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MULTICRITERIA ASSESSMENT OF TECHNICAL PERFORMANCE IN BATTERY ELECTRIC VEHICLES

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Abstract:

The rapid electrification of road transport is reshaping the automotive market, particularly in Europe, where battery-electric vehicles (BEVs) are becoming increasingly prevalent. Evaluating vehicle-level technological performance is critical for understanding competitiveness in this evolving landscape. This study aims to systematically assess and rank 174 BEV models in the B and C segments, considering technical and performance criteria, to identify technologically competitive vehicles and to compare the technological performance of Chinese manufacturers with that of established global brands. Eight technical indicators were selected to capture key dimensions of competitiveness: driving range, battery capacity, energy efficiency, fast-charging speed, maximum speed, trunk capacity, acceleration, and full-charging time. An integrated multicriteria decision-making (MCDM) framework was applied, combining Shannon's entropy, the CRITIC method for objective weighting, the TOPSIS method for ranking, and the Borda count for consensus aggregation. The proposed MCDM framework offers a replicable and robust approach for benchmarking technological performance across heterogeneous BEV models. The analysis reveals that European manufacturers, particularly German brands, continue to dominate the highest-ranking positions due to well-established engineering capabilities, long-term investment in innovation, and patent-based technological leadership. Chinese producers included in the sample, while representing a growing share of the market, display strong performance in battery technology, cost efficiency, and manufacturing scale. Yet, their presence in the European B and C segments remains limited. The results further highlight that BEV competitiveness is multidimensional, reflecting trade-offs between performance, efficiency, and usability. C-segment vehicles tend to prioritise extended driving range and larger battery capacity, whereas B-segment models focus on energy efficiency and compact design, catering to urban mobility requirements. The study demonstrates that a single attribute cannot determine technological competitiveness; rather, it depends on a balanced combination of multiple criteria. These findings provide policymakers, manufacturers, and investors with insights into the technological strengths and weaknesses of contemporary BEV models, supporting evidence-based discussions on sustainable mobility and industrial development.

Keywords: *Battery electric vehicles, technological competitiveness, multicriteria decision-making, TOPSIS, Chinese electric vehicles*

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1. Introduction

The transition to electromobility is reshaping the automotive industry's competitive landscape. In Europe, the sector remains central to economic activity while facing increasing pressure to meet climate objectives (European Alternative Fuels Observatory [EAFO], 2024; Pichler et al., 2021). This transformation reflects not only technological change but also intensifying global competition among manufacturers seeking leadership in the rapidly expanding electric vehicle market.

Battery electric vehicles (BEVs), powered exclusively by rechargeable batteries (Faraz et al., 2020), have expanded rapidly across advanced and emerging markets. In the European Union (EU) alone, nearly 5.9 million BEVs were registered by 2024, representing a 117-fold increase since 2013 (Eurostat, 2026). Although temporary slowdowns followed subsidy reductions and regulatory adjustments (International Energy Agency [IEA], 2025), the long-term trajectory remains upward (EAFO, 2024). As BEV adoption accelerates, the technological characteristics of individual vehicle models increasingly influence market competitiveness.

Market development is shaped by regulation, incentives, charging infrastructure, and battery innovation (Razmjoo et al., 2022; Mariasiu et al., 2023). While policy instruments and infrastructure facilitate diffusion (Jurlin, 2023; Gómez Vilchez et al., 2019; Peng et al., 2024), consumer preferences and vehicle-level attributes remain key determinants of market success (Adnan et al., 2018; Jena, 2020; Lieven, 2015; Sierzchula et al., 2014). Consequently, evaluating the technological performance of individual BEV models has become an important component of understanding competitiveness in the evolving electromobility ecosystem.

Global competition in electromobility has intensified, particularly with the rapid rise of Chinese manufacturers. Supported by large-scale domestic production, strong policy incentives, and rapid advances in battery technology, China has become both the world's largest EV market and a major exporter of BEVs (Altenburg et al., 2022; Bencivelli et al., 2024; Shao, 2024; Zhao et al., 2024; Zhou et al., 2019). By 2023, China accounted for 29% of global BEV exports, while the share of Chinese-made BEVs in EU registrations increased from 0.4% in 2019 to 19.5% in 2023 (Khaleel et al., 2024). These developments have intensified competition between established global manufacturers and emerging Chinese producers.

Despite this growing competition, there is still no comprehensive, large-scale, model-level assessment that objectively compares the technological competitiveness of BEVs across manufacturers and countries of origin. Existing studies typically rely on small sample sizes, use subjective weighting approaches, or focus primarily on economic or policy dimensions rather than on harmonised technical benchmarking. As a result, it remains unclear which BEV models demonstrate the strongest technological performance and whether Chinese models outperform competitors under uniform evaluation criteria. To address this gap, our study introduces a comprehensive, objective assessment of BEV technological competitiveness.

In this context, the study's objective is to evaluate and rank 174 BEV models based exclusively on technical and performance criteria to determine which models demonstrate the strongest overall technological competitiveness and whether Chinese models achieve superior positions relative to other manufacturers. The analysis considers eight technical criteria: driving range, battery capacity, energy efficiency, fast-charging speed, maximum speed, trunk capacity, acceleration, and full-charging time. Price is excluded to ensure the assessment reflects technological capability rather than market positioning. All analysed models belong to segments B and C, which represent a substantial share of the global passenger BEV market.

This study makes four key contributions to the literature on BEV competitiveness:

1. It provides one of the largest model-level assessments in the literature, evaluating 174 BEV models from segments B and C (mostly crossovers/SUVs). This far exceeds prior studies, which were limited to small samples or aggregated data. This scale enables robust, generalisable insights into manufacturer performance.
2. Rather than subjective methods, this approach uses entropy and CRITIC weighting. This makes it more reliable by combining information entropy with contrast-based measures for criterion importance.
3. It integrates TOPSIS (for multicriteria distance to ideal solutions) with Borda count

aggregation, yielding a consensus ranking that mitigates biases from single techniques.
4. It provides well-structured evidence on the performance of Chinese BEVs in relation to those of European and other competitors, contributing to discussions on global competition and policy responses, such as EU duties.

By integrating complementary objective weighting techniques with a consensus-based ranking procedure, the proposed framework provides a more robust benchmarking for large-scale technological comparisons of heterogeneous EV models.

The next section reviews the relevant literature on electric vehicle competitiveness and multicriteria decision-making methods. The subsequent section presents the methodology and dataset used in the analysis. The results section reports the ranking outcomes and comparative evaluation of BEV models. Finally, the discussion and conclusion sections interpret the findings and outline implications for research and policy.

2. Literature Review

Multicriteria decision-making (MCDM) methods are widely used in electromobility research to evaluate vehicles across technical, economic, and environmental dimensions. However, applications differ substantially in scope, scale, and methodological structure. The objective of this literature review is to identify the main methodological approaches used for evaluating electric vehicle performance and to highlight existing research gaps in large-scale, objective benchmarking of electric vehicle models. The review, therefore, focuses on studies that apply TOPSIS and related MCDM techniques to the assessment of electric vehicles.

Ashraf et al. (2025) applied an entropy–TOPSIS framework to evaluate the carbon footprint of various vehicle types, identifying battery manufacturing as the dominant source of emissions and ranking hybrid vehicles as the most environmentally favourable option. The study confirms the applicability of objective MCDM techniques for vehicle-level environmental benchmarking, although it focuses primarily on emission performance rather than technological competitiveness.

Dwivedi and Sharma (2023) assessed 15 commercially available electric vehicles using entropy-based weighting and the TOPSIS method across 10 technical and operational criteria. Their results revealed trade-offs between performance indicators and practical constraints such as charging time and battery capacity, demonstrating the effectiveness of dispersion-based objective weighting. However, the inclusion of price-related variables extends the analysis beyond purely technical benchmarking.

Gupta et al. (2022) combined AHP, TOPSIS, and DEA to analyse green vehicle alternatives in the Indian market. By integrating stakeholder-based weighting with efficiency analysis, the study offered a multidimensional evaluation covering technical, economic, and policy-related factors. While methodologically robust, the framework incorporates subjective preferences and adoption-oriented criteria rather than focusing solely on intrinsic technological performance.

Hybrid and fuzzy extensions further broaden the methodological landscape. Tian et al. (2023) proposed an HIFSs–ORESTE–BWM model combining subjective and objective weights; Onat et al. (2015) applied intuitionistic fuzzy TOPSIS for lifecycle sustainability assessment; Sinha and Chattopadhyay (2024) used fuzzy AHP–TOPSIS for sustainable vehicle prioritisation; and Samaie et al. (2020) integrated fuzzy TOPSIS with game-theoretic modelling to evaluate policy incentives. These contributions demonstrate the flexibility of TOPSIS-based frameworks, yet frequently incorporate preference-driven or policy-oriented dimensions rather than large-scale, purely technical benchmarking.

An interesting benchmarking study was conducted by Gökgöz and Yalçın (2024), who analysed electric vehicle performance and efficiency across the EU using decision-analysis methods. The study demonstrates that objective, market-level benchmarking of multiple electric vehicle models is feasible within a unified framework. At the same time, the methodological structure differs from the integrated entropy–CRITIC–TOPSIS approach used here, as it does not combine dual-objective weighting with an additional consensus aggregation stage. The present study, therefore, builds on this benchmarking logic while extending the methodological integration.

In addition to evaluation frameworks, weighting procedures represent an important methodological component in MCDM applications. Puška (2025) applied the CRITIC method within an ideal-solution ranking framework for evaluating electric vehicles. This confirms the relevance of correlation-sensitive objective weighting in the field. However, entropy-based dispersion weighting was not implemented jointly, limiting the ability to balance variability and inter-criteria correlation effects within a single structure.

Tadić et al. (2025) ranked 18 electric vehicles using a fuzzy TOPSIS–COPRAS model based on technical attributes. While methodologically advanced, the framework incorporates fuzzy preference structures and group assessments, introducing subjective elements into weight determination. In contrast, the present study relies exclusively on objective statistical weighting to isolate intrinsic technological competitiveness.

Golui et al. (2023) proposed a correlation-based measure within a Fermatean fuzzy TOPSIS framework and conducted sensitivity analysis to assess ranking stability. Although the article makes a valuable methodological contribution in conditions of uncertainty, its primary focus is on fuzzy modelling rather than on large-sample, harmonised benchmarking of observable technical parameters.

Across this literature, several regularities emerge. First, subjective or semi-subjective weighting approaches remain common. Second, many empirical studies rely on relatively small samples, often fewer than 20 vehicles, which limits dispersion-based differentiation. Third, technical, economic, environmental, and behavioural variables are frequently combined within composite indices, making it difficult to isolate engineering-level competitiveness.

In this study, competitiveness is understood as technological competitiveness, referring exclusively to the relative ability of BEV models to deliver superior technical performance, energy efficiency, and functional usability, as reflected in observable vehicle attributes. This interpretation focuses on technological characteristics embodied in the vehicle itself and does not encompass market, financial, pricing, or policy dimensions. While technological competitiveness has traditionally been discussed at the firm level as the ability to create and effectively utilise technological capabilities (Ambastha & Momaya, 2004; Aiginger, 2006), the concept can also be applied at the product level, where technical performance serves as a direct manifestation of technological capability.

In contrast to single-method weighting in Dwivedi and Sharma (2023) or Puška (2025), this study integrates entropy (to capture criterion variability) with CRITIC (to account for inter-criteria correlations). This balanced approach is more effective at addressing the limitations of isolated methods, as it provides more robust weights. While TOPSIS is a common method (e.g., Ashraf et al., 2025; Tadić et al., 2025), it lacks a consensus mechanism for rank stability. Our approach integrates Borda count aggregates with TOPSIS rankings and probabilistic simulations, addressing the limitations observed in Gökgöz and Yalçın (2024) and Golui et al. (2023) by reducing rank reversals. Finally, hybrid/subjective models (Gupta et al, 2022; Tian et al, 2023) involve the isolation of objective technical criteria. This has enabled us to achieve unparalleled granularity in engineering competitiveness, without the need for economic or subjective distortions.

Collectively, these patterns indicate the absence of a large-scale, purely technical benchmarking framework based exclusively on objective statistical weighting and consensus rank aggregation. Addressing this configuration constitutes the methodological and empirical focus of the present study. We attempt to address two research questions. How do European BEV brands perform in the technological competitiveness rankings? Do Chinese brands have a technical edge over vehicles from other manufacturers?

3. Criteria and Objects Selected in the Study

In line with the research objective, the analysis includes eight technical criteria: driving range, battery capacity, efficiency, fast-charging speed, maximum speed, trunk capacity, acceleration, and full-charging time. These indicators were selected for their frequent use in previous MCDM studies (see Table 1) and their direct relevance to vehicle performance and operational characteristics. They capture the multidimensional nature of technological competitiveness defined above.

Table 1 is structured to illustrate the evolution of MCDM applications in electric vehicle research, moving from small-sample, subjective or hybrid methods, through entropy- and CRITIC-based approaches, to benchmarking frameworks, culminating in the present study's integrated, fully objective approach.

To enhance analytical clarity and reduce conceptual overlap, the criteria were organised into four coherent groups presented in Table 2.

Environmental indicators (e.g., lifecycle emissions) were excluded because the study focuses on comparing intrinsic technological and performance characteristics of vehicles rather than broader environmental impacts, which depend strongly on external factors such as national energy mixes. Furthermore, the sample includes models from comparable market segments (primarily B and C segments), ensuring structural similarity in vehicle size and intended use, thereby increasing the validity of cross-model comparisons.

Table 1. MCDM-based evaluation of electric vehicle models and brands

Author (year)	Methods	No of vehicles	No of criteria	Criteria specification	
Tian et al. (2023)	HIFSs ORESTE BWM sentiment analysis	8	8	C1 – comfort, C2 – cost performance, C3 – appearance, C4 – interior,	C5 – fuel consumption, C6 – space, C7 – handling, C8 – power.
Gupta et al. (2022)	AHP TOPSIS DEA	16	12	C1 – looks, C2 – price, C3 – dimension, C4 – average, C5 – performance, C6 – eco-friendly,	C7 – brand, C8 – technological features, C9 – affordable insurance, C10 – clearance from RTO, C11 – ownership cost, C12 – ease of resale.
Dwivedi & Sharma (2023)	Entropy TOPSIS	15	10	C1 – total power, C2 – electric range, C3 – battery capacity, C4 – top speed, C5 – cargo volume,	C6 – acceleration, C7 – base price, C8 – fast charge time, C9 – full charge time, C10 – unladen weight.
Kaczyńska et al. (2023)	Interval TOPSIS	15	10	The repeated experiment of Dviwedi and Sharma (2023)	
Pal, Saraswat & Budhraja (2023)	Entropy TOPSIS	13	6	C1 – price, C2 – acceleration, C3 – battery capacity,	C4 – maximum power, C5 – range, C6 – charging time.
Tadić et al. (2025)	Fuzzy TOPIS Fuzzy COPRAS	18	10	C1 – driving range, C2 – price, C3 – nominal battery capacity, C4 – usable battery capacity, C5 – charging time,	C6 – seating capacity, C7 – torque, C8 – power, C9 – top speed, C10 – acceleration.
Puška (2025)	EDISA CRITIC	14	10	C1 – acceleration, C2 – range, C3 – power, C4 – torque, C5 – battery capacity,	C6 – cargo maximum, C7 – carrying capacity, C8 – charging, C9 – consumption, C10 – price.
Gökgöz & Yalçin (2024)	PSI ADAM DEA	20	10	C1 – purchasing price, C2 – acceleration, C3 – energy consumption, C4 – fast charging time, C5 – torque,	C6 – top speed, C7 – range, C8 – insurance/maintenance cost, C9 – sales, C10 – actual market share.
This study	Entropy CRITIC TOPSIS Borda count	174	8	C1 – driving range, C2 – battery capacity, C3 – efficiency, C4 – fast charging speed,	C5 – maximum speed, C6 – trunk capacity, C7 – acceleration, C8 – full charging time.

ADAM - Axial-Distance-Based Aggregated Measurement, AHP - Analytic Hierarchy Process, BWM - Best-Worst Method, COPRAS - Complex Proportional Assessment, CRITIC - Criteria Importance Through Inter-criteria Correlation, DEA - Data Envelopment Analysis, EDISA - Evaluation by Distance from Ideal Solution of Alternatives, HIFSs - Hesitant Intuitionistic Fuzzy Elements, ORESTE - Organísation, Rangement et Synthése de Données Relarionnelles, PSI - Preference Selection Index, TOPSIS - Technique for Order of Preference by Similarity to Ideal Solution.

Table 2. Classification of technological competitiveness criteria

Dimension	Criterion	Operational meaning	Unit	Key literature
Technical performance	driving range	operational autonomy per charge	km	Dwivedi & Sharma (2023), Kaczyńska et al. (2023), Pal, Saraswat & Budhraja (2023), Tadić et al. (2025), Puška (2025), Gökgöz & Yalçin (2024)
	acceleration	dynamic responsiveness and drivetrain efficiency	s	Dwivedi & Sharma (2023), Kaczyńska et al. (2023), Pal, Saraswat & Budhraja (2023), Tadić et al. (2025), Puška (2025), Gökgöz & Yalçin (2024)
	maximum speed	powertrain capability and engineering potential	km/h	Dwivedi & Sharma (2023), Kaczyńska et al. (2023), Tadić et al. (2025), Gökgöz & Yalçin (2024)
	fast-charging speed	integration with high-power charging infrastructure	kW	Dwivedi & Sharma (2023), Kaczyńska et al. (2023), Pal, Saraswat & Budhraja (2023), Tadić et al. (2025), Puška (2025), Gökgöz & Yalçin (2024)
Efficiency	energy consumption	energy used per distance travelled	kWh/100 km	Tian et al. (2023), Gupta et al. (2022), Dwivedi & Sharma (2023), Puška (2025), Gökgöz & Yalçin (2024)
Usability	trunk capacity	functional cargo usability under battery constraints	Litres	Dwivedi & Sharma (2023), Kaczyńska et al. (2023), Puška (2025)
	full-charging time	charging system performance under standard conditions	Hours	Dwivedi & Sharma (2023), Kaczyńska et al. (2023), Pal, Saraswat & Budhraja (2023), Tadić et al. (2025), Puška (2025), Gökgöz & Yalçin (2024)
Energy storage capacity	battery capacity	total stored energy available for propulsion	kWh	Dwivedi & Sharma (2023), Kaczyńska et al. (2023), Pal, Saraswat & Budhraja (2023), Tadić et al. (2025), Puška (2025)

4. Methodology

As noted earlier, this study evaluates and ranks 174 BEV models from the B and C segments to assess technological competitiveness across manufacturers, with particular attention to the relative position of Chinese brands. An integrated MCDM framework is applied, combining Shannon's Entropy and CRITIC for objective weighting, followed by TOPSIS ranking and Borda count aggregation. The overall research design is presented in Fig. 1.

The dataset was collected in September 2025 from publicly available sources, including the European Alternative Fuels Observatory (EAFO) and the EV Database, which provide harmonised technical specifications for BEVs. The initial dataset was screened to remove duplicate entries, models with incomplete technical specifications, and inconsistent records. Only fully electric passenger vehicles with complete data for all eight technical criteria were retained, resulting in a final sample of 174 models. All calculations and data processing were conducted using Microsoft Excel. Because the study relies exclusively on publicly available vehicle technical specifications, it does not involve human participants or personal data and therefore does not require ethical approval. The focus on BEV models from segments B and C allows the results to be interpreted primarily for the compact- and mid-size-passenger BEV market.

4.1. Data Sources and Pre-Processing

Criteria were classified as beneficial (higher values preferred: driving range, battery capacity, maximum speed, fast-charging speed, trunk capacity) and non-beneficial (lower values preferred: acceleration time, energy consumption, full-charging time). The TOPSIS method does not involve converting non-beneficial alternatives into beneficial ones, as in AHP. Instead, it employs two distinct approaches to determine ideal and anti-ideal solutions. The specific formulas are outlined in Section 4.3.

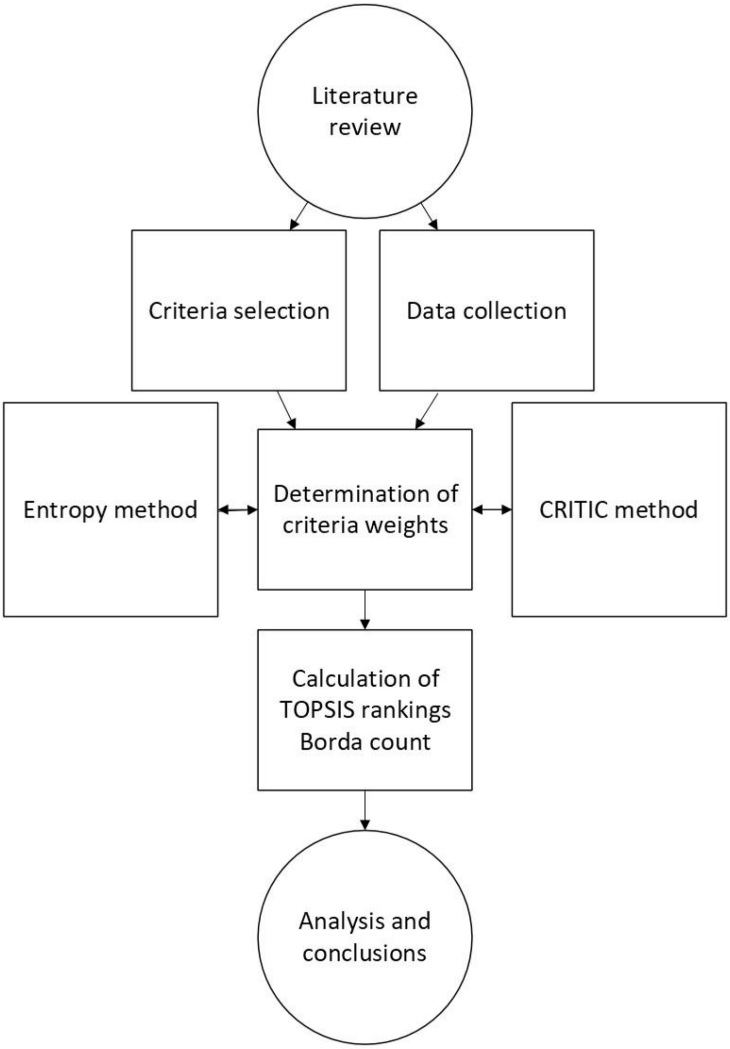

Fig. 1. Methodology framework of this study

4.2. Entropy and CRITIC Weighting

Shannon's Entropy

Entropy determines criterion weights based on data dispersion (Shannon, 1948). Greater variability implies higher information content and, therefore, higher importance.

Given a decision matrix $Q_{N\times K}$, the data are normalised, and the entropy-based divergence for each criterion is calculated as (Bartosiewicz & Jadczak, 2023):

$$d_j = 1 + \frac{1}{\ln N}\sum_{i=1}^{N} \widehat{m}_{ij} \ln \widehat{m}_{ij} \tag{1}$$

Weights are obtained by normalisation:

$$w_j = \frac{d_j}{\sum_{j=1}^{K} d_j} \tag{2}$$

Entropy reflects only the intrinsic distribution of values within each criterion and does not account for inter-criterion relationships.

CRITIC method

The CRITIC method extends objective weighting by incorporating both variability and inter-criterion correlation. Criteria with high contrast intensity (as measured by standard deviation) and low redundancy (low correlation with others) receive greater importance (Fan et al., 2025; Zhang et al., 2024). The information measure for each criterion is calculated as (Hassan et al., 2023):

$$H_j = s_j \sum_{k=1}^{m} (1 - r_{jk}) \quad (3)$$

Weights are then normalised:

$$w_j = \frac{H_j}{\sum_{j=1}^{m} H_j} \quad (4)$$

While entropy captures dispersion independently, CRITIC additionally penalises redundancy between criteria. Combining both methods increases robustness by balancing pure variability with structural interdependence within the dataset.

Both Entropy and CRITIC methods are based on objective weighting techniques, though they are calculated using different mathematical assumptions. The Entropy method assigns weights based on the dispersion of criterion values, whereas CRITIC combines a dispersion measure with correlation analysis. This may result in substantial differences between the Entropy and CRITIC weight results (Diakoulaki et al., 1995).

4.3. TOPSIS Ranking Procedure

TOPSIS ranks alternatives based on their distances from the positive and negative ideal solutions (Hassan et al., 2023; Dwivedi & Sharma, 2023). After vector normalisation:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (5)$$

The weighted matrix is constructed, and distances to ideal and anti-ideal solutions are computed (Ashraf et al., 2025; Kucharski & Lekka-Porębska, 2023). Ideal (A^+) and anti-ideal (A^-) solutions:

$$A^+ = \{v_1^+, \ldots, v_k^+\} = \\ = \left\{\left(\max_i v_i^{(k)} | k \in K^+\right), \left(\min_i v_i^{(k)} | k \in K^-\right)\right\} \quad (6)$$

$$A^- = \{v_1^-, \ldots, v_k^-\} = \\ = \left\{\left(\min_i v_i^{(k)} | k \in K^+\right), \left(\max_i v_i^{(k)} | k \in K^-\right)\right\} \quad (7)$$

where $v_i^{(k)}$ is an element of the weighted normalised criteria matrix, the set K^+ corresponds to beneficial criteria, and the set K^- to non-beneficial ones.

The closeness coefficient is defined as:

$$C_i = \frac{s_i^-}{s_i^+ + s_i^-}, \; 0 \le C_i \le 1 \quad (8)$$

where s_i^-, s_i^+ are Euclidean distances of the variants from the weighted ideal solution.

Higher values of C_i indicate stronger overall performance. By integrating weights from Entropy and CRITIC, TOPSIS enables a consistent and bias-reduced evaluation of technological competitiveness across models.

4.4. Borda Count Aggregation

To obtain a consensus ranking, results derived from Entropy-TOPSIS and CRITIC-TOPSIS were aggregated using the Borda count method (Costa, 2017). The Borda method is a ranking aggregation technique in which each rank is assigned a specific number of points, summed for all items. The item with the highest total score is considered the best.

This procedure reduces sensitivity to method-specific fluctuations and ensures a stable, consensus-oriented final ordering of BEV models.

5. Results

The construction of the final decision matrix allowed the determination of criterion weights using objective weighting methods, namely Shannon entropy and CRITIC. The evaluation criteria were selected to capture key dimensions of electric vehicle assessment, including technical performance, energy efficiency, and usability.

The weights obtained using the Shannon entropy method indicate that efficiency (0.02) and top speed (0.03) have the lowest influence on the ranking, while fast charging speed (0.30) and acceleration (0.19) are the most influential criteria. Moderate importance is assigned to cargo volume (0.14) and battery capacity (0.12). Driving range (0.10) and full charging time (0.11) receive slightly lower weights.

In contrast, the CRITIC method places greater emphasis on energy efficiency (0.20) and full charging time (0.18), indicating that energy consumption and charging characteristics act as key differentiating factors among models. Relatively high weights are also assigned to cargo volume (0.15) and acceleration (0.12). In this configuration, fast charging speed (0.07) becomes less influential compared with the Entropy-based results.

To provide an additional benchmark, a mean-weighting scenario was also considered, in which each criterion receives an equal weight of 0.125. In all cases, the sum of weights equals one. Table 3 presents the complete set of weights used in the calculations and indicates whether each criterion is beneficial (max) or non-beneficial (min).

Shannon entropy assigns greater weight to data sets with high variability. This is because such data sets have lower entropy. In the CRITIC method, the lower the correlation between a given criterion and other criteria, the higher the weight. Both methods offer distinct perspectives on the data. As illustrated in Table 3, there are clear differences in weights, particularly in the 'energy efficiency' criterion.

The heatmap in Table 3 highlights the differences between the Entropy and CRITIC weighting schemes. Entropy emphasises dynamic performance and charging capability, whereas CRITIC emphasises efficiency and charging duration.

The descriptive statistics presented in Table 4 indicate that the analysed sample includes vehicles with diverse technical characteristics typical of B- and C-segment electric vehicles. The average driving range is approximately 337 km (170–565 km), while the average battery capacity equals 58.6 kWh, with most models falling within the 50–70 kWh range.

Energy consumption remains relatively consistent across models, with a mean value of 17.5 kWh/100 km. In contrast, fast charging performance shows substantial variation, reflecting technological differences between entry-level and high-performance vehicles. The average top speed equals 166 km/h, while cargo capacity averages 401 litres, mainly due to variations in vehicle body styles.

The average acceleration time is 7.8 seconds, ranging from 3.6 to 12.9 seconds, indicating the presence of both performance-oriented and economy models. The average full charging time equals approximately 6.5 hours, although some vehicles support lower charging power, which increases charging duration.

Table 3. The units, types, and a heatmap of the criteria weights for BEV evaluation obtained using the Entropy, CRITIC, and mean methods

	No.	Unit	Type	Entropy	CRITIC	Mean
Range	c_1	km	max	0.10	0.08	0.125
Battery size	c_2	kwh	max	0.12	0.10	0.125
Energy efficiency	c_3	kWh/100 km	min	0.02	0.20	0.125
Fast charge speed	c_4	km/h	max	0.30	0.07	0.125
Top speed	c_5	km/h	max	0.03	0.09	0.125
Cargo volume	c_6	litre	max	0.14	0.15	0.125
Acceleration	c_7	s	min	0.19	0.12	0.125
Full charge time	c_8	min.	min	0.11	0.18	0.125

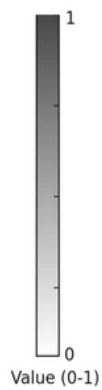

Table 4. Descriptive statistics of the BEV specifications

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8
Mean	336.7	58.6	17.5	481.8	166.4	401.2	7.8	393.5
Std dev.	66.6	12.9	1.4	177.2	17.1	92.6	1.9	83.4
Median	330	59	17	480	160	390	7.9	390
Min	170	29	15	170	132	200	3.6	195
Max	565	96.9	21	1480	235	608	12.9	645
Range	395	67.9	6	1310	103	408	9.3	450

Table 5 presents the linear correlation coefficients between the criteria. Most criteria show moderate positive correlations, typically within the 0.3–0.7 range, while only a few pairs exceed 0.7, indicating strong relationships.

The strongest correlation is between driving range and battery capacity (r = 0.933), as expected given the direct relationship between stored energy and achievable driving distance. The driving range also shows a strong correlation with fast charging speed (r = 0.751), suggesting that vehicles designed for longer travel distances tend to support faster charging.

In contrast, energy efficiency (c3) shows only a weak relationship with range (r = 0.173), indicating that energy consumption does not necessarily increase proportionally with driving range. Acceleration (c7) displays negative correlations with most criteria, particularly top speed (r = −0.726) and battery size (r = −0.505), reflecting trade-offs between performance, energy efficiency, and vehicle weight.

The distribution of BEV models by country of origin (Fig. 2) reveals a clear imbalance in the analysed sample. German manufacturers dominate the dataset, accounting for 56 models (32.2%), followed by France with 35 models (20.1%), confirming their strong position in the electric vehicle market. Chinese manufacturers represent 30 models (17.2%), reflecting their rapidly expanding presence and growing technological competitiveness (see Appendix 2). South Korea and Sweden each contribute 12 models (6.9%), while Japanese manufacturers account for 10 models (5.7%). Smaller shares are observed for Italy (4.0%) and the United States (2.9%), although these countries remain important players in the global electric vehicle industry.

Table 5. Correlations between criteria

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8
c_1	1.0000							
c_2	0.9333	1.0000						
c_3	0.1732	0.4994	1.0000					
c_4	0.7514	0.6709	0.0839	1.0000				
c_5	0.5180	0.5827	0.4101	0.6246	1.0000			
c_6	0.3993	0.4173	0.1444	0.2934	0.1995	1.0000		
c_7	-0.4393	-0.5054	-0.3908	-0.4833	-0.7264	0.0342	1.0000	
c_8	0.5858	0.6688	0.3991	0.4146	0.4250	0.3487	-0.3179	1.0000

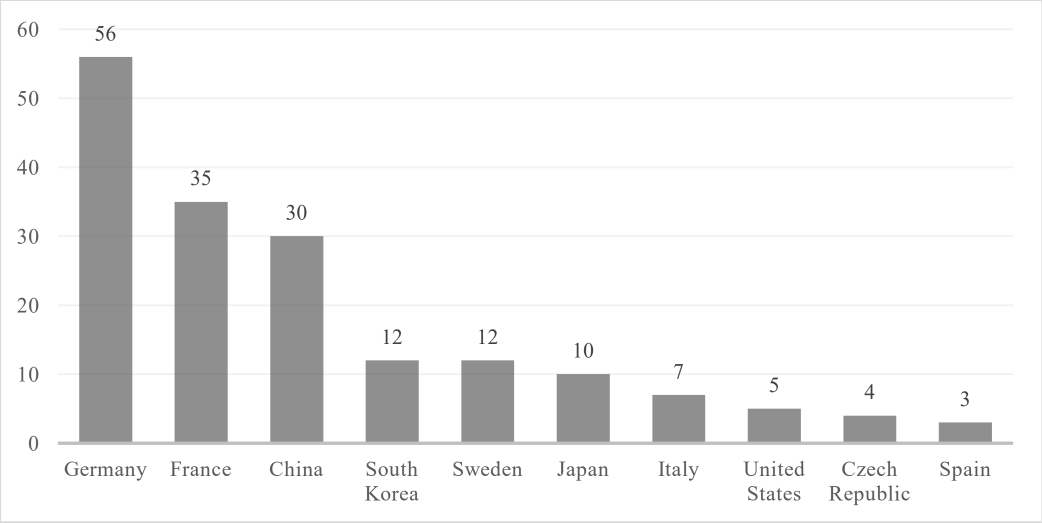

Figure 2. The distribution of model counts by country

Table 6 presents the top 30 BEV models according to the combined TOPSIS–Borda ranking. The results indicate a strong presence of European manufacturers, particularly German brands, which occupy several leading positions in the ranking. The Mercedes-Benz CLA 250+ and Mercedes-Benz CLA 350 4MATIC achieve the highest overall scores across all weighting scenarios, reflecting a balanced combination of range, charging performance, and dynamic characteristics.

South Korean manufacturers also perform strongly, with several Genesis GV60 variants appearing among the top-ranked vehicles. These models achieve high positions due to their strong acceleration performance and competitive charging capabilities.

Chinese manufacturers appear in the ranking as well, most notably with the Zeekr X Privilege AWD and MG4 Electric XPOWER, demonstrating that Chinese brands are increasingly able to compete technologically with established European producers. However, their representation among the very top positions remains limited (2 out of 30 top models).

6. Discussion

The results provide insight into BEVs' relative technological performance and highlight differences in technological competitiveness between established global manufacturers and emerging Chinese brands. The applied multicriteria framework reveals that electric vehicle competitiveness is determined by performance, energy efficiency, and practical usability. In particular, the results suggest that technological advantages are not determined by a single parameter but rather by a balanced configuration of several attributes. This finding is consistent with broader research indicating that electric vehicle adoption and competitiveness depend simultaneously on vehicle performance, operational efficiency, and consumer-oriented functionality (Alanazi, 2023; Malik et al., 2025).

The analysis also indicates that vehicle design involves trade-offs between several partially conflicting engineering objectives. High dynamic performance, large battery capacity, and long driving range must be balanced against energy efficiency and charging characteristics. Such trade-offs reflect fundamental technological constraints of electric powertrains and battery systems, which require manufacturers to optimise multiple parameters simultaneously. Similar multidimensional challenges in electric vehicle development have been emphasised in studies of the technological transition toward electrified transport systems (Dua et al., 2024; Malik et al., 2025).

Table 6. Top 30 models based on TOPSIS and Borda method

Model	Entropy	CRITIC	Mean	Borda	Place	Origin
Mercedes-Benz CLA 250+	1	1	1	519	1	Germany
Mercedes-Benz CLA 350 4MATIC	2	2	2	516	2	Germany
Genesis GV60 Sport	4	4	3	511	3	South Korea
Genesis GV60 Premium	3	12	4	503	4	South Korea
Genesis GV60 Sport Plus	5	9	5	503	5	South Korea
Ford Capri Extended Range AWD	8	6	6	502	6	United States
CUPRA Born VZ	6	7	7	502	7	Spain
Volkswagen ID.3 GTX Performance	7	13	8	494	8	Germany
Skoda Elroq RS	10	15	9	488	9	Czech Republic
Ford Capri Extended Range RWD	12	11	11	488	10	United States
Volkswagen ID.3 GTX	9	17	10	486	11	Germany
Volkswagen ID.3 Pro S	14	16	16	476	12	Germany
Audi Q4 Sportback e-tron 55 quattro	17	21	15	469	13	Germany
Skoda Elroq 85	13	30	12	467	14	Czech Republic
Audi Q4 Sportback e-tron 45	15	27	14	466	15	Germany
Audi Q4 e-tron 45	18	28	18	458	16	Germany
Volvo EC40 Twin Motor Performance	19	31	20	452	17	Sweden
Renault Scenic E-Tech EV87 220hp	50	3	19	450	18	France
BMW iX2 xDrive30	43	5	26	448	19	Germany
Audi Q4 e-tron 55 quattro	21	34	21	446	20	Germany
Audi Q4 Sportback e-tron 45 quattro	22	40	22	438	21	Germany
BMW iX1 xDrive30	46	10	29	437	22	Germany
Zeekr X Privilege AWD	24	42	30	426	23	China
CUPRA Born 170 kW - 77	11	69	17	425	24	Spain
CUPRA Born 170 kW - 59	23	41	38	420	25	Spain
Audi Q4 e-tron 45 quattro	28	53	23	418	26	Germany
BMW iX2 eDrive20	51	19	39	413	27	Germany
Peugeot e-3008 97 Long Range	16	82	13	411	28	France
MG MG4 Electric XPOWER	32	46	37	407	29	China
Volvo EX30 Twin Motor Performance	26	61	35	400	30	Sweden

Another important observation concerns structural differences between vehicle segments. Models in the C segment generally achieve better battery capacity and driving range, while smaller B-segment vehicles tend to prioritise energy efficiency and compact design. This distinction reflects the functional roles of these vehicle classes: urban-oriented models focus on efficiency and compactness, while larger vehicles emphasise extended range and performance. Such differentiation is consistent with research showing that the development of the electric vehicle market is strongly shaped by heterogeneous consumer preferences and vehicle-use patterns (Song et al., 2023; Möring-Martínez et al., 2024).

The global automotive market is experiencing increased competition from well-established brands and new participants from China. Within the scope of this study, the comparison focuses exclusively on vehicle-level technological performance rather than market or pricing factors. From a technological competitive perspective, the results indicate that European manufacturers continue to dominate the highest-ranked models. This outcome reflects the long-term technological capabilities of European automotive firms, particularly in powertrain engineering and system integration. Previous studies highlight that sustained investment in innovation and patent development has played a crucial role in building this technological base, especially in countries such as Germany (Konka & Veres, 2022). Such innovation ecosystems have contributed to strong engineering capabilities across energy storage systems, charging technologies, and electric drive components.

At the same time, the results also demonstrate the increasing technological competitiveness of Chinese manufacturers. Although their representation among the very top-ranked models remains limited, Chinese brands are already present in the higher segments of the ranking. This pattern may be associated with the rapid expansion of China's electric vehicle industry, supported by large-scale manufacturing capacity, strong domestic demand, and extensive public policy support (Altenburg et al., 2022; Zhao et al., 2024). The rapid development of battery technology and vertically integrated supply chains has further strengthened China's position within the global electric vehicle ecosystem.

The findings indicate that technological competitiveness in the analysed BEV segments is multidimensional and cannot be explained by a single vehicle attribute. While the present study focuses exclusively on technical characteristics, future competitive dynamics may also be influenced by market, industrial, and policy factors that fall outside the scope of the analysis.

7. Conclusions

This study examined the technological competitiveness of BEVs using a large-scale multicriteria decision-making framework. By applying an integrated Entropy–CRITIC–TOPSIS–Borda methodology to 174 BEV models, the analysis provides a systematic comparison of vehicle performance based exclusively on objective technical characteristics.

The results indicate that European manufacturers, particularly German brands, currently dominate the highest positions in the technological ranking. This outcome is consistent with previous studies highlighting the importance of long-term investment in engineering capabilities and innovation ecosystems that support the development of electric mobility. At the same time, Chinese manufacturers are increasingly represented among technologically competitive vehicles, consistent with the broader expansion of China's electric vehicle industry reported in previous studies. Although their representation among the top-ranked models remains relatively limited in the analysed segments, the presence of Chinese manufacturers among higher-ranked vehicles suggests increasing technological capabilities within China's BEV sector. These findings provide insight into the technological competitiveness of the analysed BEV models; however, they are based exclusively on vehicle-level technical characteristics and do not directly address broader market, trade, pricing, or policy factors.

Our study does not provide direct policy recommendations but contributes to the understanding of technological competitiveness in the analysed market. The findings may inform broader discussions on competitive dynamics and the future development of electromobility in Europe; however, the analysis is limited to BEVs and does not evaluate combustion or hybrid vehicles.

Beyond identifying competitive positions among manufacturers, the study also contributes to the literature on electric vehicle evaluation by demonstrating the usefulness of integrated MCDM methods for large-scale technological benchmarking. The combination of Entropy and CRITIC weighting with TOPSIS ranking and Borda aggregation enables a robust assessment of vehicle competitiveness while reducing methodological bias associated with single-method approaches.

Several limitations should be acknowledged. The analysis focuses exclusively on passenger vehicles from the B and C segments. It does not include SUVs, hybrid vehicles, or other vehicle classes that represent an important part of the electric vehicle market. In addition, the evaluation relies solely on technical parameters and does not incorporate environmental lifecycle impacts, consumer preferences, or policy variables that may influence market outcomes.

Future research could extend the analysis by incorporating lifecycle environmental indicators, economic factors, and behavioural dimensions affecting electric vehicle adoption. Expanding the dataset to include additional vehicle segments and dynamic market and infrastructure variables would also provide a more comprehensive understanding of competitiveness in the rapidly evolving electromobility sector. Such research would further support evidence-based decision-making for policymakers and industry stakeholders involved in the transition toward sustainable transport systems.

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Appendix 1. Values of TOPSIS Closeness Coefficients (C_i) obtained using Entropy, CRITIC and Mean Weighting methods

Model	C_i (Entropy)	C_i (CRITIC)	C_i (Mean Weight)
Mercedes-Benz CLA 250+	0.8758	0.6814	0.7935
Mercedes-Benz CLA 350 4MATIC	0.8657	0.6078	0.7566
Genesis GV60 Premium	0.6348	0.5442	0.6003
Genesis GV60 Sport	0.6288	0.5611	0.6145
Genesis GV60 Sport Plus	0.6033	0.5482	0.5953
CUPRA Born VZ	0.4810	0.5542	0.5446
Volkswagen ID.3 GTX Performance	0.4800	0.5416	0.5406
Ford Capri Extended Range AWD	0.4791	0.5586	0.5473
Volkswagen ID.3 GTX	0.4756	0.5309	0.5308
Skoda Elroq RS	0.4671	0.5397	0.5312
CUPRA Born 170 kW - 77	0.4421	0.4802	0.4905
Ford Capri Extended Range RWD	0.4412	0.5469	0.5208
Skoda Elroq 85	0.4263	0.5112	0.4980
Volkswagen ID.3 Pro S	0.4247	0.5321	0.4928
Audi Q4 Sportback e-tron 45	0.4165	0.5163	0.4937
Peugeot e-3008 97 Long Range	0.4135	0.4706	0.4959
Audi Q4 Sportback e-tron 55 quattro	0.4105	0.5245	0.4933
Audi Q4 e-tron 45	0.4041	0.5113	0.4835
Volvo EC40 Twin Motor Performance	0.4001	0.5110	0.4796
Volvo EC40 Single Motor ER	0.3923	0.4701	0.4613
Audi Q4 e-tron 55 quattro	0.3919	0.5083	0.4755
Audi Q4 Sportback e-tron 45 quattro	0.3916	0.5046	0.4739
CUPRA Born 170 kW - 59	0.3889	0.5036	0.4387
Zeekr X Privilege AWD	0.3879	0.5027	0.4527
Volvo EX30 Single Motor ER	0.3845	0.4446	0.4311
Volvo EX30 Twin Motor Performance	0.3819	0.4885	0.4432
Zeekr X Long Range RWD	0.3812	0.4886	0.4416
Audi Q4 e-tron 45 quattro	0.3809	0.4938	0.4631
Volvo EX40 Twin Motor	0.3809	0.4691	0.4561
Volvo EX40 Twin Motor Performance	0.3809	0.4691	0.4561
MG MG4 Electric 64	0.3771	0.4677	0.4197
MG MG4 Electric XPOWER	0.3757	0.5006	0.4390
Kia EV4 Hatchback 81.4	0.3747	0.4750	0.4610
Volkswagen ID.3 Pro	0.3745	0.4895	0.4227
Volvo EX40 Single Motor ER	0.3740	0.4599	0.4461
Volvo EC40 Twin Motor	0.3736	0.4578	0.4451
Smart #3 Premium	0.3733	0.4919	0.4350
Smart #3 Pro+	0.3733	0.4919	0.4350
MG MG4 Electric 77	0.3714	0.4611	0.4459
Volvo EX30 Cross Country	0.3713	0.4801	0.4340

Model	C_i (Entropy)	C_i (CRITIC)	C_i (Mean Weight)
Skoda Elroq 60	0.3670	0.4997	0.4233
Kia EV3 Long Range	0.3582	0.4712	0.4494
BMW iX2 xDrive30	0.3578	0.5592	0.4604
Smart #3 Brabus	0.3578	0.5012	0.4330
Leapmotor B10 67.1	0.3569	0.4732	0.4190
BMW iX1 xDrive30	0.3546	0.5478	0.4531
Audi Q4 Sportback e-tron 40	0.3545	0.4555	0.4066
Volvo EC40 Single Motor	0.3453	0.4714	0.4171
Smart #1 Brabus	0.3453	0.5049	0.4246
Renault Scenic E-Tech EV87 220hp	0.3425	0.5712	0.4825
BMW iX2 eDrive20	0.3411	0.5293	0.4366
Mini Countryman SE ALL4	0.3392	0.5098	0.4309
Mercedes-Benz EQA 250	0.3357	0.4341	0.3973
Smart #1 Pulse	0.3355	0.4723	0.4081
Audi Q4 e-tron 40	0.3347	0.4383	0.3883
Renault Megane E-Tech EV60 220hp	0.3328	0.5073	0.4176
BMW iX1 eDrive20	0.3317	0.5106	0.4237
Renault Megane E-Tech EV60 130hp	0.3298	0.5013	0.4119
Leapmotor B10 56.2	0.3244	0.4826	0.3885
Volvo EX40 Single Motor	0.3231	0.4119	0.3870
Alfa Romeo Junior Elettrica 54 Veloce	0.3227	0.5239	0.4100
Smart #1 Premium	0.3209	0.4454	0.3876
Smart #1 Pro+	0.3209	0.4454	0.3876
Smart #1 Pure+	0.3209	0.4454	0.3876
Mini Countryman E	0.3206	0.4783	0.4055
Mercedes-Benz EQA 350 4MATIC	0.3201	0.4442	0.3922
Peugeot e-208 54	0.3201	0.4908	0.3849
Lancia Ypsilon 54 HF	0.3197	0.4999	0.3958
Opel Corsa Electric 54	0.3154	0.4612	0.3713
Ford Puma Gen-E	0.3124	0.5401	0.3961
Ford Capri Standard Range RWD	0.3100	0.5528	0.4112
Lancia Ypsilon 54	0.3098	0.4770	0.3740
Skoda Elroq 50	0.3095	0.5296	0.4003
Lynk&Co 02	0.3094	0.4745	0.4096
Volkswagen ID.3 Pure	0.3065	0.4629	0.3701
MG MGS5 EV 64	0.3053	0.4840	0.3952
Hyundai Kona Electric 65	0.3039	0.5068	0.4101
Opel Astra Sports Tourer Electric	0.3028	0.5187	0.3909
Mercedes-Benz EQA 300 4MATIC	0.3011	0.4188	0.3703
Opel Grandland 82	0.3006	0.4436	0.4106
Opel Astra Electric	0.2994	0.4912	0.3764
Alfa Romeo Junior Elettrica 54	0.2974	0.4802	0.3676
Citroen C5 Aircross Comfort Range	0.2973	0.4473	0.4032

Model	C_i (Entropy)	C_i (CRITIC)	C_i (Mean Weight)
Mercedes-Benz EQA 250+	0.2972	0.4159	0.3825
Citroen e-C4 X 54	0.2917	0.5171	0.3861
Mini Cooper SE	0.2906	0.4639	0.3670
Kia EV4 Hatchback 58.3	0.2883	0.4537	0.3697
Opel Corsa Electric 51	0.2877	0.4671	0.3568
Jeep Avenger Electric	0.2876	0.4629	0.3539
Peugeot e-3008 73	0.2872	0.4747	0.4025
Kia EV3 Standard Range	0.2852	0.4978	0.3807
Peugeot e-2008 54	0.2846	0.4958	0.3661
Peugeot e-308 SW	0.2817	0.5230	0.3871
Peugeot e-208 51	0.2816	0.4621	0.3508
Audi Q4 Sportback e-tron 35	0.2814	0.4128	0.3448
Peugeot e-208 50	0.2773	0.4670	0.3481
Citroen e-C4 X	0.2772	0.4986	0.3638
Peugeot e-3008 73 Dual Motor	0.2771	0.4783	0.3939
DS 3 E-Tense	0.2754	0.4520	0.3427
Mini Cooper JCW	0.2749	0.4585	0.3606
Citroen e-C4 54	0.2726	0.4680	0.3521
DS N°4 E-Tense	0.2719	0.4810	0.3764
Audi Q4 e-tron 35	0.2711	0.4107	0.3461
Lancia Ypsilon	0.2704	0.3808	0.3227
Opel Grandland 73	0.2699	0.4503	0.3823
Peugeot e-408 58	0.2672	0.5211	0.3890
Renault Scenic E-Tech EV60 170hp	0.2663	0.5024	0.3839
Fiat 600e	0.2656	0.4594	0.3431
MG ZS EV Long Range	0.2645	0.4554	0.3742
Opel Mokka-e 54	0.2638	0.4430	0.3328
Opel Corsa Electric 50	0.2632	0.4468	0.3317
Kia Niro EV	0.2630	0.5050	0.3888
Citroen e-C4	0.2623	0.4550	0.3336
Renault 5 E-Tech 52 150hp	0.2614	0.4951	0.3624
Peugeot e-2008 50	0.2611	0.4873	0.3476
Opel Mokka Electric	0.2608	0.4301	0.3251
Mini Aceman JCW	0.2606	0.4596	0.3516
MG MGS5 EV 49	0.2604	0.3784	0.3158
Mini Aceman SE	0.2594	0.4445	0.3380
BYD ATTO 3	0.2581	0.4694	0.3630
Renault 4 E-Tech 52 150hp	0.2563	0.5113	0.3645
Zeekr X Core RWD	0.2557	0.4827	0.3539
Volvo EX30 Single Motor	0.2543	0.4218	0.3271
Alpine A290 Electric 220 hp	0.2541	0.4617	0.3480
Peugeot e-308	0.2523	0.4456	0.3321
Alpine A290 Electric 180 hp	0.2451	0.4489	0.3356
MG MG5 Electric Long Range	0.2402	0.5251	0.3756
Smart #3 Pro	0.2397	0.4275	0.3257

Model	C_i (Entropy)	C_i (CRITIC)	C_i (Mean Weight)
firefly firefly	0.2373	0.5056	0.3431
BYD DOLPHIN 60.4 kWh	0.2372	0.4432	0.3440
Mini Cooper E	0.2371	0.4481	0.3199
Opel Mokka-e 50	0.2361	0.4175	0.3032
SsangYong Korando e-Motion	0.2314	0.4839	0.3485
MG MG4 Electric 51	0.2226	0.3539	0.2910
Mini Aceman E	0.2178	0.4594	0.3126
Smart #1 Pro	0.2153	0.3921	0.2969
Smart #1 Pure	0.2153	0.3921	0.2969
Renault 5 E-Tech 40 120hp	0.2149	0.4671	0.3163
Kia e-Soul 64	0.2123	0.3050	0.2974
MG MG5 Electric Standard Range	0.2105	0.4913	0.3349
Honda e:Ny1	0.2099	0.4141	0.3194
Renault Megane E-Tech EV40 130hp	0.2065	0.4797	0.3184
Toyota Urban Cruiser 61.1 AWD	0.2044	0.4511	0.3217
BYD DOLPHIN SURF 43.2 Comfort	0.2014	0.4432	0.2998
Suzuki e VITARA 61 4WD AllGrip	0.2003	0.3833	0.2959
Opel Frontera Extended Range	0.1986	0.4340	0.3035
Nissan Leaf e+	0.1971	0.3376	0.2952
BYD ATTO 2	0.1956	0.4570	0.3058
Renault 4 E-Tech 40 120hp	0.1948	0.4402	0.2938
Citroen e-C3 Aircross Extended Range	0.1944	0.4189	0.2960
Toyota Urban Cruiser 61.1	0.1941	0.3876	0.2956
GWM ORA 03 63	0.1931	0.3864	0.2982
Suzuki e VITARA 61 2WD	0.1895	0.3750	0.2888
BYD DOLPHIN 44.9 Boost	0.1878	0.4291	0.2911
Fiat Grande Panda	0.1875	0.4309	0.2855
GWM ORA 03 GT	0.1870	0.3764	0.2891
Citroen e-C3 Aircross	0.1793	0.4352	0.2871
Nissan Leaf	0.1791	0.3768	0.2647
Opel Frontera 44	0.1789	0.4326	0.2848
BYD DOLPHIN SURF 43.2 Boost	0.1785	0.4069	0.2723
Hyundai Kona Electric 48	0.1770	0.4255	0.2932
Citroen e-C3	0.1731	0.3989	0.2639
GWM ORA 03 48	0.1726	0.4080	0.2763
Renault 5 E-Tech 40 95hp	0.1711	0.4491	0.2896
MG ZS EV Standard Range	0.1710	0.3355	0.2611
Mazda MX-30	0.1645	0.4547	0.2826
Renault Zoe ZE50 R135	0.1594	0.4065	0.2759
Toyota Urban Cruiser 48.8	0.1590	0.3937	0.2638
Suzuki e VITARA 49 2WD	0.1532	0.3882	0.2587
BYD DOLPHIN 44.9 Active	0.1422	0.3840	0.2488
Renault Zoe ZE50 R110	0.1400	0.3871	0.2597
Dongfeng Box 42.3	0.1293	0.3055	0.2035
BYD DOLPHIN SURF 30 Active	0.1253	0.3295	0.2048
Dongfeng Box 31.4	0.1035	0.2005	0.1390

Appendix 2. List of vehicle models originating from China

Model
BYD ATTO 2
BYD ATTO 3
BYD DOLPHIN 60.4 kWh
BYD DOLPHIN SURF 30 Active
BYD DOLPHIN SURF 43.2 Boost
BYD DOLPHIN SURF 43.2 Comfort
firefly firefly
GWM ORA 03 48
GWM ORA 03 63
GWM ORA 03 GT
Leapmotor B10 56.2
Leapmotor B10 67.1
Lynk&Co 02
MG MG4 Electric 51
MG MG4 Electric 64
MG MG4 Electric 77
MG MG4 Electric XPOWER
MG MG5 Electric Long Range
MG MG5 Electric Standard Range
MG MGS5 EV 49
MG MGS5 EV 64
MG ZS EV Long Range
MG ZS EV Standard Range
Zeekr X Core RWD
Zeekr X Long Range RWD
Zeekr X Privilege AWD
BYD DOLPHIN 44.9 Active
BYD DOLPHIN 44.9 Boost