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A Community Preference-Based Approach to Public EV Charging Station Site Selection Using ANP and ELECTRE I

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ABSTRACT

The provision of adequate charging infrastructure is crucial to support the adoption of electric vehicles (EVs) and advance sustainable energy policies. As one of Indonesia's largest metropolitan areas, Surabaya is transitioning toward electric mobility but currently suffers from a limited number of public EV charging stations (EVCS). This study proposes an integrated multi-criteria decision-making (MCDM) model combining the Analytic Network Process (ANP) and the ELECTRE method to address the EVCS site selection problem. ANP was employed to structure the decision model and determine the weights of the criteria, while ELECTRE was used to rank the alternative locations. A community preference-based approach was adopted to incorporate the perspectives of potential EV users—currently conventional vehicle drivers interested in switching to EVs. The results show that usage-related factors (66.68%) were prioritized over travel-related aspects (33.32%). Among the criteria, cleanliness and tidiness (36.40%) and security (31.90%) were the most influential, followed by road condition (10.72%) and the availability of cafés and restaurants (8.71%). Less dominant factors included retail facilities (4.20%), malls and entertainment (4.27%), and traffic volume (3.80%). Three candidate locations—previously identified based on expert judgment considering accessibility, energy availability, and population density—were evaluated. The final ranking of locations was derived using the weighted criteria and performance scores. Sensitivity analysis confirmed the stability and robustness of the results. This study provides a comprehensive and user-centered framework for EVCS site selection that enhances both technical feasibility and social responsiveness to urban mobility needs.

Keywords: *electric vehicle charging station (EVCS); location selection; multi-criteria decision making (MCDM); community preferences; charging infrastructure*

INTRODUCTION

Fossil energy sources have several critical drawbacks, particularly regarding environmental concerns and their non-renewable nature (Mufutau Opeyemi, 2021). Their use produces exhaust emissions that contribute to global warming and negatively impact human health (Lelieveld et al., 2019). Additionally, fossil fuels are finite resources that are bound to deplete over time (Capellán-Pérez et al., 2014). In Indonesia, the transportation sector is the second-largest contributor to carbon emissions after power generation. It accounts for 23% of total emissions, with 90% of this figure originating from land-based transportation (IESR, 2023; Kementerian LHK, 2022).

The development of electric vehicles (EVs) has become a key part of global strategies to address the 3144odelly crisis and climate change. According to Gelmanova et al. (2018), Evs are highly energy-efficient and can utilize renewable energy sources, thereby significantly reducing carbon emissions and offering a sustainable transportation solution. In line with this, Indonesia has started promoting the transition to low-emission vehicles as part of its efforts to decarbonize the transport sector, setting various EV adoption targets (IESR, 2023).

One of the major challenges in this transition is the availability of charging infrastructure, particularly public electric vehicle charging stations (EVCS). The development of charging stations is crucial to address public concerns over the limited driving range of Evs, commonly known as range anxiety (Burra et al., 2024). Moreover, the spatial placement of EVCS plays a vital role. Choosing strategic locations for EVCS greatly influences the success rate of EV adoption (Zou et al., 2020). This remains an issue in Indonesia. According to IESR (2023), EV adoption in Indonesia has grown significantly but still falls short of national targets. A public survey by Candra (2022) revealed that one of the biggest barriers to adoption is the lack of adequate charging infrastructure.

At the local level, Surabaya—one of Indonesia's largest metropolitan cities—has begun embracing electric mobility. However, charging infrastructure in the city remains insufficient. The latest data show there are at least 11 operational EVCS units in Surabaya (Agus, 2025; Alvin, 2025). This number is relatively low, and the locations of these stations do not adequately support intra-city mobility needs, as they are generally situated in limited-access or privately managed areas. Most existing EVCS units are located in shopping malls and hotels, which generally restrict access to customers of those establishments. Others are situated at PLN (state electricity company) offices, which are more accessible internally, typically serving PLN employees and visitors, although they are technically open to the public. Moreover, they primarily serve as demonstration models for public awareness rather than being optimized for practical daily use (Syofiadi, 2024). Given these limitations, expanding the number of EVCS in Surabaya is essential, and selecting strategic locations is critical to meeting urban EV mobility demands.

The 3145odellis of EVCS deployment is influenced by a variety of factors,3145odellingg technical considerations like electricity grid availability, accessibility, and distribution, as well as other contextual elements. Thus, selecting EVCS locations requires a systematic approach that accounts for multiple factors. Multi-Criteria Decision Making (MCDM) methods are widely recommended and have been extensively applied in EVCS site selection studies (Banegas & Mamkhezri, 2023). MCDM facilitates decision-making based on multiple, often conflicting, factors by incorporating subjective assessments. Among these methods, the Analytic Hierarchy Process (AHP) is the most frequently used, often in combination with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). These methods are popular due to their simplicity and structured approach—AHP is used for weighting preferences, while TOPSIS helps in ranking alternatives (Banegas & Mamkhezri, 2023).

However, AHP and TOPSIS have notable limitations. TOPSIS allows full compensation between criteria, where weaknesses can be offset (compensated) by strengths, potentially leading to suboptimal results—as seen in the AHP-TOPSIS integration by Kaya et al. (2021). AHP, on the other hand, assumes all criteria are independent, limiting its accuracy in capturing real-world interrelations, as shown in Mahdy et al. (2022). Despite these drawbacks, AHP remains widely used due to its simplicity, as noted in a systematic review by Banegas & Mamkhezri (2023). Guler & Yomralioglu (2020) improved preference reliability by combining AHP, fuzzy AHP, and WLC, though these methods still lacked interdependency 3145odelling. As a result, most studies continue to focus on refining criteria rather than shifting to methods that better reflect decision-making complexity.

Furthermore, current approaches are predominantly based on expert judgment—inputs from infrastructure or energy specialists—which results in decisions that mainly reflect the developer's perspective while overlooking those of end users (Banegas & Mamkhezri, 2023). However, community inclusion is crucial. Some studies have started to adopt user-based approaches, such as preference-based selection schemes using AHP-TOPSIS (Habbal & Alrifaie, 2024), Best–Worst Method and GRA (Saleh, 2024), or Discrete Choice Modeling (Bhat et al., 2024), but these either lack comprehensive inter-criteria analysis or rely on limited empirical input. Similarly, Deveci et al. (2023) examined charger types from the user's view. These studies show rising interest in user-based approaches, but few address urban complexity or stakeholder conflict.

To address these gaps, this study adopts the *Analytic Network Process* (ANP) and the *Elimination Et Choix Traduisant la Realité* (*ELECTRE*) method. ANP, an extension of AHP, has been applied successfully in complex decision contexts like nuclear power plant siting (Topaloğlu, 2025) and offers flexibility in 3145odelling interrelated elements. *ELECTRE*, on the other hand, improves on TOPSIS by applying outranking logic, thus handling conflicting criteria through dominance rather than full compensation (Rocha, 2023). Although both methods are rarely applied in EVCS site selection literature (Banegas & Mamkhezri, 2023), their characteristics make them suitable for urban EV infrastructure planning. By combining ANP and *ELECTRE*, this study aims to develop a community-responsive, multi-criteria model that addresses the interdependence and conflict among selection factors while reflecting user needs.

Based on the identified challenges and opportunities, this study aims to develop a community preference-based approach for public EV charging station (EVCS) site selection in Surabaya by integrating the *Analytic Network Process* (ANP) and *ELECTRE I* methods. The specific objectives of this research are: (1) to identify potential EVCS locations in Surabaya to support EV adoption; (2) to determine the criteria for EVCS location selection based on future users' needs; (3) to develop a multi-criteria decision-making model that reflects interrelated and conflicting criteria while incorporating community preferences; (4) to apply the model to determine criteria weights and rank EVCS location alternatives; and (5) to identify priority EVCS locations based on the model outcomes. The benefits of this research include providing a holistic and practical framework for urban planners and infrastructure developers, ensuring that EVCS development is not only technically feasible but also socially responsive to real urban mobility needs and public preferences, thereby ultimately accelerating the transition towards sustainable urban transportation in Indonesia.

METHOD

This study follows four main steps, as shown in Figure 1: data collection, criteria weighting with ANP, alternative ranking using ELECTRE, and sensitivity analysis to evaluate the robustness of the ranking results.

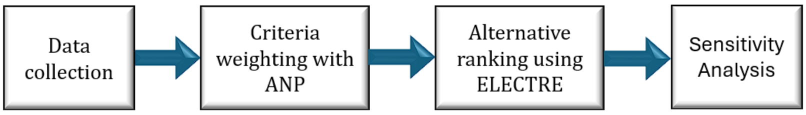

Figure 1. Research framework

The data collected in this study consist of two primary components: pairwise comparisons of the criteria and performance scores of the location alternatives. The pairwise comparisons were used in the ANP process to derive the relative weights of each criterion. These weights, combined with the alternative scores, were then processed using the ELECTRE method to rank the potential locations. Data were gathered through an online questionnaire distributed via Google Forms. A number of 10 respondents were involved, residing in various areas across Surabaya who have driving experience. The questionnaire included items to assess respondents' interest in driving an electric vehicle (EV) in the future (if not already), as well as their level of understanding of electric vehicle charging stations (EVCS). This approach ensured a targeted and contextually relevant respondent base.

To maintain the quality of the pairwise comparison data, it was essential to ensure that respondents' inputs met an acceptable level of consistency. To facilitate this, an interactive questionnaire was developed using Google Gemini, an artificial intelligence–based assistant, which was prompted to generate a consistency-aware ANP form, available at this link: https://g.co/gemini/share/3e31ce030201. The tool enabled real-time calculation and display of the consistency ratio (CR) for each set of responses, allowing participants to revise their inputs immediately if the CR exceeded 0.1. This mechanism improved the overall efficiency of the data collection process by eliminating the need for repeated follow-ups, which are commonly required in traditional surveys where inconsistencies are detected only after submission. To ensure further accuracy, all final responses were subsequently validated using Super Decisions, a globally recognized software for decision-making analysis.

The decision model in this study was structured using a 4-level network configuration in accordance with the Analytic Network Process (ANP) framework. Unlike the hierarchical nature of AHP (Analytic Hierarchy Process), the ANP model accommodates relevant interdependencies among elements, allowing selective rather than exhaustive connections, as shown in Figure 2, reducing the number of necessary pairwise comparisons.

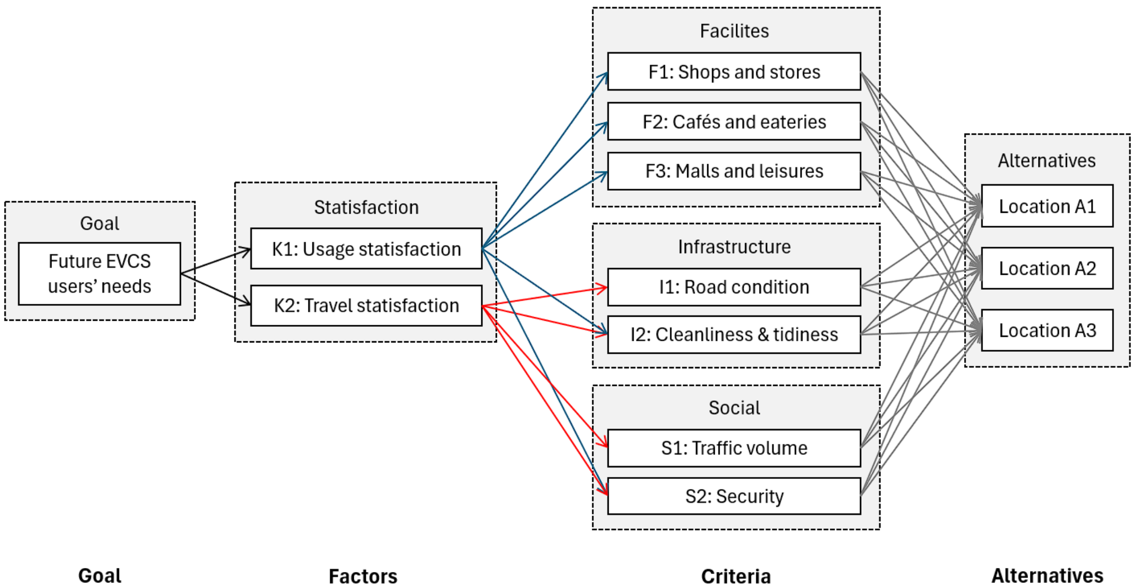

Figure 2. Network Model

The model is designed to capture the future needs of EVCS users, represented as the ultimate goal. It consists of two main factors—usage satisfaction and travel satisfaction—which are influenced by a set of criteria categorized into facilities, infrastructure, and social dimensions. These criteria are further linked to the location alternatives being evaluated. The selection of criteria in this study was grounded in a comprehensive review of relevant literature and further refined through a focus group discussion (FGD) involving four selected respondents from different residential areas. Table 1 presents the list of criteria along with their descriptions, sources, and interdependencies within the model. No feedback relations were considered.

Table 1. List of Criteria

Cluster	Element	Code	Description	References	Dependencies
Satisfaction	Usage satisfaction	K1	User satisfaction during the EVCS charging process.	(Hanni et al., 2024; Sabzi & Vajta, 2024)	Goal (future EVCS users' needs)
	Travel satisfaction	K2	Satisfaction while driving an electric vehicle to/from the EVCS.	(Lyu et al., 2024; Mouratidis, 2020)	Goal (future EVCS users' needs)
Facilities	Shops and stores	F1	Availability of minimarkets, convenience stores, traditional markets, supermarkets, etc.	(Csiszár et al., 2020; Hanni et al., 2024; Schmidt et al., 2021)	Usage satisfaction
	Cafés and eateries	F2	Availability of cafés, restaurants, coworking spaces, etc.	(Csiszár et al., 2020)	Usage satisfaction
	Malls and entertainment	F3	Availability of shopping centers, recreation areas, and entertainment venues.	(Dong et al., 2019; Y. Li et al., 2021; Sun, 2020)	Usage satisfaction
Infrastructure	Road condition	I1	Quality of road surfaces (no damage, potholes, or roughness).	(Ajayi et al., 2024; M. Li et al., 2022)	Travel satisfaction
	Cleanliness and tidiness	I2	The area is not slum-like and the infrastructure is properly constructed and organized.	(ISO 37120:2018; M. Li et al., 2022)	Usage satisfaction & travel statisfaction
Social	Traffic volume	S1	The smoothness of traffic flow around the area.	(Csiszár et al., 2020)	Travel satisfaction
	Security	S2	Potential to avoid crime, vandalism, and related safety concerns.	(Ademulegun et al., 2022; Xu et al., 2013)	Usage satisfaction & travel statisfaction

Source: Author's analysis results (2024)

Within the facilities criteria, the term "availability" is deliberately used in this study instead of the commonly used "proximity" to emphasize a broader interpretation. While previous studies—particularly those utilizing Geographic Information System (GIS)-based spatial analysis—tend to define the facilities criteria in terms of distance and quantity, "availability" in this paper also includes qualitative dimensions such as brand, size, type, and perceived quality. This broader perspective reflects the subjective evaluations of community respondents, offering more comprehensive and user-centered insights into EVCS site preferences.

The candidate EVCS locations in this study were adopted from a prior spatial analysis by Ummah & Diyono (2024), who identified 20 potential sites in Surabaya using Spatial Multi-Criteria Evaluation (SMCE) and AHP, based on input from infrastructure and energy experts. Their evaluation included four main factors: environmental aspects (e.g., vegetation, river proximity, slope), transportation infrastructure (e.g., road access, intersections, public transit), energy supply (e.g., gas stations, existing EVCS, grid access), and socio-economic conditions (e.g., proximity to CBDs, public facilities, and residential areas). Socio-economic aspects were used to approximate demand, assuming activity levels and purchasing power affect EV adoption. The inclusion of major roads was aimed at ensuring accessibility. This research focuses specifically on fast-charging EVCS for intra-city mobility. Therefore, the selected locations are intended to be stand-alone or roadside facilities—not those embedded within private establishments like malls, offices, hotels, or hospitals. From their findings, the top three sites with the highest composite scores were selected for further analysis in this study. Details of these sites—including codes, street names, and coordinates—are shown in Table 2. This research extends their work by applying a more community-focused decision model to a smaller set of alternatives.

Table 2. List of Location Alternatives

Code	Address	Coordinates
A1	Mayjend Jonosewojo Street	7°17'35.1"S, 112°40'33.5"E
A2	Raya Darmo Street	7°16'57.9"S, 112°44'24.3"E
A3	Perak Timur Street	7°12'50.4"S, 112°44'01.2"E

Source: Adapted from Ummah & Diyono (2024)

All criteria weighting was conducted using Super Decisions software, version 4.2. The network model includes only the top three levels: goal, satisfaction factors, and criteria, as ANP in this study is applied solely for weighting the criteria, not for evaluating alternatives. Figure 3 shows the software's interface displaying the constructed network model. All calculations were performed automatically by the software, generating a weighted supermatrix and a limit supermatrix. The input consisted of pairwise comparisons among the criteria, averaged using the geometric mean from 20 respondents and verified for consistency.

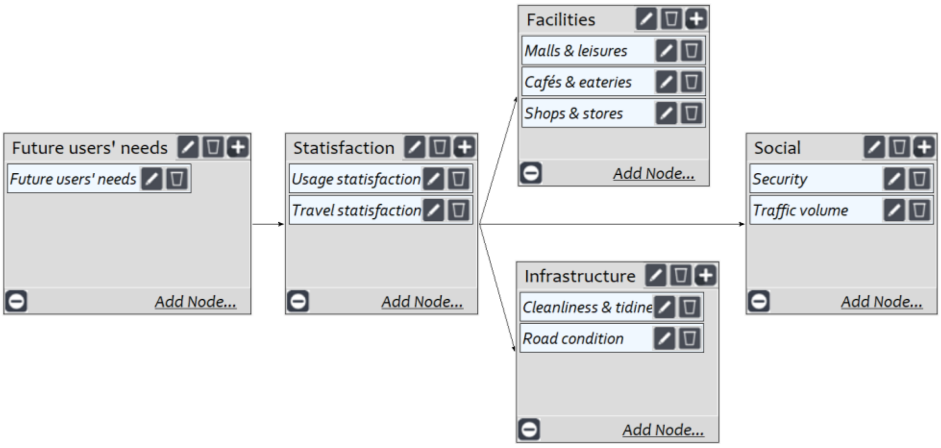

Figure 3. Criteria Network Model in Super Decisions

Source: Questionnaire results, processed by the author (2024)

ELECTRE I (Elimination and Choice Translating Reality) was applied to determine the priority ranking of alternatives using the outranking approach. ELECTRE I was selected for its simplicity in ranking. ELECTRE II, which provides both strong and weak rankings, was not deemed necessary for this study. Meanwhile, ELECTRE III focuses on fuzzy values, which are also not relevant to the research objectives.

Respondents were asked to rate each location on a scale from 0 to 10 for every criterion, based on their personal experience and knowledge, assisted by online map information from Google Maps. The 0–10 scale was used for its simplicity and ease of understanding. The coordinates of the candidate locations, along with Google Maps links, were provided in the questionnaire. Arithmetic mean was used for aggregation. Since all scores are within a uniform scale of 0 to 10, normalization was deemed unnecessary.

The ELECTRE process was carried out using Microsoft Excel, following these steps:

Step 1: Constructing the input matrix from the alternative scores and ANP-derived criteria weights.

The input matrix was constructed as the initial step. It contains the alternative scores obtained from the data collection process and the global weights of the criteria derived from the ANP analysis.

Step 2: Weighted Matrix.

This step involves multiplying each score with the corresponding criterion weight and aims to incorporate the influence of criteria weights into the decision matrix using Equation 1:

$$V = \left(v_{ij}\right) \text{n} \times \text{m} \tag{1}$$

Step 3: Determining Concordance Sets.

ELECTRE divides the decision criteria into two subsets for each pair of alternatives: the concordance set (C_{kl}) and the discordance set (D_{kl}). The comparison considers the nature of the criteria (benefit or cost) and determines which criteria support or oppose one alternative over another. C_{kl} is set of criteria in which alternative k performs better or equal to alternative l, indicating support for dominance. Formally:

$$C_{kl} = \left\{j \middle| x_{kj} \geq x_{lj}\right\} \tag{2}$$

Step 4: Constructing the Concordance Matrix

The concordance index is calculated as the sum of weights associated with the concordance set:

(3)

$$c_{kl} = \sum_{j \in C_{kl}} w_j$$

The concordance matrix (C) is then constructed as:

$$C = \begin{bmatrix} - & c_{12} & \cdots & c_{1n} \\ c_{21} & - & \cdots & c_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{m(m-1)} & - \end{bmatrix} \tag{4}$$

Step 5: Constructing the Concordance Dominance Matrix (F)

A Boolean matrix (F) is constructed to indicate dominance relationships based on a concordance threshold $\bar{c}$. Each element is determined as (Equation 5):

$$f_{kl} = \begin{cases} 1 & if\ c_{kl} \geq \bar{c} \\ 0 & if\ c_{kl} < \bar{c} \end{cases} \tag{5}$$

The threshold $\bar{c}$ may be assumed (e.g., 0.7), but in this study we computed as (Equation 6):

$$\bar{c} = \sum_{\substack{k=1 \\ k \neq l}}^{m} \sum_{\substack{l=1 \\ l \neq k}}^{m} \frac{c_{kl}}{m(m-1)} \tag{6}$$

Step 6: Determining Discordance Sets.

D_{kl} is set of criteria where alternative k performs worse than alternative l, indicating opposition to dominance:

$$D_{kl} = \{j | x_{kj} < x_{lj}\} = J - C_{kl} \tag{7}$$

Step 7: Constructing the Discordance Matrix

This step focuses on the degree to which one alternative underperforms compared to another. The discordance index is calculated as follows (Equation 8):

$$d_{kl} = \frac{\max_{j \in D_{kl}} |v_{kj} - v_{lj}|}{\max_{j \in J} |v_{kj} - v_{lj}|} \tag{8}$$

The discordance matrix (D) is formed similarly (Equation 9):

$$D = \begin{bmatrix} - & d_{12} & \cdots & d_{1n} \\ d_{21} & - & \cdots & d_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & \cdots & d_{m(m-1)} & - \end{bmatrix} \tag{9}$$

Values range between 0 and 1. A higher d_{kl} indicates that alternative k is significantly worse than l, while a lower value indicates relative superiority.

Step 8: Constructing the Discordance Dominance Matrix (G)

Similarly, a discordance dominance matrix (G) is constructed with a threshold $\bar{d}$, which may be assumed (e.g., 0.3), but we calculated as:

$$\bar{d} = \sum_{\substack{k=1 \\ k \neq l}}^{m} \sum_{\substack{l=1 \\ l \neq k}}^{m} \frac{d_{kl}}{m(m-1)} \tag{10}$$

Each element of matrix G is determined in contrast to the concordance index, where a value of 1 is assigned if the discordance index is less than or equal to the discordance threshold $(\bar{d})$, and 0 otherwise. Formally:

$$g_{kl} = \begin{cases} 1 & if\ d_{kl} \leq \bar{d} \\ 0 & if\ d_{kl} > \bar{d} \end{cases} \tag{11}$$

Step 9: Constructing the Aggregate Dominance Matrix I

This final step intersects matrices F and G to form the aggregate dominance matrix (E). Each element e_{kl} is calculated as:

$$e_{kl} = f_{kl} \times g_{kl} \tag{12}$$

The resulting matrix contains only 0 or 1 values for $k \neq l$, indicating whether alternative k outranks alternative l. By analyzing the number of times each alternative outranks others (i.e., counting the number of 1s in each row), a final ranking of the alternatives can be established.

RESULTS AND DISCUSSION

FINDINGS

Collected data from the questionnaire are the pairwise comparisons of the criteria as shown in Table 3 to Table 7. They are the geometric mean of all the 20 respondents' answers and the input for ANP process.

Table 3. Pairwise Comparisons of The Facilities With Respect to Usage Satisfaction

Criteria	Code	Malls & leisures F3	Cafés and eateries F2	Shops & stores F1
Malls & leisures	F3	1	0,495	1,006
Cafés and eateries	F2	2,021	1	2,094
Shops & stores	F1	0,994	0,478	1

Source: Questionnaire results, processed by the author (2024)

Table 4. Pairwise Comparisons of the Infrastructure Aspects with Respect to Travel Satisfaction

Criteria	Code	Road condition I1
Cleanliness and tidiness	I2	0,768

Source: Questionnaire results, processed by the author (2024)

Table 5. Pairwise Comparisons of the Social Aspects with Respect to Travel Satisfaction

Criteria	Code	Traffic Volume S1
Security	S2	2,781

Source: Questionnaire results, processed by the author (2024)

Table 6. Pairwise Comparisons of The Satisfaction Factors with Respect to The Goal

Criteria	Code	Travel Statisfaction K2
Usage Statisfaction	K1	2,001

Source: Questionnaire results, processed by the author (2024)

Table 7. Pairwise Comparisons of The Clusters with Respect to Satisfaction

Cluster	Facility	Infrastructure	Social
Facility	1	0,902	1,949
Infrastructure	1,109	1	1,587
Social	0,513	0,630	1

Source: Questionnaire results, processed by the author (2024)

The other collected data is the alternative scores. The arithmetic mean of all 10 participants' answers is shown in Table 8. This is part of the input for the ELECTRE process.

Table 8. Collected Data: Alternative Scores

No.	Criteria		Score (0-10) Location A1	Location A2	Location A3
1	Shops and stores availability	F1	6,7	5,4	6,4
2	Cafés and eateries availability	F2	7,7	6,6	5,1
3	Malls and entertainment availability	F3	6,8	5,4	4,7
4	Road condition	I1	6,8	8,6	6,5
5	Cleanliness and tidiness	I2	7,2	8,1	6,3
6	Traffic volume	S1	6,6	7,0	7,8
7	Security	S2	7,2	7,9	6,3

Source: Questionnaire results, processed by the author (2024)

Criteria weighting with ANP gives 2 results: weighted supermatrix and limit supermatrix. The non-zero values are extracted. For limit supermatrix, normalization is necessary. Weighted supermatrix gives information on local weights: weights only considering the direct dependencies, given in Table 9. While limit supermatrix gives the overall priorities (global weights), considering both direct and indirect dependencies, given in Table 10. Both of the statisfaction factors only have direct connections to the goal, thus the limiting process doesn't change their values. Because of this, for statisfaction factors, we use the local weight values as the global weights.

Table 9. ANP Result: Weighted Supermatrix of The Criteria

		Future EVCS users' needs	Usage statisfaction	Travel statisfaction
Elemen	**Code**	**Goal**	**K1**	**K2**
Usage satisfaction	K1	0,6668	0,0000	0,0000
Travel satisfaction	K2	0,3332	0,0000	0,0000
Shops and stores availability	F1	0,0000	0,0630	0,0000
Cafés and eateries availability	F2	0,0000	0,1306	0,0000
Malls and entertainment availability	F3	0,0000	0,0640	0,0000
Road condition	I1	0,0000	0,0000	0,3218
Cleanliness and tidiness	I2	0,0000	0,4224	0,2471
Traffic volume	S1	0,0000	0,0000	0,1140
Security	S2	0,0000	0,3200	0,3171
Total		**1,0000**	**1,0000**	**1,0000**

Source: Super Decisions v4.2 processed by the author (2024)

Table 10. ANP Result: Overall Priorities of The Criteria

Criteria	Code	Global weight normalized by cluster	Global weight	Rank
Facility:				
Shops and stores	F1	0,24455	0,0420	6
Cafés and eateries	F2	0,50699	0,0871	4
Malls and entertainment	F3	0,24847	0,0427	5
			0,1718	
Infrastructure:				
Road condition	I1	0,22757	0,1072	3
Cleanliness and tidiness	I2	0,77243	0,3640	1
			0,4712	
Social:				
Traffic volume	S1	0,10641	0,0380	7
Security	S2	0,89359	0,3190	2
			0,3570	

Source: Super Decisions v4.2 processed by the author (2024)

The ELECTRE process uses the results from ANP. The input matrix is shown in Table 11, which consists of: Alternative scores from Table 8 and criterion weights from Table 10.

Table 11. Input Matrix for ELECTRE Process

	Criteria						
Alternatives	**F1**	**F2**	**F3**	**I1**	**I2**	**S1**	**S2**
A1	6,7	7,7	6,8	6,8	7,2	6,6	7,2
A2	5,4	6,6	5,4	8,6	8,1	7	7,9
A3	6,4	5,1	4,7	6,5	6,3	7,8	6,3
Weight	**0,0420**	**0,0871**	**0,0427**	**0,1072**	**0,3640**	**0,0380**	**0,3190**

Source: Results of questionnaire and ANP data processing by the author (2024)

The ELECTRE method gives concordance and discordance set, as well as the weighted values differences. This matrices give information on how the alternatives outrank eachother with respect to each criterion. The final result of the ELECTRE would be the general matrix (aggregate domincance matrix) as shown in Table 15.

Table 12. Concordance Set

	F1	F2	F3	I1	I2	S1	S2	Total
A1 vs A2	0,0420	0,0871	0,0427	0,0000	0,0000	0,0000	0,0000	0,1718
A1 vs A3	0,0420	0,0871	0,0427	0,1072	0,3640	0,0000	0,3191	0,9620
A2 vs A1	0,0000	0,0000	0,0000	0,1072	0,3640	0,0380	0,3191	0,8282
A2 vs A3	0,0420	0,0871	0,0427	0,1072	0,3640	0,0000	0,3191	0,9620
A3 vs A1	0,0000	0,0000	0,0000	0,0000	0,0000	0,0380	0,0000	0,0380
A3 vs A2	0,0420	0,0000	0,0000	0,0000	0,0000	0,0380	0,0000	0,0800

Source: Results of the calculation of ELECTRE I by the author (2024)

Table 13. Differences of The Weighted Values

	F1	F2	F3	I1	I2	S1	S2
A1—A2	0,05461	0,095799	0,059755	-0,193	-0,32756	-0,0152	-0,22334
A1—A3	0,012602	0,226434	0,089632	0,032167	0,327559	-0,04559	0,287145
A2—A1	-0,05461	-0,0958	-0,05975	0,193003	0,327559	0,015197	0,223335
A2—A3	-0,04201	0,130635	0,029877	0,22517	0,655117	-0,03039	0,51048
A3—A1	-0,0126	-0,22643	-0,08963	-0,03217	-0,32756	0,04559	-0,28715
A3—A2	0,042008	-0,13064	-0,02988	-0,22517	-0,65512	0,030394	-0,51048

Source: Results of the calculation of ELECTRE I by the author (2024)

Table 14. Discordance Set

	F1	F2	F3	I1	I2	S1	S2
A1—A2	0	0	0	0,193003	0,327559	0,015197	0,223335
A1—A3	0	0	0	0	0	0,04559	0
A2—A1	0,05461	0,095799	0,059755	0	0	0	0
A2—A3	0,042008	0	0	0	0	0,030394	0
A3—A1	0,012602	0,226434	0,089632	0,032167	0,327559	0	0,287145
A3—A2	0	0,130635	0,029877	0,22517	0,655117	0	0,51048

Source: Results of the calculation of ELECTRE I by the author (2024)

In the concordance set (Table 12), the non-zero values indicates dominance. The values shown are the weights of the related criteria, irrelevant to interpretation, but used for equations. The discordance set (Table 14) shows the values of the non-dominances extracted from the Table 13. The values shown are the differences of the weighted values. Table 13 gives more understanding of how much an alternative outranks others.

Table 15. ELECTRE Result: The Dominance Matrix

	A1	A2	A3
A1	0	0	1
A2	1	0	1
A3	0	0	0

Source: Results of the calculation of ELECTRE I by the author (2024)

In the aggregate dominance matrix (Table 15), a value of 1 indicates that the alternative in the left column outranks the alternative in the top row. The results show that:

- A1 outranks A3;
- A2 outranks both A1 and A3; and
- A3 does not outrank any other alternative.

Therefore, the final prioritization of alternatives is: $A_2 \rightarrow A_1 \rightarrow A_3$.

A sensitivity analysis was conducted by focusing on the two criteria with the highest weights: security (S2) and cleanliness & tidiness (I2). The weights of these two criteria were increased and decreased to create 10 different scenarios for comparison. The weights of the remaining criteria were adjusted proportionally to ensure the total weight remained equal to 1. The weight scenarios and the resulting rankings are shown in Table 16. The analysis shows that the ranking remains consistent across all scenarios, indicating the robustness of the model and confirming that the final ranking is stable and reliable: $A_2 \rightarrow A_1 \rightarrow A_3$.

Table 16. Sensitivity Analysis

Analyzed criteria	Scenario	Weight	Dominance matrix				Location ranking		
				A1	A2	A3	1	2	3
Security (S2)	1	0,3190	A1	0	0	1		A1	
			A2	1	0	1	A2		
			A3	0	0	0			A3
	2	0,4000	A1	0	0	1		A1	
			A2	1	0	1	A2		
			A3	0	0	0			A3
	3	0,4500	A1	0	0	1		A1	
			A2	1	0	1	A2		

Analyzed criteria	Scenario	Weight	Dominance matrix				Location ranking		
				A1	A2	A3	1	2	3
			A3	0	0	0			A3
	4	0,2700	A1	0	0	1		A1	
			A2	1	0	1	A2		
			A3	0	0	0			A3
	5	0,2000	A1	0	0	1		A1	
			A2	1	0	1	A2		
			A3	0	0	0			A3
Cleanliness & tidiness (I2)	1	0,3640	A1	0	0	1		A1	
			A2	1	0	1	A2		
			A3	0	0	0			A3
	2	0,3500	A1	0	0	1		A1	
			A2	1	0	1	A2		
			A3	0	0	0			A3
	3	0,4000	A1	0	0	1		A1	
			A2	1	0	1	A2		
			A3	0	0	0			A3
	4	0,2500	A1	0	0	1		A1	
			A2	1	0	1	A2		
			A3	0	0	0			A3
	5	0,2000	A1	0	0	1		A1	
			A2	1	0	1	A2		
			A3	0	0	0			A3

Source: Results of the calculation of ELECTRE I by the author (2024)

DISCUSSION

This study proposes an EVCS location selection approach that incorporates the preferences of road users from the general public, diverging from previous studies that relied primarily on expert judgment. By engaging public users, the assessment of facility-related criteria encompasses broader and more contextual qualitative dimensions—such as comfort, quality, brand, type, and size of nearby facilities—rather than relying solely on quantitative indicators like distance or number. Accordingly, this study adopts the term *"availability"* rather than merely *"proximity,"* acknowledging that users' perception of a facility's presence is not always based on physical distance but is shaped by their experience, observation, and subjective perception of its presence and quality.

The decision-making model integrates ANP and ELECTRE methods. The ANP structure distinguishes two key dimensions of perceived user satisfaction: *usage satisfaction* (at the EVCS location) and *travel satisfaction* (to and from the EVCS). ANP results indicate that usage satisfaction holds a higher weight (64.30%) than travel satisfaction (35.70%), suggesting that users prioritize comfort during the charging process over travel conditions to the site.

At the criteria level, the limiting supermatrix results show that *cleanliness & tidiness (I2)* is the most important factor (0.3640), followed by *security (S2)* (0.3190), *road condition (I1)* (0.1072), *cafés & eateries availability (F2)* (0.0871), *malls & entertainment (F3)* (0.0427), *shops (F1)* (0.0420), and *traffic volume (S1)* (0.0380). These findings highlight that cleanliness and safety are primary concerns, while commercial facilities like shops and malls are considered less influential in users' decision-making.

At the cluster level, infrastructure is the most prioritized aspect (0.4712), followed by social (0.3570) and facility (0.1718), indicating that users in Surabaya place greater emphasis on the physical and social environment around the EVCS than on the surrounding commercial amenities.

The relative weights within each cluster further clarify user preferences. In the *facility* cluster, cafés and eateries (F2) are ranked highest (0.50699), followed by malls (F3) (0.24847) and shops (F1) (0.24455). In the *infrastructure* cluster, cleanliness and tidiness (I2) dominate (0.77243) over road condition (I1) (0.22757). Within the *social* cluster, security (S2) holds a dominant position (0.89359) compared to traffic volume (S1) (0.10641).

In terms of modeling efficiency, the ANP network structure only requires nine pairwise comparisons between elements, as opposed to twelve comparisons in a conventional AHP hierarchy. This demonstrates that ANP not only captures interdependencies among criteria more realistically but also offers implementation efficiency.

The ELECTRE method was used to replace the direct comparison of alternatives typically performed within ANP, particularly to address the complexity arising from a larger number of location options. The ELECTRE results rank *A2 (Jl. Raya Darmo)* as the top candidate, followed by *A1 (Jl. Mayjen Jonosewo)*, and *A3 (Jl. Perak Timur)* as the least favorable. A2 excels in infrastructure and social aspects—the most influential clusters—while A3, which only performs well on traffic volume (a minor criterion with a weight of 0.0380), scores poorly in key dimensions like cleanliness and security.

A sensitivity analysis was conducted on the two most influential criteria—cleanliness & tidiness (0.3640) and security (0.3190)—by adjusting their weights across multiple scenarios. The results indicate that the ranking remains stable (A2 → A1 → A3), confirming that the proposed model is robust and consistent despite varying respondent preferences.

Overall, the findings offer clear strategic guidance for urban EVCS planning. Priority should be given to cleanliness, safety, and road conditions, as these factors significantly influence user satisfaction. While the presence of commercial facilities may support decision-making, they should not be considered primary criteria. This user-centered approach captures more personal and nuanced evaluation dimensions and complements previous expert-driven studies.

In addition to the global (limiting) weights presented in Table 10, the weighted supermatrix (Table 9) also provides strategic insight for decision-making. While the limiting weight reflects the overall priority, the weighted supermatrix enables a more flexible and context-sensitive analysis—especially useful when planning efforts are focused on a specific aspect.

For instance, when prioritizing *travel satisfaction* (K2), the key considerations are *road condition (I1)* at 0.3218, followed by *security (S2)* (0.3171) and *cleanliness & tidiness (I2)* (0.2471). Conversely, if the focus is on *usage satisfaction* (K1), the highest influence comes from *cleanliness (I2)* (0.4224) and *security (S2)* (0.3200). Therefore, ANP enables a richer and more contextual interpretation compared to AHP, which yields a single set of global priorities without accounting for interdependencies.

This approach allows policymakers to formulate adaptive EVCS development strategies, such as enhancing road infrastructure and safety along travel corridors or improving the charging site's comfort for users during the charging process.

CONCLUSION

This study presents a comprehensive, user-centered approach to selecting electric vehicle charging station (EVCS) locations by integrating the *Analytic Network Process* (ANP) with the *ELECTRE* method, shifting the focus from expert judgment to capturing the preferences of road users. By distinguishing between usage satisfaction and travel satisfaction, the ANP model highlights the greater importance of usage satisfaction factors such as cleanliness, tidiness, and security, while also underscoring the value of cafés and eateries as key amenities during charging. The *ELECTRE* application effectively manages a broad set of candidate sites, identifying Jl. Raya Darmo (A2) as the top location excelling in infrastructure and social aspects, with results confirmed by robust sensitivity analysis. The model's flexibility—enabled by weighted and limiting supermatrices—and its ability to capture interdependencies among criteria demonstrate clear advantages over traditional methods like AHP. Overall, this study advances a realistic, preference-sensitive framework that prioritizes user comfort and safety, offering valuable guidance for policymakers and urban planners to improve EVCS deployment and promote electric vehicle adoption. For future research, it is suggested to extend this framework by incorporating dynamic user behavior data and real-time usage patterns to further refine site selection and operational strategies in evolving urban mobility contexts.

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