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Factors Influencing Electric Vehicle Charging Station Locations and Policy Implications: Empirical Lessons from Seoul Metropolitan Area in Korea

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Abstract: The growth of electric vehicle (EV) demand in Korea is closely tied to the challenge of optimal charging station placement. Despite the quantitative increase in charging stations, their uneven spatial distribution remains a significant issue, as highlighted by several related studies. This research analyzes the factors influencing the location of public electric vehicle fast-charging stations (PEVFCSs) in Korea's Seoul Metropolitan Area (SMA). Our analysis reveals that the SMA has yet to implement a systematic urban planning approach for PEVFCS placement. Interestingly, traffic volume is negatively correlated with PEVFCS location, contrary to expectations. Through a comprehensive diagnosis of the current situation, we offer valuable insights and lessons learned from the SMA experience. These findings contribute to the development of plausible policies for more effective PEVFCS distribution in urban areas.

Keywords: electric vehicle; public electric vehicle fast-charging station; determinants; Seoul Metropolitan Area (SMA); geographically weighted logistic regression

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1. Introduction

Motivated by the need to decarbonize the global energy system and achieve air quality benefits [1], electric vehicles (EVs) have revolutionized the automobile industry. Global sales of EVs are expected to outpace those of conventional internal combustion engine vehicles (ICEVs) by as early as 2030 [2]. While global demand for EVs may be slowing down somewhat due to higher purchase costs and a lack of charging infrastructure, the outlook for the EV market remains promising.

Recent growth trends in the EV market have been somewhat moderated due to increased economic uncertainty following the global pandemic (COVID-19) and the limitations of EVs. Nevertheless, EVs are seen as essential for sustainable economic development because of their environmental benefits and ability to utilize multiple energy sources, making them a prime investment target. The presence of a high-tech complex, represented by the chasm, may signal either the start of a crisis or a rebound in the EV market. What is clear, however, is that the EV market is considered a "blue ocean" with significant growth potential. Although EV market shares may vary by region and country, Korea is no exception to this trend. There has been a consistent stream of interest, investment, and government support aimed at enhancing Korea's competitiveness in the global market and aligning with demand. According to the Korea Automotive Mobility Industry Association (KAMA), EV sales in Korea have more than quadrupled, rising from 134,962 in 2020 to 543,900 in 2023 [3]. This upward trend is expected to continue.

The transition from ICEVs to EVs can be seen as part of a global effort to address environmental issues. Expanding EV charging infrastructure to meet the growing demand for EVs is the most urgent policy priority for fostering widespread EV adoption. A systematically developed EV charging infrastructure can reduce drivers' anxiety and encourage greater EV usage [4–6]. As in many advanced countries where EV adoption is expanding, the biggest EV challenge facing Korea in 2024 is the lack of electric vehicle charging stations (EVCSs). Although the number of EVCSs continues to increase, the shortage has worsened. As of 2022, there were approximately 205,000 EVCSs registered, but this is only sufficient for half of the 390,000 EVs on the road [3]. The most significant barrier to EV adoption in Korea is the lack of charging facilities, with an overwhelming majority of respondents expressing this concern [3]. Consequently, there is a strong demand for research on EVCS supply strategies to advance the era of EVs in Korea.

In response, the Korean government has been promoting EVCS support projects since 2014 and increasing subsidies annually. Thanks to this active support policy, the number of EVCSs has grown significantly. However, the issue of optimal charging station locations remains a critical challenge. There are ongoing questions about whether current locations maximize supply efficiency within the constraints of a limited budget. Research on the factors influencing the location of EVCSs in Korea is still limited, leaving these determinants largely unexplored. To develop an effective EVCS supply policy, it is crucial to identify suitable locations. Understanding these location factors, along with regional differences, is essential for creating policies that are both effective and efficient. With this knowledge, policymakers can revise EVCS deployment strategies, fostering a virtuous cycle that enhances user convenience.

This study aims to explore the determinants of EVCS locations in the Seoul Metropolitan Area (SMA) in Korea and to share lessons for expanding charging infrastructure. Specifically, the study first examines the local coefficients of the location determinants of EVCSs to identify regional variations. To achieve this, we utilize geographically weighted regression (GWR) to account for spatial non-stationarity in the regression model. Furthermore, we critically interpret the findings from Korea to suggest strategies for EVCS placement, addressing the persistent challenge of infrastructure expansion.

The focus of this study is on electric vehicle fast-charging stations (EVFCSs), which are crucial for the success of EVs. Fast-charging stations must be widely available to enable consumers to use EVs as conveniently as ICEVs. Therefore, EVFCSs are considered the most critical component for promoting EV adoption. This study specifically looks at public EVFCSs (PEVFCSs), which are designed to serve an unspecified number of users to maximize public utility. Information on the location factors of PEVFCSs is particularly vital compared to those provided by the private sector.

The composition of this study, excluding the Introduction, is as follows. Section 2 reviews previous studies and presents the necessity and distinction of this study. Section 3 explains the methodology, data, and variables. Section 4 provides in-depth results and shares Korean experiences. Finally, Section 5 summarizes the main findings and suggests policy implications and future research tasks.

2. Literature Review

For some time, the location of EVCSs has been recognized as one of the most critical considerations in urban planning. This is closely tied to the rapid growth of the EV market and the surge in demand observed in recent years. A growing body of research directly supports this trend [7–18]. While the electrification of transportation is understood to be a key strategy for achieving sustainable development and substantial environmental benefits, most studies related to EVCS locations have identified several limitations. Specifically, the limited availability and accessibility of charging facilities can lead to consumer concerns, which, in turn, may hinder the demand for EVs.

Empirical studies on smart charging strategies for EVs, particularly those seeking to identify optimal EVCS locations, are highly relevant to this research. Moghaddam et al. [19] examined optimal EVCSs as a multi-objective optimization problem, presenting simulation results that extended the model to metaheuristic solutions. This study positively influenced subsequent research by employing quantitative methods to identify optimal EVCS locations. Another example involves decision support based on network design, which conducts empirical analyses of EVCS locations by incorporating network characteristics and suggests areas for improvement [20]. The study is significant for its use of sophisticated network analysis to explore EVCS placement. A mathematical model using the Modified Primal-Dual Interior Point Algorithm (MPDIPA) has been developed to identify optimal EVCS locations, leading to improvements that more accurately reflect EV charging demand while minimizing network losses [21]. Addressing the shortage of charging stations requires a spatial approach that accounts for travel distances and considers that charging times vary depending on whether the travel behavior involves short-distance commuting or long-distance travel. A mathematical model to explore the location of EVCSs has evolved efficiently, and the attempt to control various constraints in the model can be evaluated positively.

Jordán et al. [22] presented significant findings by applying a genetic algorithm (GA) that considered several constraints, including charging station power, the average time required for a single charge, EV power consumption, average daily travel distance, average daily electricity demand of EVs, and the number of charges per day. The application of genetic algorithms is common in related research due to their methodological advantages in comprehensively addressing the various economic and environmental costs, as well as factors affecting EV charging challenges, such as the shortage of charging stations, their uneven distribution across regions, and the high costs associated with installation and siting [9,22,23].

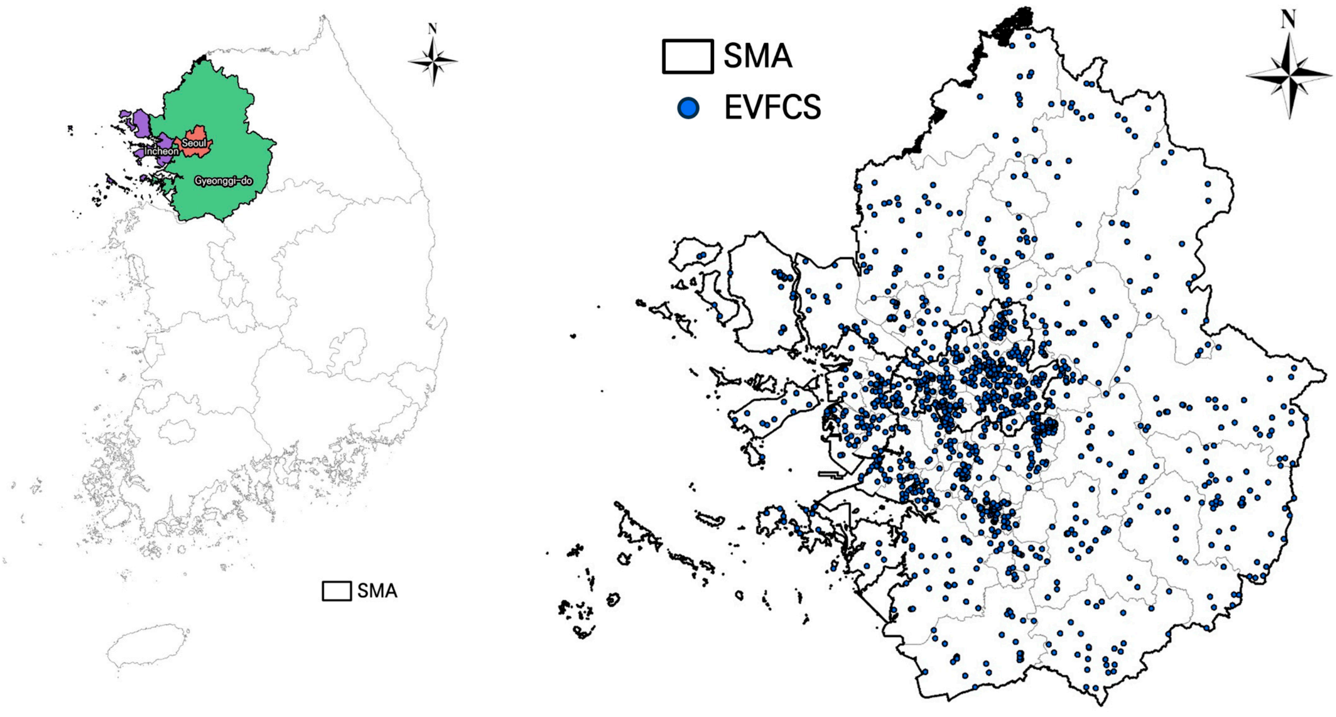
Various factors influence the location of EVCSs. The most crucial factor is demand, specifically traffic volume [12,24–26]. It is preferable to use actual traffic volume data associated with EVCS usage rather than potential traffic volume [12]. To identify suitable locations for EVCSs, a multi-criteria decision support model can be used to achieve the sustainability, efficiency, and performance goals of local communities [27]. In this context, [28] found that investment cost, expected profit, land use, drag distance, waiting time, charging demand, and available power supply form a multi-layered structure affecting EVCS location [25,29,30] emphasized the impact of land use characteristics, along with various factors, on EVCS location. Their discussions begin with the same premise: the necessity of considering EVCSs as significant factors in urban planning. This means recognizing the limitation of failing to meet charging demand despite the increasing number of EVCSs, while also considering land use characteristics, such as frequently parked areas, to meet charging needs beyond trip-specific characteristics [31] argued that the regional imbalances in EVCS availability have a counterproductive effect on stimulating EV demand, which is a common problem in many countries experiencing widening regional disparities in EVCS access. The nature of demand may vary depending on the socioeconomic characteristics of the local population, which can provide useful insights for determining charging loads, such as EV charging times [32].

Overall, related studies have addressed and analyzed the location challenges of EVCSs to effectively meet the demand for EVs as a proactive response to environmental issues and as a substitute for traditional vehicles. However, these studies exhibit the following limitations: (1) despite the use of mathematical optimization models based on objective functions and constraints, some of the studies failed to thoroughly consider relevant influencing factors centered on socioeconomic variables. To date, the determinants of EVCSs have primarily been limited to estimating global parameters. In urban planning, the heterogeneous characteristics of regions can lead to varying interpretations of the regional context, which are essential for crafting effective policies. Therefore, further research in this area is urgently needed. This study seeks to address these limitations by focusing on the case of the Korean capital region.

3. Study Area and Methodology

3.1. Study Area

The study area is the Seoul Metropolitan Area (SMA), comprising three metropolitan regions: Seoul, Incheon, and Gyeonggi-do. As of 2023, the SMA, located at the heart of Korea, accounts for 52.5% of the nation's GRDP and is home to 26.19 million people, representing 50.6% of the national population. The number of registered EVs in the SMA exceeds that of other regions, with 227,451 out of a national total of 543,900, accounting for 41.8%. The number of EVCSs in the SMA continues to grow, and the quality of EV charging services is also improving. Thanks to various initiatives, 1011 EVFCSs have been installed in the SMA, making up 44.9% of the nation's total [3], primarily centered on transportation hubs such as roadsides and public parking lots. However, many EV owners continue to express dissatisfaction with the insufficient availability of EVFCSs (Figure 1).



(**a**) (**b**)

Figure 1. (**a**) Location of the Seoul Metropolitan Area (SMA) in Korea; (**b**) location of electric vehicle fast-charging stations (EVFCSs) in the SMA.

Given the high traffic volume in the region, the current number of EVFCSs does not meet the rapidly growing demand for EVs. The shortage of EVFCSs contributes to a reluctance among residents to purchase EVs, and the suitability of existing EVFCS locations is deemed inadequate [33]. Currently, PEVFCSs are primarily situated near existing public facilities, such as public parking lots, without adequately accounting for traffic volume. Therefore, identifying optimal locational characteristics for PEVFCSs in the SMA is essential, and sharing the insights gained from this research could provide valuable guidance for other regions facing similar challenges.

3.2. Method

This study employs a geographical multiple regression model with a discrete dependent variable as its analysis method. Unlike standard geographical multiple regression models, which handle continuous dependent variables, our model focuses on a discrete dummy variable that indicates the presence or absence of PEVCSs. Consequently, our approach integrates logistic and geographically weighted regression models to analyze a dependent variable with a general linear form (as credited to [34]). The geographically weighted logistic regression (GWLR) model is characterized by the use of local coefficients instead of global coefficients to account for spatial heterogeneity.

This feature is critical as it allows the model's parameters to vary across the geographic area of interest, thereby revealing spatially varying relationships between variables [35]. GWLR assumes non-stationarity, meaning that the relationship between the binominal dependent variable (labeled 0 or 1) and the continuous explanatory variables changes across different locations. GWLR is expressed as follows:

$$\begin{aligned} logit(p_i) &= log\left(\frac{p_i}{1-p_i}\right) \\ &= \sum_i \beta_i(u_j, v_j)x_{ij} + \epsilon_j \end{aligned} \quad (1)$$

Here, $log\left(\frac{p_i}{1-p_i}\right)$ represents the probability of the presence of a PEVCS for the j-th observation; the terms x_{ij} and ϵ_j denote the i-th independent variable and error at the j-th observation, respectively. The x, y location of j-th observation is expressed as (u_j, v_j). The term $\beta_i(u_j, v_j)x_{ij}$ represents the coefficient for the i-th independent variable at the j-th observation.

The weighting matrix (W) is a critical component of the model, as it reflects spatial characteristics based on latitude and longitude. Here, u_i and v_i represent the latitude and longitude of the k-th spatial unit, respectively, based on the administrative region number. To apply W as a weight to the estimator, only the diagonal elements of the matrix shall reflect the latitude and longitude information of each spatial unit under analysis, as shown below

$$W(u_i, v_i) = \begin{pmatrix} w_1(u_i, v_i) & 0\cdots & 0 \\ 0 & w_2(u_i, v_i) \ddots & \vdots \\ 0 & \cdots & w_n(u_i, v_i) \end{pmatrix} \quad (2)$$

Several kernel functions can define the weighting matrix, including Gaussian, exponential, box-car, bi-square, and tri-cube models [36]. In this study, we employed the bi-square spatial kernel function, which is characterized by a weighting form inversely proportional to the square of the bandwidth parameter b, as shown in Equation (3). This function accounts for the distance between regions and adopts an adaptive method [36], enabling the kernel to adjust for various spatial distribution characteristics rather than assuming a uniform distribution of predictor variables.

$$w_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{b}\right)^2\right]^2, if\ d_{ij} < b \\ 0,\ otherwise \end{cases} \quad (3)$$

where d_{ij} represents the Euclidean distance between the i-th and j-th locations. Since the selected kernel function is directly influenced by the bandwidth b, it is crucial to select an appropriate bandwidth. Cross-validation (CV) can assist in estimating the optimal bandwidth by minimizing all the prediction errors [36].

The Akaike Information Criterion (AIC) is used to derive the bandwidth by minimizing the AIC, providing a trade-off between goodness of fit and degrees of freedom [36]. In this study, the AIC is applied to determine the optimal bandwidth for the estimation.

3.3. Variables and Data

The choice of spatial units for analysis is critical in addressing structural issues associated with aggregated data, such as the ecological fallacy [37] and the modifiable areal unit problem [38]. Microscopic spatial data, which are free from these issues, allow for more accurate analysis. In this study, all variables were constructed using a 100 m $\times$ 100 m grid, the smallest spatial unit available in Korea. Table 1 lists all the variables used in the analysis, with data from the base year 2023.

Table 1. Definition of variables for GWLR.

Variable		Description
Dependent	**Location of EVFCS**	**1 If EVFCS Is Present; 0 Otherwise**
Independent	Traffic volume	Traffic volume within a 5 km radius (measured in million vehicles)
	Resident population	Resident population of individuals in their 40s and 50s within a 5 km radius (measured in 10,000 persons)
	Population in 40s and 50s	Total population of individuals in their 40s and 50s (measured in 10,000 persons)
	Distance to IC	Distance to highway IC (measured in 100 km)
	Distance to arterial road	Distance to arterial roads (measured in km)
	Residential area	1 if the area is classified as residential; 0 otherwise

The dependent variable is the presence or absence of public electric vehicle fast-charging stations (PEVFCSs). In the dataset, a PEVFCS is coded as 1 if present and 0 otherwise. Data on PEVFCSs were sourced from the operational status of public EV charging facilities [39]. Independent variables were selected based on previous studies examining the relationship between the built environment and PEVFCS locations. These factors include local traffic volume, resident population, the population in their 40s and 50s, distance to highway interchange (ICs), distance to arterial roads, and proximity to residential areas.

Traffic volume refers to traffic within a 5-kilometer radius, and we used View T data provided by the Korea Transportation Research Institute, which offers spatial big data on actual traffic volumes. Generally, higher traffic volumes correlate with a greater likelihood of PEVFCS locations [24,25]; however, studies in Korea have shown an opposite trend [33]. This study seeks to determine whether this trend applies to the SMA. The resident population is defined as the registered population within a 100 m $\times$ 100 m grid located within a 5-kilometer radius. Special consideration was given to the population in their 40s and 50s, as this age group accounts for approximately 50% of EV owners in Korea [33]. Including this age group helps ensure that areas with higher EV demand are adequately supplied with PEVFCS. Distances to highway ICs and arterial roads were included to evaluate accessibility. Data on these distances were obtained by extracting relevant layers from the national transportation database and measuring the shortest straight-line distance to a PEVFCS using ArcGIS 10.8's Near Tool. Areas with better accessibility to major transportation facilities are preferable for PEVFCS placement. Finally, a residential area dummy variable was included to account for high population density and demand for PEVFCS. Residential areas were identified using the Land Characteristics Survey data from the Ministry of Land, Infrastructure, and Transport, which were extracted at the parcel level.

To further examine demand characteristics related to accessibility, variables for the distance to highway ICs and arterial roads were included. The data processing for these variables is summarized as follows. Firstly, the relevant layers were extracted from the national transportation database. Next, the shortest straight-line distance to PEVFCSs was measured using ArcGIS's Near Tool. Ideally, PEVFCSs should be abundant in areas with good access to major transportation facilities. Additionally, a dummy variable for residential areas was included, as these areas are expected to have high population densities and consequently, higher demand for PEVFCSs. Residential areas were identified using the parcel-level Land Characteristics Survey data from the Ministry of Land, Infrastructure, and Transport.

4. Results

4.1. Descriptive Statistics

Table 2 presents descriptive statistics of all variables. Among the 1,351 datasets, the dependent variable—location of the PEVFCS—was present in 75% of cases. The average traffic volume in a 5 km radius of the PEVFCS was 83.65 million vehicles, reflecting the high population density of the SMA. However, some locations had almost no traffic volume within this radius. The maximum resident population within a 5 km radius of the PEVFCS was 188.03 (10,000 persons), revealing a significant disparity compared to the minimum population of 0.01 (10,000 persons). The average population of individuals in their 40s and 50s was 20.52 (10,000 persons), with a relatively large standard deviation of 16.85 (10,000 persons). The average distance to ICs was 4.67 (100 km). Since highways in the SMA are primarily concentrated in Seoul and the southern part of Gyeonggi-do, the distance between a PEVFCS and highway ICs tends to be relatively long. The average distance to arterial roads was 1.40 km, indicating that PEVFCSs were generally located near major arterial roads. Finally, 34% of PEVFCSs were situated in residential areas based on zoning data.

Table 2. Descriptive statistics of variables.

Variable	Mean	SD	Min	Max
Location of EVFCS (location = 1, otherwise = 0)	0.75	0.43	0.00	1.00
Traffic volume (million vehicles)	83.65	85.66	0.00	335.48
Resident population (10,000 persons)	63.30	52.91	0.01	188.03
Population in 40s and 50s (10,000 persons)	20.52	16.85	0.00	59.31
Distance to IC (100 km)	4.67	0.23	4.05	5.49
Distance to arterial roads (km)	1.40	2.10	0.02	18.66
Residential areas (residential area = 1, otherwise = 0)	0.34	0.47	0.00	1.00

The descriptive statistics reveal significant variation among the independent variables and the location of the PEVFCS, reflecting the regional diversity of the SMA. Despite the presence of numerous large cities within the SMA, substantial areas are agricultural, and many urban–rural mixed cities exist. This strong regional heterogeneity in the SMA affects the locations of PEVFCSs, supporting the validity of applying GWLR in this context.

4.2. Results of Empirical Analysis

Before discussing the GWLR analysis results, we compared the model fit between the Binary Logit Model (BLM) and GWLR to assess the validity of GWLR. Model fit was evaluated using AICc and Pseudo R^2. A lower AICc value indicates better model performance, whereas a higher Pseudo R^2 value suggests a better fit. As shown in Table 3, GWLR demonstrates a higher Pseudo R^2 (0.530) and the lowest AICc (3266.64) compared to the BLM, indicating that GWLR outperforms BLM.

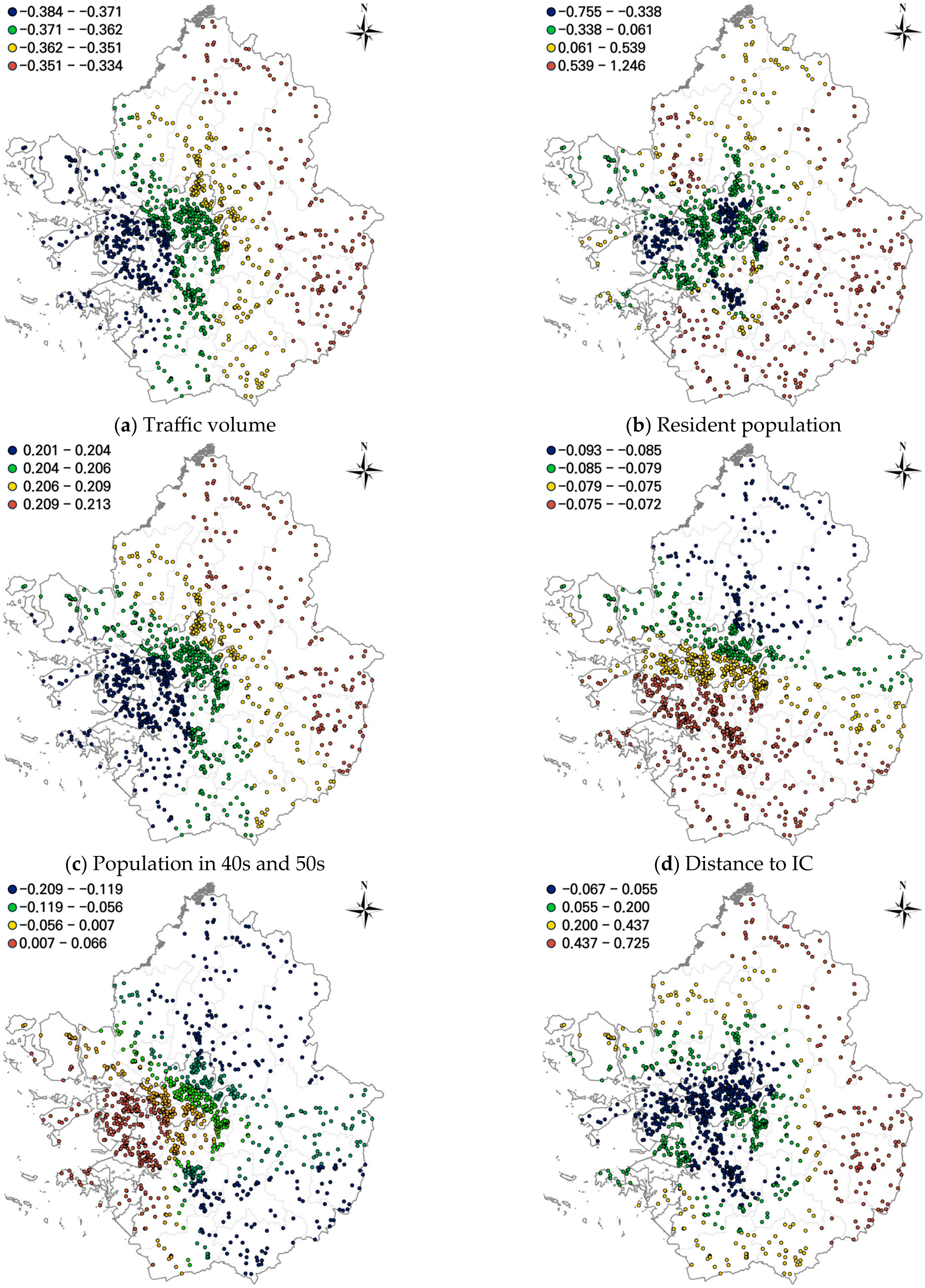
Table 3. GWLR results.

Variables	BLM		GWLR				
	Coefficients	***p*-Value**	**Mean**	**SD**	**Min**	**Median**	**Max**
Intercept	0.001	0.531	0.384	0.001	0.382	0.384	0.387
Traffic volume	−0.054	0.398	−0.364	0.010	−0.384	−0.3661	−0.334
Resident population	−3.043	0.002	−0.013	0.465	−0.756	−0.244	1.246
Population in 40s and 50s	3.043	0.014	0.206	0.002	0.201	0.205	0.213
Distance to IC	−0.041	0.753	−0.079	0.005	−0.094	−0.078	−0.072
Distance to arterial roads	0.020	0.030	−0.056	0.073	−0.210	−0.052	0.067
Residential areas	0.161	0.000	0.128	0.185	−0.067	0.054	0.726
AICc	3266.64		2896.13				
Pseudo R^2	0.348		0.530				

Based on the GWLR results presented in Table 3 and Figure 2, the determinants of PEVFCS locations can be interpreted as follows. GWLR revealed a consistently negative effect of traffic volume on PEVFCS locations across all regions. Although spatial variations in local coefficients were not significant, the direction of influence remained consistent. This finding contrasts with the studies of [24,25] but aligns with [33], indicating that PEVFCS locations in the SMA are not influenced by traffic volume. Many PEVFCSs are situated in existing public facilities, often located in areas with low traffic volume, which underscores this issue.

Previous studies have shown that the resident population is closely associated with electric vehicle charging stations [24,31]; the effect of the resident population on PEVFCS locations varied by region in the SMA. The effect was positive on the outskirts of the SMA (mainly Gyeonggi-do) and negative in the central part of the SMA around Seoul. When considered within the context of the SMA's spatial structure and land use patterns, this result carries several implications. PEVFCSs on the outskirts are generally located in residential areas with dense populations, while in central areas such as Seoul and Incheon, many PEVFCSs are situated in commercial, business, and industrial zones with small populations.

The population of individuals in their 40s and 50s significantly influenced the location of PEVFCSs across all areas, but the regional heterogeneity in this demographic group was not significant. Given that individuals in this age group are a key demographic for EV adoption in Korea, the concentration of PEVFCSs in areas with a high population of this age group could facilitate future EV growth. As in the case of Korea, efforts to identify the link between key EV customers' age and PEVFCSs can provide vital information for determining the location of PEVFCSs.



(**a**) Traffic volume (**b**) Resident population

(**c**) Population in 40s and 50s (**d**) Distance to IC

(**e**) Distance to arterial roads (**f**) Residential areas

Figure 2. GWLR results. Note: the natural breaks classification method is adopted to classify the level.

Proximity to the road is an important consideration when selecting the location of EVFCSs [40]. The regression results in the SMA partially supported this claim. The distance to highway ICs negatively impacted the likelihood of PEVFCS locations, with minimal regional variations. As EVs traditionally have shorter travel ranges, the presence of a PEVFCS near highway ICs enhances convenience for EV users. The relationship between the distance to arterial roads and PEVFCS locations varied significantly by region. In the western part of the SMA, proximity to arterial roads did not significantly influence PEVFCS locations, while being closer to arterial roads increased the likelihood of PEVFCS locations in other regions. This finding suggests that proximity to arterial roads is as crucial as proximity to highway ICs for providing convenient charging opportunities. Consequently, additional PEVFCSs should be considered in areas with better accessibility to arterial roads.

The relationship between land use and PEVFCS locations in the SMA aligns with the findings of [25]. The GWLR analysis revealed considerable regional heterogeneity in residential areas. In areas with a high concentration of commercial and business districts, primarily in the central SMA, residential areas showed a negative effect on PEVFCS locations. Conversely, in other areas, particularly on the outskirts of the SMA, residential land use had a positive effect on PEVFCS placement. The prevalence of PEVFCSs in residential areas presents both advantages and challenges. While having PEVFCSs near the homes of EV owners is beneficial, it can limit availability in major urban areas with high traffic volumes, such as commercial and business districts, where daytime charging demand may be higher.

5. Concluding Remarks

This study set out to address a crucial question: Is Korea systematically preparing for the era of EVs through effective urban planning? By examining the factors influencing the location of PEVFCSs in the SMA, we have provided insights into the current state of EV infrastructure planning. Our analysis focused on how EV demand, supply, and land use characteristics shape PEVFCS locations, with particular attention to regional variations.

The comparison between the BLM and GWLR demonstrated that GWLR is superior in capturing the spatial heterogeneity of the data. This makes GWLR a more suitable method for analyzing PEVFCS location factors, emphasizing the importance of considering regional differences in urban planning. One of the key findings from the regression analysis is that the SMA must take a more systematic approach to preparing for the EV era. In the case of Korea, traffic volume was found to negatively correlate with PEVFCS locations, contrary to expectations. This result challenges the conventional assumption that higher traffic volumes should naturally lead to more PEVFCSs and underscores a critical disconnection between current PEVFCS placements and actual traffic conditions. Historically, the placement of PEVFCSs has been driven by budget constraints, resulting in their concentration in existing public parking lots. This approach overlooks the need to align PEVFCS locations with areas of high traffic volume, which could significantly enhance their utility and efficiency. A major challenge identified in this study is the limited availability of data on EV traffic volume in Korea. The lack of accurate data has led to policies that fail to adequately address the real demand for EVs, causing inefficiencies and potential budget waste. Locating PEVFCS in high-traffic areas could better balance supply with demand, optimize their utilization, and minimize redundant investments.

Proximity to highways and arterial roads was also identified as a crucial factor in determining PEVFCS locations, reflecting the need for convenient charging options, particularly given the shorter travel ranges of earlier EV models. However, regional disparities were evident, with northern areas of the SMA having a stronger correlation between PEVFCS locations and proximity to highway interchanges. Residential areas, particularly on the outskirts of the SMA, were more likely to host PEVFCSs, while commercial and business districts in central areas showed a negative correlation. This imbalance may limit access to PEVFCS in urban centers where demand could be higher during business hours.

The lessons from the SMA are clear: significant improvements are required in the approach to PEVFCS location planning. Policies must be revised to actively incorporate traffic volume considerations, and countries transitioning to the EV era can take valuable insights from Korea's experience. Local governments need to develop customized strategies tailored to their specific location characteristics, traffic patterns, and financial resources. A comprehensive plan for PEVFCS supply should be developed, integrating these efforts into broader urban planning initiatives. To this end, PEVFCSs should be included in important urban planning facilities and managed spatially. In order for PEVFCSs to function correctly, the installation criteria must be established in detail. A flexible installation criteria application plan for each region must be devised. Effective cooperation between the public and private sectors is also essential for the successful deployment of EVFCSs. The public sector should incentivize private sector investment by ensuring profitable opportunities, while the private sector should work closely with public plans to avoid overlapping facilities and maximize coverage. In Korea, private charging businesses have not been active due to low profitability caused by insufficient demand for EVFCSs. Shortly, when the profitability of EVFCSs increases, EVFCSs will shift to private sector-led businesses. During the transition period from public to private, the public sector should sign business agreements with local companies to increase EVFCSs and support the effective transition to private sector-led charging businesses. In order to enhance the competitiveness of the private sector, it is necessary to establish a support system tailored to each growth stage of companies, including subsidies and technical support. Local governments should integrate information management and minimize inconvenience to citizens.

While this study provides valuable insights into the regional determinants of PEVFCS locations, it is limited by the lack of current data. Future research should prioritize collecting detailed data on EVFCS usage patterns and user characteristics, developing spatial panel data models that incorporate these variables, examining the impact of different land use types on PEVFCS placement, and exploring dynamic pricing strategies to optimize PEVFCS utilization across various locations and times of day. Further studies are encouraged to investigate the factors influencing EVFCS placement in various regions or to develop a systematic methodology for determining optimal locations.

When selecting the optimal location for EVFCSs, an effective spatial model should consider four major constraints: driving distance, round trips, budget, and total demand. Various methodologies, such as the Flow-Refueling Location Model [41] and the Human–Machine Mutual Trust Level [42], are emerging as suitable models. In the future, along with the development of new models to identify optimal locations for EVFCSs, integration with big data should also be explored.

The issue of EVFCS placement must be addressed comprehensively by local governments. The immediate task is to develop locally tailored strategies that reflect EV users, traffic volume, and financial conditions. To this end, a comprehensive EVFCS supply plan, including PEVFCSs, should be established urgently. Alternatively, addressing the supply plan for EVFCSs as one of the leading transportation plans would be a practical approach. Furthermore, collaboration between the public and private sectors is essential for successful EVFCS supply. The public sector should actively encourage and support private sector participation by creating profitable opportunities. Conversely, the private sector should align with the public sector and cooperate on efforts such as coordinating overlaps in EVFCS-related efforts. An economic cost–benefit analysis should also be carried out to explore optimal EVFCS placements. The EVFCS infrastructure is an emerging industry with significant potential. As the industry is still in its early stages, there remains an opportunity to establish an effective public–private cooperation framework.

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