly grown, leading to increased traffic congestion and greenhouse gas emissions. The transition of ride-hailing fleets to Electric vehicles (EVs) presents a considerable opportunity to reduce emissions in the transportation sector. Despite this potential, the carbon emission benefits of electrifying ride-hailing vehicles remain inadequately quantified. This study introduces a framework designed to assess carbon emission reductions resulting from EVs, specifically accounting for emissions transferred from electricity during the operational phase of ride-hailing vehicles. The study employs field data from Chengdu and Xi'an, China for case studies using the proposed framework. Our findings indicate that emission reductions are markedly influenced by the grid electricity emission factors specific to each city. The daily reduction in emissions due to electrification of ride-hailing vehicles is equivalent to eliminating approximately 133,307 and 63,162 trips of gasoline vehicle in the ride-hailing services of Chengdu and Xi'an, respectively. More importantly, this study identifies equilibrium points that establish the necessary grid electricity emission factors for achieving emission reductions across all ride-hailing trips when transitioning from gasoline to EVs through sensitivity analysis. For Chengdu and Xi'an, the thresholds of grid electricity emission factors are 156.25 g/kWh and 131.09 g/kWh, respectively. This study offers an applicable analytical framework to evaluate emission reductions of ride-hailing electrification across various urban contexts, thereby aiding in the determination of conditions conducive to effective integration of EVs into ride-hailing services.

1. Introduction

Ride-hailing services provided by transportation network companies (TNCs) such as Uber, Lyft, and Didi represent a new form of on-demand mobility [1–3]. In less than a decade, Uber and Lyft have collectively facilitated 5.5 billion rides for over 50 million users, marking a remarkable achievement [4]. In 2023, Didi Chuxing reported an average of 31.3 million orders per day, amounting to approximately 11.4 billion transactions for the year [5]. With around 587 million annual active users and 23 million annual active drivers, Didi continued to enhance its services and technological capabilities to improve operational efficiency [6]. This significant growth of ride-hailing vehicles has led to increased traffic congestion and substantial greenhouse gas (GHG) emissions. While ridesplitting, a form of ride-hailing service that matches riders with similar routes to share the same vehicle and fare, has shown potential to alleviate the issues, its actual environmental benefits are limited [7]. In Chengdu, China, only 8.92% of ridesplitting trips result in emission reductions when considering the rides that shift from public transit. In Xi'an, China, this figure is even lower at 4.68% [8].

One transition that may help ride-hailing services to reduce emissions is the adoption of a cleaner vehicle fleet through the integration of electric vehicles (EVs) [9–12]. Some companies have already introduced EVs to replace gasoline vehicles (GVs) in ride-hailing service. Ride-hailing electric vehicles (REVs) have been vigorously promoted worldwide. For instance, Uber introduced the Green Future program, aiming to assist drivers in transitioning to EVs by 2025 [13]. Didi successfully launched 1 million EVs for ride-hailing service in 2020, with a future target of scaling this number to 10 million EVs by 2028 [14,15]. The trend toward electric ride-hailing vehicles has been evident in China. With the comprehensive implementation of policies encouraging EVs in cities such as Shenzhen, Guangzhou, and Wuhan. As

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of January 1, 2021, ride-hailing gasoline vehicles (RGVs) are no longer able to apply for ride-hailing operation permits. Existing permits for RGVs have also become invalid, with REVs completely replacing RGVs in these cities. However, the environmental benefits of REVs completely replacing RGVs have not been thoroughly investigated.

The question of whether EVs truly reduce GHG emissions in mobility systems remains a topic of debate. While EVs are celebrated for their zero emissions during operation, the upstream emissions from electricity generation are often overlooked [16,17]. Accounting for these upstream emissions is crucial, as vehicle electrification can sometimes lead to increased emissions, depending on the carbon intensity of the electricity used. Variations in energy structure and efficiency mean that the carbon emissions of EVs can differ significantly [18–20]. For instance, the use of Vehicle-to-Grid (V2G) technology may increase carbon emissions, particularly when replacing peak energy [21], and smart charging strategies might lead to higher GHG emissions in regions with low renewable energy penetration [22]. Thus, assessing the emission reductions from EVs without considering the emissions associated with electricity generation offers an incomplete picture.

To address this gap, our study introduces a novel framework that specifically evaluates emission reductions in electric ride-hailing services by accounting for emissions transferred from the electricity grid. This approach adds a unique perspective to the existing literature by focusing on the operational phase emissions, offering a more comprehensive understanding of the environmental impact of electrifying ride-hailing fleets. The main contributions of this study can be summarized as follows:

1. A framework for evaluating emission reductions: This study develops an analytical framework to assess emission reductions in ride-hailing service based on empirical data. It provides empirical evidence on the real-world impacts of REVs on carbon emissions to facilitate policy making for transportation network companies and governments.
2. Emission reduction modeling: To develop a versatile model applicable to various datasets, this study introduces a novel approach that integrates field data collected from GVs using portable devices with data from EVs recorded at different scales. A specialized deep learning algorithm is then employed to accurately estimate the emission reductions in ride-hailing service by comparing GVs and EVs.
3. Emission reduction analysis: This study provides an analytical framework to determine whether a ride-hailing trip leads to emission reductions, quantify the amount of emissions reduced, and identify the reasons behind increased emissions for some trips. More importantly, this study introduces a method to explore the conditions for achieving emission reductions across all trips in ride-hailing services.

The remaining sections are structured as follows. Section 2 introduces the related works. Section 3 elaborates on the methodology, including proposed framework, data processing methods, modeling of emission from gasoline and EVs, and emission reduction estimation. Section 4 presents case studies and subsequent results. Section 5 summarizes the findings, implications, limitations and future directions.

2. Literature review

Thanks to the potential of EVs in reducing GHG emission, EVs have been encouraged worldwide to meet the net zero emission targets [23, 24]. Over the past decades, the environmental benefits of EVs have generated significant attention. For example, Isik et al. [25] analyzed the impacts of CO_2 reduction policies on costs and air emissions within the transportation sector of New York City, utilizing a technology-rich and bottom-up energy system optimization model. Their findings highlighted the necessity of electrifying light-duty vehicles to achieve deeper reductions in traffic-related emissions. Donateo et al. [26] investigated EVs that recharged through the public Enel Distribuzione recharging infrastructure in Rome. The impact of EVs on CO_2, CO, NO_x, HC, PM and HC+ NO_x were quantified. This study demonstrated that the pollutants emitted from EVs in Italian were lower than those from conventional vehicles on the New European Driving Cycle. It indicates that EVs are a good alternative to conventional vehicles. Küfeoğlu et al. [27] studied the contribution of battery electric vehicle and plugged in Hybrid Electric Vehicles on Green House Gas emission reductions in the UK transport sector, with a focus on meeting carbon targets by 2050. Their results revealed that the UK transport sector might fail to meet the 4th, 5th, 6th and 7th carbon budget targets. Consequently, authorities might need to consider discussing a hybrid car ban in the near future. These studies underscore the critical role that EVs can play in achieving substantial emission reductions.

The vast majority of research focuses on the broader significance of EVs rather than the specific role of REVs in emission reduction. Several studies revealing the potential of EVs in shared mobility have provided important insights into the electrification of ride-hailing fleets. Li et al. [28] evaluated the emission benefits of shared autonomous electric vehicle fleets in California. They found that the adoption of shared autonomous electric vehicle could reduce greenhouse gas emissions by up to 34% of the total traffic emissions by 2025, even compared to other sustainable options such as public transport, walking, and cycling [29,30]. Yang et al. [31] predicted environmental and emissions benefits of electrifying taxi fleets, providing insights through specific case studies in Nanjing. A 48% reduction in emission were reported by integrating EVs into taxi fleets. Teixeira et al. [32] evaluated the effects of replacing engine-powered vehicles with EVs on carbon dioxide emissions and energy consumption. A simulation was performed under different scenarios of total or partial fleet replacement over a period of 15 years. The simulations showed that the electric energy consumption by EVs is about four times lower than the fuel energy consumption by conventional vehicles undergoing a standard test schedule.

Although these studies implied the significant potential of EVs in reducing emissions within shared mobility, it is evident that most prior research discusses emission reduction theoretically, with only a few empirical studies examining real-world impacts [33]. This theoretical focus using different assessment methods can sometimes yield conflicting results, highlighting the necessity for empirical studies to provide more robust insights into the actual outcomes [13,34]. In empirical scenarios, the effectiveness of emission reduction also depends on various factors beyond vehicle type, such as charging activities [35], specifications of vehicles [36], and driving conditions such as speed and traffic patterns [37]. These factors interact in complex ways to influence the overall emissions performance of electrifying vehicles in shared mobility. Additionally, the emission reductions achieved through electrifying vehicles in shared mobility are significantly influenced by the emission factors associated with electricity generation [16]. The cleanliness of the electric grid, whether it relies on fossil fuels or renewable sources, plays a crucial role in determining the environmental benefits of EVs. Efforts should continue to address these influencing factors and their threshold effects in empirical scenario to maximize the environmental benefits.

Moreover, the discussion of EVs in a ride-hailing context is rare. Although limited studies have investigated the environmental benefits of EVs in the ride-hailing context using field data, gaps remain. For example, Zhao et al. [38] established a comprehensive feasibility–economic–environmental assessment system to explore the applicability, life-cycle economic, and carbon reduction benefits of ride-hailing electrification. They found that electrification for full-time drivers can achieve synergistic economic and environmental benefits, saving \$14,000–\$24,500 and reducing 47–66 tons of CO_2 emissions over a vehicle's lifetime. Ride-hailing electrification for full-time drivers can achieve synergetic economic and environmental benefits by saving 14000–24500\$ and

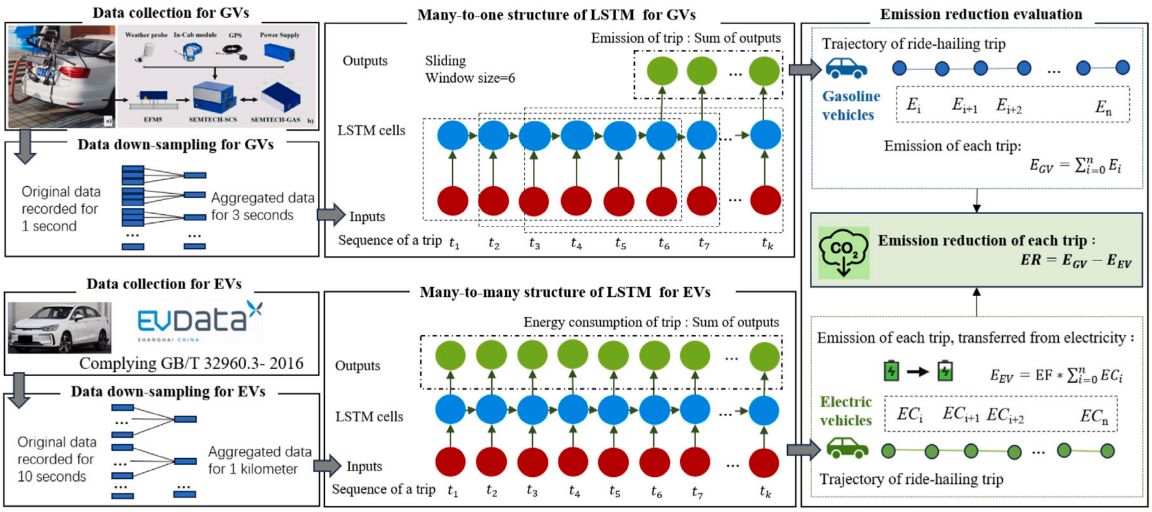

Fig. 1. Framework of methodology.

reducing 47–66 t of CO_2 emissions in a whole lifetime. Jenn [4] studied empirical data on the usage of EVs in Uber and Lyft fleets, using data from various electric vehicle charging network providers and TNCs. The findings reveal that the daily emission savings from electrifying ride-hailing services averaged 38.7 kg of CO_2. From early 2017 to May 2018, the total savings across all 1000 battery electric vehicles amounted to 1142 tons of CO_2. However, these conclusions may not be applicable to all cities worldwide, as the energy structure and emission factors vary by region. More importantly, the studies do not specify the conditions under which all REVs reduce emissions.

Therefore, this study assesses emission reductions in empirical ride-hailing services within the Chinese context based on empirical data. Our goal is to provide empirical evidence on the real-world impacts of REVs on carbon emissions. Some rides where REVs lead to an increase in CO_2 emissions are identified, and the reason for these increases are explored. Additionally, a sensitivity analysis and balance point analysis are conducted to determine the requirements for grid emission factors to achieve overall emission reductions in ride-hailing service. This framework will help cities worldwide to understand the potential environmental benefits in REVs and the necessary conditions for the effective integration of REVs in their ride-hailing services.

3. Methodology

3.1. Analysis framework

The framework of the analysis methodology is shown in Fig. 1. We define emission reduction electrifying ride-hailing vehicles by comparing with a scenario in which all these vehicles were gasoline. This study collects emission data from GVs using portable emission measurement systems (PEMS). Whereas, dataset of EVs is sourced from Shanghai Electric Vehicle Public Data Collection Monitoring and Research Center, which complies GB/T 32960.3-2016 standard. The analysis begins with data down-sampling, aiming to standardize the resolution across the different datasets including PEMS gasoline emission dataset, electric vehicle dataset and ride-hailing dataset. Then, we construct emission estimation models for RGVs and REVs using data-driven deep learning algorithm. The PEMS dataset and EV dataset are used to modeling emission estimation models. Subsequently, we evaluate the CO_2 emission reduction in the ride-hailing service using these models. The difference of CO_2 emission between RGVs and REVs are compared based on trajectory data provided by ride-hailing dataset, which is determined as emission reduction.

3.2. Data down-sampling for standardized resolution

Before proceeding with modeling, it is essential to standardize the resolution for feature extraction across the three datasets: the PEMS dataset is recorded at 1-second intervals, the EV dataset at 10-second intervals, and the ride-hailing dataset at 3-second intervals. This standardization ensures seamless integration of ride-hailing trajectory data with the emission models trained on the PEMS and EV datasets. Down-sampling is performed on these datasets separately. For GVs, we standardized the modeling and emission reduction evaluation to a 3-second time step. For EVs, the emissions and modeling were standardized to a 1-kilometer time step. Specifically, we use the PEMS and ride-hailing datasets at 3-second time step to extract features, construct model, and calculate emissions from RGVs, while we use the EV and ride-hailing datasets at 1-kilometer time step for REVs. The total emissions for the entire trip are calculated as the sum of all data points for that trip.

3.3. Emission estimation models

The emission estimation is defined as a supervised learning task trained using Long Short-Term Memory (LSTM) networks, chosen for their ability to capture temporal dependencies and patterns in sequential data like time series data of vehicle emissions [39,40]. LSTM, a type of recurrent neural network, is well-suited for this task due to its capability to model long-range dependencies in the data [41,42], crucial for accurately estimating emissions over time. Moreover, LSTM networks have been successfully applied in various time series prediction tasks, making them suitable for modeling the complex and dynamic nature of emissions data.

3.3.1. Emission estimation model for RGVs

The structures of LSTM for RGVs and REVs emission estimation differ, as shown in Fig. 1. For RGVs, the structure involves single-step time series forecasting. The sum of all outputs for each trip represents the total emissions for that trip. The target values used to train RGVs emission estimation is the sum mass of CO_2(g) in each time step. The selection of features for modeling RGVs and REVs emission estimation encompasses key factors during the driving process, including distance, duration, duration of idling, average speed, average acceleration, and vehicle-specific power (VSP). The duration of idling is defined as the period when the vehicle speed is 0 km/h while the trip has not concluded. In urban environments, traffic lights and congestion often lead to frequent idling, during which energy consumption cannot be ignored. GVs consume a considerable amount of fuel during this period, contributing to emissions and environmental impacts. Additionally, to refine the models further, VSP is also incorporated as a feature when training the RGVs emission model. VSP is a measure of the power demand on a vehicle, influenced by factors such as speed, acceleration, road grade, and vehicle mass. It plays a significant role in determining the energy consumption of GVs. Including VSP helps capture the dynamic nature of energy consumption, improving the accuracy of emission estimations. In this study, a simplified formulation is used to estimate VSP, which is determined by the following formula:

$$VSP = v\,(1.1a + 9.81\sin\theta + 0.132) + 3.02\times10^{-4}v^3, \tag{1}$$

where v, a and θ denote speed (km/h), accelerate (m/s^2) and road grade (°), respectively.

3.3.2. Emission estimation model for REVs

For REVs, a multi-step time series forecasting approach is necessary to account for the strong correlation between energy consumption and the vehicle state. The 10-second resolution of our data for EVs is inadequate for estimating emissions based on instantaneous state. Consequently, a multi-step forecasting approach is employed to capture the relationship between energy consumption and changes in the vehicle state over the course of an entire trip. The goal is to train a model to understand the relationship between relevant features and energy consumption rather than direct emissions, as emissions from RGVs can be derived from energy consumption and emission factors as

$$Emission = EC \times EF, \tag{2}$$

where EF represent emission factors, which are illustrated in Table 1 across various years. The emission factors are derived from China Regional Power Grid Carbon Dioxide Emission Factors at 2023. The values for 2025, 2030, 2035 years are predicted values in this report. The energy consumption EC (kw/h) is determined as

$$EC = 1/3600 \times 1/1000 \times V\,I\,\Delta t, \tag{3}$$

where V and I represent the battery voltage and current, and Δt represents the time period. In this study, we calculate the target values based on $\Delta t = 10$ s, which provides the highest resolution to ensure the accuracy.

The features incorporated in the emission estimation model for REVs include average speed, distance, duration, and duration of idling. The duration of idling is particularly vital for REVs because EVs can undergo energy recovery during deceleration or idling, which influences their energy consumption patterns and overall efficiency. Consequently, the duration of idling has a significant impact on energy consumption. Thus, we also consider it in modeling for REVs. The sequence length for RGVs and REVs models are set to 6 and 30, respectively. Both of two models are composed of 2 layer of LSTM units, in which each LSTM layer has 8 hidden units. We trained the model for 500 epochs and employed early stopping to achieve the best performance.

3.4. Estimation of emission reduction for electrifying ride-Hailing vehicles

After modeling, the CO_2 emission from all ride-hailing trips can be quantified using above models. We assume that all GVs would be substituted by EVs in ride-hailing service. The type of GVs replaced in ride-hailing are consistent with the type used in our PEMS test, and the type of EVs are consistent with that collected in the EV dataset. The CO_2 emission reduction from electrifying ride-hailing vehicles is determined by comparing with a scenario in which all these vehicles were EVs. The difference of emission from REVs and RGVs is

$$ER = Emission_{RGV} - Emission_{REV}, \tag{4}$$

where $ER > 0$ denotes emission reduction resulting from the substitution by REVs. $ER < 0$ denotes emission increase resulting from the substitution by REVs. $Emission_{RGV}$ denotes the emission from the replaced RGVs, while $Emission_{REV}$ denotes the emission from REVs. For solo ride, the emission is the total emission along the entire trajectory. Whereas, for shared rides, the emission is determined by

$$Emission_{shared} = E_{solo\_segment} + 1/2E_{shared\_segment}. \tag{5}$$

where $E_{solo\_segment}$ represents emission from non-shared segments of trajectories, and $E_{shared\_segment}$ represents emission from shared segments with another passengers.

Table 1
The provincial grid emission factor across various years.

	2018	2020	2025	2030	2035
Chengdu ($kgCO_2$/kWh)	0.103	0.117	0.104	0.075	0.040
Xi'an ($kgCO_2$/kWh)	0.767	0.641	0.607	0.601	0.515

4. Empirical analysis

4.1. Case description

We analyze two representative cases in the Chinese ride-hailing market: Chengdu and Xi'an. Chengdu is a major metropolis in the southwest, while Xi'an is the largest city in the northwest. As shown in Fig. 2(a), the data in Chengdu spans an area of 8.5 × 8.5 km^2, encompassing prominent business districts like Tianfu Square and Chunxi Road. Presented in Fig. 2(b), the data in Xi'an covers an area of 8.5 × 9.0 km^2, including well-known business clusters such as Xi'an Tower and Xiaozhai. Three datasets are utilized in case studies: the PEMS dataset for modeling emissions estimation from RGVs, the EV dataset for modeling emission estimation from REVs, and the ride-hailing dataset for empirically evaluating carbon emission reductions in a case city in China.

(1) PEMS dataset

The PEMS dataset is obtained by field campaign using portable emission measurement systems (PEMS) and test light-duty gasoline vehicles (LDGVs), as shown in Fig. 1. PEMS is a widely used equipment to collect real-time emission data from motor vehicles. SEMTECH, as a typical PEMS, was employed as our experimental measurement device. It consists of seven modules, including Supply and Communication System, Gas Analysis Systems, Exhaust Flow Measurement, Global Positioning System, Weather Probe, In-Cab Module, and Power Supply. SEMTECH-SCS Module is the main source for data acquisition, which measures concentrations, emission rates, and emission volumes of different emission gases [43,44]. All the data is collected at 1 s interval.

Table 2 shows the tested LDGVs under the two most commonly found emission standards on the road in China. China V and China VI are distinct emission standards, with vehicles emitting less under the China VI standard. The China VI emission standard is a critical policy for China to achieve its carbon peak by 2023. To support the transition from China V to China VI, many regions in China have implemented relevant regulations. For instance, as of July 1, 2020, all newly sold vehicles in Shanghai must comply with the China VI emission requirements. Compared to LDGV 2 under China VI emission standard, the model of LDGV 1 under China V emission standard is more frequently used in ride-hailing services. Therefore, we primarily evaluate emission reductions using data points from LDGV 1. Data points from LDGV 2 are used for comparison in the sensitivity analysis. The test vehicles used gasoline RON 95 as the fuel type during the Real Driving Emissions test, which was conducted in both urban area (Xuhui District) and suburban area (Minhang District) in Shanghai from September 9, 2021, to September 12, 2021. The test routes comprise various roads of different types, such as expressway (A1–A4), arterial road (B1–B4), secondary road (C1–C4), branch (D1–D4). The detailed test routes can be reviewed in our previous study [43,45]. These four

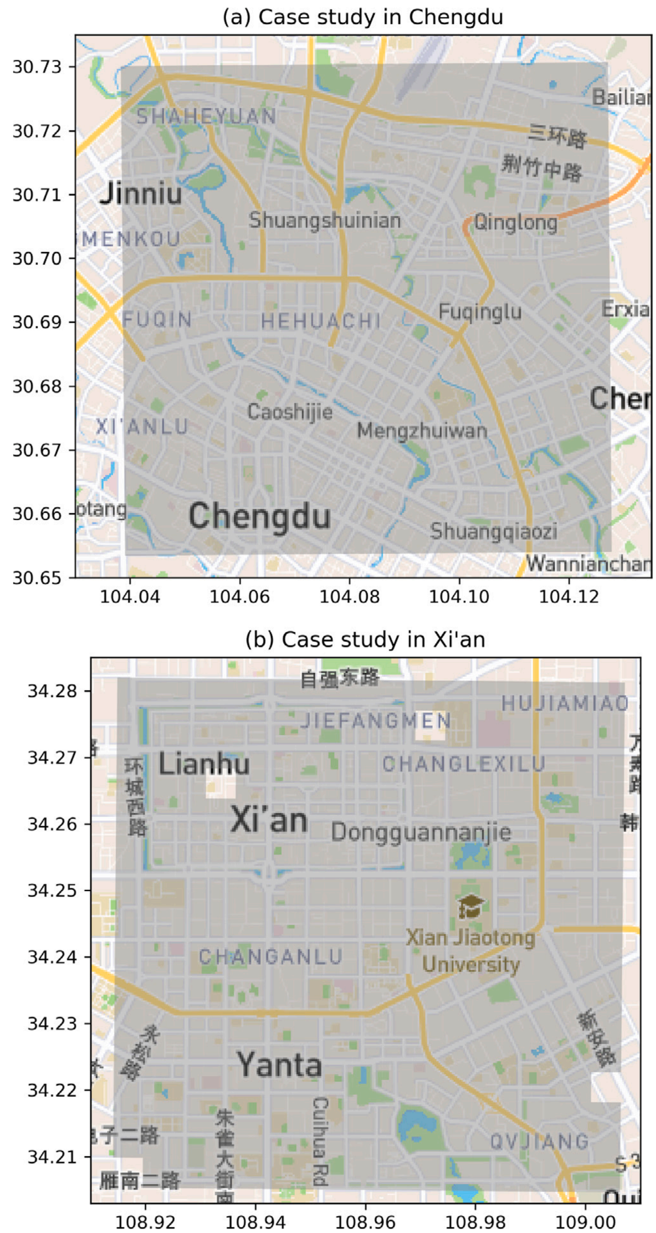

Fig. 2. Case study in two cities.

road types indicated in the legends are typical urban roads in China, designed for speeds of 80, 60, 50, and 40 km/h respectively. This allows us to construct generic models for various speeds and traffic conditions. Finally, the number of cleaned data points obtained from two type of vehicles are 13,372 and 6,178, respectively.

(2) EV dataset

The EV dataset is sourced from the Shanghai Electric Vehicle Public Data Collection Monitoring and Research Center. It encompasses a comprehensive range of EV data such as driving records, charging records, and alarm records, all collected in accordance with the GB/T 32960.3-2016 standard. All the recorded values in the dataset are instantaneous, captured at 10-second intervals, and generated in Shanghai. In this research, we specifically utilize data from 22 sedans equipped with ternary material batteries, each having a capacity of 50.8 kWh. Our analysis focuses on the data related to timestamps, vehicle status,

Table 2
Tested vehicles in PEMS dataset.

	LDGV 1	LDGV 2
Fuel type	Gasoline	Gasoline
Emission standard	China V	China VI
Model	Sagitar	GL8
Model year	2016	2020
Manufacture year	2018	2020
Vehicle manufacturer	Volkswagen	Buick
Engine capacity (L)	1.6	2.0
Engine type	Direct injection	Direct injection

speed, mileage, voltage, and current, spanning from June 1, 2022 to June 1, 2023.

We marked the start and end points of each trip based on the vehicle status, a categorical field used to classify whether the vehicle is running or turned off. If the vehicle remains in the turned-off status for more than 15 min, we consider this point as the end of the trip, allowing us to extract the data subset for each trip. Within each trip, we smooth the original data to achieve more consistent variations in features. Identifying the most effective smoothing interval remains a complex task. Guided by recent research that demonstrates a significant correlation between trip distance and energy consumption, the decision was made to apply smoothing on a per-kilometer basis. Additionally, we filter out outliers and invalid records. We select trips with a distance ranging from 3 km to 20 km. Ultimately, the cleaned dataset comprises 4210 trips, accumulating a total mileage of 28,267 km.

(3) Ride-hailing dataset

The ride-hailing dataset is sourced from Didi Chuxing through the GAIA Open Data Initiative (https://gaia.didichuxing.com). This dataset includes order IDs, driver IDs, and longitude and latitude coordinates recorded every three seconds for each ride-hailing trip between October 1, 2018, and November 30, 2018. For this study, we primarily analyze trips during a typical week from November 3, 2018, to November 9, 2018. The dataset encompasses both solo rides and shared rides. Solo rides are the trips where a single passenger or a group of passengers traveling together as one party hires the vehicle exclusively. No other passengers are picked up or share the ride with them. shared rides are ride-hailing trips where multiple passengers from different parties share the same vehicle. The ride-hailing service picks up and drops off passengers along a route. This type of ride is typically cheaper than solo rides and helps reduce the number of vehicles on the road, potentially lowering traffic congestion and emissions. The methodologies for identifying shared rides are thoroughly detailed in our previous study [7]. Thus, the dataset selected in this study comprises 986,597 ride-hailing trips in Chengdu and 663,211 ride-hailing trips in Xi'an, captured throughout this typical week. The shared rides in Chengdu and Xi'an are 60,674 and 40,572, respectively.

4.2. Model performance

The data used to feed emission estimation model for GVs includes approximately 40,000 valid records, where the data used to train energy consumption model for EVs includes more than 4000 travel events. We filter out trips with distances greater than 30. The Table 3 illustrates the performance of CO_2 emission for GVs and energy consumption for EVs. The unit of data points used to calculate these losses are g and g/km for GVs and EVs respectively. The R^2 values for GVs under China V and China VI emission standards are 0.760 and 0.790, respectively, indicating strong performance and generalization. In contrast, the models for EVs exhibit lower performance due to the higher resolution dataset available for GVs.

To further verify the validation of our models, we statistically compare the emission factor (gCO_2/km) of GVs and energy efficiency (kWh/km) of EVs obtained by our models with those from other studies. Table 4 presents the statistical values of emission factors and energy

Table 3
The performance of CO_2 emission for GVs and energy consumption for EVs.

	R^2	MAE	MSE	RMSE
GVs (China V standard)	0.760	0.652	1.076	1.037
GVs (China VI standard)	0.790	1.16	4.58	2.14
EVs	0.651	0.018	0.002	0.035

efficiency for ride-hailing trips in Chengdu and Xi'an, which is obtained by predicted values for each trip. It shows that emission factors for most trips in Chengdu ranges from 210 to 374, which is basically consistent with the variation range of emission factors of different road sections in Zhu's study [43]. The emission factors in Xi'an are higher than that in Chengdu. This is because, in the fourth quarter of 2018, Xi'an's Baidu Congestion Index was higher than that of Chengdu [46]. The energy efficiency in both Chengdu and Xi'an ranges from 0 to 0.39 kWh/km, with an average value of 0.17 kWh/km. This is consistent with previous research, where the energy consumption was 28 kWh per 100 miles, equivalent to 0.174 kWh/km [4].

4.3. Emission reduction and influencing factors for REV electrification

4.3.1. Estimation of emission reduction

We estimate emission savings from electrifying ride-hailing vehicles by comparing a scenario in which all these vehicles were gasoline-powered. To ensure robust outcomes, we analyze all ride-hailing trips during a typical week in Chengdu and Xi'an. The following findings in this section are obtained based on data from tested electric vehicle and gasoline vehicle under China V standard. Because tested gasoline vehicle under China V is more frequently used type in ride-hailing service than that under China VI. We assume that all ride-hailing vehicles comply with tested vehicles. Our findings show that REVs in both cities lead to significant emission reductions compared to GVs. In Chengdu, almost all solo and shared rides result in emission reductions. In Xi'an, 98.6% of all rides result in emission reductions, with solo rides accounting for 98.5% and shared rides accounting for 99.9% of emission reduction trips. This finding, based on data from October 1, 2018, to November 30, 2018, shows no significant variation across different days.

Then how much emission has been reduced by the use of REVs in ride-hailing services? Across all rides during this typical week, the daily emission reduction in two cities averages 239 tons and 135 tons of CO_2, respectively, due to the electrification of the ride-hailing service. This results in total CO_2 emission reductions in Chengdu and Xi'an of 1675 tons and 945 tons, respectively. The average emission reduction per trip in the two cities is 1.699 kg and 1.427 kg, respectively, which is equivalent to reducing approximately 5.18 and 3.80 vehicle kilometers traveled using GVs in ride-hailing. Please note that these equivalents are based on tested vehicles in this study. On a per-trip basis, this daily reduction equates to removing approximately 133,307 and 63,162 travel events using GVs in ride-hailing.

Additionally, it is worth noting that the emission reduction effects of electrifying ride-hailing vehicles differ between shared rides and solo rides. Although the portion of shared trips leading to emission reduction is higher compared to solo rides, the per-trip emission reduction for shared rides is not as high as that for solo rides. In Chengdu, the per-trip emission reductions for shared rides and solo rides are 1.34 kg and 1.55 kg, respectively. In Xi'an, the per-trip emission reductions for shared rides and solo rides are 1.25 kg and 1.44 kg, respectively. This difference is because emission reduction is calculated as the difference between the emissions of GVs and EVs. Shared rides have lower gasoline vehicle emissions compared to solo rides, so the emission reductions achieved through electrification are less pronounced for shared rides.

4.3.2. Potential factors association with emission reduction

Although most ride-hailing trips contribute to emission reductions and the overall reduction is significant, it is important to investigate why some trips lead to an increase in CO_2 emissions. We find that the portion of ride-hailing trips leading to increased emissions is significantly associated with speed. In Fig. 3, green bars represent the portion of ride-hailing trips leading to emission reductions, while pink bars represent the portion of ride-splitting trips leading to emission increases. For each speed interval, the sum of the portions of ride-hailing trips leading to emission reductions and increases is 100%. To observe generate patterns, we select intervals where the total number of trips more than 30. There are almost no ride-hailing trips leading to emission increases in Chengdu, so we present this figure with data points from Xi'an. As shown in Fig. 3, the portion of trips leading to emission reductions decreases with higher speeds. This pattern is consistent across different days, revealing a strong negative relationship between emission reductions and speed.

We also analyzed the quantitative relationship between emission reduction and various potential factors. As demonstrated in Fig. 4(a), The equation provided on the plot fits the data points well. The curve shows a negative exponential relationship, indicating that as the speed increases, the mean emission reduction per trip decreases. At lower speeds (around 10 km/h), the emission reduction is at its highest, around 2500 g. As speed increases, the emission reduction decreases significantly. By the time the speed reaches 60 km/h, the emission reduction drops to below 500 grams. As speed increases, the vehicle's energy consumption rises due to factors such as increased air resistance and rolling friction. This results in reduced emission savings because the vehicle's efficiency decreases at higher speeds. Fig. 4(b) illustrates the relationship between the distance of a trip and emission reduction per trip. The curve indicates a quadratic relationship between distance and emission reduction, where the emission reduction first increases with distance and then decreases after reaching a peak. The maximum emission reduction is observed around a distance of 10 kilometers, where the emission reduction reaches its highest value, close to 1900 grams. From distances of 4 to 10 km, the emission reduction increases significantly, indicating that up to a certain point, longer trips benefit more from emission reductions. Beyond approximately 10 kilometers, the emission reduction starts to decrease, suggesting that very long trips do not achieve as much emission reduction per trip as medium-length trips. This could be due to increased energy consumption over longer distances, such as the need to maintain higher speeds or the additional energy required for extended periods of driving, which may offset the benefits of longer trips. Fig. 4(c) illustrates the relationship between the duration of a trip and emission reduction per trip. The plot shows a clear linear relationship between trip duration and emission reduction, with emission reduction increasing consistently as trip duration increases. The plot shows a clear linear relationship between trip duration and emission reduction, with emission reduction increasing consistently as trip duration increases. It suggests that longer trips benefit from the cumulative effect of the vehicle's energy efficiency.

4.4. Spatiotemporal patterns of emission reduction for REV electrification

4.4.1. Temporal patterns

We observe that emission reductions per trip vary with the hour of the day. Similar temporal patterns are found for both cities, so Fig. 5 illustrates the emission reductions across different days in Chengdu as an example. On weekdays, emission reductions fluctuate with traffic demand, peaking at 8:00 and 18:00. On weekends, emission reductions also follow traffic demand, reaching their highest values at 18:00 on Saturday and 17:00 on Sunday. Based on the analysis in Section 4.3.2, we understand that these patterns are due to the strong correlation between emission reductions and speed. During peak hours, road congestion results in very low driving speeds, making the advantages of EVs in emission reduction more pronounced.

Fig. 3. Emission reduction probability in Xi'an across different days.

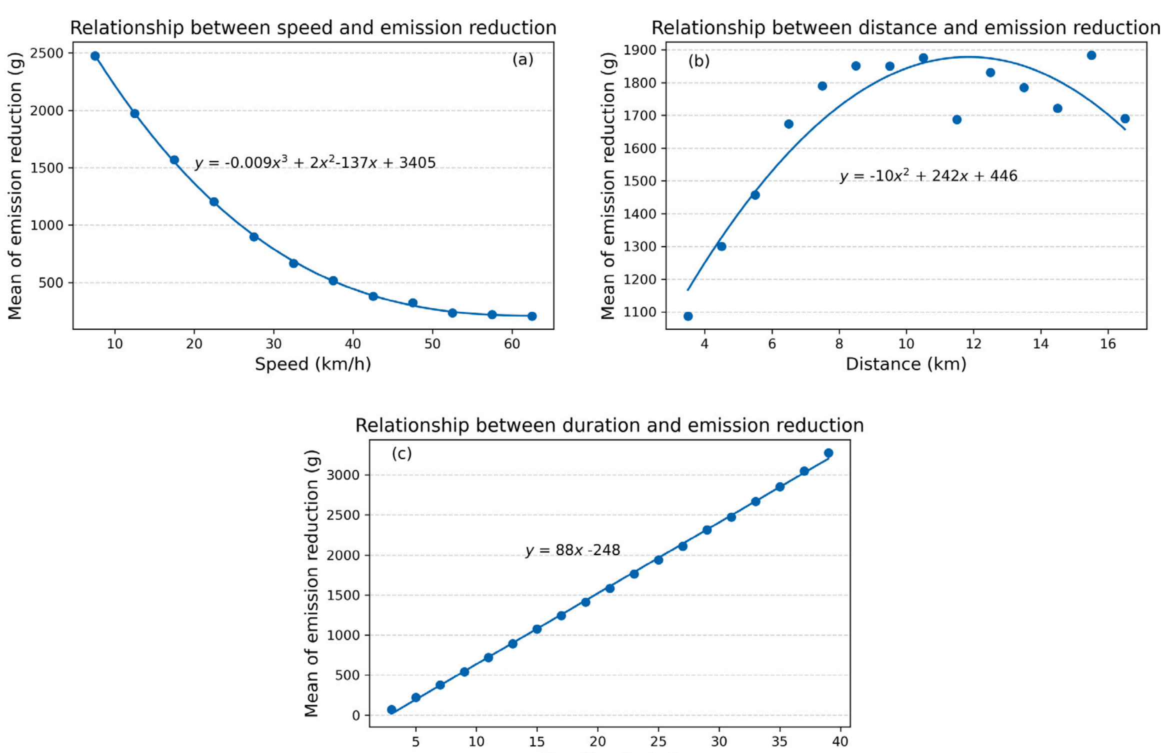

Fig. 4. The relationship between emission reduction and factors.

Table 4
Emission factors and energy efficiency obtained by our models.

		Count	Mean	Std.	Min.	25%	50%	75%	Max.
Chengdu	Emission factors (China V)	985 526	328.41	131.17	12.41	234.86	322.27	410.39	1530.03
	Emission factors (China VI)	985 526	183.47	128.35	2.94	96.85	150.12	228.43	1250.98
	Energy efficiency	985 526	0.16	0.02	0.00	0.15	0.16	0.17	0.39
Xi'an	Emission factors (China V)	662 472	376.66	133.08	13.51	288.76	367.56	451.15	1546.99
	Emission factors (China VI)	662 472	183.79	119.75	3.73	108.40	152.44	217.27	1366.49
	Energy efficiency	662 472	0.16	0.02	0.01	0.15	0.16	0.17	0.39

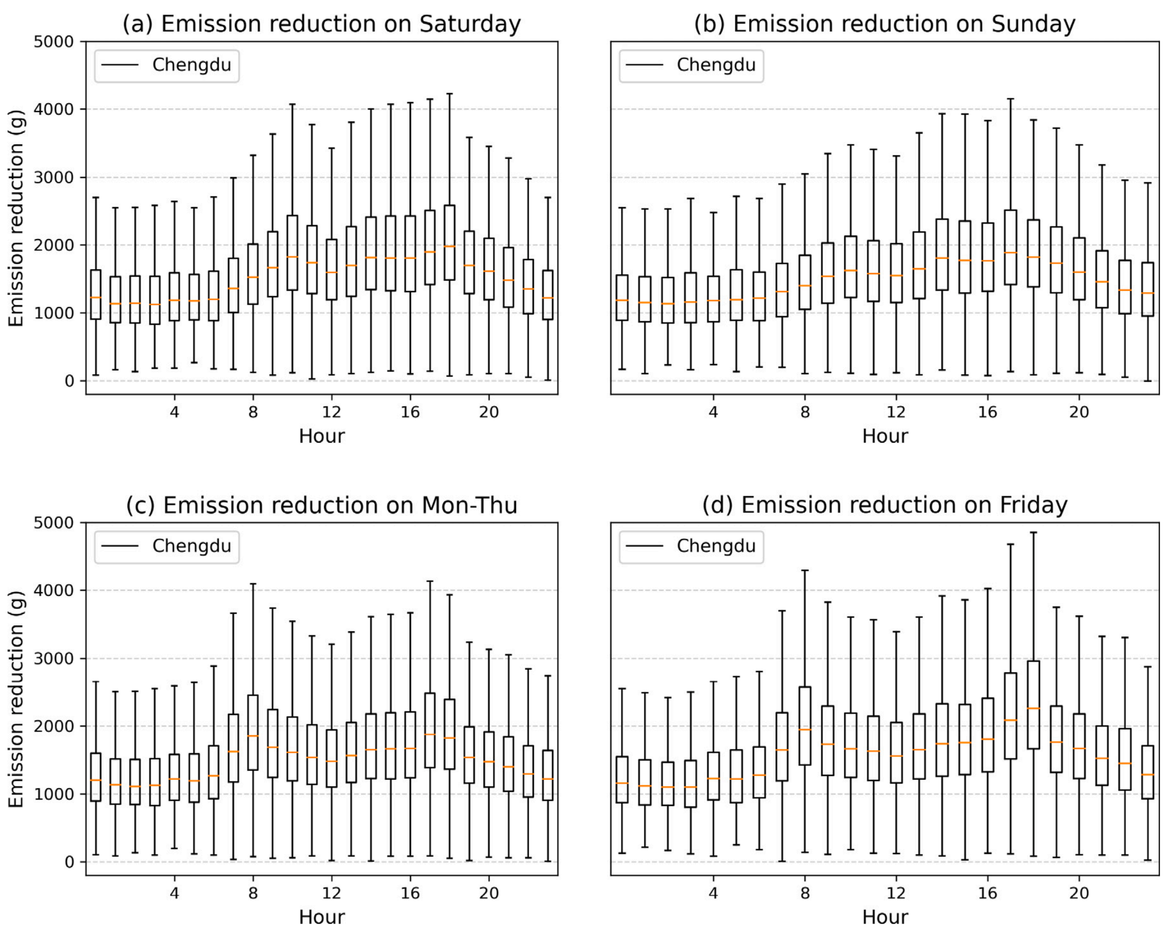

Fig. 5. Temporal patterns of emission reduction per trip across different days.

4.4.2. Spatial patterns

Fig. 6 displays spatial patterns of emission reduction per trip in Chengdu and Xi'an. We demonstrate both of shared trips and solo trips to compare emission reduction effects. As analyzed in Section 4.3.1, the emission reductions due to shared rides are lower than solo rides. Thus, we set different scales for solo rides and shared rides to highlight their spatial characteristics. The color gradient ranges from blue (lower emission reduction) to red (higher emission reduction). The black lines in maps are expressways. From the maps, it is evident that regardless of the city, both shared rides and solo rides show higher emission reductions within the ring road. This is because the areas within the ring road are the city center, where traffic volume is higher and congestion is more severe. The lower average driving speeds in these areas result in higher emission reductions. However, in areas with dense expressways, where driving speeds are high, the reduction in emissions is smaller. This verifies the conclusion that emission reduction is negatively associated with driving speed.

4.5. Sensitivity analysis and balance point of emission factors

4.5.1. Sensitivity analysis considering different emission factors

Fig. 7 shows sensitivity analyses of CO_2 emission reductions in Chengdu and Xi'an under China V and China VI emission standards across different years. For China V in Fig. 7(a), the emission reductions are relatively stable over the years, with median values consistently around 1600 grams. The interquartile range remains relatively constant, suggesting that the variability in emission reductions does not significantly change over the years. Almost all of the trips have achieved emissions reductions. Whereas, for China VI, there have been many trips that have not achieved emissions reductions until 2035. The emission reductions are consistently lower compared to the China V standard, with median values around 750 grams. This is because emission reduction is calculated as the difference between emissions from GVs and EVs. GVs under the China VI standard emit less CO_2 than those under the China V standard. Therefore, achieving comprehensive

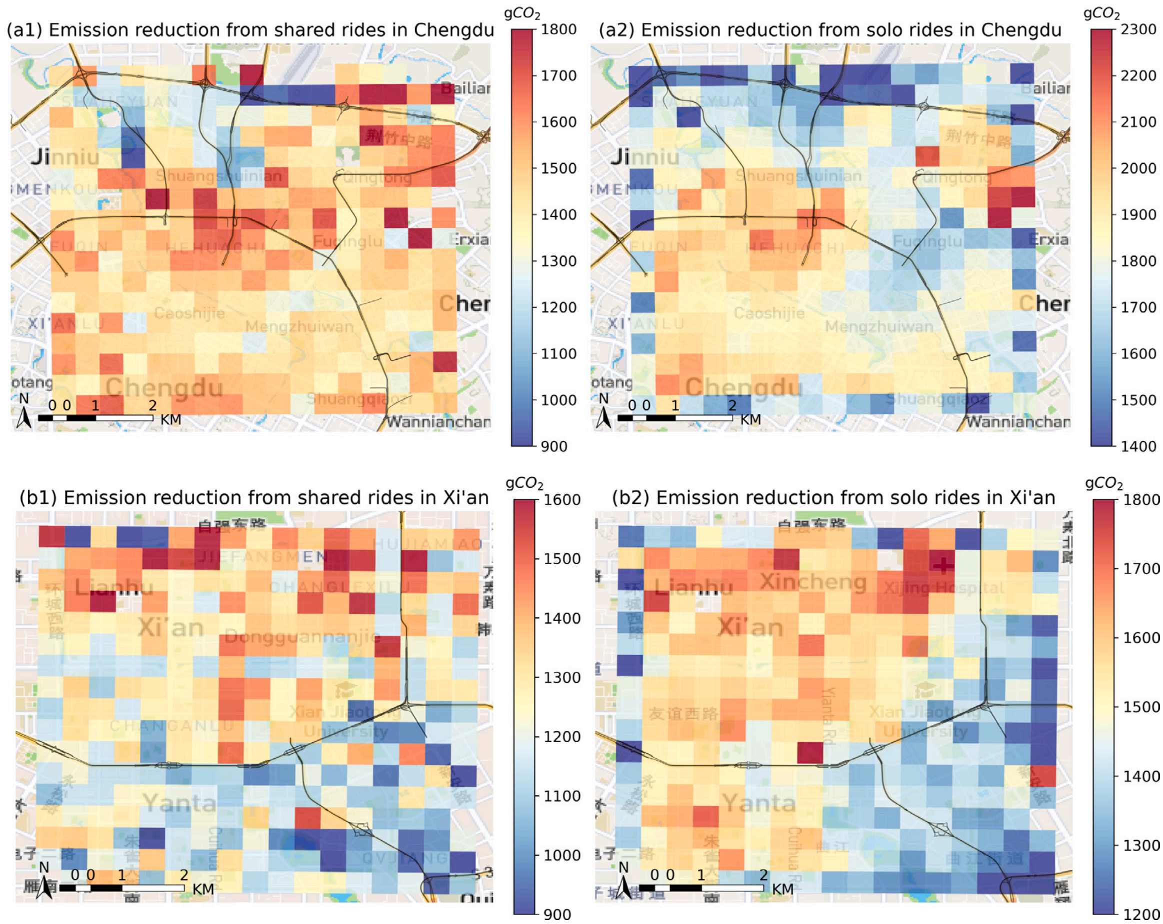

Fig. 6. Spatial patterns of average emission reduction per trip in two cities.

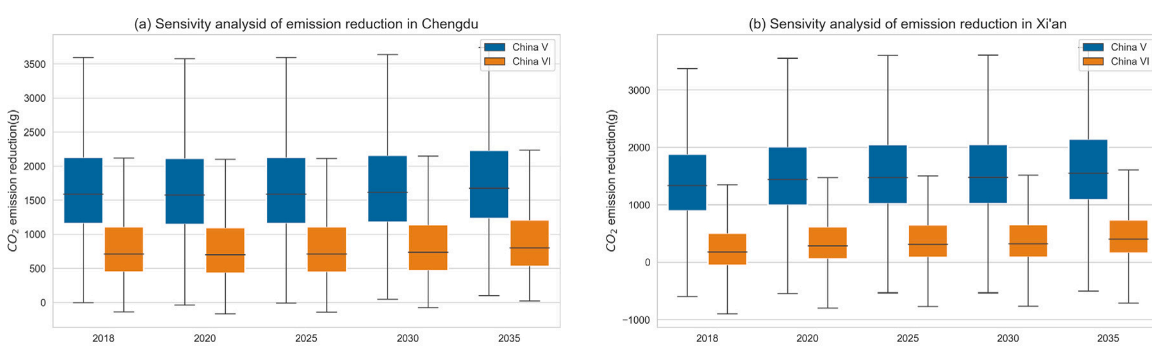

Fig. 7. Emission reduction under different emission standard from 2018 to 2035.

emission reductions under the China VI standard requires even cleaner electricity to maximize the benefits of EVs in ride-hailing service.

Compared to Chengdu, the benefits of REVs in Xi'an are not as significant. This observation is supported by Fig. 7(b), which clearly shows a substantial portion of trips that do not result in emission reductions. Additionally, regardless of whether EVs are compared with China V or China VI GVs, the median values of emission reduction in Xi'an are consistently lower than those in Chengdu. These findings suggest that the transition from GVs under the China VI standard to EVs has a long way to go to achieve comprehensive emission reductions. One primary reason for this is Xi'an's high grid emission factor, which diminishes the overall effectiveness of the switch to EVs in terms of reducing emissions.

4.5.2. Balance point of emission factors

Based on the above analysis, grid emission factors are crucial for achieving overall emission reductions. Therefore, we analyze the balance points of grid emission factors to determine the threshold values required for all ride-hailing trips to achieve CO_2 emission reductions. Fig. 8 provides balance points for different speed, distance, and duration intervals in Chengdu and Xi'an. The balance point represents the grid emission factor at which the emissions from RGVs are equal to the emissions from REVs. The curves of different colors are plotted based on the minimum emission reduction within each interval.

The balance points for different speed, distance, and duration are 156.25 g/kWh, 372.68 g/kWh, and 380.56 g/kWh, respectively. This means that for all trips within the speed interval, the grid emission factor needs to be 156.25 g/kWh or less for REVs to achieve emission

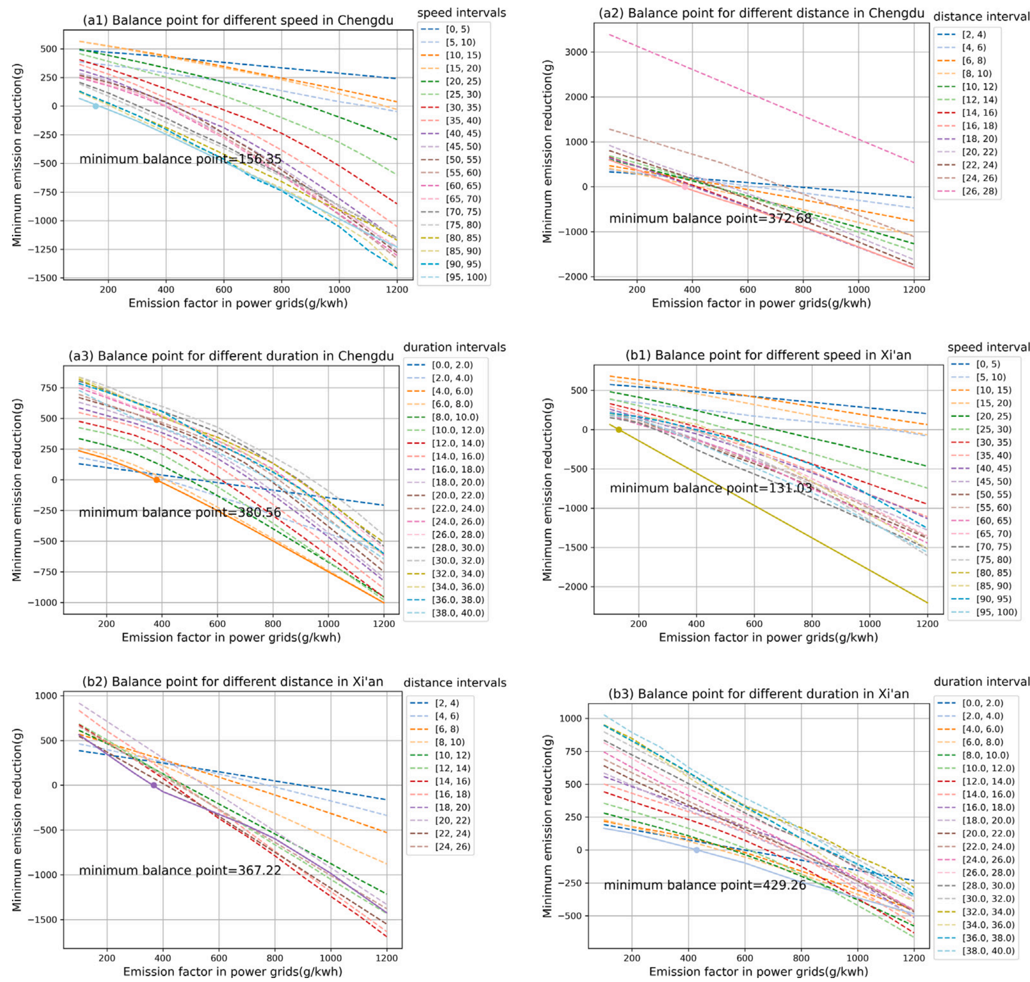

Fig. 8. Balance point of electric emission factors in two cities.

reductions compared to RGVs. For all trips with different distances, 372.68 g/kWh is the threshold grid emission factor required for EVs to provide emission reductions. For trips of varying durations, the grid emission factor must be 380.56 g/kWh or lower for EVs to be beneficial. The empirical grid emission factor in the studied year is 108 g/kWh, which is already lower than these balance points. Thus, almost all the trips in Chengdu lead to emission reductions, which is consistent with the findings in the above analysis.

In Xi'an, the outcome differs due to the high grid emission factor. For different speeds, the minimum balance point is 131.09 g/kWh. This lower balance point compared to Chengdu indicates that Xi'an requires even cleaner electricity for EVs to be beneficial. For different distances, the minimum balance point is 367.22 g/kWh, similar to that of Chengdu. For different duration, the minimum balance point is 429.26 g/kWh. Notably, the empirical grid emission factor in Xi'an is higher than these balance points. Consequently, a significant number of trips lead to increased emissions compared to RGVs in Xi'an. Therefore, for Xi'an, a grid emission factor below 131 g/kWh is required.

5. Conclusion

This study conducts a comprehensive analysis of CO_2 emission reductions assuming all RGVs are replaced by REVs. Comparing REVs with RGVs under China V emission standard, the detailed outcomes are provided for two typical cities in China including Chengdu and Xi'an. In Chengdu, almost all solo and shared rides result in emission reductions. In Xi'an, 98.6% of all rides result in emission reductions, with solo rides accounting for 98.5% and shared rides accounting for 99.9% of emission reduction trips. The daily emission reduction in two cities averages 239 tons and 135 tons of CO_2, respectively, due to the electrification of the ride-hailing service. The average emission reduction per trip in the two cities is 1.699 kg and 1.427 kg, respectively, which is equivalent to reducing approximately 5.18 and 3.80 vehicle kilometers traveled using GVs in ride-hailing. On a per-trip basis, this daily reduction equates to removing approximately 133,307 and 63,162 travel events using GVs in ride-hailing. This daily reduction is equivalent to removing approximately 132,572 and 63,162 gasoline vehicle trips in Chengdu and Xi'an, respectively.

For ride-hailing trips that lead to increased CO_2 emissions, higher driving speeds are a significant factor, as increased speed significantly reduces emission reductions. Another factor contributing to emission reduction is the grid emission factor, due to an insufficiently clean power structure. For Chengdu and Xi'an, the grid emission factors required to achieve overall emission reductions for all ride-hailing trips are 156.25 g/kWh and 131.09 g/kWh, respectively. Although these findings are obtained based on trips in Chengdu and Xi'an, the analytical framework in study can be used to evaluate emission reductions in worldwide cities with varying energy structures. This framework assists in identifying the conditions required for eco-driving and facilitates the effective integration of REVs into ride-hailing services.

The findings of this study have significant implications for both policy-making and practical implementation in the context of reducing CO_2 emissions through the electrification of ride-hailing services. The results highlight the importance of local energy structures in determining the effectiveness of ride-hailing electrification policies. For instance, the varying grid emission factors required to achieve overall emission reductions in Chengdu and Xi'an suggest that local governments need to consider the cleanliness of their power grids when planning and promoting EVs adoption. This can guide the development of region-specific strategies and support the setting of realistic and achievable emission reduction targets. The study's framework can also inform national policies by identifying areas where improvements in power grid infrastructure could lead to substantial emission reductions when combined with the electrification of ride-hailing services.

Additionally, our study still has several limitations. First, due to the constraints in data sources, this study focuses on emissions transferred from electricity during the operational phase, excluding those from other phases such as vehicle production. Future studies could provide a more comprehensive assessment of emission reductions resulting from EVs by incorporating Life Cycle Analysis insights, including the emissions associated with both the vehicle and the electricity used to power it [47]. Second, this study focuses on estimating carbon emissions for fully electric vehicles, based on the assumption that all gasoline vehicles are replaced by fully electric vehicles. We did not consider plug-in hybrid vehicles, as their emissions include contributions from both gasoline and electric power. Due to data limitations, we are currently unable to obtain the gasoline emissions from hybrid vehicles. Therefore, this study exclusively focuses on emissions derived from the energy consumption of fully electric vehicles. Third, the emission factors used in this study are derived from China Regional Power Grid Carbon Dioxide Emission Factors report, which provides the annual average emission factor for each province. Due to data limitations, we are unable to construct the model using emission factors that vary by time and space. The average emission factors can provide an overall understanding. If a more detailed investigation is needed in future studies, the deviations caused by the limitations of the emission factors can be calibrated once more granular data becomes available. Fourth, our datasets used in case study are derived from China, providing a specific Chinese context for emission reduction resulting from electrification in urban ride-hailing services. Globally diverse data are necessary to enable comparative evaluation across different contexts and to obtain general and city-specific outcomes.

CRediT authorship contribution statement

Zhe Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Qing Yu:** Writing – review & editing. **Kun Gao:** Supervision, Writing – review & editing, Conceptualization, Methodology, Funding acquisition, Formal analysis. **Hong-Di He:** Supervision, Funding acquisition, Data curation. **Yang Liu:** Writing – review & editing. **Haichao Huang:** Methodology.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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