The 11th International Congress
Motor Vehicles & Motors 2026
Kragujevac, Serbia
October 8th - 9th, 2026

Motor Vehicles & Motors

MVM2026-069
https://doi.org/10.24874/CMVM2026.069
Technical paper

Saša Jovanović[1]
Zorica Đorđević[2]
Danijela Nikolić[3]
Lozica Ivanović[4]
Saša Milojević[5]

A SAW–BASED DECISION SUPPORT MODEL FOR THE SELECTION OF NEW AND USED PASSENGER CARS

ABSTRACT: The selection of a passenger car is a complex decision–making problem involving technical, economic, operational, safety and practical characteristics, together with individual buyer preferences. The problem becomes particularly complex when new and used vehicles of different ages are considered simultaneously. This paper proposes a decision–support model based on the Simple Additive Weighting (SAW) method. Sixteen anonymized SUV/crossover alternatives are considered: four new vehicles and twelve used vehicles divided into approximately three–, six–, and ten–year–old groups. Ten criteria are used, including effective acquisition cost, age, mileage, fuel consumption, maintenance cost, reliability, safety, performance, practicality, and equipment/comfort. Three weighting scenarios represent balanced, economy–oriented, and family/safety-oriented buyers. The results show different preferred alternatives for the three profiles and demonstrate that a recent used vehicle can outperform new alternatives under suitable buyer priorities. Weight–sensitivity and input–data uncertainty analyses further distinguish robustness to preference changes from robustness to uncertain input values.

KEYWORDS: passenger car selection, multicriteria decision–making, SAW, new and used vehicles, vehicle age, buyer preferences

[1] *Dr Saša Jovanović, full prof. Faculty of Engineering University of Kragujevac, Kragujevac 34000, Sestre Janjić 6, Serbia, dviks@kg.ac.rs, https://orcid.org/0000-0001-5916-2483*
[2] *Dr Zorica Djordjević, full prof. Faculty of Engineering University of Kragujevac, Kragujevac 34000, Sestre Janjić 6, Serbia, zoricadj@kg.ac.rs, https://orcid.org/0000-0003-0194-4698*
[3] *Dr Danijela Nikolić, full prof. Faculty of Engineering University of Kragujevac, Kragujevac 34000, Sestre Janjić 6, Serbia, danijelan@kg.ac.rs, https://orcid.org/0000-0003-3267-3974*
[4] *Dr Lozica Ivanović, full prof. Faculty of Engineering University of Kragujevac, Kragujevac 34000, Sestre Janjić 6, Serbia, lozica@kg.ac.rs, https://orcid.org/0000-0002-9503-593X*
[5] *Dr Saša Milojević, prof. assist. Faculty of Engineering University of Kragujevac, Kragujevac 34000, Sestre Janjić 6, Serbia, sasa.milojevic@kg.ac.rs, https://orcid.org/0000-0003-0569-047X*

SAW MODEL PODRŠKE ODLUČIVANJU ZA IZBOR NOVIH I UPOTREBLJAVANIH PUTNIČKIH AUTOMOBILA

REZIME: Izbor putničkog automobila predstavlja složen problem odlučivanja koji obuhvata tehničke, ekonomske, eksploatacione, bezbednosne i praktične karakteristike, kao i individualne preferencije kupca. Problem je posebno složen kada se istovremeno razmatraju nova i polovna vozila različite starosti. U radu je predložen model podrške odlučivanju zasnovan na metodi Simple Additive Weighting (SAW). Razmatrano je 16 anonimizovanih SUV/crossover alternativa: četiri nova i dvanaest polovnih vozila podeljenih u grupe starosti približno tri, šest i deset godina. Ocena je izvršena prema deset kriterijuma, uz tri scenarija pondera koji predstavljaju uravnoteženog, ekonomično orijentisanog i porodično/bezbednosno orijentisanog kupca. Rezultati pokazuju da se optimalna alternativa menja sa prioritetima kupca, kao i da relativno novo polovno vozilo može nadmašiti nova vozila. Analize osetljivosti pondera i nesigurnosti ulaznih podataka dodatno ukazuju na razliku između stabilnosti prema preferencijama i stabilnosti prema kvalitetu ulaznih podataka.

KLJUČNE REČI: izbor putničkog automobila, višekriterijumsko odlučivanje, SAW, nova i upotrebljavana vozila, starost vozila, preferencije kupca

INTRODUCTION

The selection of a passenger car is a multicriteria decision problem in which purchase price must be considered together with vehicle age, mileage, fuel consumption, maintenance requirements, reliability, safety, performance, practicality, and equipment. The importance of these attributes differs among buyers: a cost–conscious buyer may prioritize acquisition and operating costs, while another buyer may emphasize safety, reliability, practicality, or comfort.

The decision becomes more complex when the choice is not restricted to new vehicles. Within a similar budget, a buyer may simultaneously consider a new vehicle with modest equipment, a more extensively equipped recent used vehicle, or an older vehicle at a substantially lower price. The lower price of an older vehicle can be accompanied by higher mileage, maintenance requirements, reduced reliability, or technological obsolescence, whereas a recent used vehicle may offer higher performance or equipment at a competitive price.

Multicriteria decision-making (MCDM) methods provide a systematic framework for such problems. Byun (2001) applied the Analytic Hierarchy Process to automobile purchase model selection, while Raut et al. (2011) and Sakthivel et al. (2013) introduced fuzzy, hybrid, and integrated approaches. Ulkhaq et al. (2018) also applied an AHP–TOPSIS combination to car selection. More recent research has increasingly focused on electric–vehicle selection, including combinations of subjective and objective weighting and ranking methods, as demonstrated by Grdinić-Rakonjac and Lučić (2025), Lučić and Grdinić–Rakonjac (2025), Tian et al. (2023), and Ziemba et al. (2024). Simple methods such as SAW remain attractive when transparency and direct interpretation are important.

Despite the substantial literature on vehicle selection, many published models consider relatively homogeneous sets of alternatives, particularly new cars or electric vehicles. Comparatively less attention has been devoted to a realistic purchasing situation in which new and used vehicles of substantially different ages compete directly in the same decision matrix. Introducing used vehicles adds decision dimensions such as age, accumulated mileage, maintenance requirements, and breakdown reliability.

Furthermore, the concept of the “best” passenger car cannot be separated from buyer preferences. A ranking obtained using one fixed set of criterion weights represents only one preference structure. Changes in the relative importance of economic, technical, safety, and practical characteristics may result in a different preferred alternative. Accordingly, this study develops a transparent SAW–based model for the simultaneous evaluation of new and used passenger cars belonging to different age groups. Sixteen anonymized alternatives are assessed according to ten criteria under three buyer profiles. The main contribution is not the identification of a universally best vehicle, but the explicit analysis of trade–offs between acquisition cost, age, mileage and other relevant characteristics, together with an assessment of ranking robustness.

METHODOLOGY

The proposed decision-support model includes selection of vehicle alternatives, definition and quantification of evaluation criteria, development of buyer–specific weighting scenarios, SAW ranking, and robustness assessment through weight sensitivity and input–data uncertainty analyses.

SAW Method

Let $A_i (i = 1, \dots, m)$ denote the vehicle alternatives and $C_j (j = 1, \dots, n)$ the evaluation criteria. The decision matrix is $X = [x_{ij}]$, where x_{ij} represents the performance of alternative A_i according to criterion C_j. Since the criteria have different units and optimization directions, min–max normalization was applied. For benefit (MAX) criteria, for which higher values are preferred, Eq. (1) was used, whereas cost (MIN) criteria, for which lower values are preferred, were normalized according to Eq. (2):

$$r_{ij} = (x_{ij} - x_{j,min})/(x_{j,max} - x_{j,min}), \text{ for benefit (MAX) criteria} \quad (1)$$

$$r_{ij} = (x_{j,max} - x_{ij})/(x_{j,max} - x_{j,min}), \text{ for benefit (MIN) criteria} \quad (2)$$

The overall SAW score for alternative A_i and buyer profile p was calculated as:

$$S_i(P) = \sum_{j=1}^{n} w_j(P) \cdot r_{ij}, \quad w_j(P) = 1 \quad (3)$$

Where are:

- S_i – The overall score of the *i–th* alternative.
- P – If it denotes a specific alternative (e.g., a passenger car–P).
- w_j – The weighting coefficient of the criterion.
- r_{ij} – The normalized value of the alternative with respect to the criterion.
- n – The number of criteria.

Alternatives were ranked in descending order of $S_i(P)$. The decision matrix remained unchanged for all buyer profiles; only criterion weights were varied.

Vehicle Alternatives

The case study comprises 16 SUV/crossover alternatives divided into four age groups: four new vehicles (2026), four approximately three–year–old vehicles (2023), four approximately six–year–old vehicles (2020), and four approximately ten–year–old vehicles (2016). Petrol, diesel, HEV and MHEV powertrains were included; battery–electric vehicles were excluded. The maximum acquisition–price threshold during selection was approximately EUR 35,000. Used vehicles with reported substantial existing damage capable of materially affecting the advertised price were excluded.

To avoid brand–related perceptions, the alternatives are anonymized as V1–V16. Exact vehicle identities, configurations and sources were retained in the internal research database for traceability.

Evaluation Criteria

The selection of new and used passenger cars requires the consideration of several technical, economic, operational, and environmental factors. Therefore, a set of evaluation criteria was defined to enable a comprehensive and systematic assessment of the available alternatives. The selected evaluation criteria are presented in Table 1.

Effective acquisition cost (C_1) includes the selling price and any immediate registration expenditure required after purchase. Vehicle age (C_2) and mileage (C_3) were retained separately because vehicles of the same age can have substantially different usage histories. Fuel consumption (C_4) was expressed in L/100 km, using harmonized values where different certification procedures required improved comparability, as reported by Tsokolis et al. (2016). Maintenance cost (C_5) represents standardized annual workshop/maintenance expenditure, primarily based on data provided by ADAC (2026a); technically matched proxy variants were used where an exact configuration was unavailable.

Table 1 Evaluation criteria considered in the decision–making process

Criterion	Description	Unit/scale	Type
C_1	Effective acquisition cost	EUR	MIN
C_2	Vehicle age	years	MIN
C_3	Mileage	km	MIN
C_4	Fuel consumption	L/100 km	MIN
C_5	Standardized maintenance cost	EUR/year	MIN
C_6	Breakdown reliability	0–100	MAX
C_7	Safety	0–100	MAX
C_8	Performance	0–100	MAX
C_9	Practicality	0–100	MAX
C_{10}	Equipment and comfort	0–100	MAX

Breakdown reliability (C_6) was primarily derived from the ADAC breakdown statistics, as reported by ADAC (2026b). The original breakdown frequency was transformed into a benefit-oriented 0–100 score, as shown in Equation (4).

$$C_{6i} = 100 \cdot (B_{max} - B_i)/(B_{max} - B_{min}) \quad (4)$$

Where are:

- C_{6i} – The normalized value of the 6th criterion for the i-th alternative.
- 6 – Denotes the ordinal number of the criterion.
- i – Denotes the alternative (vehicle).

Safety (C_7) was calculated as the arithmetic mean of the four Euro NCAP domains, as defined by the European New Car Assessment Programme (n.d.): Adult Occupant Protection (AOP), Child Occupant Protection (COP), Vulnerable Road Users (VRU), and Safety Assist (SA), Equation (5).

$$C_{7i} = (AOP_i + COP_i + VRU_i + SA_i)/4 \quad (5)$$

Performance (C_8) combines normalized 0–100 km/h acceleration and specific power with equal weighting, whereas practicality (C_9) combines normalized luggage volume and payload. Equipment and comfort (C_{10}) use a ten–feature binary checklist, with 10 points for each confirmed feature:

$$C_{8i} = 0.50 \cdot A_i^* + 0.50 \cdot SP_i^* \quad (6)$$

$$C_{9i} = 0.70 \cdot L_i^* + 0.30 \cdot PL_i^* \quad (7)$$

$$C_{10i} = 10 \cdot \sum_k e_{ik} \quad (8)$$

Where are:

- A_i^* – The normalized value of A_i.
- SP_i^* – The normalized value of $S_i(P)$.
- L_i^* – The normalized value of indicator L for the i–th alternative.
- PL_i^* – The normalized value of indicator PL for the i–th alternative.
- $(0.50, 0.70 \text{ and } 0.30)$ – The weighting coefficients.

For used vehicles, a conservative confirmed–equipment–only principle was applied. Where exact configuration–specific data for $C_5 - C_{10}$ were unavailable, technically matched proxy or, where necessary, imputed values were used and recorded as such.

Buyer Profiles and Criterion Weights

Three scenario–based profiles were considered: P1–balanced, P2–economy–oriented, and P3–family/safety–oriented. The weights are predefined preference scenarios rather than consumer–survey–derived values.

Table 2 Evaluation criteria considered in the decision–making process

Criterion	P1 Balanced	P2 Economy	P3 Family/Safety
C1	0.1	0.2	0.1
C2	0.1	0.07	0.07
C3	0.1	0.1	0.08
C4	0.1	0.18	0.06
C5	0.1	0.18	0.07

Table 2 (continuation)

C6	0.1	0.12	0.15
C7	0.1	0.07	0.22
C8	0.1	0.03	0.04
C9	0.1	0.03	0.13
C10	0.1	0.02	0.08
Σ	1	1	1

Sensitivity and Input–Data Uncertainty Analysis

Each criterion weight was independently varied by $\pm 20\%$, while the remaining nine weights were proportionally rescaled to maintain their sum equal to one. Including the baseline case, 21 scenarios were evaluated for each buyer profile (63 SAW calculations). Selected uncertain inputs were stress-tested separately, distinguishing preference uncertainty from uncertainty in individual decision–matrix values.

DECISION MATRIX AND CASE STUDY

Market and technical data were collected from official manufacturer specifications, standardized vehicle databases and testing organizations, and actual used–vehicle advertisements during 2026. The resulting matrix is divided into cost and benefit criteria for readability, Table 3 and 4.

Table 3 Decision matrix – cost criteria

Alt.	C_1**, EUR**	C_2**, y**	C_3**, km**	C_4**, L/100 km**	C_5**, EUR/y**
V1	27,322	0	0	6.80	1,020
V2	29,832	0	0	6.35	888
V3	34,233	0	0	4.90	912
V4	28,063	0	0	6.50	1,116
V5	26,500	3	73,266	6.70	1,464
V6	23,262	3	111,181	5.30	1,416
V7	20,304	3	148,485	5.40	1,740
V8	28,044	3	152,000	5.50	1,164
V9	26,500	6	180,000	7.10	1,716
V10	27,027	6	139,563	5.80	1,140
V11	30,262	6	102,261	6.10	1,872
V12	16,999	6	229,000	5.50	1,716
V13	12,800	10	214,000	7.38	1,800
V14	15,558	10	232,000	5.88	1,080
V15	12,800	10	146,300	7.50	1,464
V16	15,000	10	248,376	6.00	1,488
Type	MIN	MIN	MIN	MIN	MIN

Table 4 Decision matrix – benefit criteria

Alt.	C_6	C_7	C_8	C_9	C_{10}
V1	93.16	77.25	34.91	80.33	70
V2	98.05	75.75	56.40	41.87	50
V3	75.59*	84.25	39.10	29.48	60
V4	82.81	86.75	30.15	33.94	50
V5	93.16	77.25	74.02	73.74	100
V6	82.81	86.75	80.50	33.94	60
V7	100.00	74.00	0.00	36.97	80
V8	98.83	80.00	34.65	71.77	30
V9	83.01	73.50	68.71	100.00	100
V10	0.00	85.50	97.22	42.32	100
V11	93.16	89.00	61.09	32.05	60
V12	86.72	80.00	36.38	79.05	40
V13	69.92	78.25	55.91	43.56	70
V14	39.84	75.75	29.42	54.41	80
V15	58.59	77.50	4.87	38.92	70
V16	79.30	80.00	41.24	80.78	20
Type	MAX	MAX	MAX	MAX	MAX

** V3 reliability is based on an imputed baseline value and is separately examined in the uncertainty analysis.*

RESULTS AND DISCUSSION

Application of the SAW method produced three rankings of the same 16 alternatives. The preferred vehicle changes with the priorities assigned to the criteria; no alternative is universally optimal for all profiles.

Ranking Results for Different Buyer Profiles

The ranking results for the different buyer profiles are presented in Figure 1, which compares the SAW scores of the leading alternatives and highlights the differences in vehicle preferences among the considered buyer profiles.

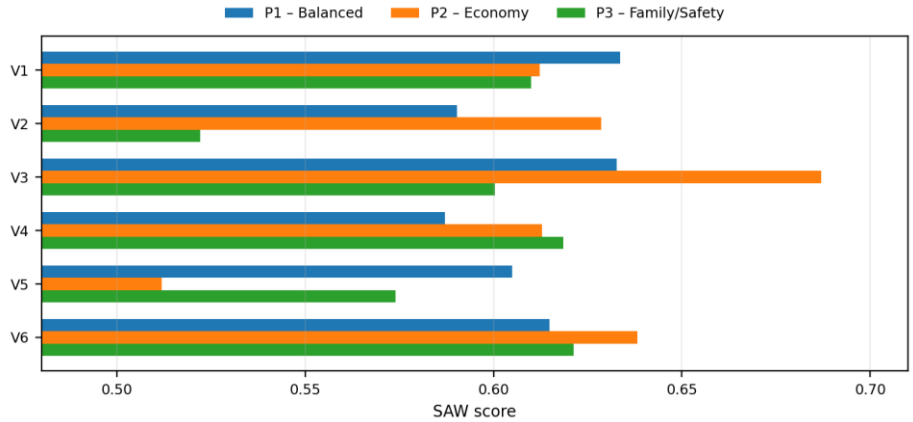


Figure 1 SAW scores of the leading alternatives for different buyer profiles

For P1, V1 achieved the highest score (0.6335), closely followed by V3 (0.6327) and V6 (0.6148). The difference between V1 and V3 is only 0.0008; therefore, these two alternatives should be regarded as highly competitive rather than interpreting first position as clear superiority.

For P2, V3 becomes the preferred alternative (0.6869), followed by V6 (0.6383) and V2 (0.6286). The relatively high acquisition cost of V3 is compensated by favorable fuel consumption, maintenance cost, age, and mileage, which receive considerable importance under this profile.

For P3, V6 achieves the highest score (0.6212), followed very closely by V4 (0.6185), while V1 ranks third (0.6100). Unlike the winners of P1 and P2, V6 is a three–year–old used vehicle. Thus, a recent used vehicle can outperform new alternatives when disadvantages related to age and mileage are compensated by favorable performance in criteria important to the buyer.

V1, V3, and V6 appear among the three highest–ranked alternatives under all profiles. The model therefore identifies a relatively stable group of competitive alternatives, while the final preference within this group depends on buyer priorities.

Influence of Vehicle Age and Buyer Preferences

Vehicle age alone does not determine attractiveness. New vehicles benefit from zero age and mileage and generally favorable maintenance characteristics, but require comparatively high acquisition expenditure. Recent used vehicles can compensate for age and mileage through lower purchase prices and favorable safety, reliability, performance, practicality, or equipment characteristics.

The result for V6 is illustrative: despite being approximately three years old, it ranks third for P1, second for P2, and first for P3. Conversely, the approximately ten–year–old alternatives generally occupy lower positions. Their price advantage is insufficient to compensate simultaneously for age, mileage and, depending on the vehicle, less favorable maintenance, reliability, consumption, performance, or equipment values.

Sensitivity Analysis

Ranking robustness was evaluated by independently varying each criterion weight by $\pm 20\%$ while proportionally rescaling the remaining weights. The main results are summarized in Table 5.

P2 exhibits the highest robustness: V3 remains first in all 21 scenarios. In P1, V1 retains first position in 13 scenarios (61.9%), while V3 becomes preferred in eight; however, V1 never falls below second place. This is consistent with

the very small baseline difference between V1 and V3 and indicates sensitivity of the order of two close competitors rather than a fundamental change in the preferred group.

Table 5 Summary of the weight sensitivity analysis

Profile	Baseline Winner	Winner Retained	Retention, %	Different Winners	Rank Range
P1–Balanced	V1	13/21	61.9	2	1-2
P2–Economy	V3	21/21	100.0	1	1-1
P3–Family/Safety	V6	13/21	61.9	3	1-2

A similar pattern occurs for P3. V6 remains first in 13 scenarios (61.9%), V4 becomes first in six, and V1 in two. V6 nevertheless remains first or second in all scenarios. These findings distinguish winner stability from leading–group stability: a change in first position does not necessarily imply an unstable decision model when the same small group remains dominant.

Input–Data Uncertainty and Limitations

Weight sensitivity does not account for uncertainty in decision–matrix values. This issue is relevant because exact model–year, engine, transmission, drivetrain and equipment data are not always available for every used vehicle. Technically matched proxy values were therefore used where necessary and explicitly identified.

The most important case concerns V3 reliability. A directly corresponding breakdown statistic was unavailable, so the baseline C6 value was imputed. In a separate stress test, the V3 reliability score was varied from 0–100. At the baseline score of 75.59, V3 ranks second for P1, first for P2 and fourth for P3. At substantially lower reliability scores, V3 loses first position under P2 and V6 becomes preferred; at very high assumed reliability, V3 can become preferred under all three profiles.

Thus, V3 is fully stable under the P2 weight–sensitivity scenarios but not unconditionally robust to uncertainty in its reliability input. Preference uncertainty and data uncertainty should therefore be interpreted separately.

A second stress test examined the V10 maintenance–cost proxy at EUR 1,140, 1,428 and 1,632 per year. These changes affected the individual score and rank of V10 but did not change the preferred alternative for any profile. This uncertainty is therefore less consequential for the main conclusions.

Discussion of the Main Findings

The comparison of the three profiles supports the central assumption of the proposed model: the “best vehicle” is conditional on the buyer’s preference structure. The same objective vehicle characteristics produce different preferred alternatives when criterion importance changes. This finding is consistent with the general rationale of MCDM-based vehicle-selection studies. Byun (2001), Raut et al. (2011), Sakthivel et al. (2013), Ulkhaq et al. (2018), Tian et al. (2023), Grdinić–Rakonjac and Lučić (2025), and Ziemba et al. (2024) have demonstrated the applicability of MCDM approaches to vehicle selection. However, the present case study extends the decision setting by allowing new and used vehicles of substantially different ages to compete directly.

The results also support retaining age and mileage as separate criteria. Alternatives within the same age group exhibit substantial differences in accumulated mileage. Similarly, maintenance cost and reliability provide different information: standardized maintenance expenditure does not necessarily correspond directly to breakdown frequency. Keeping these dimensions separate gives a more differentiated representation of used–vehicle ownership characteristics.

The model does not systematically favor new or used vehicles. Two new alternatives lead P1 and P2, while a three-year-old used alternative leads P3. At the same time, the oldest group generally remains outside the leading positions despite substantially lower acquisition prices. This suggests that price advantages alone are insufficient when age, mileage, ownership–related characteristics, safety, performance, practicality, and comfort are evaluated jointly.

Several limitations should be acknowledged. First, some C5–C10 values required technically matched proxies rather than exact configuration–specific observations. Second, C10 uses a conservative confirmed–equipment–only principle; an unreported feature was not assumed to be present, which may understate equipment scores for sparsely documented used vehicles. Third, Euro NCAP protocols evolve over time, so the C7 composite is transparent but not fully time–harmonized across vehicle generations. Finally, buyer–profile weights are scenario–based rather than survey–derived.

These limitations do not invalidate the model but define the appropriate interpretation of its results. SAW scores should be viewed as transparent decision–support indicators rather than exact measures of absolute vehicle

superiority. The practical value of the approach lies in structuring a complex purchasing problem, making trade–offs explicit, and showing how the preferred solution changes with buyer priorities and uncertain inputs.

For practical implementation, the internal database should therefore be maintained together with metadata describing the source and confidence level of each input. This is particularly important when the model is updated with new advertisements, model years, or reliability statistics, because the ranking may change not only due to market prices but also due to improved data quality.

CONCLUSIONS

This paper proposed a SAW–based multicriteria decision–support model for the simultaneous selection of new and used passenger cars belonging to different age groups. Sixteen anonymized alternatives were evaluated according to ten economic, age/use–related, operational, safety, performance, and practical criteria under three buyer profiles. Different alternatives achieved the highest rank for the three profiles: V1 for the balanced profile, V3 for the economy–oriented profile, and V6 for the family/safety–oriented profile. The fact that V6 is a three–year–old used vehicle demonstrates that a used vehicle may outperform new alternatives when its age and mileage disadvantages are compensated by favorable values of other criteria. Conversely, the generally lower positions of the oldest vehicles show that a low acquisition price alone is not sufficient to offset disadvantages associated with age, mileage, operating characteristics, maintenance, reliability, and other attributes.

Weight sensitivity showed that P2 is highly robust, whereas the exact first position in P1 and P3 changes under several $\pm 20\%$ perturbations. Nevertheless, the baseline winners remain within the top two in all tested scenarios. Input–data stress tests further showed that robustness to weight changes does not necessarily imply robustness to uncertain data, particularly when an uncertain value belongs to a highly ranked alternative.

The main advantage of the proposed approach is not identification of a universally optimal car, but transparent examination of how the preferred alternative changes with buyer priorities. Future research should include empirically elicited buyer weights, comparison with additional MCDM methods, and a more comprehensive treatment of input uncertainty and different powertrain and operating conditions.

ACKNOWLEDGMENTS

This research was performed as a part of activities within the projects 451–03–33/2026–03/200107 and 451–03–34/2026–03/200107, supported by the Republic of Serbia, Ministry of Science, Technological Development and Innovation.

REFERENCES

Allgemeiner Deutscher Automobil-Club e.V. (ADAC). (2026). ADAC Pannenstatistik 2026: Die Gewinner und Verlierer. https://www.adac.de/rund-ums-fahrzeug/unfall-schaden-panne/adac-pannenstatistik-2026/

Allgemeiner Deutscher Automobil-Club e.V. (ADAC). (2026). Übersicht: Autokosten aller Modelle von A bis Z. https://www.adac.de/rund-ums-fahrzeug/auto-kaufen-verkaufen/autokosten/uebersicht/

Byun, D. H. (2001). The AHP approach for selecting an automobile purchase model. *Information & Management*, 38(5), 289–297. https://doi.org/10.1016/S0378-7206(00)00071-9

European New Car Assessment Programme. (n.d.). Vehicle safety ratings and domain scores. https://www.euroncap.com/en/ratings-rewards/

Grdinić-Rakonjac, M., & Lučić, M. (2025). Electric vehicle selection with easy applicable MCDM methods. *Transportation Research Procedia*, 90, 782–789. https://doi.org/10.1016/j.trpro.2025.06.079

Lučić, M., & Grdinić-Rakonjac, M. (2025). Defining a new set of criteria for electric vehicle selection. *Transportation Research Procedia*, 83, 569–576. https://doi.org/10.1016/j.trpro.2025.03.027

Raut, R. D., Bhasin, H. V., & Kamble, S. S. (2011). Multi-criteria decision-making for automobile purchase using an integrated analytical quality fuzzy (AQF) technique. *International Journal of Services and Operations Management*, 10(2), 136–167. https://doi.org/10.1504/IJSOM.2011.042515

Sakthivel, G., Ilangkumaran, M., & Gaikwad, A. (2013). A hybrid MCDM approach for evaluating an automobile purchase model. *International Journal of Information and Decision Sciences*, 5(1), 50–85. https://doi.org/10.1504/IJIDS.2013.052017

Tian, Z. P., Liang, H. M., Nie, R. X., Wang, X. K., & Wang, J. Q. (2023). Data-driven multi-criteria decision support method for electric vehicle selection. *Computers & Industrial Engineering*, 177, 109061. https://doi.org/10.1016/j.cie.2023.109061

Tsokolis, D., Tsiakmakis, S., Dimaratos, A., Fontaras, G., Pistikopoulos, P., Ciuffo, B., & Samaras, Z. (2016). Fuel consumption and CO_2 emissions of passenger cars over the New Worldwide Harmonized Test Protocol. *Applied Energy*, 179, 1152–1165. https://doi.org/10.1016/j.apenergy.2016.07.091

Ulkhaq, M. M., Wijayanti, W. R., Zain, M. S., Baskara, E., & Leonita, W. (2018). Combining the AHP and TOPSIS to evaluate car selection. In *2018 2nd International Conference on High Performance Compilation, Computing and Communications (HP3C)* (pp. 112–117). https://doi.org/10.1145/3195612.3195628

Ziemba, P., Kannchen, M., & Borawski, M. (2024). Selection of the family electric car based on objective and subjective criteria–analysis of a case study of Polish consumers. *Energies, 17*(6), 1347. https://doi.org/10.3390/en17061347