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Impact of COVID-19 on private driving behavior: Evidence from electric vehicle charging data

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ABSTRACT

The COVID-19 pandemic has given rise to a major impact on traffic mobility. To implement preventive measures and manage transportation, understanding the transformation of private driving behavior during the pandemic is critical. A data-driven forecasting model is proposed to estimate daily charging demand in the absence of the COVID-19 pandemic by leveraging electric vehicle (EV) charging data from four cities in China. It serves as a benchmark for quantifying the impact of the COVID-19 pandemic on EV charging demand. A vector autoregressive (VAR) model is then used to investigate the dynamic relationship between the changes in charging demand and potential influencing factors. Potential influencing factors are selected from three aspects: public health data, public concern, and the level of industrial activity. The results show that the magnitude of the decline in EV charging demand varied by city during the pandemic. Furthermore, COVID-19 related factors such as daily hospitalizations and national confirmed cases are the primary causes of the decline in charging demand. The research framework of this paper can be generalized to analyze the changes in other driving behaviors during the pandemic. Finally, three policy implications are proposed to assist other countries in dealing with similar events and to stimulate the recovery of the transport system during the post-pandemic period.

1. Introduction

The novel coronavirus disease (COVID-19) has caused one of the world’s worst health crises (Wu et al., 2020). Humans had experienced previously epidemics such as H1N1, SARS, Zika, and Ebola, but unlike these epidemics, COVID-19 has been rapidly spreading across the globe because of the virus’s high contagiousness, causing major disruptions in people’s daily activities (Kumari and Toshniwal, 2020; Muley et al., 2021). As a country that has been severely affected by the pandemic, China has implemented several a series of measures to control the disease spread. On January 23, 2020, the Chinese government imposed a lockdown in Wuhan city, and most provinces followed suit with policies to suppress the virus (Li et al., 2020; Sohrabi et al., 2020). As of March 1, 2020, more than 80,000 positive cases had been confirmed in China, with over 2,000 deaths (NHC, 2020). Under this pattern, human movement has been severely restricted and travel modes have undergone significant changes.

The COVID-19 outbreak had significant impacts on the transportation industry, no matter public transit, or personal vehicles. The magnitude of the effects of the COVID-19 pandemic varies among different regions as well as different modes of travel (Hu et al., 2021). Therefore, these differences present new research challenges and opportunities for researchers to investigate the widespread impact of the pandemic on transportation-related behaviors. According to the accounting results from the Ministry of Transport of the People’s Republic of China (2020), the total passenger volumes of road, waterway, railway, and passenger transport in February 2020 decreased by 52.9%, 55.7%, 87.2%, and 49.7%, respectively, compared with the same period last year. Hu and Chen (2021) stated that socioeconomic disparities contributed to different declines in transit ridership during the pandemic. Zhang and Fricker (2021) investigated the impact of COVID-19 on non-motorized activities in different cities using a Bayesian structural time series model. The results showed that the COVID-19 pandemic resulted in a decrease in non-motorized activities in densely populated cities and an increase in less densely populated cities. Some studies further stated that private transport modes became more popular during the pandemic because they can reduce unnecessary contact compared to public transport modes (Das et al., 2021). Private modes of transport could serve as efficient alternatives to public transport within the COVID-19 context. The COVID-19 pandemic was...
expected to have an impact on the driving behavior of electric vehicles (EVs), which are becoming an increasingly popular mode of private travel. It is a topic worth discussing to investigate the impacts of COVID-19 on charging behavior of EVs with the development of the pandemic.

Although changes in traffic mobility can be observed during the pandemic, the reasons for these changes need to be explained. From the demand side, people’s perception of risk and media attention to the pandemic may contribute to the reduction in transport usage. For instance, Hu et al. (2021) examined mobility trends in the United States during the pandemic using mobile device location data. They found that the decline in mobility was primarily due to the fear of being infected by the virus. Several recent reports claimed that the presence of new social media and communication technologies caused transit demand to plummet (Hensher et al., 2021; Osorio et al., 2022). From the supply side, in order to reduce congestion in passenger space, transit agencies are forced to reduce the level of services. Although factors affecting traffic mobility during the COVID-19 pandemic have been discussed, it is unclear whether these effects are statistically significant and how much these factors explain the decline in traffic mobility.

Existing studies assessing the impact of the pandemic on driving behavior and traffic mobility have some limitations due to the limited availability of data resources and methods. First, few studies have been conducted to date to investigate the impact of the pandemic on the private driving behavior. The shift in EV charging demand reflects people’s attitudes and preferences toward private transportation during the pandemic, which has been overlooked in prior studies. Second, a frequently used method to quantify the impact of the pandemic on driving behavior is to directly calculate the difference between the pre-pandemic period and the year 2020 (de Haas et al., 2020; Lee et al., 2020). External factors, such as the weather and holidays, may have an impact on people’s mobility needs and driving behavior (Kashfi et al., 2016). As a result, although the use of data from previous years is a simple choice, it will inevitably result in large deviations and cannot effectively measure the impact of the pandemic. Third, most of the existing researches are descriptive and simply examine the changes in driving behavior caused by the pandemic. There is a lack of effective tools for multivariate time series analysis to investigate the relationship between the changes in driving behavior and the factors that influence them. Moreover, it is vital to estimate how much of the decline can be attributed to COVID-19 related factors, and how these factors may have imposed long-term or short-term effects on the driving behaviors.

The main contributions of this study are summarized as follows. First, EV charging data from charging stations are combined with heterogeneous data sources such as weather, search engine queries, and public health data to deeply investigate the impact of COVID-19 on the EV charging demand. Second, a data-driven forecasting model is proposed to provide an accurate prediction of the EV charging demand in the absence of the COVID-19 pandemic, allowing the impact of the pandemic to be quantified. Third, this study investigates the relationship between the changes in charging demand and potential influencing factors, and checks the importance of included factors with VAR model. This study is vital to provide insights into accurately assessing the impact of COVID-19 on private driving behavior and inform supporting policies for local governments to better manage transportation during the pandemic.

The remainder of this study is organized as follows. The research framework and methods are presented in Section 2. Section 3 introduces the study area and data source. The empirical findings and discussion are provided in Section 4. Finally, Section 5 provides the conclusions and policy implications.

2. Research design

2.1. Research design

To quantify the impact of the COVID-19 pandemic on EV charging demand, multi-layer perceptron (MLP) is used to forecast the counterfactual outcome (i.e., charging demand in the absence of COVID-19). As a result, we collected EV charging data from January 1, 2019 to February 29, 2020.

First, the sample data before the pandemic (i.e., from January 1, 2019 to January 21, 2020) are randomly divided into training, testing, and validation sets. Then, time variables and weather variables are chosen as the input features to improve the reliability of the prediction of counterfactual outcomes. Finally, the training set is used to train the MLP model, the validation set is used to optimize the hyper-parameters, and the testing set is used to verify the forecasting performance of the model.

2.1.2. Relative impact calculation

First, the counterfactual time series are constructed, which requires the assumption that the pandemic did not occur. The counterfactual charging demand during the COVID-19 pandemic can be predicted using the MLP trained by data before the pandemic. Then, the relative impact is obtained by calculating the difference between the actual charging demand during the pandemic and the prediction, which could be interpreted as the decline in charging demand caused by COVID-19.

Traditional technologies or a direct comparison of changes between 2019 and 2020 cannot provide an accurate estimate because they ignore potential factors that may affect charging demand level. In our case, weather and time variables can be distinguished from the pandemic, which ensures that the counterfactual forecasting results are more accurate. Therefore, we use the MLP to quantify the impact of COVID-19
investigated the short-term impact of the pandemic on China’s air quality and discovered a strong relationship between industrial activity and environmental quality. During the lockdown period, the air quality in Chinese cities improved considerably because of a significant reduction in air pollutants. Furthermore, once the lockdown is lifted, the amount of pollutant emissions will rebound as social production activities resume (Wang and Yang, 2021). Therefore, we used Air Quality Index (AQI) to measure the level of industrial activity during the pandemic.

There is a complex multi-dimensional relationship between COVID-19 related factors, public concern, the level of social activity, and EV charging demand. For example, fear of infection and shutdown of social activity slow down the spread of COVID-19. Conversely, a rise in the number of COVID-19 cases results in an increase in public concern (size of the BI), as well as a decrease in charging demand and social activity. In this study, the VAR model is used to analyze the impact of various factors on EV charging demand during the pandemic.

2.2. Deep learning-based EV charging demand forecasting

A variety of methods have been used in the field of EV charging demand forecasting, including support vector regression (Duan et al., 2018), artificial neural networks (Panapakidis, 2016), and random forest forecast (Lu et al., 2018). In different research settings, each method behaved differently. Deep neural networks are more complex than the traditional shallow hidden neural networks, which can extract features and manage large amounts of sequential datasets (Guo et al., 2018). To quantify the impact of the pandemic on EV charging demand, the MLP is used to predict daily EV charging demand in the absence of the COVID-19 pandemic.

2.2.1. Multi-layer perceptron neural network

The MLP is a feed-forward neural network that maps a set of input values to appropriate output values. The MLP architecture is composed of three layers: input layer, hidden layer, and output layer, with information propagating from the input layer towards the output layer. Fig. 2 shows a MLP network with three hidden layers.

Each layer of MLP is made up of a group of neurons or nodes. Neurons in the hidden layer are called the hidden neurons. Many factors influence the performance of the hidden layer, including the number of layers, the number of nodes, the activation function of the nodes, etc. To improve the network performance, the number of hidden neurons and layers can be adjusted. The MLP predicted result is described as (Massaoudi et al., 2021):

\[
\hat{y} = \phi_o \left( \sum_{j=1}^{M} w^o_{jp} \phi_H \left( \sum_{i=1}^{N} w^h_{ij} x_i \right) \right)
\]

where \( w^o_{jp} \) and \( w^h_{ij} \) denote the output and hidden layer weights, respectively. \( \phi_o \) and \( \phi_H \) represent the activation functions in the output and hidden layers, respectively.

The hyperbolic tangent and sigmoid function are the two most common activation functions. The expressions of hyperbolic tangent and sigmoid functions are, respectively, shown as follows:

\[
\tanh(z) = \frac{e^z + e^{-z}}{e^z - e^{-z}}
\]

\[
\sigma(z) = \frac{1}{1 + e^{-z}}
\]

To guarantee the best performance of the MLP on training set, the loss function needs to be minimized on the training stage. In this study, mean squared error (MSE) is chosen and formulated as follows:

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} \left( y_i - \hat{y}_i \right)^2
\]
where $N$ is the total number of samples, $\hat{L}_i$ is the prediction charging demand, and $L_i$ is the actual observation value.

### 2.2.2. Model structure and configuration

The choice of input variables is critical for developing forecasting models and improving forecasting ability. Based on the previous work (Buzna et al., 2021), the inputs used in this model include two kinds of variables:

1. Time variables: year (2019–2020), month (1–12), days (1–31), day of the week (1–7), and holiday (0–1).
2. Weather variables: temperature, wind speed, and rain.

The MLP hidden layer structure needs to be adjusted to further improve prediction performance. The ranges of the hyper-parameters are shown in Table 1.

| Hyper-parameters                          | Range          |
|-------------------------------------------|----------------|
| The number of epoch                       | [1, 500]       |
| The number of hidden layers               | [1, 5]         |
| The number of neurons in each hidden layer| [10, 200]      |
| Activation Function                       | [Hyperbolic tangent, Sigmoid] |

### 2.2.3. Evaluation criteria

In this study, root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are used to measure the bias between the forecasted values and true values. The mathematical expressions of the VAR model of order $p$ can be expressed as follows:

$$ y_t = C + a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_p y_{t-p} + \epsilon_t $$

where $y_t$ is an endogenous vector, $C$ is the model constant, and $\epsilon_t$ is white noise, which represents a disturbance vector.

In the practical application, Akaike information criterion (AIC), Hannan–Quinn information criterion (HQ) and Schwartz Criterion (SC) can be used as penalizing criteria to define the order ($p$) of the VAR model. These penalizing criteria with the lowest values will help determine the best model and number of lags. The formulas of these criteria are presented in Eqs. (9)–(11).

| Criteria           | Formula                                      |
|--------------------|----------------------------------------------|
| AIC ($\hat{p}$)    | $\text{AIC}(\hat{p}) = \ln \sum (p) + \frac{2 \ln n}{T}$ |
| HQ ($\hat{p}$)     | $\text{HQ}(\hat{p}) = \ln \sum (p) + \frac{\ln(\ln T)}{T} \ln n$ |
| SC ($\hat{p}$)     | $\text{SC}(\hat{p}) = \ln \sum (p) + \frac{\ln T}{\ln n}$ |

### 2.3. Co-integration test

For non-stationary time series, a differencing method can be used to eliminate the non-stationary trend. However, the transformed time series leads to difficulties in interpreting the time series model. In order to tackle this problem, Engle and Granger (1987) proposed the co-integration theory and methods to provide an alternative way of modelling non-stationary series. The Johansen cointegration test method, which is applicable to the analysis of multivariate co-integration (Johansen and Juselius, 1990), is based on the following formula:

$$ \Delta y_i = \sum_{i=1}^{p-1} f_i \Delta y_{i-1} + \Pi y_{i-1} + \epsilon_i $$

where $\Pi = \sum_{i=1}^{p-1} A_i - I$ and $f_i = -\sum_{j=i}^{p-1} A_j$.

We can use trace test to determine the number of co-integration relationships and establish the co-integration equation in the VAR model (Johansen, 1988). The trace test is given as follows:

$$ T_{\text{trace}} = -T \sum_{i=1}^{r} \ln (1 - \lambda_i) $$

where $T$ is the sample size and $\lambda_i$ is the $i$th eigenvalue ordered by size.

### 2.3.4. Impulse response function

The impulse response function is used to characterize the dynamic structure of the VAR model. The impulse response function describes the behavior of the endogenous variables immediately following the application of an external shock (Ueda et al., 2020). This function also assesses the time required for the variable to stabilize after the shock effect.

### 2.3.5. Variance decomposition

In addition to the impulse response function, variance decomposition is another common technique for explaining the dynamic behavior and relationship between VAR variables. We can determine the relative importance of each variable and the relative involvement of each shock effect using variance decomposition (de Senna and Souza, 2016).

### 3. Study area and data sources

#### 3.1. Study area

As the first country in the world to effectively control the pandemic (Wang and Yang, 2021), China experienced three stages (before the pandemic, the lockdown period, and the economic recovery period). The
selection of the major Chinese cities for the research objects can serve as a reference for other countries dealing with similar events. The purpose of this study is to investigate the relationship between city-level changes in EV charging demand and its influencing factors during the pandemic. EV charging datasets have been collected from four prefecture-level cities in Anhui province of China.

These cities were chosen for the following reasons:

(1) These cities are located in Anhui province in the Yangtze River Delta region. Anhui is adjacent to the Hubei and has been one of the most affected provinces in China (Shahzad et al., 2020). By February 27, 2020, the total number of accumulated confirmed cases in Anhui province had reached 990. During the pandemic, each city conducted interventions and put in place control measures to limit human mobility.

(2) Although other cities in Anhui province, such as Fuyang and Huainan, have been severely affected by the COVID-19 pandemic, EVs are not widely used there. These four cities had a steady level of EV charging demand before the pandemic, which was able to better highlight the decline in EV charging demand during the pandemic.

### 3.2. Data sources

EV charging datasets are extracted from a platform that monitors different charging stations in Anhui province, which connects charging piles to obtain real-time charging records. The data used in this study includes 1,184,518 charging records. The charging records contain the user’s code, charging method, charging energy, start time, and end time. Table 2 shows a description of the charging record.

COVID-19 public health data were obtained from the China Stock Market & Accounting Research Database (https://www.gtarsc.com) and

| Attribute name | Attribute description | Data type |
|----------------|----------------------|-----------|
| User           | Unique ID of each user | Nominal   |
| Charging pile  | Unique ID for every charging pile | Nominal   |
| Charging start time | Start time of each charging record | Numeric   |
| Charging end time | End time of each charging record | Numeric   |
| Transaction energy | Amount of charging energy | Numeric   |
| Transaction cost  | Cost of charging | Numeric   |

**Table 2** Description of EV charging record data.

EV charging demand in four cities in different stages of the COVID-19 pandemic.

![Fig. 3. EV charging demand in four cities in different stages of the COVID-19 pandemic.](image)

**Table 3** Performance indicators on the testing set.

| City      | RMSE (MWh) | MAE (MWh) | MAPE (%) |
|-----------|------------|-----------|----------|
| Hefei     | 0.684      | 0.563     | 5.8%     |
| Lu’an     | 0.599      | 0.473     | 6.4%     |
| Wuhu      | 0.922      | 0.701     | 8.4%     |
| Chuzhou   | 0.561      | 0.399     | 6.2%     |

**Fig. 4.** Evolution of MSE in four scenarios.

![Fig. 4.](image)
the Chinese Center for Disease Control and Prevention (http://2019ncov.chinacdc.cn/2019-nCoV/). COVID-19 data, such as daily confirmed cases, deaths, and hospitalizations, were integrated for all cities studied. The daily search engine query data related to COVID-19 with “pandemic” as the keyword in our study for public attention analysis. The search volume time series data based on BI can be obtained from its website (https://index.baidu.com). The original AQI data used to reflect the changes in industrial activities were downloaded from the Air Quality Publishing Platform of China (https://www.aqistudy.cn/his torydata).

4. Results and discussion

The impact of the COVID-19 pandemic was studied in this paper for 39 days from January 22 to February 29, including the main periods of the COVID-19 outbreak in Anhui. Despite the fact that the first case of COVID-19 was reported in November 2019, all social activities were operating normally during that time. Additionally, there was no media coverage or government control. On January 22, the government announced the start of the pandemic prevention and control work and advised people to reduce their travel (http://wjw.ah.gov.cn/xwzx /gzdt/51944061.html). Except for essential travel, WFH has become the norm. Social activities and transport system had gradually returned to normal by March. Fig. 3 presents the actual EV charging demand in four cities.

As shown in Fig. 3, the daily EV charging demand in each city began to decline around January 20, 2020, and gradually increased after the COVID-19 pandemic was contained. The extraordinary drop in charging demand reflects the impact of the COVID-19 pandemic on traffic mobility and private driving behavior. Furthermore, by mid-February, there was a noticeable rebound of EV charging demand level was obvious by mid-February, indicating a resumption of industrial activity. The first confirmed case in Anhui was identified in Hefei on January 22 (green vertical line in Fig. 3), and the total number of confirmed cases in Anhui reached 15 on January 23, followed by the launch of the Level-1 public health emergency response in Anhui on January 24, 2020 (red vertical line). Due to the improvement of the pandemic situation, the emergency response level in Anhui was downgraded to Level-2 on February 25, 2020 (purple vertical line). The public health emergency response was reduced to Level-3 on March 15, 2020 (blue vertical line) and human activities were mostly back to normal. At the same time, it is worth noting that the daily charging demand in Wuhu was significantly higher than that of other cities due to the rapid development of the automotive industry in Wuhu and the support of the local government (Chen et al., 2020).

4.1. Charging demand reduction estimations

In this section, we use the MLP model to forecast charging demand in the absence of the COVID-19 pandemic, which allows us to quantify the impact of the pandemic. Time series data before the pandemic (i.e., from January 1, 2019, to January 21, 2020) were used to train the MLP model
in each city. These time series data are randomly divided into training set, validation set and testing set in proportions of 70%, 10%, and 20%, respectively. Outlier data are filled with linear interpolation, and duplicate data are moved to improve the forecasting accuracy. In addition, we choose a three-hidden-layer MLP with 50 nodes in the hidden layer and 500 epochs as the basic model for our experiment. The learning rate is set as 0.1. To check whether the model converges or not, we used the error graphs of the training and validation set. The evolution of MSE in four scenarios are shown in Fig. 4.

After training and validating, we obtained the best performance forecasting model with the minimum forecasting errors in validation set. The forecasting results by the MLP for testing set are listed in Table 3.

Based on the final trained model, we estimated the EV charging demand changes. Fig. 5 shows the counterfactual forecasting results and the decline of EV charging demand in four cities from January 22 to February 29, 2020.

As shown in Fig. 5, the general trend in the decline of EV charging demand is similar in four cities, as characterized by increasing growth in early stages and decreasing growth in later stages. Furthermore, the impact of the pandemic on EV charging demand in four cities was different at the early stages of the COVID-19 outbreak. Forecasted values in Chuzhou were lower than true values in the first few days, indicating that there is a lag of approximately 6 days in the response to the decline of EV charging demand to the pandemic. However, Hefei, the capital of Anhui province, was severely affected by the pandemic from the onset. Changes in EV charging demand at four cities during the pandemic are summarized in Table 4. The magnitude of the drop in charging demand varied across the four cities. From January 22 to February 29, 2020, the daily average charging demand in Hefei, Lu’an, Wuhu, and Chuzhou decreased by 78.3%, 70.7%, 68.3%, and 50.4%, respectively, compared to the predicted values. Hefei, the capital of Anhui province, has been hit harder than other cities. Our results support previous findings that cities with high population density and a high level of economic activity are more vulnerable to the pandemic (Zhang and Fricker, 2021).

4.2. Descriptive statistics

In this study, we discussed potential influencing factors during the COVID-19 pandemic to explain the reasons for the changes in charging demand. Fig. 6 depicts the key metrics in four cities. As shown in Fig. 6a, the number of new confirmed cases per day across the country increased from January 22 to February 4, 2020. Following that, the number of daily confirmed cases decreased, indicating that lockdowns and control measures significantly reduced the spread of the virus. However, the number of daily confirmed cases in China peaked on February 12, with approximately 15,153 new cases. After February 14, the number of new confirmed cases has gradually decreased.

As shown in Fig. 6b and c, daily hospitalizations and the BI in all cities followed a similar pattern to that in Fig. 6a, but with a diverse magnitude. Public attention toward COVID-19 reached a peak on February 13, probably because of the sudden increase in the number of confirmed cases the day before (Fig. 6a). However, there were significant regional differences. Hefei had a significantly higher BI and number of daily hospitalizations than other cities, which could be attributed to local economic development and population size. Fig. 6d shows the changes in the AQI in four cities. The AQI fluctuated greatly because of the weather and the Chinese New Year. As control measures resulted in a
significant decrease in the percentage of public transit usage and a nearly complete decrease in factory production, air quality improved dramatically and the AQI trended in the opposite (Sahraei et al., 2021). Furthermore, as the pandemic was gradually brought under control, industrial activity resumed and the AQI began to rise after February 15, 2020.

4.3. Overall time series analysis

When non-stationary time series are used for simulation analysis, there will be a phenomenon of spurious regression and the estimated parameters will be deviated (Wang et al., 2020). The unit root tests ADF, PP, and KPSS are applied to confirm the effective results. The results of the unit root tests for all variables are given in Appendix A. According to Lin et al. (2012) and Peri and Baldi (2010), the results of the three tests are not completely consistent, but there is still sufficient reason to accept the null hypothesis that the level series are non-stationary. At a significance level of 1%, 5%, or 10%, the null hypothesis of a unit root can be rejected in first differences and all variables are first-difference stationary. Therefore, we can perform the co-integration test.

Because the series is non-stationary, we cannot use variables to explain the time series model directly. According to the co-integration theory (Engle and Granger, 1987), the linear combination of these variables can be a stationary sequence and the linear combination is referred to as a co-integrating equation. The Johansen co-integration test was used in this study to examine the long-term correlation between multiple non-stationary series. The results of the Johansen co-integration test are in Appendix B. The trace test indicates that there is only one co-integration equation in the VAR model.

The lag order should be determined reasonably to improve the accuracy of the VAR model. We chose lags based on the AIC, HQ, and final prediction error for this purpose, and the results are presented in Appendix C. Furthermore, the VAR models calibrated in this study can satisfy the stability condition.

4.4. Interactive effects: impulse response function and variance decomposition

4.4.1. Hefei case study

The impulse response function analysis can reflect the behavior of the variable after it has been subjected to an external shock. The impulse response analysis in this paper presented the dynamic feedback of a reduction in charging demand caused by a unit shock in other variables. The impulse response analysis for Hefei is shown in Fig. 7. The dotted
As shown in Fig. 7, the response of CDR is more sensitive to the NCCs per day than other influencing factors. In response to the NCCs, the reduction in EV charging demand was initially negative, but it has gradually turned positive. In the long run, this positive effect will diminish. This could be because the movement of people was strictly restricted in the early stages of the pandemic (Zhang and Fricker, 2021). However, this is a transient phenomenon. With the stabilization of the pandemic and the gradual resumption of production activities, the impact of the confirmed COVID-19 cases would diminish in the long term (Wang and Su, 2020). Similarly, the response of CDR to the number of daily hospitalizations is negative in the short term, but positive in the long term. Furthermore, the response of the reduction in EV charging demand to BI is positive in the long term. Because of concerns of disease transmission, people might reduce non-essential travel. Fear will not vanish as soon as the pandemic is over (Zheng et al., 2021).

In general, using variance decomposition to supplement the impulse response function does not imply that a factor with a higher proportion in the variance decomposition has a higher sensitivity in the impulse response. The variance decomposition results are shown in Fig. 8. The most important contributor to explaining the change in charging demand is NCCs shock. It accounts for approximately 2.29% of the charging demand variance in the second period and increased to 27.71% after ten periods. The number of daily hospitalizations accounts for a significant portion of the variance and ranks second in terms of relative contribution. This shock accounts for approximately 2.16% of the variance at first and 10% after ten periods. AQI shocks rank third in their relative contribution. This shock accounts for 5.57% of the variance in the long run. BI does not have significant impact on charging demand in either the short or the long term. The variance it explains in the entire period is below 1%.

4.4.2. Lu’an case study
For Lu’an, the number of NCCs per day is the most important factor influencing the decline in EV charging demand in the long run (Fig. 9). In the short term, NCCs per day have a positive effect on the decrease in charging demand, and the impact effect began to decline after the fifth period. For AQI, the response of the reduction in EV charging demand is negative in the short term but stabilizes in the eighth period. This is because the closure of businesses and factories in the early stages had an impact on the movement of people and transportation. However, as industrial activity resumes, EV charging demand would eventually increase.

Fig. 10 shows the results of variance decomposition for Lu’an,
presenting the relative importance of the various driving forces of the change in charging demand. According to the variance decomposition, NCCs are the most important contributor in explaining the changes in charging demand over the analyzed period. It explains approximately 40% of the variance in the sixth period. Furthermore, daily hospitalizations and AQI play significant roles in influencing charging demand, eventually accounting for approximately 7% and 4% of the variance, respectively. Although all variables are correlated with changes in charging demand, BI had little significant impact on charging demand in either the short or long term by analyzing Figs. 9 and 10. It is important to note that there were significant delay effects between public concern and the real-world COVID-19 data. Therefore, the correlation between the BI and changes in charging demand can be improved at a lag of some days.

4.4.3. Wuhu case study

The impulse response analysis for Wuhu is depicted in Fig. 11. The number of daily hospitalizations has a strong direct impact on the change in charging demand. The reduction in EV charging demand is a positive response to the number of hospitalizations, and this effect will decrease in the long term. We discovered that NCCs have a significant effect on the change in charging demand in the short term, but this effect will decline rapidly after the fourth period. Furthermore, BI has a negative effect on the decrease in charging demand from the first to the fifth period. The change in charging demand shows a positive response in the sixth period and stabilizes after the tenth period.

The variance decomposition results are shown in Fig. 12, which supports the findings of the impulse response analysis in Fig. 11. The number of hospitalizations is the most important influencing factor for the changes in charging demand. In the second period, it explains 11% of the variance and increased to 50% in the long term. Both NCCs and AQI can explain a significant portion of the entire period forecast error variance. In the long term, BI explains approximately 2% of the variance, indicating that this factor does not have a significant effect on EV charging demand during the COVID-19 pandemic.

4.4.4. Chuzhou case study

As shown in Fig. 13, the change in charging demand is most sensitive to the number of daily hospitalizations, which is consistent with findings from Wuhu. The shock of NCCs has an immediate positive effect on the change in charging demand, but the effect decreases in the long term. On the contrary, BI and AQI shocks have little impact on the change in charging demand.

Fig. 14 shows the proportion of all influencing factors in the variance
decomposition. The number of hospitalizations is the most important contributor to explaining the change in charging demand. It explains 30% of the variance in the fourth period and increased to 60% in the long term. Conversely, BI and AQI have a low degree of explanation across all periods, indicating that neither has a significant impact on EV charging demand during the analyzed period.

The impulse response function and variance decomposition support the conclusion that, when compared with other influencing factors, COVID-19 related features are the most significant and robust factor influencing the decrease in charging demand across all cities. First, control measures implemented by the government are based on the severity of the pandemic. In the post pandemic period, COVID-19 may have an indirect influence on the EV charging demand through other influencing factors such as public attention and industrial activity. This is because EV charging demand did not recover rapidly to normal after the pandemic was under control. Second, there is a lag in public awareness of the pandemic because people become concerned after confirmed cases are announced and not all individuals know how to search online (Tu et al., 2021). The AQI is susceptible to other factors, making it difficult to guarantee the accuracy of the level of industrial activity.

5. Conclusions and policy implications

Using time series data from the pandemic period, this paper deeply investigated the main factors and relationships between EV charging behavior in different cities while taking into account dynamic changes in the VAR model. Our findings show that the response of different city to the level of implementation of lockdown measures has slightly different. The impact of COVID-19 on Hefei started earlier than in other cities. When compared with the counterfactual outcome from January 22 to February 29, 2020, the actual charging demand in Hefei, Lu’an, Wuhu and Chuzhou decreased by 78.3%, 70.7%, 68.3%, and 50.4%, respectively. Moreover, for Hefei and Lu’an, the impact of NCCs on the change in charging demand is stronger compared to the other influencing factors, while the changes in EV charging demand in Wuhu and Chuzhou are more sensitive to the number of daily hospitalizations. Overall, the variables that represent public health data are the most important metrics on changes in EV charging demand. Policy-makers in other countries/cities with available data can use this research framework to quantify the impact of the COVID-19 pandemic and infer the magnitude of influence of various explanatory factors.

There are limitations in this work. First, some potential variables such as social distance and socio-demographics have been ignored.
because of data availability constraints, which prevent more in-depth analysis. Second, although previous studies have found a strong correlation between improved air quality and decreased industrial activity during the pandemic, air quality is also influenced by meteorological conditions and atmospheric dispersion. Therefore, given the uncertainties of the AQI, the estimates of the study should be interpreted with caution. In the future, we hope to develop a comprehensive evaluation model to investigate the effect of other parameters on changes in EV charging demand.

Based on the findings of this study, the following policy implications are recommended to deal with similar events and mitigate the impact of the COVID-19 pandemic on transport system.

This study indicates that EV charging demand in each city decreased rapidly during the Level-1 response period and began to rebound as the emergency response level declined. During the COVID-19 outbreak, it is important to adopt strict control measures such as lockdown and social distancing rules, which can stop the movement of people and the spread of the virus. Furthermore, there are some technologies that can be further developed to reduce unnecessary contacts such as distribution robots, telecommuting, and distance learning (Cui et al., 2021). During the later stages, as cases decreased, transportation departments should work with local governments to identify streets for private transportation modes such as private bicycles and cars in the context of inconvenient public transportation.

Policy makers should seek further improvement to the policy timeliness and rationality. The results of the VAR model indicate that COVID-19 related factors are the primary causes of the decline in EV charging demand. National and regional epidemic control should frame contingency policies tailored for different types of cities rather than one size fits all strategy (Naveen and Gurtoo, 2022). The government should adopt timely control measures and expand the lockdown during the initial period of the pandemic will not only contain the spread but also mitigate its impact. However, given the strong resistance to policies due to the desire for mobility, local government should conduct a comprehensive analysis and optimize operating arrangements based on the pandemic situation.

Although the transport needs may increase in the post-pandemic period, it seems unlikely that there will be a return to pre-pandemic levels for some considerable time (Abdullah et al., 2021). On the one hand, the downturn in industrial and commercial activity remains. On the other hand, public’s fear of the pandemic will not dissipate in a short time. In this study, BI, which reflects public attention on COVID-19, plays no significant role in influencing EV charging demand, most likely due to a lag in public reaction to the outbreak. The government should actively communicate with the public and accelerate the resumption of social activities (Mogaji et al., 2022). In the long run, policy makers and relevant authorities should guide people to use private and public transport properly and support sustainable transportation through subsidies and incentives, which is beneficial for the recovery of the transport system.

Author statement

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Appendix

Appendix A. Results of the unit-root test

Table A1

| Variables | ADF | PP | KPSS |
|-----------|-----|----|------|
|           | ln level | d = 1 | ln level | d = 1 | ln level | d = 1 |
| CDR       | -1.028 | -4.408*** | -6.742 | -36.893*** | 0.245*** | 0.112 |
| HOS       | -2.004 | -2.425 | -0.060 | -32.739*** | 0.269*** | 0.135* |
| NCC       | -2.010 | -3.358* | -5.121 | -33.656*** | 0.247*** | 0.126* |
| BI        | -3.381* | -3.323* | -7.571 | -35.431*** | 0.215** | 0.138* |
| AQI       | -2.305 | -4.599*** | -28.718* | -42.210*** | 0.128* | 0.128* |

Note: *, ** and *** denote the null hypothesis of a unit root is rejected at the 1, 5 and 10% significant level, respectively. d indicates a series in first differences.

Table A2

| Variables | ADF | PP | KPSS |
|-----------|-----|----|------|
|           | ln level | d = 1 | ln level | d = 1 | ln level | d = 1 |
| CDR       | -2.805 | -3.569** | -8.474 | -31.947*** | 0.217*** | 0.182** |
| HOS       | -1.256 | -1.960 | -0.099 | -21.909** | 0.258*** | 0.143** |
| NCC       | -2.010 | -3.358* | -5.121 | -33.656*** | 0.247*** | 0.126* |
| BI        | -3.411* | -3.112 | -7.005 | -33.572*** | 0.230*** | 0.141** |
| AQI       | -1.974 | -3.464* | -19.616** | -47.229*** | 0.166** | 0.098 |
### Table A3
Results of unit root test (Wuhu).

| Variables | ADF | PP | KPSS |
|-----------|-----|----|------|
|           | In level | d = 1 | In level | d = 1 | In level | d = 1 |
| CDR       | -2.274 | -3.401* | -4.164 | -55.189*** | 0.262*** | 0.167** |
| HOS       | -4.403*** | -4.247** | -31.159*** | -57.570*** | 0.269*** | 0.152** |
| NCC       | -2.010 | -3.358* | -5.121 | -33.656*** | 0.247*** | 0.126* |
| BI        | -3.447* | -3.142 | -7.899 | -35.390*** | 0.213*** | 0.147** |
| AQI       | -1.767 | -3.959** | -24.557*** | -43.485** | 0.167** | 0.111 |

### Table A4
Results of unit root test (Chuzhou).

| Variables | ADF | PP | KPSS |
|-----------|-----|----|------|
|           | In level | d = 1 | In level | d = 1 | In level | d = 1 |
| CDR       | -1.574 | -3.894** | -3.913 | -46.162*** | 0.267*** | 0.129* |
| HOS       | -1.512 | -2.744 | -1.602 | -39.459*** | 0.261*** | 0.093 |
| NCC       | -2.010 | -3.358* | -5.121 | -33.656*** | 0.247*** | 0.126* |
| BI        | -3.271* | -3.320* | -7.439 | -33.237*** | 0.227*** | 0.141* |
| AQI       | -1.851 | -3.478* | -15.211 | -33.998*** | 0.147** | 0.112 |

### Appendix B. Results of the co-integration test

#### Table B1
Johansen co-integration rest (Hefei).

| Hypothesized No. of CE(s) | Eigenvalue | Trace statistic | 0.05 Critical value |
|---------------------------|------------|-----------------|---------------------|
| None**                    | 0.672      | 94.28           | 76.07               |
| At most 1                 | 0.511      | 53.01           | 53.12               |
| At most 2                 | 0.314      | 26.54           | 34.91               |
| At most 3                 | 0.192      | 12.54           | 19.96               |
| At most 4                 | 0.118      | 4.66            | 9.24                |

* denotes rejection of the hypothesis at the 0.05 level.

#### Table B2
Johansen co-integration rest (Lu’an).

| Hypothesized No. of CE(s) | Eigenvalue | Trace statistic | 0.05 Critical value |
|---------------------------|------------|-----------------|---------------------|
| None**                    | 0.498      | 78.31           | 76.07               |
| At most 1                 | 0.412      | 52.81           | 53.12               |
| At most 2                 | 0.336      | 33.17           | 34.91               |
| At most 3                 | 0.265      | 18.00           | 19.96               |
| At most 4                 | 0.164      | 6.64            | 9.24                |

* denotes rejection of the hypothesis at the 0.05 level.

#### Table B3
Johansen co-integration rest (Wuhu).

| Hypothesized No. of CE(s) | Eigenvalue | Trace statistic | 0.05 Critical value |
|---------------------------|------------|-----------------|---------------------|
| None**                    | 0.498      | 78.31           | 76.07               |
| At most 1                 | 0.412      | 52.81           | 53.12               |
| At most 2                 | 0.336      | 33.17           | 34.91               |
| At most 3                 | 0.265      | 18.00           | 19.96               |
| At most 4                 | 0.164      | 6.64            | 9.24                |

* denotes rejection of the hypothesis at the 0.05 level.

#### Table B4
Johansen co-integration rest (Chuzhou).

| Hypothesized No. of CE(s) | Eigenvalue | Trace statistic | 0.05 Critical value |
|---------------------------|------------|-----------------|---------------------|
| None**                    | 0.659      | 92.83           | 76.07               |
| At most 1                 | 0.482      | 52.99           | 53.12               |
| At most 2                 | 0.397      | 28.65           | 34.91               |
| At most 3                 | 0.190      | 9.91            | 19.96               |
| At most 4                 | 0.055      | 2.10            | 9.24                |
**Appendix C. Results of the lag selection**

Table C1  
Selection of the model order (Hefei).  

| Lag | AIC   | HQ    | FPE     |  
|-----|-------|-------|---------|  
| 1   | 36.334| 36.795*| 6.122e+15|  
| 2   | 36.226*| 37.701| 5.989e+15*|  
| 3   | 36.250| 37.458| 7.277e+15|  

*a represents the best order of lag selected by the model.

Table C2  
Selection of the model order (Lu’an).  

| Lag | AIC   | HQ    | FPE     |  
|-----|-------|-------|---------|  
| 1   | 32.590| 33.051*| 1.447e+14|  
| 2   | 32.341*| 33.186| 1.229e+14*|  
| 3   | 32.618| 33.846| 2.044e+14|  

*a represents the best order of lag selected by the model.

Table C3  
Selection of the model order (Wuhu).  

| Lag | AIC   | HQ    | FPE     |  
|-----|-------|-------|---------|  
| 1   | 28.682| 29.143*| 2.907e+12|  
| 2   | 28.631| 29.475| 3.007e+12|  
| 3   | 28.300*| 29.528| 2.725e+12*|  

*a represents the best order of lag selected by the model.

Table C4  
Selection of the model order (Chuzhou).  

| Lag | AIC   | HQ    | FPE     |  
|-----|-------|-------|---------|  
| 1   | 28.280| 28.740*| 1.943e+12|  
| 2   | 28.089*| 28.933| 1.748e+12*|  
| 3   | 28.694| 29.921| 4.038e+12|  

*a represents the best order of lag selected by the model.

** denotes rejection of the hypothesis at the 0.05 level.

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