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Evaluating the Importance of Criteria for Electric Vehicle Implementation: A Case Study of Lithuania

Victor Hugo^{1*}, Daniel Cruz¹, Javier Salazar²

Abstract

This research outlines a structured framework comprising 7 primary categories and 50 underlying sub-factors designed to evaluate the rollout of electric vehicles (EVs). To establish the local importance weights for these sub-factors, the study employed two approaches: variants of the Average Rank Transformation and the Analytic Hierarchy Process (AHP). Consensus among the specialists was achieved by averaging the rankings assigned to both the main categories and the sub-factors, thereby resolving the assessment task. The mean local weights were further derived using three distinct Multiple Criteria Decision-Making (MCDM) techniques, thereby enhancing the overall reliability of the outcomes. Consequently, the overall (global) weights and ranking order of the sub-factors were determined. According to the specialists, the nationwide advancement of EVs is predominantly influenced by the elevated expenses associated with producing and acquiring EVs, the provision of monetary subsidies to buyers of EVs, the elimination of tailpipe emissions, the rollout of rapid charging facilities, and the current shortage of supporting infrastructure across the nation's five major urban centers. The analysis indicates that, among the 50 sub-factors, the top 10 most influential ones (predominantly tied to economic considerations) collectively account for over 35% of the total global weight. Meanwhile, the 22 highest-priority sub-factors exceed the mean weight threshold (0.2) and together represent roughly 65%. These insights offer practical guidance for government officials responsible for shaping EV adoption strategies.

Keywords Electric vehicle, Expert systems, Hierarchical systems, Road vehicles, Sustainable transportation, Weight measurement

*Correspondence:

Victor Hugo

victor.hugo@unal.edu.co

¹ Department of Intelligent Energy Systems, Faculty of Engineering, National University of Colombia, Bogota, Colombia

² Department of Smart Grid Analytics, Faculty of Engineering, University of Antioquia, Medellin, Colombia

Introduction

Achieving the vision of a smart city requires upgrading the transportation network, especially by shifting toward electrification to curb air and noise pollution levels. Data from the European Automobile Manufacturers' Association (ACEA) indicate a sustained long-term reduction in CO₂ emissions from vehicles produced across Europe (EU + EFTA + UK), yet emissions rose by 0.3%–1.8% between 2017 and 2019 [1]. From 2020 to 2021, Europe experienced a 6.4% uptick (reaching 114.7 g/km). In Lithuania, newly registered vehicles showed a sharper 13.7% increase, climbing to 135.7 g/km [2]. To mitigate the environmental burden from road transport emissions, the European Parliament and Council agreed that, starting in 2035, every new passenger car and van registered in Europe must produce zero emissions [3]. This regulatory mandate compels automakers to align their future strategies with full electrification. Such profound shifts in vehicle propulsion technology pose major hurdles for both consumers and those developing charging networks.

Although EVs have recently seen notable gains in market presence, their actual presence on roads remains modest. This stems from the typical lag in market penetration for innovative products—particularly in nations with moderate or lower income levels—where EVs carry substantially higher price tags than traditional internal combustion engine (ICE) vehicles. Furthermore, moving to electrified mobility raises broad societal challenges, including the need to embrace novel technologies and the economic disruptions of shifting away from petroleum-based fuels toward electricity [4]. The pace and success of EV adoption differ across nations, shaped by vehicle pricing, energy infrastructure, and other variables; nonetheless, the underlying drivers often vary. While inadequate charging facilities frequently emerge as a key obstacle to EV expansion studies, separate scrutiny is warranted of fiscal factors, governmental policies, and societal views on environmental protection. Variations in citizens' and businesses' financial capacity also lead to wide differences in the typical age of national vehicle stocks. Since EV rollout hinges on diverse factors and national contexts, gathering expert assessments to gauge the relative importance of these elements is valuable. This paper offers two linked contributions. The first involves creating two variations of Average Rank Transformations alongside the Analytic Hierarchy Process to compute local weights tailored to this particular subject. The second applies these developed techniques to pinpoint the most critical factors influencing EV rollout within a defined geographic and social setting, providing actionable input for policymakers and agencies promoting sustainable mobility.

Literature Review

Electric vehicle deployment issues in different regions

Various nations and regions face both shared and unique barriers to expanding EV adoption. China leads globally in EV production; in 2023, it accounted for roughly 60% of worldwide new EV registrations, with projected annual growth of 7% [5]. Insights from the Chinese experience, therefore, serve as a useful reference for advancing alternative propulsion in transportation. A sensitivity study in Shandong province revealed that, at lower EV adoption rates, the focus should be on the number and placement of public charging stations. As EV share rises, greater priority shifts to fast-charging options [6]. Moreover, mobile charging needs, varied charging patterns, and station configurations are closely linked to service standards and EV integration levels [6, 7]. Further research on China's EV uptake showed that short-term gains were achieved through financial subsidies and regulatory measures. At the same time, longer-term progress relies on removing purchase barriers, expanding charging networks, government fleet purchases, and fuel pricing dynamics [8].

Agent-based modeling has examined how subsidies and ecological factors drive EV adoption [9]. The model incorporated consumer decisions, charging behavior, and infrastructure investments as key variables for anticipating future financial commitments. Simulations using Beijing data suggested that balanced subsidy ranges for buyers, plus investments in charging facilities, support steady EV growth. Sharp fluctuations in EV prices, fuel costs, electricity rates, or driving range could alter trajectories, making targeted policy actions appropriate for stabilization.

In France, mixed-effects regression examined socio-demographic, technical, and cost-related influences on market shares of battery electric vehicles (BEVs) versus plug-in hybrids (PHEVs) [10]. Model availability and energy pricing are positively linked to both categories (often grouped as PHEVs). Fast chargers were correlated with higher BEV sales, whereas slower or mid-power options were more closely tied to PHEVs; national subsidies, however, showed a negative association with PHEV uptake. Suggested policy adjustments included reevaluating subsidies, lowering electricity costs, providing targeted support for appropriate charger types and locations, and offering incentives for solar panel installations.

Increased wind energy investments in Northern Europe are projected to lessen reliance on new coal or gas plants, but only if vehicle-to-grid (V2G) systems are rolled out [11]. U.S.-based modeling indicated that incentives for wind generation speed up EV and charging infrastructure growth [12]. The same analysis noted that elevated gasoline prices spur corporate investment in renewables. Studies of driving patterns across U.S. states found that low-power charging networks adequately address EVs' range constraints with lower capital needs, though fast chargers remain essential on major highways [13].

Regression-based forecasting in Thailand projected EV penetration under varying scenarios tied to GDP and population trends [14]. Three adoption pathways were assessed for sustainable impacts on transport and power sectors. Policies promoting renewable electricity production were evaluated for their potential to achieve substantial reductions in transport emissions. Key challenges included coordinating capacity additions, grid upgrades, managed charging, and time-based pricing, with an accelerated V2G offering promise. Overall, robust governmental backing was deemed essential for success. Another Thai study pointed to risks from uncoordinated residential charging [15]. Expanding public fast charging emerged as a way to handle peak demand. In Abu Dhabi, an integrated smart transport-energy framework was proposed for coordinated management [16].

Large-scale EV adoption across Europe underscores the need for intelligent V2G systems [17]. National socio-economic conditions and climate factors significantly affect power grid modeling and user preferences. In Spain, shifting from uncontrolled fast charging to workplace-hour charging was shown to cut costs and stabilize demand [18]. Dynamic charging helps offset EV drawbacks by reducing expenses and load variability [19]. Mobile apps delivering advanced services represent a vital step in building public support for electric mobility [20]. Reviews confirm the ongoing relevance of features such as charger reservations and energy-efficient route planning, which warrant stronger app integration.

Early assessments of Lithuania's public EV charging setup found higher station density in resort areas than in comparably sized cities [21]. MCDM-based predictions for accelerated charger deployment stressed the need for better-coordinated incentive allocation among local governments.

An alternative study explored the psychological drivers behind EV purchases and private charger use [22]. Results highlighted alignment between EV buying intent and broader green product trends. A hybrid choice model incorporated both observable and hidden variables in EV purchase decisions [23], allowing for nonlinear utility relationships. Survey data indicated a strong interest in EVs among those who favor cutting-edge technology.

Expert evaluation-based studies for sustainable transport

Reliable modeling of EVs' effects on roadways demands detailed surveys of charging facilities and electricity loads, as standard national travel data lacks sufficient granularity [24]. Standardized surveys across similar regions are advised for comparable insights. When applying group aggregation in AHP, anticipating individual biases and preferences in criterion judgments is crucial [25]. Smaller, cohesive expert panels perform better with pairwise matrices, though only in restricted scenarios. Two aggregation strategies for AHP-based survey data depend on panel homogeneity [26]. This varies when field specialists (not AHP experts) participate.

Semi-structured interviews in Brazil identified EV pricing, charging availability, and public policies as primary hurdles to wider use [27]. Proposed remedies—relevant beyond Brazil—included raising awareness of ICE emissions, offering tax and non-tax benefits for EV acquisition and use, and advancing battery efficiency and recharge speed. In India, interviews informed prioritization of user and technical needs for market growth via Quality Function Deployment and AHP [28]. Scarce public chargers ranked as the chief obstacle, with vehicle upkeep and recharge duration deemed least critical.

A streamlined AHP variant demonstrated flexibility, ranking parking options by availability, proximity, and fees (with predefined alternatives) [29].

AHP-assisted multi-criteria ranking of emission-reduction tactics showed preference for “reduce” approaches over “avoid” or “replace,” though integrated mixes were advised for broader CO₂ cuts [30]. In Yurihonjo, Japan, a three-phase AHP survey captured expert views on transport, emphasizing public transit alignment with user needs for EV promotion [31].

MCDM tools help forecast sustainable transport options and rank policy bundles from expert standpoints [32]. Merging content analysis with AHP enables holistic, smart-city sustainability evaluations [33], prioritizing areas such as livability, ecology, economy, governance, mobility, society, infrastructure, technology, and ICT. The study noted divergences between expert and public perspectives and advocated comprehensive, forward-looking sustainability approaches.

Simulations of vehicle turnover under policy variants using choice modeling found that standalone promotion efforts were insufficient for major reductions in particulate matter [34]. Adapted to road-transport stock dynamics, the model blended the probabilities of selecting EVs versus ICE vehicles, and in South Korea, combining diesel restrictions with rebates led to notable reductions in emissions.

Investigations across regions often reach similar conclusions: successful EV market integration depends on sound political choices (e.g., appropriate subsidies), technological readiness (e.g., preparedness of smart grids and charging infrastructure), societal purchasing power, and technology attitudes. Despite overlapping challenges, country-specific rules, capabilities, consumer mindsets, and expectations differ markedly. Accordingly, this paper examines the context in the Republic of Lithuania.

A model for the Dynamics of EV Deployment in Lithuania

Electric vehicles first appeared in the early automotive era around the 1900s, briefly outnumbering ICE vehicles in the US [35]. This early prominence faded as ICE dominance took hold following innovations such as the electric starter and the Ford Model T's mass production. Limited electricity access and steep costs at the time halted further progress. Throughout the 20th century, the sector saw fluctuating interest in electric propulsion, culminating in the commercialization of hybrid electric vehicles (HEVs) late in the period. The 21st century advanced HEVs further, introduced plug-in hybrids (PHEVs), and revived pure battery EVs. **Figure 1** illustrates historical and projected market shares for various powertrain types, alongside three EV adoption forecast scenarios.

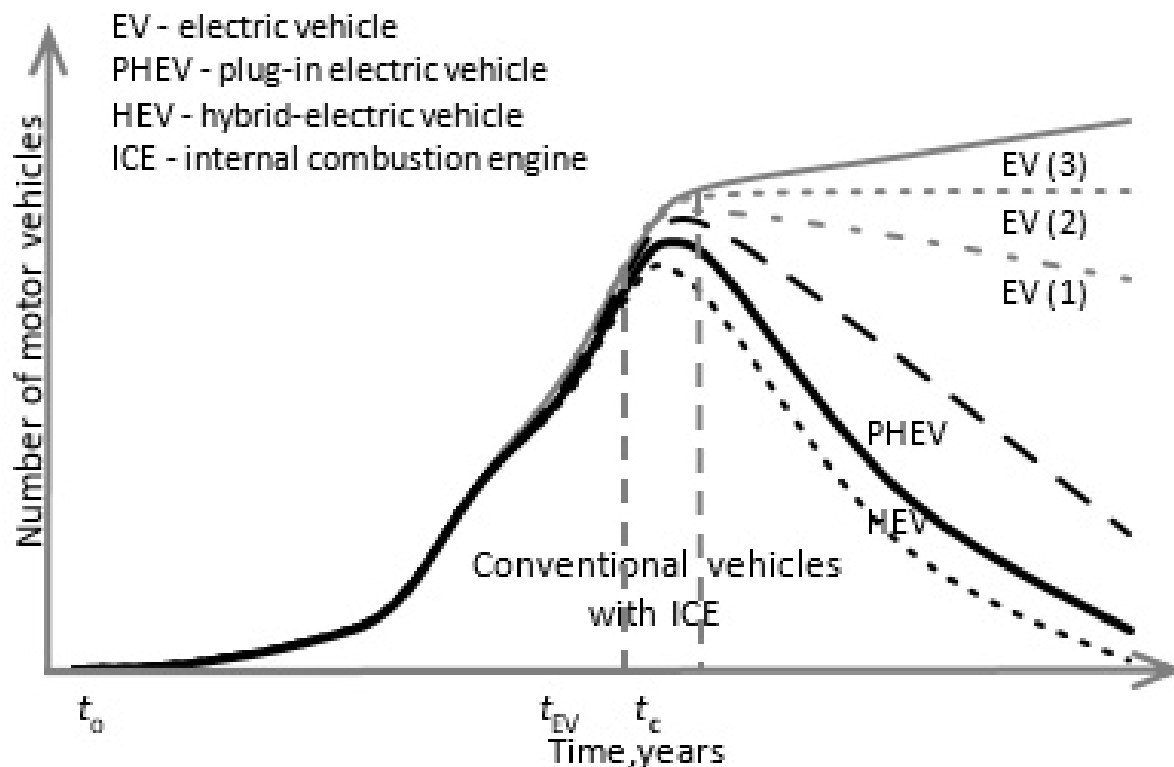


Figure 1. Model illustrating the evolution of the national vehicle fleet under various electric vehicle adoption scenarios (t_0 —onset of conventional motor vehicle production, t_{EV} —onset of electric vehicle production, t_c —present time).

Three distinct future pathways for electric vehicle (EV) penetration have been projected (**Figure 1**): a declining trajectory—EV (1); a stable trajectory—EV (2); and a rising trajectory—EV (3). The proportion of vehicles powered by internal combustion engines (ICE) is expected to decline over time. In contrast, the combined market presence of hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs) is anticipated to stay relatively flat, yet considerably smaller than the share held by fully electric vehicles. The European Union has committed to phasing out the manufacture of new passenger cars and vans powered by conventional ICEs by 2035. However, in other parts of the world, this timeline is likely to be postponed by 5 to 10 years or more, depending on each region's economic maturity. As a result, vehicles running on fossil fuels will continue to occupy a meaningful portion of the global vehicle parc for years to come.

Additionally, the emergence of synthetic e-fuels may allow certain premium or niche manufacturers to sustain ICE-based models in limited segments. Nevertheless, the widespread adoption of battery-electric vehicles is a cornerstone of the broader shift toward Society 5.0, integrating smart mobility solutions that contemporary society is already beginning to experience [36]. The move to electrification is also expected to accelerate innovations in areas such as vehicle-to-everything (V2X) communication and self-driving systems, underscoring the importance of pursuing genuinely sustainable progress.

According to statistics compiled by the European Automobile Manufacturers' Association (ACEA), the proportion of newly registered electric vehicles (battery electric only) in Europe neared 15% (specifically 14.6%, based on data from January through July) in 2023 [4]. During the first six months of 2023, the combined share of EVs and PHEVs in North America reached 12%—reflecting a 50% year-on-year increase—while in China the figure stood at 5.2%, up 37% from the previous year [37]. In Lithuania, however, EVs (including PHEVs) accounted for only 1% of the total passenger car fleet in 2023 [34]. These figures highlight stark regional and national disparities. Closing such gaps will demand prompt yet carefully designed governmental policies and concrete implementation steps to accelerate the transition to low- and zero-emission transport.

Policymakers, industry leaders, and infrastructure planners often highlight one or more drivers they believe are critical to accelerating national EV adoption, often reflecting personal viewpoints or prevailing opinions within their professional circles. The scarcity of rigorously derived, collective expert judgments quantifying the relative importance of every relevant factor motivated the present investigation. Accordingly, this paper seeks to outline a comprehensive hierarchical framework of the determinants influencing country-wide EV rollout and to assign objective importance weights to those determinants based on expert subjective evaluations processed through Multiple Criteria Decision-Making (MCDM) techniques.

Factors influencing EV deployment at the national level

Drawing on the authors' accumulated expertise, a thorough review of existing literature, consultations and exchanges with specialists in road transport advancement and quality enhancement, and examination of relevant legislation, the study identified 50 distinct factors that either facilitate or impede the expansion of electric vehicles in Lithuania. Given the large number of elements involved, a three-tier hierarchical model was adopted to organize them systematically (**Figure 2**).

- Level 1 (overall goal) — Nationwide deployment of electric vehicles
- Level 2 (primary criteria) — Seven overarching categories, labeled A through G
- Level 3 (detailed sub-criteria) — Between 5 and 10 specific sub-factors nested under each primary criterion

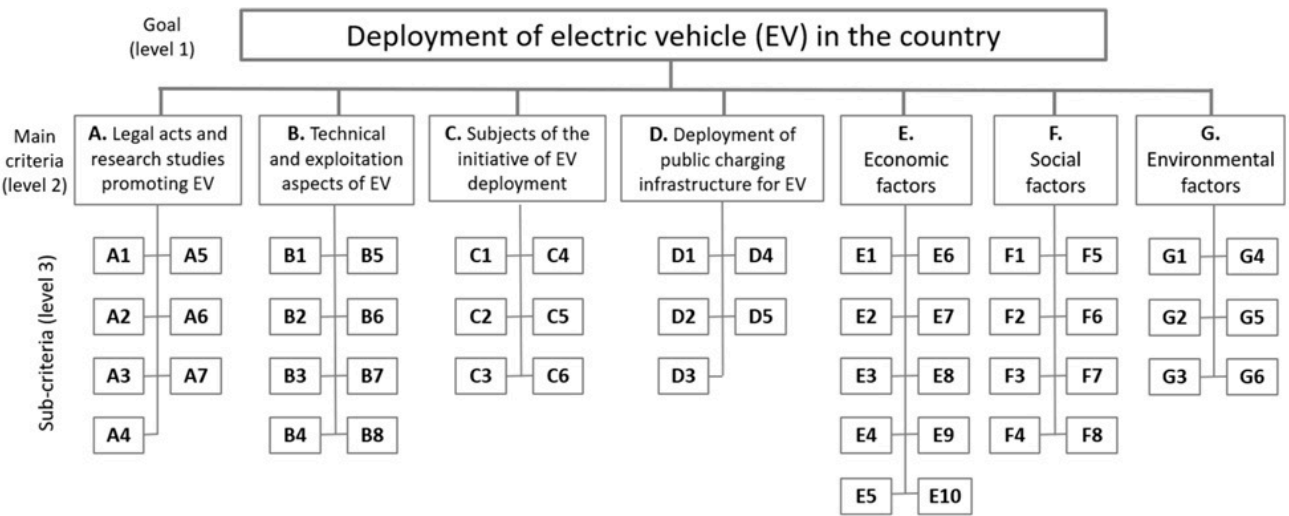


Figure 2. Hierarchical framework of determinants influencing nationwide electric vehicle (EV) rollout.

To enable participating specialists to grasp the essence of each element and assign numerical importance scores, each main criterion and sub-criterion was assigned a concise label (code) along with a clear explanation. These definitions were incorporated directly into the expert survey questionnaire and are listed below.

Primary criteria

- A. The preparation of regulations on the evaluation of EV benefits, deployment, and exploitation.
- B. Technical and exploitation parameters of the used electric vehicles.
- C. The initiative's action is subject to EV deployment.
- D. The installation and development of public charging infrastructure.
- E. Economic factors.
- F. Social factors.
- G. Environmental factors.

Sub-criteria under primary criterion A (Regulatory frameworks)

- A1. Comprehensive studies and strategic projects assessing the necessity and feasibility of building EV charging infrastructure.
- A2. Traffic rules permit EVs to use bus lanes.
- A3. Deployment of road signage and pavement markings indicating that certain standard traffic restrictions do not apply to EVs.
- A4. Regulatory provisions defining dedicated parking markings for electric vehicles.
- A5. European standards and safety/technical requirements for high-power charging facilities.

A6. Enactment of national legislation specifically addressing EV promotion and usage.

A7. Alignment with major policy documents: the EU White Paper on Transport (roadmap to a single European transport area), the Paris Agreement under the UN Framework Convention on Climate Change, European Commission strategies for low-emission mobility, and resolutions from the Glasgow COP26 conference.

Sub-criteria under primary criterion B (Technical & operational parameters)

B1. Vehicle brand/manufacture reputation, build quality, production standards, and warranty duration.

B2. Battery lifespan, measured by the number of viable charge–discharge cycles.

B3. Comfort, interior ergonomics, and overall driving experience in EVs.

B4. Single-charge driving range, active and passive safety features, top speed, and acceleration performance.

B5. Mandatory installation of acoustic vehicle alerting systems (AVAS) to warn pedestrians.

B6. Compact dimensions and straightforward handling make EVs particularly well-suited for urban environments.

B7. Substantially higher energy demand for cabin heating in cold weather or winter conditions.

B8. Extended charging durations (compared with conventional refueling) and regulatory restrictions (effective from 2022) prohibiting indefinite occupation of charging bays.

Sub-criteria under primary criterion C (Stakeholder initiatives)

C1. Leadership and support from public authorities (e.g., Ministry of Transport and Communications, Ministry of Economy and Innovation, local municipalities).

C2. Proactive engagement by private-sector companies active in the EV ecosystem.

C3. Grassroots motivation and decisions among private individuals (potential EV purchasers).

C4. Formation and activities of the Lithuanian Electric Vehicle Association.

C5. Creation of international expert or working groups dedicated to advancing electromobility in Lithuania.

C6. Direct promotional efforts and market activities undertaken by EV manufacturers themselves.

Sub-criteria under primary criterion D (Public charging infrastructure)

D1. Rollout and expansion of low- and medium-power AC charging stations (up to 22 kW) equipped with Type 2 connectors.

D2. Installation and scaling of high-power DC fast-charging stations (above 22 kW).

D3. Current shortages of publicly accessible charging points in Lithuania's five largest cities, major resorts, and along the Trans-European Transport Network (TEN-T) corridors.

D4. Proactive reservation and planning of charging locations in new urban development zones.

D5. Provision of low-power charging facilities at private residences (single-family homes).

Sub-criteria under primary criterion E (Economic factors)

E1. Capital costs of constructing charging stations and the associated electrical grid connections (power supply infrastructure).

E2. Rising electricity prices and potential future supply constraints at public charging locations.

E3. Availability of tax reductions, rebates, and direct financial incentives for EV purchases.

E4. Markedly higher manufacturing and retail prices of EVs relative to comparable conventional (fossil-fuel) vehicles.

E5. Lower per-kilometer electricity costs compared with fuel (though the differential has been narrowing).

E6. Substantial expense of replacing a depleted high-voltage battery pack.

E7. Reluctance or refusal among competing businesses to collaborate on fair, non-discriminatory terms in EV-related projects.

E8. Opportunities to utilize surplus emission allowances to support EV-related investments.

E9. Waiver of parking fees for EVs in paid public parking zones.

E10. Reduced long-term operating expenses for EVs (no engine oil/filter changes, slower brake wear due to regenerative braking).

Sub-criteria under primary criterion F (Social factors)

F1. Widespread recognition that every individual bears responsibility for curbing environmental pollution.

F2. Positive societal messaging, improved perceptions of quality of life, and increased visibility of climate activism supporting EV growth.

F3. EV owners feel a sense of prestige, modernity, and technological leadership.

F4. Favorable opinions are expressed by family, friends, colleagues, and respected figures toward electric vehicles.

F5. Perceived lower risk of theft for EVs compared with conventional cars.

F6. Strong compatibility of EVs with urban car-sharing schemes.

F7. Mandatory use of EVs by public-sector employees when vehicles are acquired using pollution-related funds.

F8. Inclusion of electromobility topics in higher education curricula (colleges and universities).

Sub-criteria under primary criterion G (Environmental factors)

G1. Zero tailpipe emissions during vehicle operation.

G2. Absence of fluid leaks (oil, coolant, etc.) after accidents, preventing soil and water contamination at crash sites.

G3. Enhanced environmental performance when electricity originates from nuclear, wind, solar, or hydropower sources.

G4. Lower overall emissions attributable to electricity generation for EVs compared with the exhaust emissions of equivalent ICE vehicles.

G5. Significantly reduced powertrain noise (although tire and aerodynamic noise remain comparable to conventional vehicles).

G6. Current limitations in lithium-ion battery recycling efficiency, difficulties in extinguishing battery fires, and elevated toxic emissions during such incidents.

The complete hierarchical model shown in **Figure 2**, along with its constituent primary criteria and nested sub-criteria, was evaluated independently by the expert panel using established expert-judgment techniques.

Each specialist received a two-part questionnaire. The first part contained detailed descriptions of all primary and secondary criteria requiring ordinal ranking. The second part consisted of eight pairwise comparison matrices following the Analytic Hierarchy Process (AHP) format. Experts completed these matrices by assessing the relative importance of each pair of criteria (or sub-criteria) to ensure transitivity.

Local weights for the criteria were computed from the averaged rank orders using two Average Rank Transformation methods: the linear variant (ARTIW-L) and the nonlinear variant (ARTIW-N) [38]. For the AHP approach, each pairwise comparison matrix was processed to obtain the principal eigenvector, yielding normalized local weights; the consistency of each matrix was also verified using the consistency ratio (CR).

Materials and Methods

Principles for assigning criterion importance

The literature and practical applications offer several established approaches for quantifying the relative significance of decision criteria (also called indicators, attributes, or factors). Among the most straightforward and widely used techniques is simple criterion ranking [39]. Another common method involves directly assigning percentage weights or fractional values that sum to 1 [40]. In many cases, however, weights are derived indirectly.

The present study applied three Multiple Criteria Decision-Making (MCDM) techniques—ARTIW-L, ARTIW-N, and AHP—to determine the importance of both the primary criteria and their sub-criteria shaping national EV deployment. These methods translate expert-provided ordinal ranks and intensity judgments (captured via nine-point pairwise comparison scales) into robust numerical weights.

The selected approaches enabled thorough validation of expert consistency:

- For AHP, CR was calculated for each of the 96 pairwise comparison matrices.
- Group-level agreement among the 12 participating experts was assessed for both main criteria and sub-criteria rankings using Kendall and Gibbons [39] coefficient of concordance (W).

No single method is theoretically superior in all contexts; AHP remains the most widely adopted yet also the most computationally and cognitively demanding.

All three algorithms share a fundamental logic:

- The criterion judged most important receives the largest weight.
- Weight magnitudes are inversely related to rank position (lower rank number → higher weight).

- Weights are normalized so that their sum across all criteria in a given level equals 1.

ARTIW-L method

The ARTIW-L (Average Rank Transformation into Weight – Linear) procedure converts the mean-rank values assigned to the criteria into properly normalized subjective weights. For any given criterion, the normalized weight $\omega_i^{\text{ARTIW-L}}$ is computed using the expression:

$$\omega_i^{\text{ARTIW-L}} = \frac{(m+1) - \bar{R}_i}{\sum_{i=1}^m \bar{R}_i}, \quad (1)$$

Where m represents the total number of criteria at the level under consideration (either the seven primary criteria describing national EV deployment or the set of sub-criteria nested within one primary criterion; $i = 1, 2, \dots, m$),

$\bar{R}_i$ is the arithmetic mean of the ranks assigned to the i -th criterion across all experts:

$$\bar{R}_i = \frac{\sum_{j=1}^n R_{ij}}{n}, \quad (2)$$

Where n is the number of participating experts ($j = 1, 2, \dots, n$),

R_{ij} denotes the rank that the j -th expert assigned to the i -th criterion.

This formulation establishes a strict linear inverse relationship between the derived weight $\omega_i^{\text{ARTIW-L}}$ and the average rank $\bar{R}_i$. When plotted, the points lie exactly on a straight line, yielding a coefficient of determination (R^2) of 1.

Assessing the concordance of expert judgments

The aggregated group judgment—whether in the form of average ranks or derived weights—can be adopted as the final solution only if the individual expert opinions exhibit a sufficient degree of agreement (i.e., they are statistically non-contradictory) [38]. Kendall and Gibbons [39] quantify the extent of this agreement within the expert panel coefficient of concordance W , which is calculated as follows:

$$W = \frac{12S}{n^2 (m^3 - m)}. \quad (3)$$

Where S is the sum of squared deviations of the column sums of ranks (i.e., the sum of ranks received by each criterion across all experts) from the expected average under complete randomness:

$$S = \sum_{i=1}^m \left[\sum_{j=1}^n R_{ij} - \bar{R} \right]^2, \quad (4)$$

And the overall average rank $\bar{R}$ is given by:

$$\bar{R} = \frac{1}{2} n (m + 1). \quad (5)$$

The numerical value of W alone does not indicate whether the level of agreement is statistically meaningful; it must be tested against a critical threshold. When the number of criteria (objects) $m \geq 7$, Kendall [41] demonstrated that the statistic

$$\chi^2 = Wn(m-1), \quad (6)$$

Follows, under the null hypothesis of no agreement, a chi-square distribution with $v = m - 1$ degrees of freedom. For a pre-selected significance level α (commonly $\alpha = 0.05$ or the more stringent $\alpha = 0.01$), the corresponding critical value $\chi^2_{\{v,\alpha\}}$ is obtained from standard chi-square tables [42]. If the computed χ^2 exceeds this critical value, the expert assessments are deemed to be concordant (i.e., there is statistically significant agreement).

For smaller panels of criteria ($3 \leq m \leq 7$), the χ^2 approximation can be conservative, potentially failing to detect genuine agreement. In such cases, it is preferable to consult exact probability tables for W or critical values of the raw sum-of-squares statistic S when the number of objects lies in this range [42].

An alternative practical threshold is the minimum acceptable value of the concordance coefficient $W_{\min}$, above which the group judgment may reasonably be regarded as consistent [43]:

$$W_{\min} = \frac{\chi^2_{v,\alpha}}{n(m-1)}, \quad (7)$$

Where $\chi^2_{v,\alpha}$ is the tabled critical value of the Pearson chi-square statistic [44].

Beyond merely determining whether concordance exists, it is valuable to quantify the strength of agreement. For this purpose, the consistency index, k_c , is defined as:

$$k_c = \frac{\chi^2}{\chi^2_{v,\alpha}} = \frac{W}{W_{\min}}. \quad (8)$$

When $k_c > 1$, the expert panel's opinions are considered concordant. Furthermore, by comparing the obtained k_c with its theoretical maximum $k_{c\max}$ (which corresponds to perfect unanimity, $W = 1$), the relative degree of concordance can be expressed as the ratio $k_c / k_{c\max}$. The maximum attainable consistency coefficient is:

$$k_{c\max} = \frac{W_{\max}}{W_{\min}} = \frac{1}{W_{\min}}. \quad (9)$$

This ratio indicates how close the actual level of agreement is to the theoretical maximum uniformity.

ARTIW-N method

The Average Rank Transformation into Weight – Nonlinear (ARTIW-N) procedure provides an alternative way of converting mean ranks into normalized criterion weights. Unlike the linear variant, ARTIW-N produces weights that exhibit a strongly nonlinear (near-functional) inverse relationship with the average ranks $\bar{R}_i$ [38].

The method first computes an intermediate importance score u_i for each criterion by relating it to the most important criterion (the one with the lowest average rank $\bar{R}_{\min}$):

$$u_i = \frac{\min_l \bar{R}_l}{\bar{R}_i} \quad (10)$$

The normalized weight $\omega_i^{\text{ARTIW-N}}$ is then obtained by dividing each u_i by the sum of all u values across the m criteria:

$$\omega_i^{\text{ARTIW-N}} = \frac{u_i}{\sum_{l=1}^m u_l} \quad (11)$$

Because of the nonlinear transformation, ARTIW-N tends to amplify the weights assigned to both the highest-priority (lowest-ranked) and lowest-priority (highest-ranked) criteria while compressing the weights of criteria lying in the middle of the importance spectrum. A comparison of the resulting weights $\omega_i^{\text{ARTIW-N}}$ with those from the linear method (ARTIW-L) clearly reveals this differential emphasis.

Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP), developed by Saaty [45], is a widely used Multi-Criteria Decision-Making (MCDM) method for determining criterion weights and comparing alternatives. At the core of this method is the pairwise comparison of criteria [45]. The criteria, initially arranged, are compared in pairs using a nine-point intensity scale. A square pairwise comparison matrix of criteria $\mathbf{A} = \|a_{ij}\|_{m \times m}$ ($i = 1, 2, \dots, m$) is populated, with the elements a_{ij} ranging from 1/9 to 9. The values of a_{ij} in the pairwise comparison matrix indicate the relative importance of the criterion in the row compared to the criterion in the column.

A key advantage of the AHP method is that it simplifies the process for experts, allowing them to compare pairs of criteria that influence electric vehicle (EV) deployment, rather than evaluating all criteria simultaneously. The pairwise comparison is straightforward and reliable, provided the expert is proficient with the AHP methodology. For the comparison matrix to be consistent, the criterion importance must be transitive. Therefore, researchers conducting the analysis are encouraged to monitor whether this condition is maintained throughout matrix completion.

The pairwise comparison matrix for a single expert is reciprocal, meaning $a_{ij} = \frac{1}{a_{ji}}$. In fact, $a_{ij} = \frac{\omega_i}{\omega_j}$ and $a_{ji} = \frac{\omega_j}{\omega_i}$:

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1j} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2j} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} & \cdots & a_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mj} & \cdots & a_{mm} \end{bmatrix} \quad (12)$$

In real-world applications, the transitivity requirement simplifies the detection of contradictory entries within the pairwise comparison matrices used in questionnaires. However, this condition is frequently violated (deemed invalid) in practice. When inconsistencies arise, the matrix is typically discarded or revised with input from an expert or evaluator.

The most precise approach for deriving the relative importance (weights) of criteria, expressed as normalized values, relies on computing the geometric mean of the row products from the pairwise comparison matrix $\mathbf{A}$ [46-49]:

$$\omega_i^{\text{AHP}} = \frac{\sqrt[m]{\prod_{j=1}^m a_{ij}}}{\sum_{l=1}^m \sqrt[m]{\prod_{j=1}^m a_{lj}}} \quad (i = 1, 2, \dots, m). \quad (13)$$

After normalizing the m -th roots of these row products in the pairwise comparison matrix, the resulting eigenvector w is obtained and is widely accepted as the set of criterion weights that reflect the judgment of an individual expert.

To assess the consistency of matrix A —constructed through pairwise comparisons of criteria and ideally satisfying transitivity—the principal (largest) eigenvalue is computed:

$$\lambda_{\max} = \frac{1}{m} \cdot \sum_{l=1}^m \frac{\sum_{j=1}^m a_{lj} \omega_j}{\omega_l^{\text{AHP}}}. \quad (14)$$

For a fully reciprocal matrix of order m , the maximum eigenvalue satisfies $\lambda_{\max} \geq m$. In a perfectly consistent matrix, where column elements are strictly proportional, $\lambda_{\max}$ equals m . The extent of inconsistency is quantified using the consistency index (C.I.), defined as the difference between $\lambda_{\max}$ and m divided by $(m-1)$:

$$C.I. = \frac{\lambda_{\max} - m}{m - 1}. \quad (15)$$

In practice, achieving a perfectly consistent matrix ($C.I. = 0$) is extremely uncommon, even when full transitivity holds among the elements. The overall consistency level is evaluated by dividing the consistency index (C.I.) by the random index (R.I.), which depends on the matrix order m and can be obtained from established tables [45] or computed using an approximation formula [50].

$$R.I. = 1.98 \frac{m - 2}{m}. \quad (16)$$

The CR of the matrix is then determined as follows:

$$C.R. = \frac{C.I.}{R.I.} = \frac{\lambda_{\max} - m}{(m - 1)R.I.}. \quad (17)$$

A matrix is generally regarded as acceptably consistent if $CR \leq 0.1$ (i.e., 10%) [45]; values up to 0.2 may sometimes be tolerated, though not recommended [51]. An inconsistency level of 10% or below indicates that any required adjustments remain minor relative to the true eigenvector components [52].

The Analytic Hierarchy Process (AHP) is particularly effective for assigning weights when evaluating seven criteria. The method is also deemed appropriate for problems with 5 to 9 criteria [53, 54].

Averaging local weights of main criteria and sub-criteria

Local weights assigned to sub-criteria often differ across the three MCDM techniques applied. Since no single method possesses a clear theoretical superiority, greater reliability is achieved by calculating the arithmetic mean of the local weights for each main criterion or sub-criterion—denoted Q^-i , and $\tilde{\omega}_{il}$ —derived from the three approaches rather than relying on any one alone. Without favoring a particular method, the average local weight of the i -th sub-criterion is computed according to:

$$\tilde{\omega}_{il} = \frac{\omega_i^{\text{ARTIW-L}} + \omega_i^{\text{ARTIW-N}} + \tilde{\omega}_i^{\text{AHP}}}{3}, \quad (18)$$

Where $\omega_i^{\text{ARTIW-L}}$, $\omega_i^{\text{ARTIW-N}}$, $\tilde{\omega}_i^{\text{AHP}}$ represent the normalized local weights (eigenvectors) of the i -th sub-criterion obtained via the ARTIW-L, ARTIW-N, and AHP methods, respectively.

Local weights for all sub-criteria with respect to their corresponding main criteria are computed independently within the hierarchical framework for electric vehicle (EV) deployment in the country.

Determination of global weights for sub-criteria

The overall importance of every factor influencing EV adoption in the country is established by calculating the global weight ω_{ig} of each sub-criterion. This involves combining the normalized weights of the main criteria, the local weights of the sub-criteria within those main criteria, and the number of sub-criteria per main criterion:

$$\omega_{ig} = \frac{\bar{Q}_{i,mc} \cdot \tilde{\omega}_{il} \cdot m_{i,mc}}{\sum_{i=1}^m \bar{Q}_{i,mc} \cdot \tilde{\omega}_{il} \cdot m_{i,mc}}, \quad (19)$$

Here, $\bar{Q}_{i,mc}$ is the normalized weight of the i -th main criterion obtained from the three MCDM methods; $\tilde{\omega}_{il}$ is the averaged local weight of the i -th sub-criterion from the three methods; $m_{i,mc}$ denotes the number of sub-criteria belonging to the i -th main criterion; and m represents the total number of main criteria ($i = 1, 2, \dots, m$).

Eq. 19 shows that both the main criterion and its constituent sub-criteria gain greater significance as their normalized global weight ω_{ig} increases. To sustain rapid progress in EV deployment within the country, policymakers and decision-makers should prioritize the sub-criteria possessing the highest global weights.

Expert Panel

This study involved twelve professionals with substantial expertise in transport engineering, all of whom have made notable practical contributions to road transport systems research and development. Notably, eleven hold doctoral degrees in relevant scientific fields, while one serves as the head of a representative office for a prominent vehicle manufacturer. These experts voluntarily completed the ranking of criteria in the questionnaire and filled out eight pairwise comparison matrices, each requiring approximately 1.5 to 2 hours. No influence from the article authors was exerted on their judgments. The research team carefully selected these individuals based on their demonstrated competence, practical experience, and academic qualifications. All participants were well-acquainted with the fundamental concepts of the AHP method, capable of constructing the necessary matrices, and experienced in applying such techniques to evaluate factors related to EV deployment.

Results and Discussion

Ranking of main criteria and sub-criteria together with consistency of expert judgments

Application of the rank correlation technique revealed varying levels of agreement regarding the importance of main criteria and their associated sub-criteria. The expert panel reached a consensus that the main criterion D—assessing the development of public EV charging infrastructure—holds the highest priority, with an average rank of $\bar{R}_D = 2.583$. Economic factors ranked second in importance, achieving an average rank of $\bar{R}_E = 3.333$. Technical and operational characteristics of EVs placed third, with an average rank of $\bar{R}_B = 3.417$. Environmental (ecological) considerations were

viewed as highly relevant, securing fourth position with an average rank of $\bar{R}_G = 3.75$ (Figure 3). Social factors were considered to exert the weakest influence on EV adoption in the country, receiving the lowest average rank of $\bar{R}_F = 6.25$.

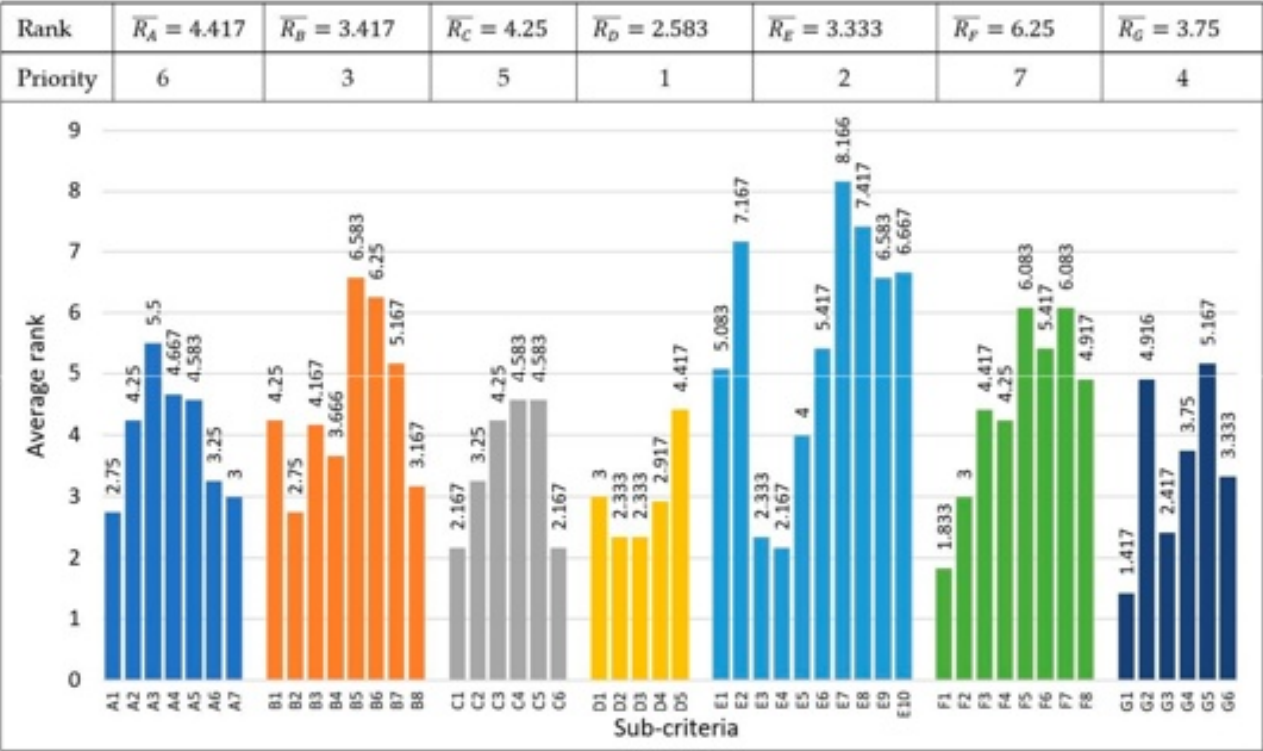


Figure 3. Average ranks and relative priority ordering of the main criteria, along with their associated sub-criteria influencing electric vehicle (EV) adoption within the country.

For the computed average rank R_i to serve as a valid and representative outcome reflecting the collective judgment of the expert panel, the assessments of the 12 participating specialists demonstrated an acceptable level of agreement, despite some individual variation. The coefficient of concordance calculated for the rankings of the main criteria reached $W = 0.2912$. The critical (minimum) threshold value of this coefficient required to establish statistical consistency at a significance level of $\alpha = 0.05$ is $W_{\min} = 0.1749$. Consequently, the ratio between the observed and the minimum acceptable coefficient—referred to as the consistency coefficient k_c —equals 1.665 (Table 1).

Table 1. The results of calculating the consistency of the ranks assigned by experts to the main criteria and sub-criteria affecting the deployment of EVs in the country, with $\alpha = 0.05$.

Statistics	Main criteria from A to G	Sub-criteria $i = 1, 2, \dots, m$						
		A1, ..., A7	B1, ..., B8	C1, ..., C6	D1, ..., D5	E1, ..., E10	F1, ..., F8	G1, ..., G6
W	0.2912	0.2222	0.3228	0.3730	0.2903	0.4810	0.3681	0.5937
$W_{\min}$	0.1749	0.1749	0.1675	0.1845	0.1977	0.1567	0.1675	0.1845
χ^2	20.96	16.00	27.11	22.38	13.93	51.93	30.92	35.62
$\chi^2_{\nu, \alpha}$	12.59	12.59	14.07	11.07	9.49	16.92	14.07	11.07
k_c	1.665	1.271	1.927	2.022	1.468	3.070	2.200	3.218

k_{cmax}	5.72	5.72	5.97	5.42	5.06	6.38	5.97	5.42
$\frac{k_c}{k_{cmax}}$	0.29	0.22	0.32	0.37	0.29	0.48	0.37	0.59

The rankings assigned by the experts to the sub-criteria within each main category (A through G) also exhibited an acceptable degree of agreement. The coefficient of concordance for these sub-criteria groupings ranged from 0.2222 (for sub-criteria A1 through A7) to 0.5937 (for sub-criteria G1 through G6). These values comfortably exceeded the corresponding critical thresholds of 0.1749 and 0.1845, respectively, required for statistical significance at $\alpha = 0.05$. The lowest level of agreement among the experts was observed for the sub-criteria under main criterion A (A1, ..., A7), where the consistency coefficient k_c reached only 1.271. In contrast, the highest level of agreement occurred for the sub-criteria under main criterion G (G1, ..., G6), with $k_c = 3.218$. This difference in agreement strength is further reflected by the normalized CRs k_c/k_{cmax} , which amounted to 0.22 for group A and 0.59 for group G (Table 1).

Given the overall adequate consistency across the assessments provided by the twelve experts, it was justified to adopt the arithmetic means of both the ranks and the derived weights as a consolidated representation of the group's collective judgment regarding the importance of the main criteria and their sub-criteria.

When implementing the Analytic Hierarchy Process (AHP), a critical requirement is that the CR of each pairwise comparison matrix—for both the main criteria and all sub-criteria groups—should remain at or below 0.1. Table 2 presents the minimum and maximum CR values recorded across all matrices. Of the 96 pairwise comparison matrices completed by the experts, only one showed a CR value exceeding the 0.1 threshold, namely CR = 0.1103. Because this value, while slightly above 0.1, stayed well below the more lenient limit of 0.2, the weights assigned by that particular expert to sub-criteria F1 through F8 were retained for inclusion in the analysis. The minor deviation introduced only a small acceptable error, and there was no compelling basis for excluding those results.

Table 2. The values of the CR of the pairwise comparison matrices of the main criteria and sub-criteria were calculated by applying the AHP method.

C.R.	Main criteria from A to G	Sub-criteria						
		A1, ..., A7	B1, ..., B8	C1, ..., C6	D1, ..., D5	E1, ..., E10	F1, ..., F8	G1, ..., G6
min	0.0080	0.0173	0.0124	0.0097	0.0082	0.0301	0.0218	0.0131
max	0.0803	0.0893	0.0826	0.0712	0.0780	0.0998	0.1103	0.0920

Local weights derived from alternative multi-criteria decision-making techniques

The normalized subjective weights assigned to the main criteria using the ARTIW-L, ARTIW-N, and AHP approaches exhibit minor variations. Nevertheless, the resulting priority ranking remains consistent across all three methods. When averaging the weights obtained from these techniques, the arithmetic mean local weights of the main criteria—denoted as $Q_{\{i,mc\}}$ —reveal that criteria D, E, and B emerge as the most influential, with values of $Q_{\{D,mc\}} = 0.2059$, $Q_{\{E,mc\}} = 0.1648$, and $Q_{\{B,mc\}} = 0.1633$, respectively (Table 3).

In the context of accelerating electric vehicle (EV) adoption in the country, the expert panel ranked environmental (ecological) considerations fourth, yielding an average weight of $Q_{\{G,mc\}} = 0.1523$. The weight of the top-ranked main criterion ($Q_{\{D,mc\}} = 0.2059$) is approximately 3.07 times greater than that of the lowest-ranked category—social factors ($Q_{\{F,mc\}} = 0.067$).

Table 3. The local weights for the main criteria for EV deployment in the country were determined using different methods, along with their priorities.

MCDM method	Main criteria $i = 1, 2, \dots, m$						
	A	B	C	D	E	F	G
$\omega_{i,mc}^{ARTIW-L}$	0.1280	0.1637	0.1339	0.1934	0.1667	0.0625	0.1518
$\omega_{i,mc}^{ARTIW-N}$	0.1212	0.1567	0.1260	0.2072	0.1606	0.0856	0.1427
$\omega_{i,mc}^{AHP}$	0.1187	0.1694	0.1123	0.2172	0.1672	0.0530	0.1622
$\bar{Q}_{i,mc}$	0.1226	0.1633	0.1241	0.2059	0.1648	0.0670	0.1523
Priority	6	3	5	1	2	7	4

The local weights assigned to all sub-criteria under each main criterion, as obtained through various MCDM techniques, along with their computed arithmetic averages and corresponding priority values, are shown in [Tables 4-10](#).

Table 4. The importance of legal acts and other documents that affect the deployment of EVs.

MCDM Method	Sub-criteria $i = 1, 2, \dots, m$						
	A1	A2	A3	A4	A5	A6	A7
$\omega_i^{ARTIW-L}$	0.1875	0.1339	0.0893	0.1190	0.1220	0.1697	0.1786
$\omega_i^{ARTIW-N}$	0.1961	0.1269	0.0980	0.1156	0.1177	0.1659	0.1798
ω_i^{AHP}	0.2107	0.1039	0.0824	0.1105	0.1149	0.1771	0.2005
$\bar{\omega}_{Ail}$	0.1981	0.1216	0.0899	0.1150	0.1182	0.1709	0.1863
Priority	1	4	7	6	5	3	2

Table 5. The significance of technical and operational parameters for EV deployment.

MCDM method	Sub-criteria $i = 1, 2, \dots, m$							
	B1	B2	B3	B4	B5	B6	B7	B8
$\omega_i^{ARTIW-L}$	0.1319	0.1736	0.1343	0.1482	0.0671	0.0764	0.1065	0.1620
$\omega_i^{ARTIW-N}$	0.1217	0.1881	0.1242	0.1411	0.0786	0.0828	0.1001	0.1634
ω_i^{AHP}	0.1198	0.2026	0.1439	0.1649	0.0545	0.0586	0.0826	0.1731
$\bar{\omega}_{Bil}$	0.1245	0.1881	0.1341	0.1514	0.0667	0.0726	0.0964	0.1662
Priority	5	1	4	3	8	7	6	2

Table 6. The importance of the activities of the initiative to develop EV and to have an effect on the deployment of electric vehicles.

MCDM method	Sub-criteria $i = 1, 2, \dots, m$					
	C1	C2	C3	C4	C5	C6
$\omega_i^{\text{ARTIW-L}}$	0.2301	0.1786	0.1310	0.1151	0.1151	0.2301
$\omega_i^{\text{ARTIW-N}}$	0.2426	0.1617	0.1237	0.1147	0.1147	0.2426
ω_i^{AHP}	0.2915	0.1536	0.1030	0.0895	0.0827	0.2797
$\tilde{\omega}Cil$	0.2547	0.1646	0.1192	0.1065	0.1042	0.2508
Priority	1	3	4	5	6	2

Table 7. The significance of installing public charging infrastructure and the factors that affect EV deployment.

MCDM method	Sub-criteria $i = 1, 2, \dots, m$				
	D1	D2	D3	D4	D5
$\omega_i^{\text{ARTIW-L}}$	0.2000	0.2445	0.2445	0.2055	0.1055
$\omega_i^{\text{ARTIW-N}}$	0.1894	0.2436	0.2436	0.1948	0.1286
ω_i^{AHP}	0.1858	0.3109	0.2444	0.1802	0.0787
$\tilde{\omega}Dil$	0.1917	0.2663	0.2442	0.1935	0.1043
Priority	4	1	2	3	5

Table 8. The importance of economic factors in shaping EV deployment.

MCDM method	Sub-criteria $i = 1, 2, \dots, m$									
	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
$\omega_i^{\text{ARTIW-L}}$	0.1076	0.0697	0.1576	0.1606	0.1273	0.1015	0.0515	0.0651	0.0803	0.0788
$\omega_i^{\text{ARTIW-N}}$	0.0886	0.0629	0.1931	0.2078	0.1126	0.0831	0.0552	0.0607	0.0684	0.0676
ω_i^{AHP}	0.0992	0.0578	0.2089	0.2075	0.1281	0.0835	0.0332	0.0497	0.0702	0.0619
$\tilde{\omega}Eil$	0.0985	0.0634	0.1865	0.1920	0.1227	0.0894	0.0466	0.0585	0.0730	0.0694
Priority	4	8	2	1	3	5	10	9	6	7

Table 9. The significance of social factors in the deployment of EVs.

MCDM method	Sub-criteria $i = 1, 2, \dots, m$							
	F1	F2	F3	F4	F5	F6	F7	F8
$\omega_i^{\text{ARTIW-L}}$	0.1991	0.1667	0.1273	0.1320	0.0810	0.0995	0.0810	0.1134
$\omega_i^{\text{ARTIW-N}}$	0.2652	0.1620	0.1100	0.1144	0.0799	0.0897	0.0799	0.0989
ω_i^{AHP}	0.2561	0.1888	0.1278	0.1217	0.0539	0.0834	0.0564	0.1119
ϕ_{Fil}	0.2401	0.1725	0.1217	0.1227	0.0716	0.0909	0.0724	0.1081
Priority	1	2	4	3	8	6	7	5

Table 10. The significance of environmental factors in EV deployment.

MCDM method	Sub-criteria $i = 1, 2, \dots, m$					
	G1	G2	G3	G4	G5	G6
$\omega_i^{\text{ARTIW-L}}$	0.2659	0.0992	0.2182	0.1548	0.0873	0.1746
$\omega_i^{\text{ARTIW-N}}$	0.3388	0.0976	0.1986	0.1281	0.0929	0.1440
ω_i^{AHP}	0.3311	0.0904	0.2383	0.1227	0.0569	0.1606
ϕ_{Gil}	0.3119	0.0957	0.2184	0.1352	0.0790	0.1598
Priority	1	5	2	4	6	3

Table 11 presents a comparison of the highest (max) Q_{mc} max (ω_{il} max) and lowest (min) Q_{mc} min (ω_{il} min) local weight values for both the main criteria and sub-criteria, together with their corresponding differences ΔQ_{mc} or $\Delta \omega_{il}$. These differences reflect the degree of sensitivity exhibited by the three MCDM approaches. A larger gap between the maximum and minimum values highlights greater emphasis on the most influential criteria and reduced importance assigned to those with the smallest local weights for electric vehicle deployment within the country. The figures in **Table 11** reveal that the AHP method produces the widest variation in local weights. Consequently, ARTIW-L emerges as the least sensitive of the three MCDM techniques, as it yields the smallest differences ΔQ_{mc} and $\Delta \omega_{il}$ between the highest Q_{mc} max (ω_{il} max) and lowest Q_{mc} min (ω_{il} min) local weight values across the criteria.

Table 11. Differences between the maximum and minimum local weights for the main criteria and sub-criteria, calculated using various MCDM methods, and their effects on EV deployment.

Main criteria and sub-criteria	Maximum, minimum weight, and the difference in weights	Method			Average of three methods
		ARTIW-L	ARTIW-N	AHP	
Main criteria	Q_{mc} max	0.1934 (D)	0.2072 (D)	0.2172 (D)	0.2059 (D)
	Q_{mc} min	0.0625 (F)	0.0856 (F)	0.0530 (F)	0.0670 (F)

	ΔQ_{mc}	0.1309	0.1216	0.1642	0.1389
Sub-criteria for the main criterion A	$\omega_{Ail} \max$	0.1875 (A1)	0.1961 (A1)	0.2107 (A1)	0.1981 (A1)
	$\omega_{Ail} \min$	0.0893 (A3)	0.0980 (A3)	0.0824 (A3)	0.0899 (A3)
	$\Delta \omega_{Ail}$	0.0982	0.0981	0.1283	0.1082
Sub-criteria for the main criterion B	$\omega_{Bil} \max$	0.1736 (B2)	0.1881 (B2)	0.2026 (B2)	0.1881 (B2)
	$\omega_{Bil} \min$	0.0671 (B5)	0.0786 (B5)	0.0545 (B5)	0.0726 (B5)
	$\Delta \omega_{Bil}$	0.1065	0.1095	0.1481	0.1155
Sub-criteria for the main criterion C	$\omega_{Cil} \max$	0.2301 (C1, C6)	0.2426 (C1, C6)	0.2915 (C1)	0.2547 (C1)
	$\omega_{Cil} \min$	0.1151 (C4, C5)	0.1147 (C4, C5)	0.0827 (C5)	0.1042 (C5)
	$\Delta \omega_{Cil}$	0.1150	0.1279	0.2088	0.1505
Sub-criteria for the main criterion D	$\omega_{Dil} \max$	0.2445 (D2, D3)	0.2436 (D2, D3)	0.3109 (D2)	0.2663 (D2)
	$\omega_{Dil} \min$	0.1055 (D5)	0.1286 (D5)	0.0787 (D5)	0.1043 (D5)
	$\Delta \omega_{Dil}$	0.1390	0.1150	0.2322	0.1620
Sub-criteria for the main criterion E	$\omega_{Eil} \max$	0.1606 (E4)	0.2078 (E4)	0.2089 (E3)	0.1920 (E4)
	$\omega_{Eil} \min$	0.0515 (E7)	0.0552 (E7)	0.0332 (E7)	0.0466 (E7)
	$\Delta \omega_{Eil}$	0.1091	0.1526	0.1757	0.1454
Sub-criteria for the main criterion F	$\omega_{Fil} \max$	0.1991 (F1)	0.2652 (F1)	0.2561 (F1)	0.2401 (F1)
	$\omega_{Fil} \min$	0.0810 (F5, F7)	0.0799 (F5, F7)	0.0539 (F5)	0.0716 (F5)
	$\Delta \omega_{Fil}$	0.1181	0.1853	0.2022	0.1685
Sub-criteria for the main criterion G	$\omega_{Gil} \max$	0.2659 (G1)	0.3388 (G1)	0.3311 (G1)	0.3119 (G1)
	$\omega_{Gil} \min$	0.0873 (G5)	0.0929 (G5)	0.0569 (G5)	0.0790 (G5)
	$\Delta \omega_{Gil}$	0.1786	0.2459	0.2742	0.2329

Experts assign varying levels of importance to preparing legal regulations, supporting documents, benefit evaluations, and promotion strategies for electric vehicle adoption, as well as to establishing implementation hierarchies. Among the seven sub-criteria under main criterion A, specialists consider sub-criterion A1 to be the most critical. This sub-criterion assesses the value of comprehensive EV rollout initiatives and research examining the requirements for EV-related communication networks along with feasible deployment options (local weight $\tilde{\omega}_{A1I} = 0.1981$). In contrast, sub-criterion A3 receives the lowest priority (local weight $\tilde{\omega}_{A3I} = 0.0899$), making it approximately 2.2 times less significant than A1 (Tables 4 and 11).

For main criterion B, which addresses the technical and functional characteristics of electric vehicles in supporting national EV adoption, the importance is reflected in the local weights $\tilde{\omega}_{BiI}$ of its eight sub-criteria and the overall priority of criterion B (Table 5). Here, sub-criterion B2 stands out as the most influential ($\tilde{\omega}_{B2I} = 0.1881$), focusing on battery longevity—specifically, the number of possible charge–discharge cycles. The least relevant is sub-criterion B5 ($\tilde{\omega}_{B5I} = 0.0667$), which concerns the requirement for Acoustic Vehicle Alerting Systems (external speakers producing audible signals for pedestrians). This makes B5 roughly 2.82 times less important than B2.

Table 6 displays the local weights $\tilde{\omega}_{CiI}$ and the priorities assigned to the five sub-criteria under the main criterion C, which cover stakeholders responsible for advancing EV production and expanding public charging infrastructure (access to charging). According to the expert assessments, sub-criterion C1—measuring the engagement of government bodies—emerges as the most significant ($\tilde{\omega}_{C1I} = 0.2547$). The lowest-ranked is sub-criterion C5 ($\tilde{\omega}_{C5I} = 0.1042$), which deals with forming an inter-agency task force to support EV-related activities in Lithuania. The weight of C1 is 2.44 times greater than that of C5.

Under main criterion D, which concerns the establishment and expansion of public EV charging infrastructure (including the network of charging points and stations), the local weights and rankings of its five sub-criteria indicate that sub-criterion D2 is the top priority ($\tilde{\omega}_{D2I} = 0.2663$). This sub-criterion evaluates the need for high-power DC fast-charging facilities. Sub-criterion D5 ranks lowest ($\tilde{\omega}_{D5I} = 0.1043$), addressing the provision of standard-power slow charging at private residences (Table 7). The ratio between the weights of D2 and D5 is 2.55.

The influence of economic aspects on EV adoption nationwide is captured through the weights and rankings of ten sub-criteria under the main criterion E (Table 8). The expert panel identifies sub-criterion E4 as the most decisive ($\tilde{\omega}_{E4I} = 0.1920$), due to its focus on the elevated manufacturing and purchase costs of EVs relative to internal combustion engine vehicles. Among the economic sub-criteria, E7 receives the lowest weighting ($\tilde{\omega}_{E7I} = 0.0466$), reflecting resistance from existing vehicle industry players to cooperate on fair, non-discriminatory terms for EV market entry. The ratio between E4 and E7 is 4.12—the largest disparity across all main criteria—indicating the experts' strongest differentiation in this domain.

Table 9 presents the local weights $\tilde{\omega}_{FiI}$ and priorities for the eight social sub-criteria influencing EV uptake in the country. The data indicate that sub-criterion F1 holds the highest importance ($\tilde{\omega}_{F1I} = 0.2401$), stemming from the view that every individual bears responsibility for reducing environmental pollution. The least valued is sub-criterion F5 ($\tilde{\omega}_{F5I} = 0.0716$), which considers the reduced risk of electric vehicle theft. The weight of F1 exceeds that of F5 by a factor of 3.35.

Main criterion G, encompassing environmental (ecological) factors, comprises six sub-criteria, with their local weights and rankings shown in Table 10. Sub-criterion G1 is rated most important ($\tilde{\omega}_{G1I} = 0.3119$), primarily because electric vehicles produce no tailpipe emissions of harmful gases during operation. Sub-criterion G5 is considered least significant ($\tilde{\omega}_{G5I} = 0.079$), relating to the quieter operation of EVs, making G1 approximately 3.95 times more relevant.

Global weights and priorities of the sub-criteria

Using Eq. 9, the combination of local weights for the main criteria and their respective sub-criteria enabled the computation of global weights ω_{ig} and global priority rankings for all 50 sub-criteria (Table 12). These global weights

exhibit clear variation. The 22 sub-criteria with the highest global importance exceed the average weight of 0.02, as illustrated in Figure 4.

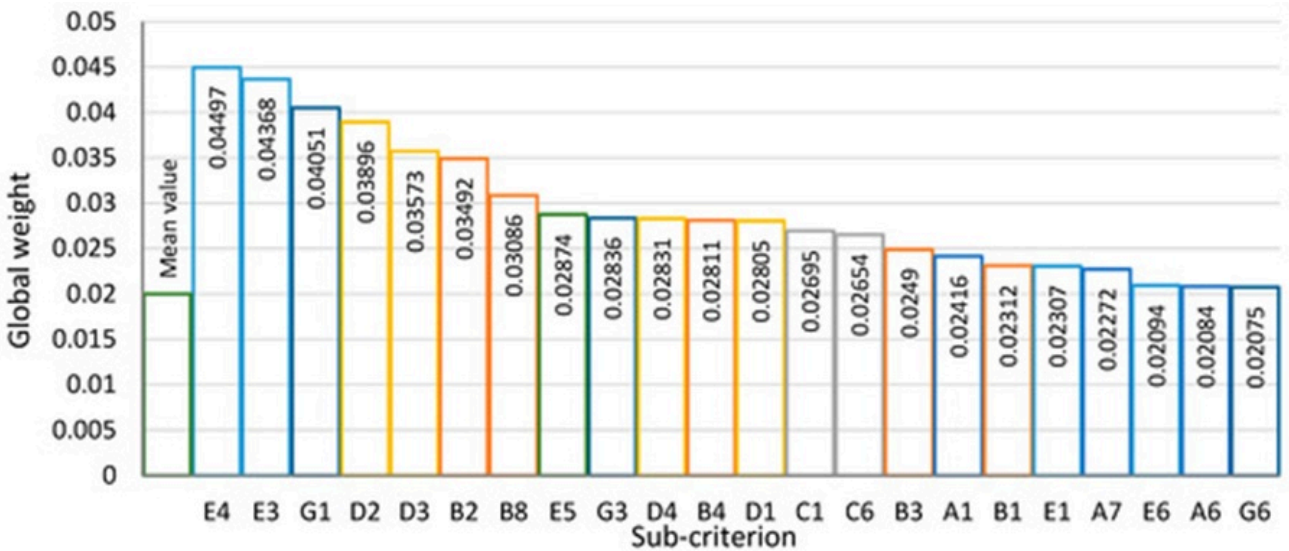


Figure 4. Ranking of the 22 sub-criteria whose global weights exceed the average value of 0.02, representing those with the strongest overall influence on the adoption and deployment of electric vehicles across the country.

Table 12. The local and global weights and priority of the criteria for EV deployment.

The main criterion and weight $Q^{-}i,mc$	Sub-criterion	Local weight ω_i	Local priority	The product $Q^{-}i,mc*\omega_i$	The product $Q^{-}i,n$
A. Studies on and legal acts regulating electric vehicle (EV) deployment $m_{A,mc}=7$ $Q^{-}A,mc=0.1226$	A1	0.1981	1	0.02429	0.1700
	A2	0.1216	4	0.01491	0.1043
	A3	0.0899	7	0.01102	0.0771
	A4	0.1150	6	0.01410	0.0986
	A5	0.1182	5	0.01449	0.1014
	A6	0.1709	3	0.02095	0.1466
	A7	0.1863	2	0.02284	0.1598
B. Technical and operational parameters for electric vehicles $m_{B,mc}=8$ $Q^{-}B,mc=0.1633$	B1	0.1245	5	0.02033	0.1626
	B2	0.1881	1	0.03072	0.2457
	B3	0.1341	4	0.02190	0.1751
	B4	0.1514	3	0.02472	0.1977
	B5	0.0667	8	0.01089	0.0871
	B6	0.0726	7	0.01186	0.0948
	B7	0.0964	6	0.01574	0.1259
	B8	0.1662	2	0.02714	0.2171

C. The action of the initiative subjects for EV deployment $mC,mc=6$ $Q^-C,mc=0.1241$	C1	0.2547	1	0.03161	0.1896
	C2	0.1646	3	0.02043	0.1225
	C3	0.1192	4	0.01479	0.0887
	C4	0.1065	5	0.01322	0.0793
	C5	0.1042	6	0.01293	0.0775
	C6	0.2508	2	0.03112	0.1867
D. Development of public EV charging infrastructure $mD,mc=5$ $Q^-D,mc=0.2059$	D1	0.1917	4	0.03947	0.1973
	D2	0.2663	1	0.05483	0.2741
	D3	0.2442	2	0.05028	0.2514
	D4	0.1935	3	0.03984	0.1992
	D5	0.1043	5	0.02148	0.1073
E. Economic factors $mE,mc=10$ $Q^-E,mc=0.1648$	E1	0.0985	4	0.01623	0.1623
	E2	0.0634	8	0.01045	0.1044
	E3	0.1865	2	0.03074	0.3073
	E4	0.1920	1	0.03164	0.3164
	E5	0.1227	3	0.02022	0.2022
	E6	0.0894	5	0.01473	0.1473
	E7	0.0466	10	0.00768	0.0768
	E8	0.0585	9	0.00964	0.0964
	E9	0.0730	6	0.01203	0.1203
	E10	0.0694	7	0.01144	0.1143
F. Social factors $mF,mc=8$ $Q^-F,mc=0.0670$	F1	0.2401	1	0.01609	0.1287
	F2	0.1725	2	0.01156	0.0924
	F3	0.1217	4	0.00815	0.0652
	F4	0.1227	3	0.00822	0.0657
	F5	0.0716	8	0.00480	0.0383
	F6	0.0909	6	0.00609	0.0487
	F7	0.0724	7	0.00485	0.0388
	F8	0.1081	5	0.00724	0.0579
G. Ecological (environmental) factors $mG,mc=6$ $Q^-G,mc=0.1523$	G1	0.3119	1	0.04750	0.2850
	G2	0.0957	5	0.01458	0.0874
	G3	0.2184	2	0.03326	0.1995
	G4	0.1352	4	0.02059	0.1235

	G5	0.0790	6	0.01203	0.0721
	G6	0.1598	3	0.02434	0.1460
Total	–	7.0000	–	–	7.0365

Based on the computed results, the panel of experts reached consensus that the elevated costs of producing and acquiring electric vehicles (sub-criterion E4), together with the availability of financial incentives for EV buyers (sub-criterion E3), are the two most critical factors influencing EV adoption in Lithuania. Ranked third in overall importance is the environmental sub-criterion G1, which highlights the absence of harmful exhaust emissions from EVs during operation.

The fourth and fifth spots are held by sub-criteria D2 and D3, both related to the establishment and expansion of public charging networks. Positions six and seven are occupied by sub-criteria B2 and B8, which address key technical and operational aspects of EVs—namely, battery lifespan (measured in charge–discharge cycles), the extended duration required to recharge EV batteries compared with refueling a conventional vehicle, and the nationwide regulation introduced in 2022 that prohibits charging sessions of unlimited length.

To speed up the nationwide rollout of electric vehicles, policymakers should allocate substantial funding and effort to strengthening the sub-criteria identified as having the highest priority. Implementing targeted measures aligned with this hierarchy is expected to deliver the most effective progress.

Future research aims to gather insights from specialists in the road transport industry on the relative importance of factors driving EV uptake, and to examine the perspectives of private individuals and organizations that already own EVs or are considering purchasing them. Since individual purchasing decisions ultimately determine the total number of EVs on the road, it is essential to design policies and initiatives that are more impactful in motivating people to switch from internal combustion engine vehicles to electric alternatives.

Conclusion

Rapidly transitioning from traditional internal combustion engine vehicles to electric vehicles (EVs) is one of the most effective ways to mitigate air pollution from road transport. The share of EVs within national vehicle fleets varies across countries, shaped by differences in economic conditions, national transport policies, consumer preferences, incentive mechanisms, infrastructure readiness, vehicle technical characteristics, and environmental standards.

A robust approach to assessing the combined impact of these and additional factors on EV penetration involves drawing on expert judgment and experience to derive subjective weights and rankings through multi-criteria decision-making (MCDM) techniques.

In this study, the authors developed a novel hierarchical framework comprising 50 sub-criteria. Twelve experts evaluated this structure, yielding local and global weights along with priority rankings. To enhance the validity and robustness of the findings, three distinct MCDM methods—ARTIW-L, ARTIW-N, and AHP—were applied. The resulting concordance coefficients and CRs confirmed a high level of agreement among the experts. The arithmetic means of the local weights obtained from these methods served as an intermediate outcome. Ultimately, the global weights and priorities enabled a direct comparison of all 50 sub-criteria.

The analysis of global weights reveals that economic considerations exert the strongest influence on EV deployment in Lithuania. Key drivers include the high manufacturing and purchase prices of EVs, as well as the availability of purchase subsidies and other financial support for buyers. Experts also emphasized that prospective EV owners place significant value on the fact that these vehicles produce no toxic emissions while in use (ranking third overall).

Infrastructure-related factors occupy the fourth and fifth positions, specifically the need to install and expand high-power DC fast-charging stations, as well as to address the current shortage of public charging points in Lithuania's five largest cities, popular resort areas, and along major trans-European transport corridors.

Technical and operational characteristics of EVs—such as battery durability (number of charge–discharge cycles) and the comparatively long charging times (exceeding the duration of a conventional fuel fill)—are ranked sixth and seventh. The eighth position belongs to the economic sub-criterion, which compares the per-distance energy cost of EVs (electricity) with that of fossil-fuel vehicles. However, electricity remains cheaper overall; this advantage is gradually diminishing.

Social factors were judged to have the weakest impact on EV adoption in the country. Sub-criteria F3 through F8 rank between 45th and 50th. The notion that every citizen shares responsibility for curbing environmental pollution (F1) is of moderate importance, ranking 23rd, while promotional efforts highlighting the environmental and quality-of-life benefits of EVs, combined with climate activism demonstrations (F2), rank 36th.

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