A Project entitled

Selecting The Ideal Electric Vehicles For Customer Needs Using TOPSIS Analysis

by

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An Abstract of

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Over the last year, sales of electric vehicles have increased by 35% compared to the year prior. Provided the increasing global adoption of electric vehicles, the need for robust decision-making frameworks to assist consumers in evaluating different EV models based on several KPIs has also been created. This study employs the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), a decision analysis method that takes multiple criteria into consideration, to use price, engine power, maximum torque, battery capacity, range, maximum speed, boot capacity, acceleration, charging power, and energy consumption as parameters to identify the 6 “best” EVs among 42 models. The selected parameters are reflective of the diverse consumer priorities such as cost-efficiency, performance, and practicality, hence ensuring a comprehensive evaluation process for the customer. Moreover, to do a more specialized analysis, we also work on finding out what set of cars would be the best for customers who have a preference for long-range travel.

The analysis strategically prioritizes minimization of costs and energy consumption, and the maximization of performance-related parameters like engine power, range, and charging efficiency. As per the technique, we use normalized weights and a comparative ranking system to highlight each model's relative

performance against the “ideal solution”. This methodology provides a balanced approach that considers both technical specifications and real-world utility, hence offering a scalable and objective framework for consumer decision-making.

This research highlights the versatility of TOPSIS in evaluating complex, multi-criteria datasets within the domain of electric vehicles, while also giving the customer an insight on what might be the best decision to make when it comes to purchasing an EV. Apart from being a guide to customers, this study also offers manufacturers valuable insights into consumer-centric design and different engineering priorities, essentially becoming a way into the mind of a potential consumer, answering the age-old question of “what does the customer want?”. This framework could see a potential expansion in future, with additional parameters including but not limited to life cycle cost analysis, environmental impact, and user satisfaction metrics being included to represent different aspects of the ecosystem not already considered in the course of this study, hence making the study more holistic.

Keywords:

Electric Vehicles (EVs); TOPSIS Analysis; Multi-Criteria Decision Analysis (MCDA);

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1 Introduction

Driven by increasing global concern with regard to global warming and other environmental problems, a transformative change has come in the automotive industry with the advent of electric vehicles (EVs). The transition from traditional combustion engines to electric vehicles has been supercharged by the global urge to reduce greenhouse emissions, shrinking fossil fuel reserves, increasing fuel costs and higher environmental consciousness. Not only do these vehicles promise to deliver operational costs, but they also reduce emissions and align with the broader goals of energy efficiency and sustainable urban development (Štilić et al. (2022))(Akram et al. (2023))(Prabakaran et al. (2023)).

After great advancement in EV technology, a lot of options are available for consumers, with different vehicles suited towards different variables, creating an interesting problem of picking the right electric vehicle for each customer basis. This complexity is created by a wide array of available models and subjective consumer priorities. Each customer demands different things from the vehicle, and each vehicle has different things to offer. Existing research, such as the use of Multi-Criteria Decision-Making (MCDM) methods like TOPSIS and fuzzy logic-based models, has shown that structured decision-making frameworks are very capable of effectively solving this problem. For example, research has shown that variables like battery capacity, range, cost and charging time affect the way we rank and select electric vehicles (Prabakaran et al. (2023))(Dhingra et al. (2020)). In a similar fashion, when consumer-centric criteria are integrated into existing evaluation models, we observe the need for a decision support system that caters to both technical and subjective parameters (Więckowski et al. (2024)).

In this study, we utilize the TOPSIS method, a state-of-the-art technique for multi-criteria decision making, to rank and evaluate 42 EV models based on a diverse and comprehensive set of criteria including but not limited to engine power, range, price, acceleration, charging power, and energy consumption.

Moreover, we extend our analysis beyond the standard "equal weights" analysis by changing the criteria for the "ideal solution" based on different customer archetypes, in this case focusing on the "long-range traveler", which is a customer who prefers a car that would specialize in traveling long distances and would thus have great standing in range and battery related variables. By using parameters related to both performance and efficiency (in cost and in power), this research provides an objective framework for identifying the EVs that align the most and least with diverse consumer priorities (Akram et al. (2023)) (Dhingra et al. (2020)).

The study offers two major implications. Firstly, it offers a methodology that is both transparent and scalable for consumers navigating the crowded EV market. Secondly, it gives manufacturers a gateway into consumer preferences, potentially streamlining for future innovations in the world of EV design and production, since the manufacturers would now be more aware of what the customer needs from each car, and how they can position themselves in the market for maximized benefit. By combining multi-criteria decision making with actual customer preferences, this research bridges the gap between technical specifications and practical utility, thereby making the decision-making process easier for every stakeholder in the ecosystem for electric vehicles (Štilić et al. (2022))(Prabakaran et al. (2023)).

2 Literature Review and Significance of the Problem

The incredible potential of electric vehicles as a game-changer in mitigating environmental challenges whilst sustainably solving global transportation requirement problems is reflected in the fact that they have received significant attention from researchers across the globe.

We conduct a thorough literature review by categorizing findings and limitations of each paper, and thus establish the foundations of this study. We conclude by reading the given papers that a big chunk of previous research was primarily focused on multi-criteria decision making (MCDM) methods, consumer preference analysis, charging infrastructure and the comprehensive EV performance metrics.

However, we also find that not much has been done to create a more holistic work in the niche of picking the right electric vehicle for every user's exact use-case. Turns out, most research done in the past that we discovered revolved around themes of MCDM, consumer preference analysis without recommendations, EV performance metrics and charging infrastructure. Below, we lay a comprehensive review of the papers we read, categorized by themes:

2.1 Multi-Criteria Decision-Making (MCDM) Methods:

EV rankings and evaluations are done very effectively with different MCDM techniques like TOPSIS, AHP and Fuzzy TOPSIS. These techniques have proven to be incredibly effective and thus are applied quite extensively in different decision-making frameworks. Below we mention each paper that used a specific MCDM methodology, see what each paper taught us, and how we felt each paper was limited. Table 2-2 demonstrates the classification of studied research Papers on Manufacturing Process Improvement Techniques based on the applied methodology, used algorithms for performance analytics, and major contributions.

Table 2-1 Classification of Studied Research Papers on Multi-Criteria Decision-Making (MCDM) Techniques

Authors and Year of Publication	Applied Methodology	Findings	Limitations
(Prabakaran et al, 2023)	TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)	Used metrics like battery capacity, range and cost to rank a set of EVs.	Limited to technical specifications; did not incorporate consumer preferences.
(Dhingra et al, 2020)	AHP-Fuzzy TOPSIS	Identified optimal EV charging station locations based on criteria like traffic density and infrastructure compatibility	Focused on charging infrastructure; did not evaluate EV models directly.
(Więckowski et al, 2024)	RANCOM and ESP-SPOTIS	Introduced hybrid MCDM techniques for personalized EV selection; combined subjective and objective weighting methods.	Lacked real-world validation and detailed consumer preference modeling.
(Štilić et al, 2022)	SWARA and MSDM	Evaluated EVs for taxi services, emphasizing battery capacity and charging efficiency	Application limited to fleet use cases; did not generalize findings for individual consumers.

While many of these studies fail to integrate real-world consumer data properly, these studies do highlight the utility of MCDM frameworks in simplifying EV evaluations.

In the next subsection, we will discuss the papers which gave us detailed consumer preference analysis.

2.2 Consumer Preference Analysis:

Some of the studies we considered for this paper were consumer-centric, in the sense that they worked to consider and discover more about what the consumer liked. Analyzing the consumer and their preferences can get manufacturers better insights regarding what to build to capture more of the market. These studies have highlighted what the customer needs and wants, and what they don't prioritize.

Table 2-2 demonstrates the classification of studied research Papers on Cold Wire Drawing Process Improvement based on applied methodology, used materials, and major findings.

Table 2-2 Classification of Studied Research Papers on Consumer Preference Analysis

Authors	**Focus**	**Findings**	**Limitations**
Akram et al. (2023)	Fuzzy CRITIC-EDAS Method	Highlighted consumer-centric criteria like driving range and cost-effectiveness.	Relied heavily on expert knowledge; lacked survey data from consumers.
Li et al. (2022)(Štilić et al. (2022)	Consumer Needs in EV Adoption	Found cost and range to be the top priorities for EV buyers globally.	Limited geographic focus: regional variations in consumer behavior were not studied.

Despite the importance of consumer preference to EV adoption strategies, many studies lack details regarding customer segmentation, demographics and user patterns. The next sub-section discusses EV performance metrics.

2.3 EV Performance Metrics

Performance metrics such as range, battery capacity, and charging efficiency remain critical in assessing EV suitability. These studies typically focus on quantifiable parameters that directly influence consumer satisfaction and usability.

Table 2-3 Classification of Studied Research Papers on EV Performance Metrics

Authors and Year of Publication	Parameters Evaluated	Findings	Limitations
Prabakaran et al. (2023)	Battery capacity, range, acceleration	Identified Mercedes-Benz EQS as the most efficient EV among six evaluated models.	Focused on a small sample of premium vehicles; lacked market diversity.
Štilić et al. (2022)	Range, charging speed, battery life	Found VW ID.3 Pro to be optimal for taxi services due to high battery efficiency.	Application was limited to fleet services and lacked generalizability.

Many studies emphasize premium models, not paying enough heed to mid-range or budget-friendly options, which make up a huge chunk of the market.

2.4 Charging Infrastructure

With EVs being integrated into normal life, a big goal is to make the recharging of these vehicles more accessible. The following papers talk more about this idea, and how we can place different charging stations most optimally to ensure greater ease in adaptation of EVs:

Table 2-4 Classification of Studied Research Papers on Charging Infrastructure

Authors and Year of Publication	**Focus**	**Findings**	**Limitations**
Dhingra et al. (2020)	Public Charging Infrastructure	Emphasized the importance of integrating EV stations with existing urban infrastructure.	Limited geographic focus; urban-centric findings may not apply to rural regions.
Viswanathan et al. (2022) *	Charging Station Placement	Proposed GIS-based frameworks for optimizing charging station locations.	Relied on simulated data without real-world implementation.

Most of the data is collected from the first world and developed countries, showing the market dynamics accurately, considering that most EVs are bought and sold in the first world. However, the unique challenges of the developing world should also be considered in the studies

2.5 Summary Table Of Reviewed Studies

Table 2-5 Classified Summary of all the read literature

Category	Key Research Works	Common Findings	Key Gaps Identified
MCDM Methods	Prabakaran et al., Dhingra et al., Więckowski et al., Štilić et al.	MCDM techniques are effective for ranking EVs.	Limited consumer-centric criteria; lacked market-specific findings.
Consumer Preferences	Akram et al., Li et al., Research Team Collection	Cost, range, and performance dominate consumer priorities.	Lack of holistic datasets that combine technical and subjective evaluations.
EV Performance Metrics	Prabakaran et al., Štilić et al.	Battery capacity and charging speed are critical for EV success.	Narrow focus on specific segments of the EV market (e.g., premium models).
Charging Infrastructure	Dhingra et al., Viswanathan et al.	Integrating charging stations with urban infrastructure is crucial.	Limited application in rural or low-density areas.

Extensive research of EV evaluation and decision-making models are discussed in this literature review. Furthermore, existing gaps like lack of comprehensive consumer-centric datasets, and limited area of application were also discussed. The insights we gained from the literature were then used to inform the approach we took in our study, in which we used TOPSIS with an emphasis on both technical specifications and consumer-centric criteria, and delivered a holistic analysis of the market.

3 Problem Statement and Objectives

Tons of players now exist in the EV market, each with their own unique set of offerings for the customer regarding specifications and performance metrics. The existence and growth of such fierce competition is a testament to the growth of the industry as a whole. While many customers look for a balance of traits in their vehicles, some people prioritize some traits over others. In this study, apart from considering the "balanced" customer, we consider the customer who travels longer distances quite frequently, and thus wants a car more tailored to long-range travel. For these long-range demanding customers, criteria such as range (how much distance a car can cover in one complete battery cycle), battery capacity and charging efficiency are more important than other variables, making their decision-making slightly more complex in comparison. In order to make lives easier for these customers when it comes to picking the right car for their needs, there is the need for a framework that can consider both customer situations and the vehicles' technical specifications.

In this analysis, we address this challenge by using TOPSIS, a robust MCDM approach, to rank EVs by using metrics more tailored to long-range requirements. This study evaluates the attributes of price, engine power, maximum torque, battery capacity, range, maximum speed, boot capacity, acceleration, maximum charging power and mean energy consumption to provide a more objective and consumer-centric framework. Through this study, we aim to assist both balanced and long-range traveling customers in identifying the best car for their use-case, whilst also giving manufacturers insight into customer behavior that could be used for further innovation in technology. With this research, we aim to bridge the gap between consumer expectations and market offerings, and thus enhance the consumer's ability to make decisions in the EV landscape.

4 Data Analysis & Results

As mentioned before, this project uses TOPSIS, a holistic MCDM approach which considers the intuitive idea that the best option out of a set of possible options would be closest to the ideal positive solution (PIS) & farthest away from the negative ideal solution (NIS).

TOPSIS has the ability to handle multiple criteria, regardless of whether they are quantitative or qualitative in nature. This is partially because of the normalization of data in this methodology, which ensures that criteria with different units are still comparable. Moreover, the ability to weigh each variable differently compared to others makes this framework highly adaptable to customer requirements.

4.1 Methodology

TOPSIS follows a very simple and intuitive set of steps to get to the desired result, which is a decision about which option to pick from the given set of options. Let's discuss each of these steps in detail:

1. In the first step, after identifying the problem we need to solve, we use the data to form a decision matrix. This decision matrix is a representation of the dataset. Each row is an option that we're considering, while each column is a variable, so each entry shows how each option performs in each variable we consider important for the decision.
   For our dataset, we considered 42 different cars, and 10 different variables, namely Price (PLN), Engine Power (KM), Max Torque (Nm), Battery Capacity (kWh), Range (WLTP) (km), Max Speed (kph), Boot Capacity (l), Acceleration (0-100 kph) (s), Max DC Charging Power (kW), & Energy Consumption (kWh/100 km). Therefore, our decision matrix is a 42 x 10 matrix.

2. In the next step, we normalize the decision matrix. For normalization, we use the simple formula of dividing each value in a column by the square root of the sum of squares of all values in the column. This allows us to compare each value to the other regardless of the unit of measurement.

3. Up next, we decide weights for each of the variables and use the weights to create a weighted normalized decision matrix, where each column of the normalized decision matrix gets multiplied by the weight assigned to that particular column. The weights can be equal or unequal, but the important thing is that the sum of weights should be equal to 1. Therefore, the idea is that the more you value one variable, the less you value another variable, in order to maintain the balance of weights. In our analysis, we first used equal weights, and then changed the weights based on customer requirements. Note that the step of selecting weights for each criterion could have been done at any point in time before this step as well, but we just did it at this point because we could use the weights immediately.

4. Now, we find the positive ideal solution and the negative ideal solution. For this, we first decide what variables to maximize and what variables to minimize, based on the nature of variables and customer requirements. In our case, we chose to maximize engine power, maximum torque, battery capacity, range, maximum speed, boot capacity and charging power, while minimizing price, energy and acceleration. The decision to minimize acceleration might seem counter-intuitive at first, but it is made because in the given dataset, acceleration was measured as the amount of time it took for a vehicle to go from 0 kph to 100 kph in seconds. Hence, we say that the less time required to achieve high speeds, the better, and minimize acceleration. Once we have the maximized and minimized variables, we use the given data to calculate the positive ideal solution (PIS) which has maximum values for maximized variables, and the minimum values for minimized

variables. Similarly, the negative ideal solution (NIS) is the solution which has minimum values for maximized variables, and the maximum values for minimized variables.

5. Once we have found PIS & NIS, the next step is to find the Euclidean distance of each member of the dataset from the ideal and the non-ideal solution.

6. Finally, we calculate each dataset member's relative distance from the ideal solution by using the formula:

$$\text{Relative Closeness} = \frac{\text{Distance from Negative Ideal Solution}}{\text{Distance from Positive Ideal Solution} + \text{Distance from Negative Ideal Solution}}$$

7. Based on relative closeness to the ideal solution, we sort the dataset in descending order to see which options are closest to the ideal solution.

Now that we know what exact steps are involved, let's take a look at the results we found for our analysis using equal weights and then different weights:

4.2 Analysis & Results for Equal Weights

For this project, we used Python to manipulate the data, due to its ease of use, accessibility and high productivity. Once we loaded the dataset in Google Colab, we formed a data frame and cleaned it so that it wouldn't have any unnecessary entries which could affect the analysis.

Once we had a clean data frame, we implemented all the steps mentioned above, and found that, when all ten variables are given equal weight, out of the 42 vehicles considered, the following 6 came out to be the top performers:

Table 4-1 Electric Vehicles ranked closest to ideal solution for equal weights

	Ev Car	Closeness	Rank
29	Porsche Taycan 4S (Performance Plus)	0.6551544284	1.0000000000
2	Audi e-tron S quattro	0.6530031048	2.0000000000
5	Audi e-tron Sportback S quattro	0.6478831674	3.0000000000
30	Porsche Taycan Turbo	0.6294682115	4.0000000000
28	Porsche Taycan 4S (Performance)	0.6232581775	5.0000000000
0	Audi e-tron 55 quattro	0.6129039647	6.0000000000

As clearly shown by the results above, the Porsche Taycan 4S (Performance Plus) ranks as the best electric vehicle for our set of criteria, with each criterion being of equal weight. It has a high relative closeness value of 0.655 compared to the rest of the competition.

Now that we have the set of vehicles closest to the ideal solution, let's take a look at the vehicles furthest away from it:

Table 4-2 Electric Vehicles ranked farthest away from ideal solution for equal weights

41	Citroën ë-Spacetourer (M)	0.4199717661	37.0000000000
20	Mazda MX-30	0.4173345856	38.0000000000
34	Skoda Citigo-e iV	0.4129922730	39.0000000000
37	Volkswagen e-up!	0.4089467983	40.0000000000
35	Smart fortwo EQ	0.3856624527	41.0000000000
36	Smart forfour EQ	0.3845681691	42.0000000000

The Smart forfour EQ ranks the worst performing EV under the given weights, with a relative closeness value of 0.384, much farther away from the Porsche Taycan 4S (Performance Plus), or even from the Audi e-tron 55 quatro, which only ranked as the sixth best vehicle for the criteria.

We drew a radar chart for the top six vehicles in order to see how each of them performed for each variable:

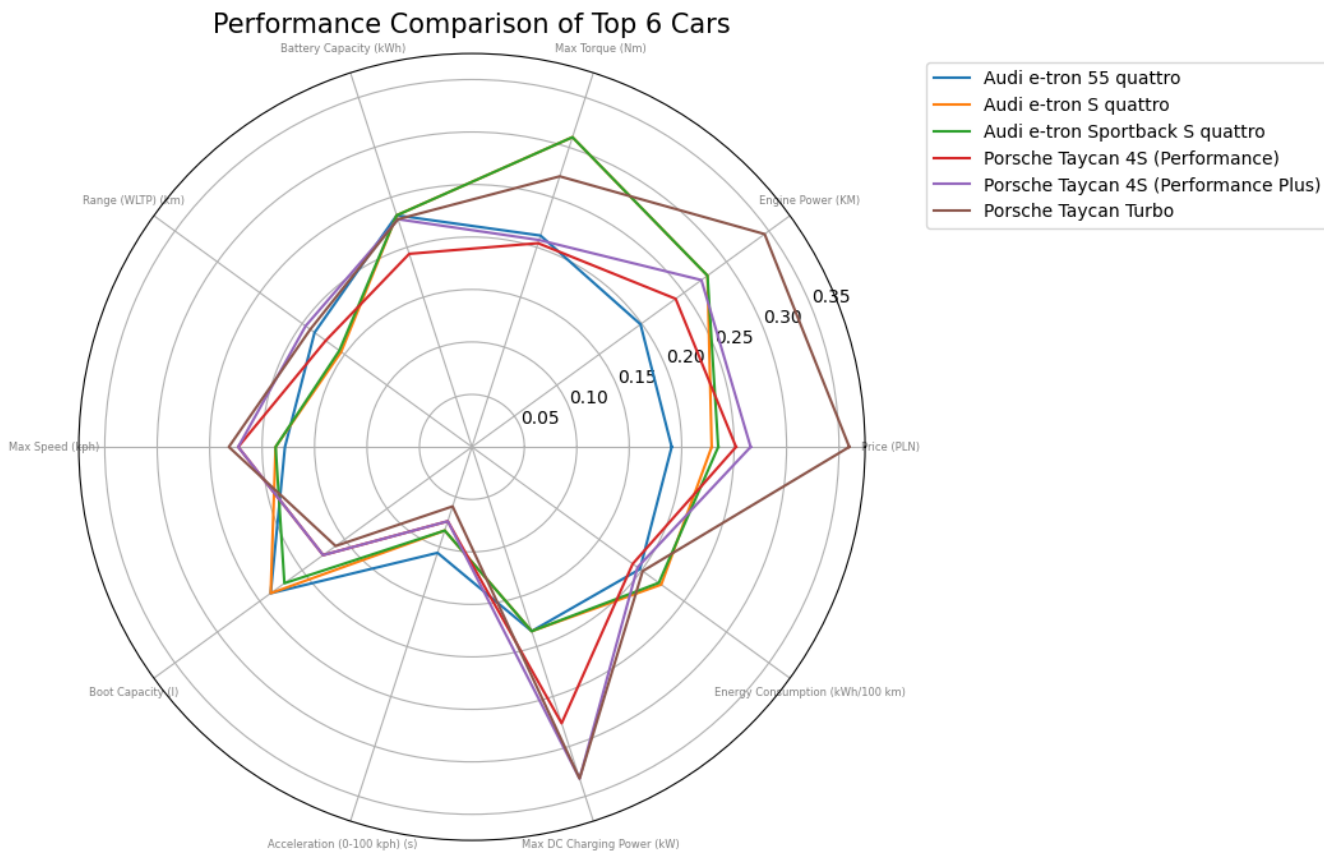

Figure 4-1. Radar Chart For Performance Comparison of top 6 EVs for equally weighed criteria

As seen from the chart, while the Porsche Taycan Turbo heavily outperforms its competition in a lot of the other variables, it is also very expensive, and since we are minimizing price, the ranking for this vehicle takes a huge hit.

However, if the weight we gave to each criterion was different, the ranking would be changed drastically.

In the next step, we consider a customer who values long-range driving capabilities and feasibility over things like power and acceleration. These are customers who want their long-distance commute to be managed effectively, and thus value things like energy consumption, charging power and range more.

Let’s see how our rankings for EVs change if we value these variables more, and other variables less in comparison:

4.3 Analysis & Results for Different Weights to consider long-range drivers

For a decent representation of what long-range drivers require in a vehicle, we change the weights assigned to each variable to be as follows:

Table 4-3 Reassignment for weights to represent change in customer requirements

```
long_range_weights = {
    "Price (PLN)": 0.05,
    "Engine Power (KM)": 0.02,
    "Max Torque (Nm)": 0.01,
    "Battery Capacity (kWh)": 0.25,
    "Range (WLTP) (km)": 0.3,
    "Max Speed (kph)": 0.04,
    "Boot Capacity (l)": 0.02,
    "Acceleration (0-100 kph) (s)": 0.03,
    "Max DC Charging Power (kW)": 0.18,
    "Energy Consumption (kWh/100 km)": 0.1
}
```

As seen in the weights, we have prioritized range, battery capacity, maximum DC charging power and energy consumption more than all other variables, with these 4 variables taking up 83% of the total assigned weight.

Multiple techniques could have been used to assign these weights, including machine learning techniques, surveys to the customers, and industry expert opinions, but we chose to assign these weights based on intuition about how we have seen such customers behave when it comes to choosing the car they want to buy.

Once the weights were assigned, we did the TOPSIS analysis again, using the steps mentioned above, and found the following results:

Table 4-4 Electric Vehicles ranked closest to ideal solution for unequal weights

	Ev Car	Ideal Distance	Rank (Long-Range)
29	Porsche Taycan 4S (Performance Plus)	0.8213229006	1.0000000000
30	Porsche Taycan Turbo	0.7860431391	2.0000000000
31	Porsche Taycan Turbo S	0.7404279084	3.0000000000
28	Porsche Taycan 4S (Performance)	0.7208509376	4.0000000000
4	Audi e-tron Sportback 55 quattro	0.6812094858	5.0000000000
0	Audi e-tron 55 quattro	0.6757128756	6.0000000000

As shown in the table, the Porsche Taycan 4S (Performance Plus) once again takes the lead, which makes sense especially if we consider its performance in the radar chart shown above, since it competes very well in all the variables with high assigned weights. This time, since we take the price a lot less into consideration, we see the Taycan Turbo take a much higher rank than previously seen with equal weights.

Table 4-5 Electric Vehicles ranked farthest away from ideal solution for unequal weights

	Ev Car	Ideal Distance	Rank (Long-Range)
34	Skoda Citigo-e iV	0.2842016607	37.0000000000
37	Volkswagen e-up!	0.2731724139	38.0000000000
22	Mini Cooper SE	0.2482572726	39.0000000000
20	Mazda MX-30	0.2419413797	40.0000000000
35	Smart fortwo EQ	0.1933448518	41.0000000000
36	Smart forfour EQ	0.1904076369	42.0000000000

The Smart forfour EQ once again comes at the bottom, but this time with a completely different distance from the ideal solution compared to before. This shows how a difference in prioritization changes the framework's perception of what's considered ideal, and hence, distance from the ideal and ranking of the options.

Now, let's take a look at the radar chart for the top 6 cars for long-range drivers:

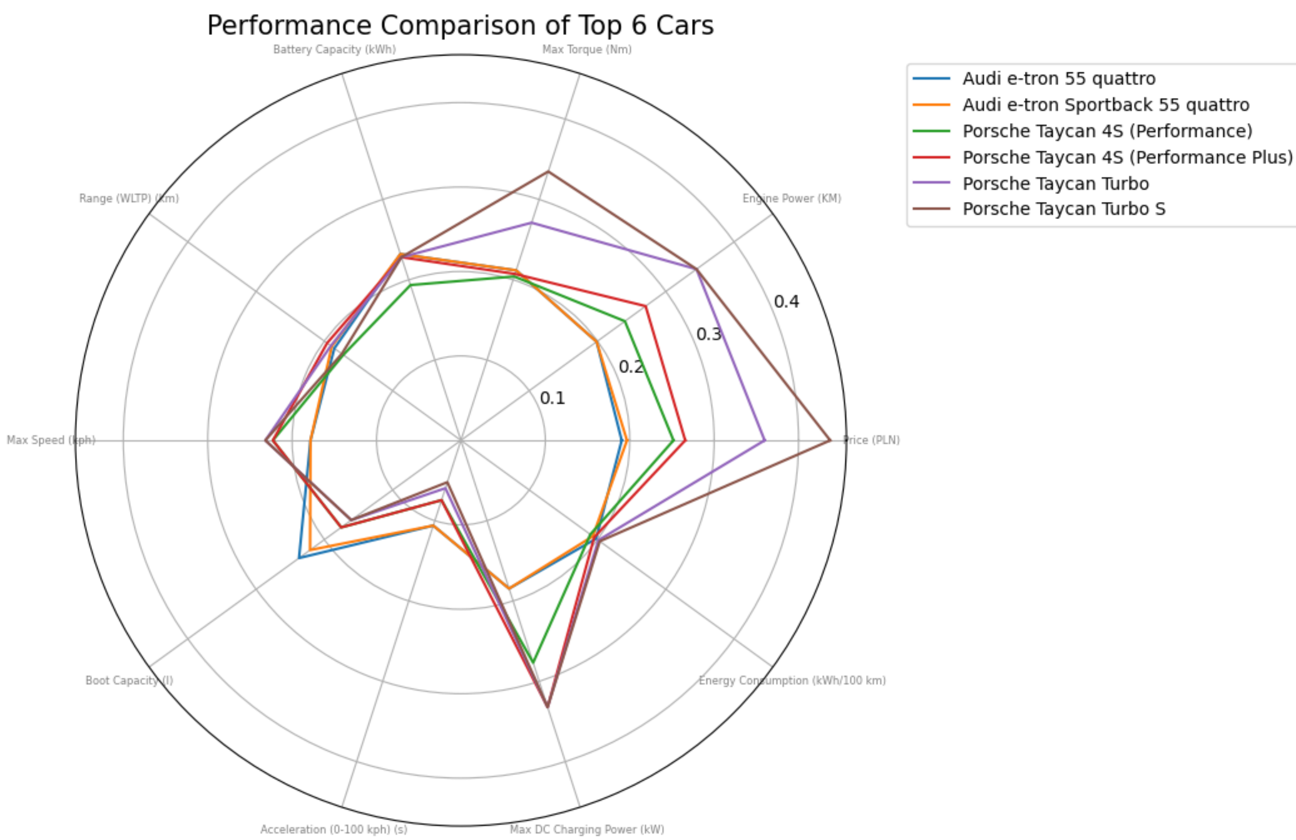

Figure 4-2. Radar Chart For Performance Comparison of top 6 EVs for long-range drivers

As we can see, the Taycan Turbo S still beats its competition in most of the criteria, but it's so expensive that its overall ranking is affected.

Now that we have concluded the analysis and results section of this report, let's move on to what we think can be done in the future to improve the project further:

5 Future Research & Improvements

Here are some of the areas of this project which we believe can see further improvements:

1. More variables can be added to represent different attributes which have an effect on a customer's decision-making but aren't considered in this study, like perceived value or public opinion.
2. With countries like China, Germany and others becoming big players in this market, the addition of more options to consider will only help the customer make a better decision.
3. The selection of weights, as mentioned before, can be an area which can be paid special attention to. We can use customer buying data in analysis and machine learning algorithms, interview customers, and talk to industry experts about what different types of customers would consider to be important or unimportant, and to what degree. This is the step that has the ability to most accurately and effectively represent customer requirements, and more research around this step can impact how impactful the entire process becomes for solving our problems.
4. We can use the analysis to educate manufacturers about what their competition has, what their customers want, what they provide, and how they stand compared to their competitors.

6 Conclusion

By using TOPSIS to rank EVs, we have highlighted the effectiveness of multi-criteria decision making (MCDM) frameworks to address complex customer needs. In this study, we have successfully ranked 42

EV models based on a set of criteria containing both technical and practical needs of the customers, hence providing value to both customers and manufacturers. We incorporate performance, cost and energy related parameters in this analysis to bridge the gap between technical specifications and real-world consumer priorities.

Through the application of TOPSIS, we demonstrated its robust nature in handling multiple criteria, normalizing diverse units and delivering results which can be scaled to any extent. The adaptable nature of this framework allows for analyses tailored to customer needs, thereby improving its relevance in specific use cases. This methodology not only aids consumers in informed decision-making, but also provides valuable insights to manufacturers regarding consumer preferences and market dynamics.

There is also much room for improvement in this research. Incorporating additional parameters like life cycle cost, environmental impact, and user satisfaction could help create a much more holistic and comprehensive analysis of the market. Furthermore, integration of real-world consumer data or leveraging machine learning techniques for weight assignment could help us make a much more accurate analysis.

In conclusion, this study utilizes TOPSIS, an MCDA approach, to understand which EVs out of the selected 42 EVs are best for customers' needs, provided that they weigh each of the 10 given variables equally, or they choose to prioritize features for optimizing long-range driving. By using a transparent and adaptable framework, we set a foundation for further advancement in consumer-centric decision making with regards to the ever-evolving world of electric vehicles.

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