Unraveling adaptive changes in electric vehicle charging behavior toward the postpandemic era by federated meta-learning

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Dear Editor,

Electric vehicle (EV) sales have significantly grown over the years to fulfill growing demands for economic travel and greenhouse gas mitigation.[1] However, the surge in the number of EVs has led to charging anxiety as users struggle to find an available charging station before running out of electricity, resulting in longer reserve and waiting times.[2] Moreover, severe mobility restrictions caused by infectious diseases, such as coronavirus disease 2019 (COVID-19), have greatly affected people's travel behavior[3,4] and hindered their willingness to use EVs, given that charging in public spaces consumes time and increases the risk of contracting the virus.[5] This implies that in the postpandemic era, in which individuals coexist with the virus, the interplay between the two important trends, namely vehicle electrification and mobility restrictions, can extensively affect people's daily commuting by using EVs.[6,7] Hence, it is vital to investigate the interaction between vehicle electrification and mobility restrictions, which is unexplored in the current literature. Since official communications regarding confirmed COVID-19 cases can influence people's travel behavior[8,9] and EV charging can directly reflect users' propensity to use EVs, quantifying vehicle electrification through EV charging data is an appropriate approach to unravel these interactions. In summary, this study aims to quantify and characterize the interaction between the two trends mentioned above, seeking to understand the diverse influences of confirmed cases and associated factors on EV charging behavior, especially when significant interactions are observed.

We collected all EV charging records, including count (x^c), duration (x^d) in minutes, and volume (x^v) in kilowatt hours, from February to May 2022 across 292 Chinese cities. These data encompassed over 240,000 charging piles associated with geo-located 28,000 charging stations. The daily confirmed COVID-19 cases in the local city (i) and neighboring cities are represented as C_i^L and C_i^N, respectively. The study identifies 116 cities for investigation, in which the local city has a minimum of 5 confirmed cases, and the daily average charging count exceeds 200 (Figure 1A). Through three correlation analyses (Pearson, Spearman, and Kendall) and three Granger causality analyses (likelihood-ratio test, the sum of squares regression-based F test, and chi-square test) conducted on $\{C_i^L, C_i^N\}$ and $\{x^c, x^d, x^v\}$, it was determined that charging behavior in 74 of the 116 cities was affected by C_i^L and/or C_i^N (Figure 1B). This conclusion is derived from the evidence that $\{C_i^L\}$ and $\{x^c\}$ in each of these cities exhibit the minimum correlation coefficient, $min(|R|)$, >0.1 (Figure 1C) and a maximum causative p value < 0.05 (Figure 1D). Furthermore, a similar pattern is also detected for $\{C_i^N\}$ and $\{x^c\}$.

We hypothesized that the changes in charging behavior were influenced by pandemic changes (I^L and I^N), geographical and social conditions (road density e^r and population density e^o), economic conditions (annual per capita disposable income e^i and gross domestic product (GDP) per capita e^g), and charging capacities (charging pile density e^p and charging station density e^s). In addition, we considered city-tiers, with 14, 17, 29, and 14 cities, respectively, belonging to tiers 1 (the most well-developed cities) to 4. Subsequently, we developed an advanced federated meta-learning model (FMM) comprising long short-term memory and multilayer perceptron to estimate the charging behavior on an hourly basis in each city. The 6-fold time series cross-validation reveals that all of the mean absolute errors (MAEs) are <10% of the largest observation value for the charging behavior (Figure 1E). In addition, the mean square error, root-mean-square error, and median square error are remarkably small. These results together indicate that the FMM has attained a highly satisfactory estimation accuracy.

To reveal data distribution patterns, we treated the changes in daily confirmed cases as a positive impulse, equivalent to the SDs of $\{C_i^L, C_i^N\}$ over the studied period, denoted by $\{I_i^L, I_i^N\}$. Using the impulse response function, we estimated hourly changes in charging behavior $\{\Delta y_t^c, \Delta y_t^d, \Delta y_t^v\}$ over 24 h on the selected day, when the values hover around the means throughout the entire period. Then, we established a linear impact expression function, $E = [I_*^L, I_*^L, e_*^r, e_*^o, e_*^i, e_*^g, e_*^p, e_*^s]$, to represent independent variables, and the dependent variable, Δy_*, is devoted to express the reaction to the positive impulse. Note that the subscript "*" represents $ln(\cdot)$ to better capture nonlinear relationships during the analysis. It was found that data distributions between the eight elements of E and Δy_*^c can vary when cities are categorized into different city tiers, levels of GDP per capita, and regions. All of the elements in E and $\{\Delta y_*^c\}$ approximately follow the Gaussian distribution in each tier, demonstrating unclear linear relationships (Figure 1F).

The aforementioned results motivate us to quantify the importance of the eight influential factors in contributing to the changes in charging counts. To achieve this, we calculated the Shapley additive explanations (SHAP) values of the eight factors in E. Specifically, the 50th percentile SHAP values of eight factors are presented in the bottom-right corner of Figures 1G–1R. They are organized into four groups for each category, with $\{\Delta y_*^c\}$ plotted in ascending order on the y axis. Note that the SHAP values are comparable within the same group since they are obtained from the same model. The results indicate an extremely strong and positive correlation between E and $\{\Delta y_*^c\}$, with the Pearson correlation coefficient R ranging from 0.86 to 0.95 ($p \leqslant 10^{-6}$) for city tiers (Figures 1G–1J), 0.83 to 0.85 ($p \leqslant 10^{-5}$) for GDP per capita levels (Figures 1K–1N), and 0.88 to 0.91 ($p \leqslant 10^{-5}$) for regions (Figures 1O–1R). In addition, R^2 falls within 0.75–0.90, 0.69–0.73, and 0.70–0.83 for the corresponding three categories, indicating a satisfactory regression for SHAP distribution statistics.

The results reveal that the 74 affected cities are predominantly situated in the 3 most dynamic economic zones: Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta. This is likely due to the high population density, and it requires relatively high travel demands in these cities to carry out socioeconomic activities, potentially resulting in an easier spread of the virus. With 74 of the 292 cities being affected, this implies that only a few major cities were affected and experienced dynamic changes in charging behavior in response to varying pandemic situations. In comparison to the benchmark without new cases reported in late May 2022, the reduced charging count was <25% for 68% of the cities and <10% for 79% of the first-tier cities. This suggests that the prevention measures had some impact on EV travel, but the effect was, however, not dramatic. Despite the three megacities in China, Beijing, Guangzhou, and Shenzhen, experiencing a slight decrease in the daily average charging count by 0.55%–5.11%, their charging duration or volume increased by 0.04%–5.75%. Moreover, Yangzhou, a second-tier city in Jiangsu province, had a 16.17% reduction in charging count but obtained a significant increase in charging duration (8.28%) and volume (15.23%). These findings reveal adaptive travel behavior with EVs and a preference for switching to the fast-charging mode to maintain the travel capability while reducing unnecessary exposure.

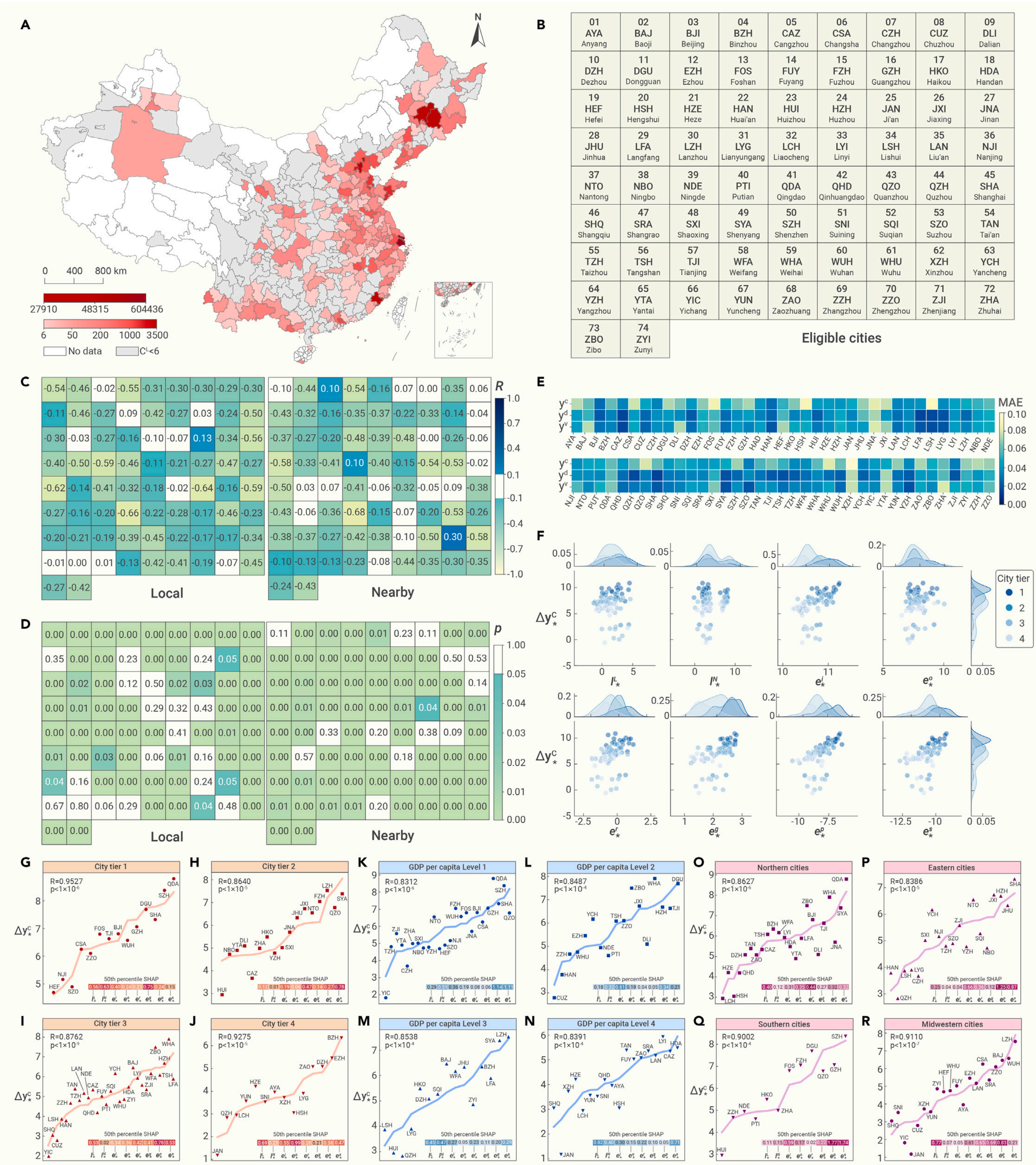

Figure 1. Analysis of hourly EV charging behavior in 74 Chinese cities (A) The total confirmed cases of cities during the studied period are presented in the red color scheme, and cities with an average daily confirmed cases of <5 are marked in gray. (B) The names and abbreviations of the cities meeting the investigation criteria are listed, corresponding to the grid locations in (C) and (D). (C) The correlation coefficient of each city, where its absolute value is the minimum among the 3 correlation coefficients. (D) The maximum p value of each city among the 3 types of Granger causality tests. (E) All of the MAEs of the estimated charging count, charging duration, and charging volume in the 74 cities are smaller than 0.01. (F) The data distribution between E and $\{\Delta y^c_*\}$ is categorized by the 4 city tiers. (G–J) The analysis is categorized into 4 city tiers. (K–N) The analysis is categorized by 4 levels of GDP per capita. Three percentile shreds (50%, 75%, 90%) are used to separate the cities into 4 levels. (O–R) The analysis is categorized into 4 regions, defined as the northern, eastern, southern, and midwestern regions.

This study used the theory of "the universal visitation law of human mobility"[9] to model the accumulated influence of influential cases from nearby cities. The influence follows a Gaussian distribution, declining based on the traveling distance from nearby cities to the local city, with the maximum distance set at 500 km, encompassing most nearby cities on a large geographical scale in China. Therefore, the model allows us, from a uniquely spatiotemporal perspective, to understand the affected charging behavior. Still taking Yangzhou as an example, it reveals that the city was typically affected by the pandemic occurring in its nearby cities, indicating that the changed charging behavior was to confront the expected upcoming new waves and implying that people's prevention awareness has increased.

Notably, 81%, 65%, and 70% of the cities respectively obtained a negative Δy^c, Δy^d, and Δy^v response to the positive impulse of $\{I^L, I^N\}$. This indicates that charging duration and volume exhibited a weaker decreasing trend compared to charging count, suggesting that people, overall, adopted adaptive charging behavior by reducing the charging frequency while attempting to maintain charging capability to avoid unnecessary exposure risks when confronting new cases in local and nearby cities. In detail, the shares of negative (Δy^c, Δy^d, Δy^v) are (71%, 50%, 50%), (94%, 71%, 71%), (90%, 72%, 79%), and (57%, 57%, 71%) for cities in tiers 1–4, respectively. This reveals two important phenomena. First, cities in tiers 1–3 followed the same overall trend, and tier 1 cities experienced the smallest reduction in the three charging behaviors, indicating that people in large cities were more likely to keep traveling to carry out socioeconomic activities. Second, small cities were less influenced by new waves, given that only 57% of the tier 4 cities got a decreased charging count, much smaller than cities in tiers 2 and 3.

The 50th percentile of the SHAP values reveals that the impulse of confirmed cases ($\{I^L_*, I^L_*\}$) significantly affected the changes in charging counts (Δy^c_*) in tier 1 cities. However, $\{I^L_*, I^L_*\}$ became less important for cities in tiers 2–4. From another perspective, $\{I^L_*, I^L_*\}$ was unimportant for cities where people are generally wealthier (corresponding to GDP per capita levels 1 and 2), whereas the trend was opposite in levels 3 and 4. This demonstrates that cities with wealthier populations had a better ability to resist the impulse of the epidemic, implying a similar phenomenon that high-income individuals could prevent infection more effectively during the massive lockdowns.[10]

For eastern and southern cities where people are generally well paid, we observed a similar result that $\{I^L_*, I^N_*\}$ was unimportant, whereas the charging capacity of e^p_* and e^s_* conclusively affected Δy^c_*. In contrast, both (I^L_*, e^r_*) in northern cities and (I^L_*, e^p_*) in midwestern cities made important contributions to Δy^c_*. This allows us to draw several important suggestions. First, charging behavior in tier 1 cities, with a large economy size and requiring frequent socioeconomic activities, could be easily affected by the pandemic. Second, cities with a higher GDP per capita tended to enable citizens to resist the shock of the pandemic better because I^L_* and I^N_* were basically unimportant. Third, less-developed cities, such as those in tier 4, GDP per capita level 4, and midwestern China, were more sensitive to I^L_* than I^N_*, whereas well-developed cities showed an opposite trend.

Our findings indicate that adaptive and instantaneous changes exist in charging behavior, responding to pandemic changes and socioeconomic conditions. To facilitate the vehicle electrification process, more charging piles or stations can be built at high-demand locations to relieve charging anxiety. In addition, scheduling service related to charging count, duration, volume, and location can be provided to guide convenient travel and increase the usage ratio of charging piles. This encourages professionals in geography, renewable energy, transportation, public health, and policy research to devise new strategies for the postpandemic era. Furthermore, the proposed analytical method, coupled with the developed FMM, offers a new approach to reveal socioeconomic phenomena hidden in complex urban systems.

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DECLARATION OF INTERESTS

The authors declare no competing interests.