Aalto University
School of Business

Application of MAVT for Car Decision Making

Assignment 2
Group C

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1 Introduction

The decision maker (DM) named V has a 3-person family and is seeking a long-term solution for their daily transportation needs. Given their regular commutes (to work, school, grocery stores, etc.), DM quickly identified that buying a car is the best and most necessary choice for the family, instead of renting cars, using public transportation, or cycling. Hence, DM's decision problem is to determine the most suitable car for their family, based on a comprehensive evaluation of fundamental objectives and below constraints set by DM.

Constraints are:

- Seating Capacity: The car must have adequate seating for at least three people, providing sufficient legroom and comfort.
- Primary Usage: The car should be highly suitable and fuel-efficient for city driving, as the primary usage involves regular, short-distance commutes.
- Fuel Type: Given the absence of DM's home charging pole for electric vehicles, the car should be a fuel-powered vehicle (gasoline).

Based on these constraints, our alternatives include only 4-seat fuel-powered cars, with a focus on fuel efficiency for city driving rather than highway driving.

The analysis begins with shortlisting fundamental objectives, followed by developing attributes for each objective. It then involves searching for different decision alternatives. Finally, the analysis compares the alternatives based on their values and the weights of each objective using the SWING method. The analysis concludes by recommending the best car choice and discussing the limitations of the analysis.

2 Problem Formulation

2.1 Fundamental Objectives

Given the family's requirements, fundamental objectives were mapped with value focused thinking approach. The following hierarchy was generated through the discussions:

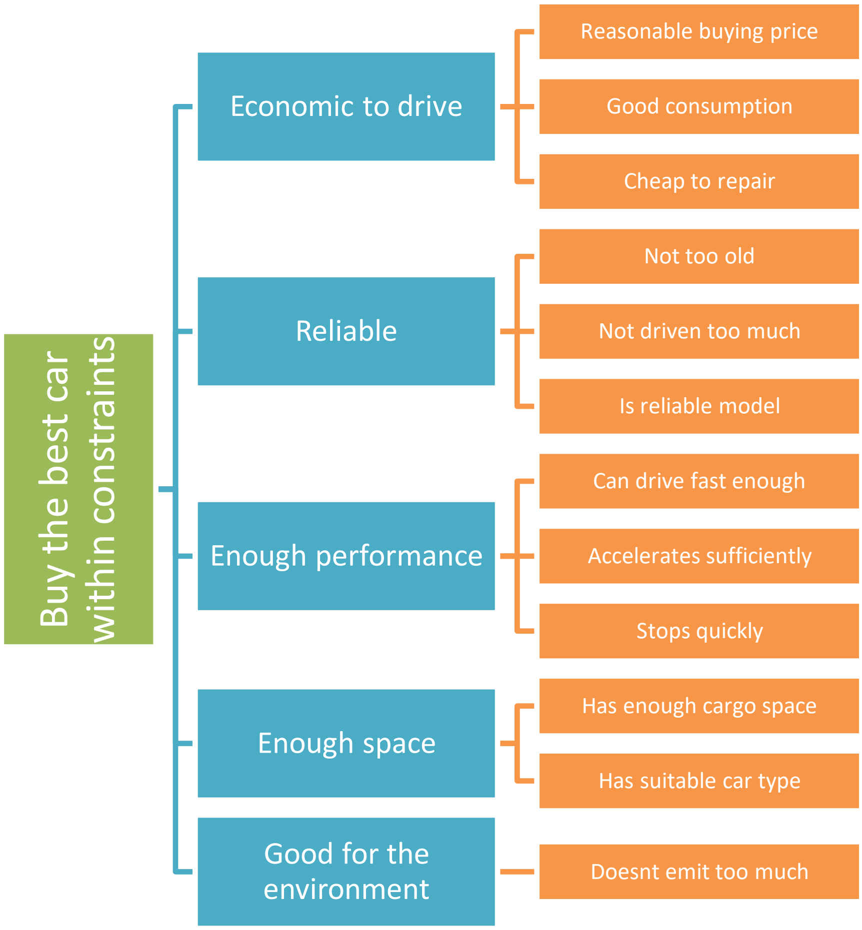

Figure 1: Fundamental objectives

2.2 Attributes

In the table below, we have outlined all the key attributes used in our model and why they are included along with the range of possible values for each attribute.

Table 1 : Attributes

Attribute	Range (worst x^0 – best x^1)	Importance
Price	€16,000 - €14,000	A key factor in budget constraints and overall affordability.
Consumption (l/100km)	10–3	Indicates fuel efficiency of city driving, directly impacting running costs.
Repairs	€3000- €200	Represents maintenance costs, affecting the long-term financial burden.
Age	10–0 years	Reflects the expected lifespan and reliability of the vehicle.
Driven (km)	120,000–20,000	Shows the extent of usage; higher kilometers can indicate more wear and potential for future issues.
Reliability ratings	0–99	Provides an overall reliability score, essential for predicting future performance and satisfaction.
Performance (Horsepower)	90–150 HP	Determines the vehicle's power and ability to meet performance expectations.
Acceleration (0–100 time)	20–6 seconds	Important for assessing the vehicle's responsiveness and suitability for different driving conditions.
Braking distance	50–10 meters	A crucial safety feature, indicating how quickly the vehicle can come to a stop.

Cargo space in liters	700–2,000 liters	Essential for evaluating the vehicle's capacity to carry goods, important for utility and practical use.
Car type	0 (=Hatchback H)–1(=Farmer F)	Specific to target user preference, ensuring the vehicle meets the needs of its primary user group.
Environment impact (CO_2 emission)	150–95 g/km	Reflects the vehicle's environmental footprint, important for sustainability and regulatory compliance.

2.3 Decision Alternatives

By reflecting to our problem statement and using the acceptable ranges of different attributes, we went online to a Finnish used car company's website (Kamux), and filtered cars according to the acceptable ranges. Dataset was formed from the cars and enriched with data from Caredge.com and J.D Power for repair cost, and reliability estimators. Following table resulted:

Alternatives	Ford Fiesta 2019	Scoda Octavia - 2017a	Mini one	Seat Leon	Volkswagen Polo - 2018	Volkswagen Polo - 2017	Scoda Octavia - 2017b	Audi A1	Ford Fiesta - 2017	Mini Cooper
Price (EUR)	14400	15400	14390	14900	14890	15200	15780	14800	15790	14800
Consumption	4.90	5.25	4.50	4.60	5.15	5.15	5.25	4.35	5.75	4.75
Average Repair Cost (EUR)	7967.20	5172.24	6213.68	5897.20	4972.60	4972.60	5172.24	8312.20	7967.20	6237.60
Age (years)	5	7	7	6	6	7	7	7	7	7
Driven (km)	43000	108000	52000	81000	89000	66000	114000	82000	38000	95000
Reliability Rating	73	80	79	76	72	73	80	77	73	79
Horsepower	101	116	102	116	95	95	116	95	101	136
Acceleration (seconds)	9.40	8.60	10.50	10.00	10.80	10.80	8.60	10.80	11.20	8.00
Braking distance (meters)	34	34	36	35	37	37	34	37	37	35
Type	H	F	H	H	H	H	F	H	H	H
Cargo space	1093	1718	941	1210	1125	1125	1718	920	1093	963
CO2 emissions (g/km)	118	119	108	113	120	118	119	127	108	125

Figure 2: Decision Alternatives

3 Problem Solving

3.1 Elicitation of attributes’ partial values

Here we have a table of the attributes and how they are scaled:

Table 2: Attributes' value functions

Attribute	Value Function	Reasoning
Price	Linear	The linear value function is used for price because the change in value is consistent and straightforward over the specified range.
Consumption (l/100km)	Linear	A linear value function is applied here as fuel consumption changes are perceived consistently over the range.
Repairs	Bisection method	The bisection method is used due to the non-linear perception of repair costs, as major repair costs are perceived with significant jumps in impact.
Age	Linear	Age is assumed to have a linear effect on the cars reliability.
Kilometers	Bisection method	The bisection method reflects non-linear perceptions, with critical levels defined at 80,000, 100,000, and 50,000 km.
Reliability ratings	Bisection method	The bisection method is suitable due to the non-linear perception of reliability ratings.
Performance (Horsepower)	Linear	A linear function is appropriate as the changes in horsepower are

		consistently perceived across the range.
Acceleration (0–100 time)	Bisection method	The bisection method is applied as acceleration changes are perceived non-linearly, with specific critical points at 10s, 8s.
Braking distance	Linear	The effect of the braking distance develops linearly with respect to car safety.
Cargo space in liters	Linear	The linear value function is suitable as changes in cargo space are consistently perceived across the range.
Car type	Binary	We only observe two car types: Farmers and sedans.
Environment impact (CO_2 emission)	Linear	A linear value function is appropriate as changes in CO_2 emissions are perceived consistently over the specified range.

3.2 Elicitation of objectives' weights

First, DM assigned scores on objective levels (DM chose the objective i that he would first like to change and assigned score 100 for this objective. Repeat the same for the rest). Then, for each objective, DM assigned scores for each attribute j within the objective.

		Attribute swung from worst to best	Consequence to compare	Rank for objective	SWING score	W_i	Rank for each attribute within the objective	w_j	w_{ij} (= W_i * w_j)
Objective i	Attribute j	Benchmark	€16 000, 10l, €3 000, 10 years, 120 000 km, 0 ratings, 90 HP, 20 seconds, 50 meters, 700 liters, Hatchback, 150 g/km)						
Economic to drive (i=1)	Price (j = 1)	($16 000, 10l, $3 000)	(€14 000, 10l, €3 000)	1	100	0.333	100	0.417	**0.139**
	Consumption (j = 2)		(€16 000, 3l, €3 000)				80	0.333	**0.111**
	Average Repair Cost (j = 3)		(€16 000, 3l, €200)				60	0.250	**0.083**
Reliability (i=2)	Age (j = 4)	(10 years, 120 000 km, 0 ratings)	(0 years, 120 000 km, 0 ratings)	2	80	0.267	80	0.333	**0.089**
	Driven (j = 5)		(10 years, 20 000 km, 0 ratings)				100	0.417	**0.111**
	Reliability Rating (j = 6)		(10 years, 120 000 km, 99 ratings)				60	0.250	**0.067**
Enough performance (i=3)	Horsepower (j = 7)	(90 HP, 20 seconds, 50 meters)	(150 HP, 20 seconds, 50 meters)	4	40	0.133	60	0.250	**0.033**
	Acceleration (j = 8)		(90 HP, 6 seconds, 50 meters)				100	0.417	**0.056**
	Braking distance (j = 9)		(90 HP, 20 seconds, 10 meters)				80	0.333	**0.044**
Enough space (i=4)	Cargo space (j = 10)	(700 liters, Hatchback)	(2000 liters, Hatchback)	3	60	0.200	80	0.444	**0.089**
	Type (j= 11)		(700 liters, Farmer)				100	0.556	**0.111**
Good for the environment (i=5)	CO2 emissions (j = 12)	150 g/km	(95 g/km)	5	20	0.067	100	1.000	**0.067**
				Total	300	1	1000		**1**

Figure 3: Weights

3.3 Results

After scaling the attributes and eliciting weights with swing, the final step was to calculate MAV scores for each car.

Alternatives	Ford Fiesta 2019	Scoda Octavia - 2017a	Mini one	Seat Leon	Volkswagen Polo - 2018	Volkswagen Polo - 2017	Scoda Octavia - 2017b	Audi A1	Ford Fiesta - 2017	Mini Cooper	Weight
Price (EUR)	0.800	0.300	0.805	0.550	0.555	0.400	0.110	0.600	0.105	0.600	0.139
Consumption	0.729	0.679	0.786	0.771	0.693	0.693	0.679	0.807	0.607	0.750	0.111
Average Repair Cost (EUR)	0.363	0.833	0.664	0.716	0.864	0.864	0.833	0.302	0.363	0.660	0.083
Age (years)	0.500	0.300	0.300	0.400	0.400	0.300	0.300	0.300	0.300	0.300	0.089
Driven (km)	0.983	0.150	0.733	0.488	0.388	0.617	0.075	0.475	1.400	0.313	0.111
Reliability Rating	0.507	0.661	0.642	0.580	0.480	0.507	0.661	0.602	0.507	0.642	0.067
Horsepower	0.183	0.433	0.200	0.433	0.083	0.083	0.433	0.083	0.183	0.767	0.033
Acceleration (seconds)	0.575	0.675	0.479	0.500	0.467	0.467	0.675	0.467	0.450	0.750	0.056
Braking distance (meters)	0.400	0.400	0.350	0.375	0.325	0.325	0.400	0.325	0.325	0.375	0.044
Type	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.089
Cargo space	0.302	0.783	0.185	0.392	0.327	0.327	0.783	0.169	0.302	0.202	0.111
CO2 emissions (g/km)	0.582	0.564	0.764	0.673	0.545	0.582	0.564	0.418	0.764	0.455	0.067
MAV	0.531	0.562	0.521	0.488	0.445	0.444	0.527	0.404	0.451	0.458	

Figure 4: MAV scores

After calculating the values, following ranking resulted. Based on this result, DM decided to choose “Scoda Octavia – 2017a”.

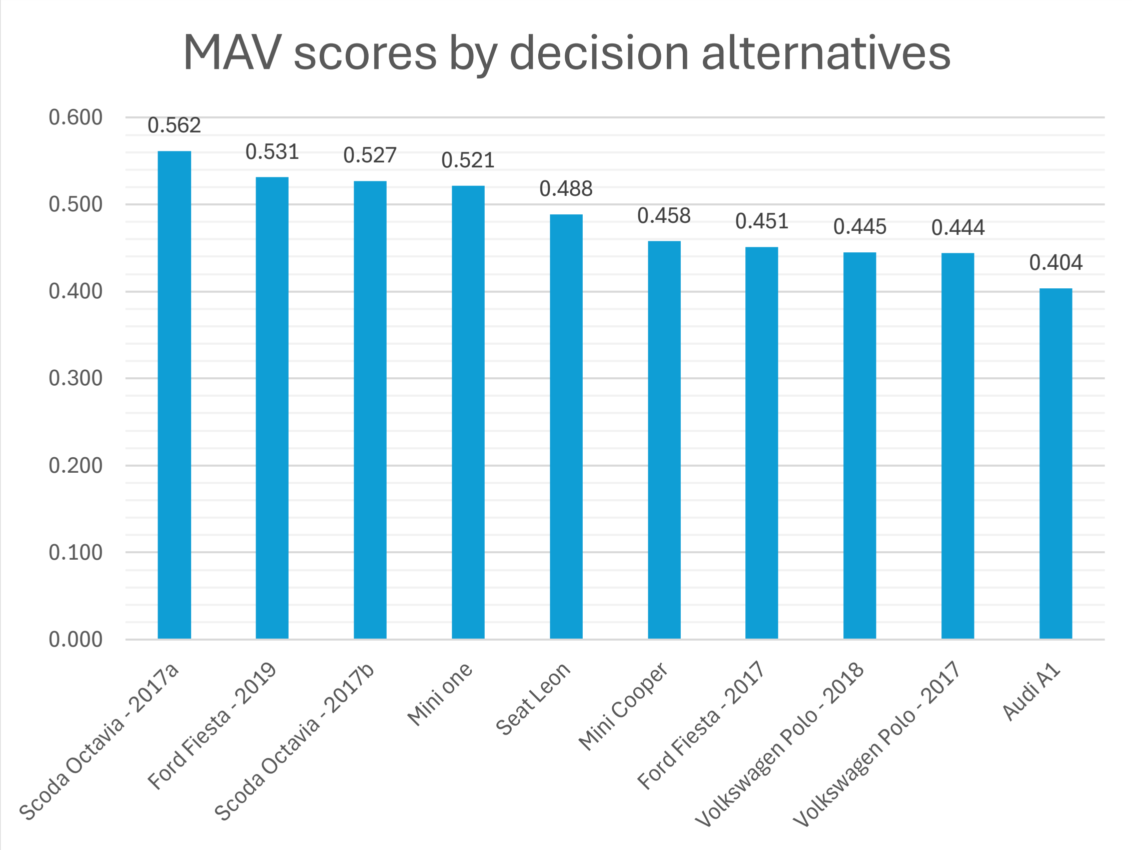

Figure 5 : Alternatives - Result

4 Discussion & Conclusion

This section aims to provide a holistic review of our entire decision-making process by discussing theoretic assumptions, behavioural issues, and limitations.

4.1 Theoretic assumptions and violations

To effectively utilize an additive-linear multi-attribute model for this decision problem, we must prove that several key assumptions hold true.

- Mutual Preference Independence (PI):
  DM stated that his preference for any attribute does not depend on the level of the remaining attributes. For example, his preference for a car with a high safety rating remains consistent regardless of its cost, fuel efficiency, etc. Hence, we can confirm that all attributes are mutually PI.

- Difference Independence (DI):
  DM's preference between changes in one attribute should be independent of the levels of other attributes. However, in practice, this assumption does not hold, as the evaluation of a price reduction depends on other factors i.e. car mileage. For example, V valued a price reduction of i.e. 500 EUR more if the car has fewer mileage (less kilometres driven).

4.2 Behavioural issues

DM is subject to below biases during decision-making process.

4.2.1 Biases related to generating objectives and alternatives

Identifying the potentially good alternatives is crucial in decision-making. However, in practice, DM's loyalty/preference for certain brands can overshadow the objective and limit the set of car alternatives (desirability bias). As we can see in this case, most car alternatives are Ford, Scoda, Volkswagen – which indeed is DM's personal favourite brands.

Omission bias can happen during the process of identifying fundamental objectives, as these objectives were listed solely by DM, without involving other stakeholders, such as his family. Due to the absence of his family participation in generating fundamental objectives process, some important objectives (based on their point of view) can be left out i.e. aesthetic preference (color/design), child-friendly features/ accessibility (child safety locks, rear seat entertainment with a screen, in-car WiFi , etc.)

Also, DM is subject to anchoring bias, especially on the price when shortlisting alternatives and define the range for 'price' attribute. DM tends to anchor over the price of his previous car – around 14000-15000 EUR and only consider alternatives falling within/near this price range.

4.2.2 Biases related to attribute scaling

To mitigate scaling biases, natural attributes were utilized whenever possible, with most data retrieved from manufacturers' websites to minimize subjectivity. For ambiguous objectives such as 'Reliability', reliability rating attribute was also referenced from external website [1] to minimizing DM's tendency to use all parts of the scale equally.

4.2.3 Biases related to attribute weights

Recognizing the potential for splitting bias, our team aimed to maintain balance within objectives by limiting attributes to 2-3 per objective. This approach prevents any single objective from being overweighted due to an abundance of attributes. Additionally, to avoid equalizing bias, we employed the SWING method to assign weights, guiding DM to prioritize the most impactful attribute changes and avoid arbitrarily equal weights.

4.3 Limitations

Our data collection for attribute values relied primarily on manufacturers' websites. However, as our alternatives primarily consist of second-hand cars, the specifications provided by manufacturers may not accurately reflect the current condition, particularly in attributes like acceleration.

Additionally, our reliance on external sources for obtaining reliability ratings introduces potential biases and variability into our analysis. Ratings sourced from consumer reports or automotive industry assessments are often subjective in nature, derived from a limited sample of consumers or experts. This subjectivity may not fully capture the nuances of real-world reliability experiences.

[1] https://www.jdpower.com/cars/ratings

To address this issue, we could incorporate more objective measures or diversify our data sources by including manufacturer recalls, warranty claims, and independent testing agencies. Also, utilizing quantitative metrics, such as Mean Time Between Failure/failure rates, could provide, and enhance the credibility of our analysis.