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Optimization of Entropy and MOORA Methods for Comparison of Family Vehicles in Indonesia

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ABSTRACT

This study addresses the issue of subjectivity in determining criteria weights within multi-criteria decision-making for selecting family vehicles in Indonesia. Decision-making in this context often involves multiple factors such as comfort, accommodation, design, features, and fuel consumption, which can lead to biased results if weights are assigned subjectively. To overcome this limitation, this research proposes a combination of the Entropy method and the MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) method within a decision support system framework. The Entropy method is utilized to objectively calculate the weights of each criterion based on data variability, thereby minimizing human bias, while the MOORA method is applied to rank the available vehicle alternatives. The research adopts a quantitative approach by analyzing several popular family vehicles, including Honda BR-V, Mitsubishi Xpander, Suzuki Ertiga, Hyundai Stargazer, and Toyota Avanza. The results indicate that the integration of Entropy and MOORA methods produces more objective and consistent rankings. Based on the calculated preference values, Toyota Avanza achieved the highest rank, followed by Mitsubishi Xpander and Hyundai Stargazer, while Suzuki Ertiga and Honda BR-V ranked lower. In conclusion, the Entropy–MOORA combination proves to be effective in enhancing the objectivity and accuracy of decision-making. This approach can be applied to other multi-criteria problems, providing a systematic and reliable decision support model.

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INTRODUCTION

In the modern era, decision-making often involves multiple, complex criteria. Therefore, a method is needed that can assist decision-makers systematically and objectively (Azimi and Chen 2025). Decision support systems (DSS) offer a solution to this problem. Decision support systems are computer-based systems that assist decision-makers in solving semi-structured problems (Yun et al., 2021). Decision support systems do not replace human decisions but instead provide recommendations based on mathematical calculations (Vasey et al., 2021).

One such decision support system method is MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis), which is used to solve decision-making problems with multiple criteria (Candro et al., 2021). This method is known for its high level of accuracy, simple calculations, and ability to handle

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both benefit and cost criteria simultaneously (Pasaribu et al., 2025). The MOORA method relies heavily on subjective criteria weighting (Mitra, 2022). If the decision-maker assigns incorrect or subjective criteria weights, the alternative ranking results will be invalid. To address this, objective weighting techniques, such as the Entropy method, are required. The Entropy method is an objective weighting technique frequently used in decision support systems (Wu & Wang, 2023). This method works by measuring the level of data uncertainty to mathematically determine the weight of each criterion without the interference of decision-maker subjectivity (Ghoushchi et al., 2021). All weights are calculated based on actual data, thereby reducing human bias. This is the author's background in conducting this research.

Based on this background, the research questions can be formulated as follows: how to overcome subjectivity in determining criterion weights using the MOORA method; how to apply the combination of the Entropy and MOORA methods to generate alternative rankings; and how effective the combination of the Entropy and MOORA methods is in increasing the objectivity of decision-making results.

Literature relevant to this research, obtained from several scientific writing sources, including: new intervals for ranking alternatives in multi-attribute decision-making problems (Soltanifar, 2024). Moora-based decision support framework for ranking healthcare service performance using patient perception data (Manurung et al., 2026), historical review and analysis of MOORA and its fuzzy extensions for various applications (Singh et al., 2024), metropolitan airport ranking using the ciritic-based MOORA method (Karatekin et al., 2025), optimized load reduction strategies using Moora fuzzy ranking (Nguyen et al., 2025). Comparative analysis between principal component analysis and entropy weighting methods for establishing indexing measurements (Wu et al., 2022), quantification of deep out-of-distribution uncertainty through entropy maximization (de Mathelin et al., 2023), multi-objective optimization and evaluation of PEMFC performance based on orthogonal experiments and entropy weighting methods (Zhang et al., 2023), entropy-based logic explanation of artificial neural networks (Barbiero et al., 2022), distribution alignment using objective complement entropy and adaptive consensus-based label refinement for partial domain adaptation (Choudhuri et al., 2023). Renewable energies projects selection: block criteria systematization with AHP and Entropy-MOORA methods in MCDM (Petrov, 2021), Optimizing the Selection of Electric Bicycles Using a Combination of the MOORA Method and Entropy Weighting (Marlinda & Dewi, 2024), Optimizing the Selection of Electric Bicycles Using a Combination of the MOORA Method and Entropy Weighting (Gamal & Mohamed, 2023), A hybrid approach for the machinability analysis of Incoloy 825 using the entropy-MOORA method (Sahu et al., 2024), An Application on Enterprise Resource Planning (ERP) Selection with Multi-Criteria Decision-Making Methods (Akpınar & Akpınar, 2025).

This study proposes the following approach: using the Entropy method to objectively calculate criterion weights based on alternative data, using the MOORA method to perform the alternative ranking process, and combining both methods (Entropy-MOORA) within a single decision support system framework.

The novelty of this study lies in the combination of objective weighting (Entropy) with the ranking method (MOORA) to improve decision accuracy and objectivity (Sahoo & Goswami, 2023), eliminate reliance on subjective judgment in determining criterion weights (Ponhan & Sureeyatanapas, 2022), and provide a decision-making model that can be replicated for other cases with multiple criteria.

To determine the effectiveness of this combination of the two methods, it must be applied to the research problem. The research problem addressed is a comparison of family vehicles available in Indonesia. Family vehicles, or MPVs (Multi-Purpose Vehicles), are the most popular choice for Indonesian families. These vehicles are designed with large capacity and spacious cabins. Family vehicles in Indonesia are a crucial necessity, especially for people who prioritize comfort, passenger capacity, and efficiency in their daily mobility.

Indonesia has a diverse selection of passenger vehicles used for daily needs, so a comparison is necessary to understand the advantages, disadvantages, and suitability of each type of vehicle for geographic conditions, economic conditions, and community needs. However, it's important to understand that this comparison is not intended to determine the absolute best vehicle, but rather serves as an example of the application of a decision support system to facilitate a more systematic and objective analysis process.

RESEARCH METHOD

Research Design

This research design uses a quantitative approach with applied research aimed at developing a decision support system (Pandey et al., 2023). The method used is a combination of Entropy to objectively determine criteria weights and MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) to rank alternatives.

The research stages can be seen in Figure 1 below:

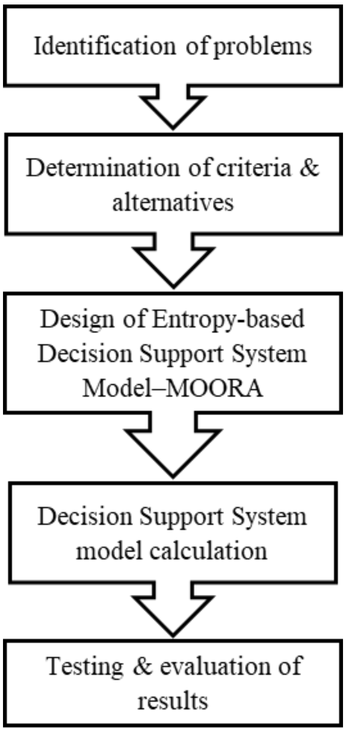

Figure 1. Research Stages

The following is an explanation of the research stages in Figure 1:

1. Problem Identification
   The initial stage of the research begins with identifying the main problem, namely subjectivity in criteria weighting.
2. Determination of Criteria and Alternatives
   At this stage, the following are determined:
   a. Assessment Criteria
      The assessment criteria are selected based on relevant factors in comparing family vehicles, such as comfort, accommodation, design, features & value for money, and fuel consumption.
   b. Vehicle Alternatives
      The alternatives used as research objects are the Honda BR-V, Mitsubishi Xpander, Toyota Avanza, Hyundai Stargazer, and Suzuki Ertiga.
3. Designing an Entropy–MOORA-Based Decision Support System Model
   This stage is the core of the research, namely designing a decision-making model using Entropy–MOORA.
4. Calculation of the Decision Support System Model
   The designed model is calculated using the formula contained in the Entropy–MOORA method.
5. Testing and Evaluation of Results
   The final stage is testing and evaluating the results of the calculations.

Research Procedure

Entropy Method Algorithm

Used to objectively determine criterion weights (Cholil, 2024).

Steps:

1. Create a decision matrix
   The decision matrix presents the assessment of each alternative based on each predetermined criterion.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix} \quad (1)$$

   where:
   m = number of alternatives
   n = number of criteria
   x_{ij} = assessment of alternative A_i on criterion C_j

2. Normalize the decision matrix
   Normalizing the decision matrix aims to scale the values of each criterion so that they are comparable to each other.

$$r_{ij} = \frac{x_{ij}}{max(x_{ij})} \quad \text{benefit criteria} \quad (2)$$

$$r_{ij} = \frac{min(x_{ij})}{x_{ij}} \quad \text{cost benefit} \quad (3)$$

   where:
   r_{ij} = normalized value of element x_{ij} in alternative i and criterion j
   x_{ij} = assessment of alternative Ai on criterion C_j
   max(x_{ij}) = maximum value of criterion j across all alternatives
   min(x_{ij}) = minimum value of criterion j across all alternatives

3. Calculate the proportion value
   The proportion pij for element rij in the normalized decision matrix is calculated by dividing the value of that element by the values of the elements in the same column (criterion j).

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \quad (4)$$

   where:
   p_{ij} = proportion of element rij
   r_{ij} = value of element in the normalized decision matrix
   m = number of alternatives

4. Calculating the entropy value
   The entropy value is used to measure the uncertainty in the distribution of data for a criterion.

$$E_j = \left[\frac{-1}{\ln m}\right] \sum_{i=1}^{n} \left[p_{ij} * ln(p_{ij})\right] \quad (5)$$

   where:
   E_j = entropy value for criterion j
   m = number of alternatives
   n = number of criteria
   p_{ij} = value of alternative i for criterion j, normalized to a proportion
   ln = natural algorithm function
   Constant $\left[\frac{-1}{\ln m}\right]$

This constant is used to normalize the entropy so that the entropy value is in the range 0 to 1. This constant ensures that the maximum entropy is 1 when maximum uncertainty is reached (all values have the same distribution).

Proportion $\left[p_{ij\,*}\,ln\left(p_{ij}\right)\right]$

p_{ij} is the proportion of element p_{ij} in the normalized decision matrix

p_{ij} * ln(p_{ij}) is the product of the proportion p_{ij} and the natural algorithm of p_{ij}

5. Calculating the dispersion value
   The dispersion value is used to measure how much a criterion contributes to the calculated entropy value.

$$d_j = 1 - E_j \quad (6)$$

where:
d_j = dispersion value for criterion j
E_j = entropy value for criterion j

6. Calculating the criterion weight
   Criterion weights indicate the relative importance of each criterion in decision making. This weight is calculated by normalizing the obtained dispersion values.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (7)$$

where:
w_j = weight for criterion j
d_j = dispersion value for criterion j
n = number of criteria

MOORA Method Algorithm
Steps (Cholil, 2021):

1. Normalization
   Unifying matrix elements so that the elements in the matrix have uniform values.

$$X_{ij} = \frac{x_{ij}}{\sqrt{\left[\sum_{i=1}^{m} x_{ij}^2\right]}} \quad (8)$$

Next, optimize the attribute value by normalizing the value x weight.

2. Reducing the maximum and minimax values.
   The more important attribute is indicated by multiplying it by a predetermined weight. The attribute weight calculation uses the following equation:

$$Y_i = \sum_{j=1}^{g} w_j x_{ij} - \sum_{j=g+1}^{n} w_j x_{ij} \quad (9)$$

3. Determining the ranking from the MOORA calculation results
   The ranking is determined based on the highest value from the calculation results.

System Testing
Testing is conducted to ensure the accuracy and effectiveness of the system:

1. Calculation Validity Test
   Ensures there are no mathematical errors
2. Sensitivity Test
   a. Changing data values or criterion weights
   b. Determining whether the ranking results change logically

Data Collection
Data collection methods include:

1. Literature review: journals, books, and research related to the Entropy and MOORA methods.
2. Observation: collecting vehicle specifications from official sources (dealers, automotive websites).
3. Documentation: vehicle technical data.
4. Interviews: with users or automotive experts to determine criteria.

RESULTS AND DISCUSSION

1. Entropy Method Algorithm

a. Determining the Decision Matrix

The decision matrix is determined using the entropy method and serves as the primary basis for the calculation process. The decision matrix is created based on vehicle criteria.
There are five established criteria:

C1: Cabin soundproofing, which is the vehicle's ability to reduce external noise, vibration, and roughness from entering the passenger compartment.
C2: Accommodation, which includes trunk capacity, small item storage, and seating comfort.
C3: Design, which focuses on functionality, space, and family comfort.
C4: Features, which are functional, comfortable, and safety features designed to support large passenger capacity and multi-purpose functions.
C5: Fuel consumption, a measure of efficiency that indicates the amount of gasoline a vehicle uses to cover a certain distance.

Of the five criteria above, the benefit criteria are: cabin tightness, accommodation, design, and features, while the cost criterion is fuel consumption.

Alternatives are the vehicles being compared. Five alternatives were used:

A1: Honda BR-V, offering powerful engine performance and comfortable driving features.
A2: Mitsubishi Xpander, known for its best-in-class suspension comfort, spacious cabin, and modern design.
A3: Suzuki Ertiga, excelling in fuel efficiency and very economical for daily use.
A4: Hyundai Stargazer, offering advanced safety features and modern cabin comfort.
A5: Toyota Avanza, a popular choice with a powerful 1500cc engine, easy maintenance, and stable resale value.

Table 1. Comparison of Criteria and Alternatives

Alternatif	Kriteria				
	C1	C2	C3	C4	C5
A1	0,7	0,8	0,6	0,6	0,9
A2	0,9	0,9	0,7	0,7	0,6
A3	0,8	0,7	0,8	0,5	0,8
A4	0,8	0,6	0,8	0,9	0,7
A5	0,9	0,9	0,9	0,8	0,5
	Benefit	Benefit	Benefit	Benefit	Cost

The values presented in table 1 were obtained through a quantitative assessment process based on literature studies, observation, documentation, and comparative analysis of vehicle specifications from official automotive sources. The research adopted an applied quantitative approach within the framework of a Decision Support System (DSS) using the Entropy and MOORA methods.

The data collection process involved gathering information from official manufacturer websites, automotive review platforms, product brochures, and comparative reviews from automotive experts. The evaluated vehicles consisted of five popular family vehicles in Indonesia, namely Honda BR-V, Mitsubishi Xpander, Suzuki Ertiga, Hyundai Stargazer, and Toyota Avanza.

The assessment criteria used in this study were determined based on factors commonly considered by consumers in selecting family vehicles, including: Cabin soundproofing (C1), Accommodation capacity (C2), Vehicle design (C3), Features and value for money (C4), Fuel consumption (C5)

The measurement scale applied in this study used a numerical rating scale ranging from 0.1 to 1.0, where higher values indicate better performance for benefit criteria, while lower values represent better performance for cost criteria. This scale was selected to simplify normalization and facilitate processing in the Entropy–MOORA calculation stages.

The scoring process was conducted using a comparative scoring approach. Each alternative vehicle was evaluated against every criterion based on specification analysis and qualitative interpretation converted into quantitative scores. The scoring principles are described as follows:

1. A score close to 1.0 indicates that the vehicle has excellent performance for the evaluated criterion.
2. A score close to 0.1 indicates relatively low performance compared to other alternatives.
3. For benefit criteria (C1–C4), higher values represent better conditions.
4. For the cost criterion (C5), lower fuel consumption values indicate better efficiency.

The values in table 1 are then arranged in the form of a decision matrix. The decision matrix is created according to equation 1.

$$X = \begin{bmatrix} 0,7 & 0,8 & 0,6 & 0,6 & 0,9 \\ 0,9 & 0,9 & 0,7 & 0,7 & 0,6 \\ 0,8 & 0,7 & 0,8 & 0,5 & 0,8 \\ 0,8 & 0,6 & 0,8 & 0,9 & 0,7 \\ 0,9 & 0,9 & 0,9 & 0,8 & 0,5 \end{bmatrix}$$

b. Decision Matrix Normalization

The normalization process ensures that each criterion contributes equally to the analysis. Normalization is performed by distinguishing between benefit and cost criteria.

The normalization of the decision matrix is done using equations 2 and 3, which results in the r_{ij} matrix.

$$r_{ij} = \begin{bmatrix} 0,78 & 0,89 & 0,67 & 0,67 & 0,56 \\ 1,00 & 1,00 & 0,78 & 0,78 & 0,83 \\ 0,89 & 0,78 & 0,89 & 0,56 & 0,63 \\ 0,89 & 0,67 & 0,89 & 1,00 & 0,71 \\ 1,00 & 1,00 & 1,00 & 0,89 & 1,00 \end{bmatrix}$$

$$\sum r_{ij} = [4,56 \quad 4,33 \quad 4,22 \quad 3,89 \quad 3,73]$$

c. Proportion

The proportion value is determined based on equation 4, and the results are arranged into a P_{ij} matrix.

$$P_{ij} = \begin{bmatrix} 0,17 & 0,21 & 0,16 & 0,17 & 0,15 \\ 0,22 & 0,23 & 0,18 & 0,20 & 0,22 \\ 0,20 & 0,18 & 0,21 & 0,14 & 0,17 \\ 0,20 & 0,15 & 0,21 & 0,26 & 0,19 \\ 0,22 & 0,23 & 0,24 & 0,23 & 0,27 \end{bmatrix}$$

d. Entropy

The Pij matrix is processed to produce the P_{ij} x $\ln(P_{ij})$ matrix.

$$P_{ij} \times ln(P_{ij}) = \begin{bmatrix} -0,30 & -0,32 & -0,29 & -0,30 & -0,28 \\ -0,33 & -0,34 & -0,31 & -0,32 & -0,33 \\ -0,32 & -0,31 & -0,33 & -0,28 & -0,30 \\ -0,32 & -0,29 & -0,33 & -0,35 & -0,32 \\ 0,33 & -0,34 & -0,34 & -0,34 & -0,35 \end{bmatrix}$$

$$\sum_{i=1}^{n} [P_{ij} \times ln(P_{ij})] = [-1,61 \quad -1,60 \quad -1,60 \quad -1,59 \quad -1,59]$$

The results of the calculation of the matrix P_{ij} x $\ln(P_{ij})$, are entered into equation 5

$$E_1 = \left[\frac{-1}{\ln 5}\right] \times -1,61 = 0,997$$

$$E_2 = \left[\frac{-1}{\ln 5}\right] \times -1,60 = 0,993$$

$$E_3 = \left[\frac{-1}{\ln 5}\right] \times -1,60 = 0,994$$

$$E_4 = \left[\frac{-1}{\ln 5}\right] \times -1,59 = 0,987$$

$$E_5 = \left[\frac{-1}{\ln 5}\right] \times -1,59 = 0,986$$

e. Dispersion

The entropy calculation results are used to find the dispersion value, using equation 6.

$$d_1 = 1 - 0,997 = 0,003$$

$$d_2 = 1 - 0,993 = 0,007$$

$$d_3 = 1 - 0,994 = 0,006$$

$$d_4 = 1 - 0,987 = 0,013$$

$$d_5 = 1 - 0,986 = 0,014$$

$$\sum_{j=1}^{n} d_j = 0,042$$

f. Criteria weighting

The criteria weighting is calculated using equation 7.

$$w_1 = \frac{0,003}{0,042} = 0,06$$

$$w_2 = \frac{0,007}{0,042} = 0,17$$

$$w_3 = \frac{0,006}{0,042} = 0,14$$

$$w_4 = \frac{0,013}{0,042} = 0,31$$

$w_5 = \frac{0,014}{0,042} = 0,33$

2. MOORA Method Algorithm

a. MOORA Normalization

Normalization in the MOORA stage simplifies ratio calculations and ensures all values are on a comparable scale.

This normalization is derived from equation 8.

$$X_{ij} = \begin{bmatrix} 0,38 & 0,45 & 0,35 & 0,38 & 0,56 \\ 0,49 & 0,51 & 0,41 & 0,44 & 0,38 \\ 0,43 & 0,40 & 0,47 & 0,31 & 0,50 \\ 0,43 & 0,34 & 0,47 & 0,56 & 0,44 \\ 0,49 & 0,51 & 0,52 & 0,50 & 0,31 \end{bmatrix}$$

The results of MOORA normalization multiplied by the weights produce attribute value optimization.

$$\begin{bmatrix} 0,02 & 0,08 & 0,05 & 0,12 & 0,18 \\ 0,03 & 0,09 & 0,06 & 0,13 & 0,12 \\ 0,03 & 0,07 & 0,06 & 0,10 & 0,16 \\ 0,03 & 0,06 & 0,06 & 0,17 & 0,14 \\ 0,03 & 0,09 & 0,07 & 0,15 & 0,10 \end{bmatrix}$$

b. Subtract the maximum and minimum values

The attribute weight is calculated using equation 9.

Table 2. Y_i Value

Alternative	Max (C1+C2+C3+C4)	Min (C5)	Yi (Max-Min)
A1	0,26	0,18	0,08
A2	0,31	0,12	0,18
A3	0,25	0,16	0,09
A4	0,32	0,14	0,18
A5	0,34	0,10	0,24

In the Max column, add up all the benefit rows, in the Min column, add up all the cost rows.

c. Ranking Determination

The ranking is obtained from the calculation of the highest value from the Y_i equation.

Table 3. Ranking

Alternative	Y_i	Rangking	Vehicle Brands
A1	0,080	5	Honda BRV
A2	0,185	2	Mitsubihi Xpander
A3	0,091	4	Suzuki Ertiga
A4	0,179	3	Hyundai Stargazer
A5	0,240	1	Toyota Avanza

The Y_i value indicates the level of preference for each alternative, where the greater the Y_i value, the better the alternative is based on the criteria used.

Based on the results of data processing using the Entropy method for criteria weighting and the MOORA method for alternative ranking, the preference values (Y_i) and ranking order of each vehicle are obtained as follows:

1. Alternative A5 (Toyota Avanza) achieved a Y_i score of 0.240 and ranked first. This indicates that the Toyota Avanza has the best performance compared to other alternatives based on the criteria used.
2. Alternative A2 (Mitsubishi Xpander) ranked second with a Y_i score of 0.185. This value indicates that the Xpander has excellent performance, although still below the Toyota Avanza.
3. Alternative A4 (Hyundai Stargazer) ranked third with a Y_i score of 0.179. This vehicle's performance is quite competitive and close to that of the alternative above it, but still slightly lower than the Mitsubishi Xpander.
4. Alternative A3 (Suzuki Ertiga) ranked fourth with a Y_i score of 0.091. This value indicates that its performance is in the lower-middle range compared to other alternatives.
5. Alternative A1 (Honda BR-V) obtained a Y_i value of 0.080 and was ranked last (fifth). This shows that based on the criteria used, Honda BR-V has the lowest level of preference among all alternatives.

3. Comparative Analysis of the Entropy–MOORA Method

The combination of the Entropy and MOORA methods in this study provides several advantages compared to conventional decision-making approaches that rely solely on subjective weighting. In traditional MOORA implementation, criterion weights are generally determined directly by decision-makers, which can introduce bias and inconsistencies in the evaluation process. By integrating the Entropy method, the weighting process becomes more objective because the weights are calculated based on the level of variation in the data for each criterion.

Compared with previous studies that used subjective weighting approaches such as AHP or direct expert judgment, the Entropy–MOORA approach demonstrates higher consistency because the weighting process depends on mathematical calculations rather than personal preferences. This result is in line with previous studies stating that objective weighting methods can reduce human intervention and improve the reliability of multi-criteria decision-making systems.

From the calculation results, the Entropy method generated different levels of importance among criteria. Criteria with higher data variability obtained larger weights because they contributed more significantly to distinguishing alternatives. Meanwhile, criteria with more uniform values produced smaller weights because they had lower discriminative power. This condition indicates that the Entropy method successfully identifies the most influential criteria in the vehicle selection process.

The ranking results generated by the MOORA method also show logical consistency with the characteristics of the evaluated vehicles. Toyota Avanza achieved the highest preference value because it consistently performed well across most benefit criteria while maintaining relatively efficient fuel consumption. Mitsubishi Xpander and Hyundai

Stargazer also achieved high rankings due to their strong accommodation, comfort, and feature values. In contrast, Honda BR-V obtained the lowest ranking because its overall performance across the evaluated criteria was less competitive compared to other alternatives.

4. Accuracy and Consistency Evaluation

The accuracy and consistency of the proposed decision support system were evaluated through sensitivity and logical consistency analysis. Sensitivity analysis was performed by observing changes in ranking when several criterion values were modified. The results showed that small changes in criterion values did not significantly alter the ranking structure, especially for alternatives with large preference differences. This indicates that the Entropy–MOORA model has stable performance and is not highly sensitive to minor data fluctuations.

Consistency evaluation was also conducted by comparing the final ranking results with actual market perceptions and general consumer preferences in Indonesia. The ranking results align with the popularity and practical considerations of family vehicles in Indonesia, where Toyota Avanza and Mitsubishi Xpander are widely recognized for their balance of comfort, accommodation, fuel efficiency, and maintenance practicality. This alignment demonstrates that the model produces realistic and rational recommendations.

In the context of a Decision Support System (DSS), the Entropy weighting mechanism significantly influences the final MOORA ranking because it objectively determines the contribution level of each criterion. Criteria with higher entropy dispersion values have stronger effects on the preference calculation process. Therefore, the integration of Entropy and MOORA not only improves objectivity but also enhances the interpretability of the decision-making results.

Overall, the comparative analysis and evaluation results confirm that the Entropy–MOORA approach provides a more systematic, objective, and consistent framework for multi-criteria vehicle selection problems. The model can therefore be considered reliable for implementation in other decision-making cases involving multiple alternatives and evaluation criteria.

CONCLUSION

The application of the Entropy method in this study plays an important role in increasing the objectivity of the decision-making process. Unlike subjective weighting approaches that depend on expert judgment or personal preferences, the Entropy method determines criterion weights mathematically based on the variability of data among alternatives. Criteria with higher variation among alternatives produce larger dispersion values and consequently receive greater weights. Conversely, criteria with relatively uniform values contribute lower entropy dispersion and receive smaller weights.

In the context of this study, the Entropy weighting mechanism significantly affects the final MOORA ranking results. Criteria that show stronger discriminatory capability among vehicles have a greater contribution to the calculation of preference values (Yi). This means that the final ranking is not only influenced by the performance of alternatives but also by the statistical importance of each criterion. As a result, the decision-making process becomes more data-driven and less dependent on subjective human intervention.

The influence of entropy weighting can also be observed in the final ranking results. Toyota Avanza achieved the highest ranking because it consistently performed well across the criteria that obtained relatively higher entropy weights. Mitsubishi Xpander and Hyundai Stargazer also produced competitive results because they excelled in several highly weighted benefit criteria such as accommodation, cabin comfort, and features. Meanwhile, Honda BR-V and Suzuki Ertiga obtained lower rankings because their overall performance was less dominant within the weighted evaluation framework.

From the perspective of a Decision Support System (DSS), the combination of Entropy and MOORA methods demonstrates an effective integration between objective weighting and alternative optimization. The DSS model developed in this research supports decision-makers by transforming complex multi-criteria data into structured and measurable recommendations. The system simplifies the evaluation process while maintaining analytical consistency and transparency.

The interpretation of the DSS results indicates that the generated rankings are rational and aligned with practical consumer considerations in Indonesia’s family vehicle market. The system successfully identifies alternatives that provide balanced performance across multiple criteria, including comfort, accommodation, features, and fuel efficiency. This confirms that the Entropy–MOORA-based DSS can function as a reliable analytical tool for supporting vehicle selection decisions.

Furthermore, the use of objective weighting improves the credibility and reproducibility of the decision-making model. Since the weighting process is derived directly from data characteristics, the model can be consistently applied to other multi-criteria decision-making problems without excessive dependence on expert subjectivity. Therefore, the proposed DSS framework has strong potential for implementation in broader applications such as product evaluation, supplier selection, employee assessment, and technology adoption analysis.

Overall, the scientific findings of this study demonstrate that the Entropy–MOORA integration not only improves ranking accuracy but also strengthens the methodological reliability, interpretability, and consistency of decision support systems in complex decision-making environments.

The model produced in this study has the potential to be developed for various other multi-criteria decision-making situations, not limited to family vehicle selection. This approach can be implemented in other areas such as product selection, performance evaluation, and data-driven recommendation systems. For further research, it is recommended to combine this method with other techniques, such as fuzzy-based methods or machine learning, to handle more complex data uncertainty. Furthermore, using a wider range of alternatives and criteria, as well as testing on real-time data, can provide more comprehensive results and improve system reliability under various decision-making conditions.

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