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The robust-reliable decision for selecting benchmark automotive platforms based on the combination of humane judgment simulation and KDD techniques

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Abstract

In this study, we address robust-reliable decision-making approach to select benchmark platforms to develop the automotive family. Activities studied included selecting the appropriate decision-making method, simulating possible scenarios to determine the relative importance of attributes by experts and stakeholders, determining the decision space and valuing attributes based on databases and Knowledge discovery in databases (KDD) techniques, statistical analysis and sensitivity assessment. The robust-reliable decision is made using the Simple Additive Weighting (SAW) method for 6223 unique cases of expert judgments and stakeholder expectations. The database used to determine decision space and attributes values included 546 automobiles designed in 11 different segments based on 34 platforms. This has led to the reliable selection of five benchmark platforms with the highest level of desirability in terms of defined attributes and the greatest robustness to uncertainties in the expert judgments and the level of expectations of stakeholders.

Introduction:

Manufacturers were forced to seek more efficient and flexible product design and manufacturing strategies to respond to pressures that included regional policies and regulations, demand for more product variety, rising costs of raw materials, labor, and manufacturing resources, and faster evolution of new technologies. One of the more successful strategies was the product platform strategy. This strategy attempts to save costs by sharing core elements among different products in the product family [1].

A product platform is a set of parts, components, subsystems, and interfaces that can be used to configure a joint structure enabling a stream of family products to be effectively developed. The concept of a product platform enables the common parts to be used to realize an entire family of derivative-related products [2].

The strategy of platform-based design in the context of the automotive industry has a long history and can be traced back to the 1960s. Back then, increasing market competition forced manufacturers to develop and produce their products less expensive and in a shorter time with higher quality. To achieve these goals, the platform-based design strategy has been introduced as a dominant method [3–5].

One of the approaches used in the design and development of complex systems such as automobiles is the benchmarking process. Benchmarking creates the opportunity for designers and decision-makers to study the strengths and weaknesses of similar products, within the lowest time and cost limits to set the right targets for attributes, objectives and expected performance of the product [6–10].

The right choice of benchmark platforms for the development of an automotive family creates the opportunity for decision-makers and designers to make the right trade-offs in the early stages of the design and development process. It also helps them to efficiently identify the characteristics and levels expected for the attributes, objectives, and design constraints. Finally, convergence on the optimal design point can be achieved faster by considering all design constraints, attributes, and objectives.

The benchmarking process helps with the comparison and modeling tasks in the process of designing a new platform or selecting an existing platform as a basis for the development of a new automotive family.

Since various attributes related to market issues, costs, technical issues, etc. are involved in the selection of benchmarks for the automotive family platform, the decision-maker needs to apply systematic methods that enable him to formulate the decision problem correctly and to choose the most appropriate alternatives by considering all the existing attributes and constraints.

Multi-Attribute Decision-Making methods are among the systematic methods that have been developed for this purpose and have been extensively applied to the fields of management, engineering, medical science, transportation planning, economics, and so on [11–15].

In the automotive industry and market, the use of MADM methods has a long background, examples of which can be found in references [16–28].

MADM is used to solve decision problems in discrete spaces with a finite number of predetermined alternatives and several attributes that are usually conflicting [11][12][29–31].

The MADM methods include four main parts [2][11][32]:

- Alternatives; which are solutions or options that should be evaluated based on attributes, ranked or selected the most appropriate of them.
- Attributes; which are properties, qualities or features of the alternatives. Attributes may be decomposed further into one or more levels of sub-attributes to form a hierarchical structure.
- The relative importance of attributes (attributes weight of importance); which is the degree of the relative importance of the attributes or sub-attributes.
- Evaluation function; which is the final criterion for evaluating and ranking the alternatives.

Various methods have already been introduced for solving MADM problems. Some of the most popular MADM methods are Simple Additive Weighting (SAW), Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), VIšekriterijumsko KOmpromisno Rangiranje (VIKOR), ELimination Et Choice Translating REality (ELECTRE) and a combination of these methods with FUZZY concepts [21–24] [11,30] [33–36].

Each of these methods has their Strengths and Weaknesses. One way to improve their performance is to use a combination of these methods in solving decision problems[12][13][29][33][34][37]. Examples of the combined use of MADM methods are given in references [13][29][34][37][38].

One of the major challenges of MADM methods is their dependence on the amount of knowledge and experience of experts and stakeholders, and since the level of knowledge and experience of individuals is different, we will always face some degrees of unreliability and lack of knowledge that lead to different

outputs for a certain problem. Uncertainties and lack of knowledge can be observed in determining the values of attributes for each alternative, the relative importance of attributes and even identifying alternatives [32,36][39–41].

Depending on the uncertainty and unreliability of the information or the lack thereof, different methods have so far been proposed to solve multi-criteria decision problems under uncertainty and sensitivity assessment of the problem outputs, which are generally based on mathematical analysis or simulation and modelling-based methods [14][32][36][39–44]. In solving real decision problems, we generally face uncertainty and unreliability in information, in which case the simulation tools are used to consider different conditions and analyze the sensitivity of the output to these uncertainties. The most common method used to simulate uncertainties is the Monte Carlo simulation method, examples of which can be seen in these references [40][45–51].

One way to reduce the level of uncertainty and lack of knowledge in designing and decision-making for a product is to use the hidden knowledge contained in similar products of the past. Especially with the development of data collection and analysis tools, a large amount of data on various topics can be collected and stored in the form of databases. Which can be extracted from these databases using KDD techniques. The concept of KDD was first introduced by Fayyad et al. in 1996, according to which:

Knowledge Discovery in Databases is the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data [52–54]. Extracting the knowledge contained in the data using KDD techniques will significantly reduce the complexity and uncertainties caused by the lack of knowledge in many decision-making and design problems [55–60].

In the automotive industry, due to the huge volume of data related to the market and customer feedbacks, as well as technical data related to successful processes, technologies and products, it is possible to use the KDD techniques to extract the necessary knowledge from this data to solve decision-making and designing problems.

In this study, the robust-reliable decision-making for selecting appropriate benchmarks for automotive platforms has been addressed aiming at developing a defined automotive family. This decision-making problem has no precedent in references and the literature.

The research questions in this study are:

1-What is the most trustable and simplest decision-making method to apply in this decision making problem?

2-How will utilizing the data of previous products helps to improve the accuracy and reliability of the decision?

3-How will it be possible to make a decision that is robust to uncertainties resulting from the expert judgments and the stakeholders’ preferences?

Appropriate utilization of previous products data and KDD techniques to reduce the level of uncertainties and lack of knowledge in determining the values of attributes, simulating possible situations for expert judgments and stakeholder preferences along with using the SAW decision-making method as the most widely used and oldest multi-attribute decision-making method[11][12][33–35][61], provides an effective approach to robust-reliable decision-making in the selection of most proper benchmark automotive platforms for the development of an automotive family.

PROBLEM STATEMENT:

The addressed decision making problem in this paper is defined as follow: Selection of the five most proper automotive platforms as benchmarks for the development of an automotive family in segments B, C and SS (Small SUV).

The expectation statement communicated from stakeholders is also defined as below:

1. The selected benchmark platforms should have the ability to support the automotive family in segments B, C and SS.
2. The automobiles that are developed based on the benchmark platforms must be less than 25 years old.
3. The potential to develop low-cost automobiles based on the benchmark platforms is desirable.
4. The potential to develop automobiles in various price classes based on the benchmark platforms is desirable.
5. The potential to develop automobile in different segments based on the benchmark platforms is desirable.
6. The potential to develop different automobile models based on the benchmark platforms is desirable.
7. More popular and trusted platforms are more desirable.

Proposed Methodology:

The proposed method for solving this decision-making problem includes the following parts:

Part 1: Problem Inputs; In this section, the expectations of stakeholders, expert judgments and the required database are collected.

Part 2: Elicitation of attributes and constraints of the problem; In this section, based on the expectations of stakeholders and the expert opinions, problem constraints and effective attributes in decision making are determined.

Part 3: Determination of the relative importance of attributes; In this section, the process of determining the relative importance of attributes by experts or stakeholders is simulated.

Part 4: Identifying decision alternatives and valuing the attributes for each alternative; In this section, according to the constraints of the problem, decision alternatives are elicited from the database. The utilization of KDD techniques to elicit models will be done to determine quantitative values for each of the attributes from the database collected in this section.

Part 5: Evaluating, ranking and storing alternatives; In this section, the final score of each alternative is calculated using the evaluation function and the alternatives are prioritized accordingly. Generated rankings are stored for later analysis.

Part 6: Statistical analysis and sensitivity assessment of outputs; In this section, statistical analysis and sensitivity assessment of iterative problem-solving outputs with relative importance simulated for attributes are discussed. Determining the frequency of positions occupied in ranking, standard deviation, the number of positions occupied by each alternative and other statistical characteristics will be examined in this section.

Part 7: Finally, with statistical analysis and sensitivity assessment of stored outputs, a robust-reliable decision will be made to select benchmark platforms. Figure 1 shows the steps required to achieve a robust-reliable decision.

Implementation Of Methodology:

In this section, the proposed methodology for the decision problem is implemented.

Process inputs:

The inputs of this procedure consist of three main parts; stakeholders expectations, experts judgments, and database.

As can be seen in Figure 1, stakeholder expectations and expert judgments contain certain and uncertain statements. Certain statements will determine the type of decision attributes and constraints. And uncertain statements will determine the relative importance of the attributes. To elicit quantitative models for attributes and determination of their values, a database of automobiles and platforms has been compiled from all over the world. This database includes information such as automobile segments, models, manufacturers, years of production, annual production number, price, type of platform and platform manufacturer.

Elicitation of constraints and decision attributes:

According to the problem statement and the seven expectations of the stakeholders, in this section, the constraints and attributes of the decision problem have been elicited.

The constraints for defining the decision space are as follows:

1. The automotive family developed based on each of the platform alternatives must include at least one of the segments of B or C or SS.
2. The first automobile manufactured based on each of the platform alternatives must be less than 25 years old.

As can be seen in the problem statement, the stakeholder expectations are qualitative in nature and the measurement criteria are not set for them. Using the expert judgments, four attributes that meet the expectations of stakeholders can be defined which are quantified based on models and values elicited from the database. The four decision attributes extracted based on stakeholder expectations and expert judgments are:

1-Segment adaptation: This attribute is vital in defining the degree of compatibility of the platform within the segments that are defined for the development of the automotive family. The valuing is done based on the degree of resemblance between developed segments based on each alternative of the platform in the database and stakeholder expected segments.

2-Price: The price attribute itself consists of two sub-attributes; the minimum price and the price range of the automobiles developed based on each platform alternative. It is worth noting that since the automobiles have been manufactured in different countries over various periods of time, all prices should be standardized based on an underlying currency. U.S. dollar with its value in 2019 has been chosen here.

3-Platform flexibility: This attribute contains two sub-attributes; the number of segments covered by each alternative platform and the number of models produced based on each platform alternatives. Basically, a greater number of segments as well as number of models indicates a more flexible platform.

4-Platform popularity: it is also known as an attribute describing the level of popularity and reliance on a platform. Here this attribute is divided into two sub-attributes; the number of manufacturers using the platform, and the annual production rate of the automobiles based on the platform.

Generation of the relative importance of attributes:

The relative importance of attributes and sub-attributes is a function of stakeholder expectations and expert judgments. Due to the uncertainty in the statements, different expert judgments and different levels of stakeholder expectations, the relative importance of the attributes will also be variable and include uncertainty. In this study, to achieve a robust-reliable decision for all expert judgments and levels of stakeholder expectations, the process of determining the relative importance of attributes by experts and stakeholders has been simulated. In the simulation with the aim of "realizing the values" and avoiding unexpected values, the following constraints are considered:

- The relative importance of the attributes should be quantified by integers 1 to 9
- The probability distribution function of the relative importance of the attributes is uniform.
- None of the sets of the relative importance of the attributes is similar to each other.

Given that there are four main attributes, and the relative importance value of each attribute can be determined with numbers 1 to 9 based on the Thomas L. Saaty method, the number of possible non-repetitive states will be equal to 6561 states. By removing sets of weights that are multiples of each other, 6223 unique sets of relative importance will remain. Finally, we make the simulated weights of importance dimensionless, so that the total weight of the values in each set is equal to one.

It should be noted that in this study, for the weight of the importance of sub-attributes, constant values are considered. The hierarchical structure of the decision-making problem has been shown in Figure 2.

In Fig. 2 (W1 to W4) are the weight of the importance of the attributes. (w2.1, w2.2, w3.1, w3.2, w4.1, w4.2) are the weight of the importance of the sub-attributes. (P1 to P34) indicates the number of platform alternatives.

Alternatives definition and valuing the attributes:

By having applied the constraints in the database, the decision space is shrunk to 34 alternatives for the benchmark automotive platforms selection. Overall, the design space includes the database with 546 automotive models in 11 automotive segments that are developed based on 34 platforms.

In the design and decision-making process for new products, using data related to successful previous products will be a smart approach to reducing the level of uncertainty and lack of knowledge. In this study, in the decision-making process, instead of determining the values of each of the attributes based on human judgment (which is always accompanied by some degree of uncertainty), the values of the attributes are elicited from the database using KDD techniques. This approach has led to the elimination of uncertainties caused by human judgment in determining the values of attributes. On the other hand, given that the database contains the information of successful products that have been produced and tested, the values obtained for the attributes will be quite reliable.

Due to the different ranges of values of each attribute, to have a correct evaluation, the values of each attribute must be normalized. Different methods have been proposed in different references to normalize the values of attributes [61][62-65]. In different references, depending on the type of data and the decision-making method used, the normalization method has been proposed [63][65]. Accordingly, in this study, the vector normalization method has been used for the attributes. Eq. 1 and 2 have been used for vector normalization.

$$(V_{ij})_{Normalized} = \frac{V_{ij}}{\sqrt{\sum_{j=1}^{n} V_{ij}^{2}}} \qquad \text{For benefit attributes} \qquad (1)$$

$$(V_{ij})_{Normalized} = 1 - \frac{V_{ij}}{\sqrt{\sum_{j=1}^{n} V_{ij}^{2}}} \qquad \text{For cost attributes} \qquad (2)$$

V_{ij} : Value of each attribute for each alternative
n : Numbers of alternatives
j : Alternative number
i : Attribute number

Table 1 presents the alternative platforms and the normalized values of each attribute. In calculating the values of the second to fourth attributes, the weights of importance of the sub-attributes are considered as follows (w2.1 = 0.5, w2.2 = 0.5 w3.1 = 0.3, w3.2 = 0.7, w4.1 = 0.5, w4,2 = 0.5).

Table 1 Normalized values of each attribute for 34 alternative platforms

Alternative number	Platform name	Segment adaptation	Price	Platform flexibility	Platform popularity
P1	BMW CLAR	0.164581341	0.182013536	0.202686229	0.095153528
P2	BMW Life-Drive	0.08429776	0.16790174	0.061128889	0.024685363
P3	BMW UKL	0.180638057	0.18160435	0.1470715	0.117095262
P4	Fiat Compact	0.216765668	0.169173644	0.158336384	0.136152202
P5	Fiat Mini	0.080283581	0.170576084	0.06940013	0.107448857
P6	Fiat-GM Small	0.240850742	0.17583018	0.21647163	0.17902298
P7	Ford Global B	0.130460819	0.167598151	0.105478735	0.078165236
P8	Ford Global C	0.130460819	0.163470422	0.105478735	0.153019627
P9	Ford C2	0.100354476	0.147776025	0.06664305	0.068347266
P10	GM Delta	0.16658843	0.178270918	0.174642301	0.241278618
P11	GM Epsilon	0.130460819	0.166632773	0.194178426	0.211685177
P12	GM Gamma	0.210744399	0.170583221	0.169364704	0.13624777
P13	GM Lambda	0.066233954	0.140584326	0.06664305	0.107185422
P14	GM Theta	0.066233954	0.1674529	0.08318553	0.204184686
P15	Hyundai-Kia J	0.130460819	0.188941466	0.157863257	0.205921376
P16	Hyundai-Kia Small	0.180638057	0.167382373	0.160856901	0.127523108
P17	Hyundai-Kia Y	0.150531714	0.165009828	0.185907185	0.146401613
P18	Mercedes-Benz MFA	0.100354476	0.150492769	0.06388597	0.057020541
P19	Mercedes-Benz W176	0.100354476	0.157383536	0.06664305	0.061432921
P20	Mitsubishi GS	0.182645146	0.173356415	0.196935506	0.237729341
P21	PSA CMP EMP1	0.100354476	0.154548261	0.06664305	0.088853527
P22	PSA EMP2	0.16658843	0.161623071	0.158099821	0.171037562
P23	PSA PF1	0.180638057	0.171256795	0.15534274	0.140163691
P24	PSA PF2	0.200708952	0.168637612	0.196935506	0.145379202
P25	Renault-Nissan B	0.244864921	0.178562202	0.299184034	0.308422349

P26	Renault-Nissan C	0.130460819	0.171880116	0.127535376	0.16117707
P27	Renault-Nissan CMF	0.232822384	0.165136531	0.20820039	0.13977093
P28	Toyota B	0.16658843	0.168483536	0.15534274	0.107789784
P29	Toyota MC	0.232822384	0.171609233	0.230257031	0.210957747
P30	Toyota TNGA	0.25088619	0.163940179	0.236007754	0.216064009
P31	VW A	0.214758578	0.173267714	0.218992147	0.210119856
P32	VW A0	0.180638057	0.175347234	0.182913542	0.201984047
P33	VW MLB	0.130460819	0.251429802	0.196935506	0.180643915
P34	VW MQB	0.266942906	0.174337794	0.307691837	0.350619573

Evaluating, ranking and storing of the alternatives:

At this stage, by determining the values of each attribute for the alternatives, and simulating the process of determining the relative importance of the attributes, the evaluation process of each alternative can begin. This process will be iterated as many times as simulation of the relative importance of attributes (6223 times) and finally, the obtained rankings will be stored for further analysis and identification of the robust-reliable decisions.

It is important to choose the right decision-making method that has the most reliable solution with the least complexity. For this study, the SAW method was selected due to the fact that this is the most widely used and oldest multi-attribute decision-making method [a, b, w, q, e, nr4]. Considering the type of the decision problem, i.e., decision-making under uncertainty with a large number of decision alternatives, this method will be superior to others in terms of reducing computational complexity. In this method, the evaluation function of each alternative is calculated using Eq. 3.

$$E_j = \sum_{i=1}^{m} (W_i)_{Normalized} (V_{ij})_{Normalized} \qquad (3)$$

E_j : The value of evolution function for each alternative

W_i : Attributes weight of importance

Statistical analysis and sensitivity assessment of outputs:

By looking at the 6223 stored data of rankings, it is possible to identify the different positions occupied by each alternative and to begin the process of analysis and sensitivity assessment accordingly. Figure 3 shows the positions occupied by each alternative in 6223 repetitions of the decision-making problem.

As can be seen in Figure 3, by changing the importance of the attributes, the alternatives occupy different positions in the ranking. Considering the five required benchmark platforms and the reduction of calculations, only the alternatives that have been able to occupy positions 1 to 5 at least once have been considered for further analysis (P6, P10, P15, P20, P25, P29, P30, P31, P33, and P34). Table 2 shows the frequency of occupancy of each position in the rankings of alternatives.

Table 2 The position occupied by each alternative and the frequency of their occurrence

Alt. No. / Position in ranking	P6	P10	P20	P25	P29	P30	P31	P33	P34
Rank 1	0	0	0	0	0	0	0	16	6207
Rank 2	0	0	0	6197	0	0	0	10	16
Rank 3	0	25	80	26	0	5499	0	593	0
Rank 4	160	104	210	0	5207	442	0	100	0
Rank 5	2162	104	528	0	726	162	2190	351	0
Rank 6	1498	171	955	0	184	96	3039	199	0
Rank 7	958	497	2142	0	106	17	784	577	0
Rank 8	685	1701	1524	0	0	5	210	875	0
Rank 9	584	1606	603	0	0	2	0	932	0
Rank 10	52	616	75	0	0	0	0	492	0
Rank 11	46	175	88	0	0	0	0	635	0
Rank 12	78	319	18	0	0	0	0	455	0
Rank 13	0	387	0	0	0	0	0	241	0
Rank 14	0	384	0	0	0	0	0	377	0
Rank 15	0	134	0	0	0	0	0	185	0
Rank 16	0	0	0	0	0	0	0	43	0
Rank 17	0	0	0	0	0	0	0	57	0
Rank 18	0	0	0	0	0	0	0	45	0
Rank 19	0	0	0	0	0	0	0	20	0
Rank 20	0	0	0	0	0	0	0	8	0
Rank 21	0	0	0	0	0	0	0	12	0
Rank 22	0	0	0	0	0	0	0	0	0
Rank 23	0	0	0	0	0	0	0	0	0
Rank 24	0	0	0	0	0	0	0	0	0
Rank 25	0	0	0	0	0	0	0	0	0
Rank 26	0	0	0	0	0	0	0	0	0
Rank 27	0	0	0	0	0	0	0	0	0
Rank 28	0	0	0	0	0	0	0	0	0
Rank 29	0	0	0	0	0	0	0	0	0
Rank 30	0	0	0	0	0	0	0	0	0
Rank 31	0	0	0	0	0	0	0	0	0
Rank 32	0	0	0	0	0	0	0	0	0
Rank 33	0	0	0	0	0	0	0	0	0
Rank 34	0	0	0	0	0	0	0	0	0

In order to make the most robust decision, the sensitivity of the positions occupied by the alternatives in the ranking should be analyzed. The positions that have the most abundance could not necessarily be a reliable criterion for making the most robust decision. The parameters of the distribution of occupied positions and the frequency of occupation of each position determine the sensitivity of the position of an alternative in the ranking to changes in the relative importance of the attributes. The concept of standard deviation is a suitable criterion for analyzing the sensitivity of the occupied position of each alternative to

the uncertainties of the relative importance of the attributes. Table 3 presents the statistical parameters related to the position of each alternative in the ranking.

Table 3 Statistical status of the alternatives in the ranking

Alt.No.	The most frequented occupied position in the ranking (Mode)	The percent of maximum repetition in the ranking	The mean value of occupied positions in the ranking (Mean rank number)	The number of occupied positions in the ranking	The standard deviation of occupied positions in the ranking
P6	Rank 5	%34.7	6.4023	9 positions	1.5801
P10	Rank 8	%27.3	9.3054	13 positions	2.3584
P20	Rank 7	%34.4	7.0700	10 positions	1.4271
P25	Rank 2	%99.5	2.0042	2 positions	0.0645
P29	Rank 4	%83.7	4.2269	4 positions	0.5803
P30	Rank 3	%88.4	3.1862	7 positions	0.5955
P31	Rank 6	%48.8	5.8415	4 positions	0.7667
P33	Rank 9	%15	9.0633	21 positions	3.5196
P34	Rank 1	%99.7	1.0026	2 positions	0.0506

Box diagrams can be used to better represent the diversity and distribution of occupied positions in the ranking. Figure 4 shows this diagram for each of the alternatives listed in Table 3.

In Figure 4, the black dots represent the mean position numbers are occupied by each alternative. The red lines indicate the median value, the lower side of the blue boxes indicates the value of the first quadrant (Q1) and the upper side indicates the value of the third quadrant (Q3). Red plus signs indicate outliers. Horizontal black lines represent the minimum and maximum values, which are defined based on Eq. 4 and 5, respectively.

$$\text{Maximum} = \begin{cases} \text{Max(position number)} & \text{if Max(position number)} \leq Q3 + 1.5 \times (Q3 - Q1) \\ Q3 + 1.5 \times (Q3 - Q1) & \text{if Max(position number)} > Q3 + 1.5 \times (Q3 - Q1) \end{cases} \quad (4)$$

$$\text{Minimum} = \begin{cases} \text{Min(position number)} & \text{if Min(position number)} > Q1 - 1.5 \times (Q3 - Q1) \\ Q1 - 1.5 \times (Q3 - Q1) & \text{if Min(position number)} \leq Q1 - 1.5 \times (Q3 - Q1) \end{cases} \quad (5)$$

Identification of the robust-reliable decision:

The following two criteria can be introduced to determine the most robust-reliable decision:

1. Achieving the highest relative position (mean position number) in the ranking for the different relative importance of attributes (desirability criterion)

Since there will be a possibility of change in the positions occupied by the alternatives for different weights of importance of the attributes, and on the other hand, for two alternatives, the highest repetitions may occur for the same positions of rankings, taking into account the mean of position numbers occupied by each alternative is a more reliable criterion for comparing the desirability of alternatives considering.

2. The lowest standard deviation in the occupied positions in the ranking (robustness criterion)

The lower standard deviation for an alternative, shown the higher focus on a given positions in ranking, that means the more robust to changing the relative importance of the attributes. In Table 4, the first five alternatives are selected based on each of the two criteria.

Table 4 Prioritization of alternatives based on two criteria of desirability and robustness

Prioritization based on the desirability			Prioritization based on the robustness		
Prioritized alternatives	Alt.No.	Mean position in the ranking	Prioritized alternatives	Alt.No.	The standard deviation of occupied positions
The first (The most desirable)	P34	1.0026	The first (The most robust)	P34	0.05064086
The second	P25	2.0042	The second	P25	0.06450266
The third	P30	3.1862	The third	P29	0.58030464
The fourth	P29	4.2269	The fourth	P30	0.59554597
The fifth	P31	5.8416	The fifth	P31	0.76667009

As can be seen in Table 4, the alternatives P34 and P25 in both criteria have a higher priority than the other alternatives. The P30 alternatives are in the third priority of desirability, while in terms of robustness, the alternative P29, which is in the fourth desirability priority, is better than the alternative P30, but this superiority is not enough to affect the final prioritization of the alternatives.

Finally, the most robust-reliable decisions to select benchmark platforms to develop an automotive family according to the defined attributes by take into account all possible scenarios for stakeholders' expectations and expert judgments can be seen in Table 5.

Table 5 The most robust-reliable decision in choosing the benchmark platforms

Prioritized alternatives	Alt.No.	Platform name
The first (The most robust-reliable decision)	P34	VW MQB
The second	P25	Renault-Nissan B
The third	P30	Toyota TNGA
The fourth	P29	Toyota MC
The fifth	P31	VW A

Discussion:

As can be seen in Tables 2 and 3, the platforms P34 and P25 have significant superiorities to other alternatives, both in terms of the frequency of occupying a particular position and in terms of the standard deviation. As for the alternatives P29 and P30, from the desirability point of view, the P30 has a superiority of almost 25% over the P29. Meanwhile, in terms of robustness, the superiority of P29 over P30 is only 2.6%. The fifth priority for both criteria is P31. But it is important to consider that according to Tables 1 and 2, alternative P31 occupies the sixth position in 48.8% of cases. As a result, position 6 is considered the position with the highest frequency for alternative P31. For the alternative P6, the fifth position is considered as the position with the highest frequency (34.7%). Also, alternative P31 ranks fifth in 35.2% of cases. In such circumstances, considering the most frequent position as a criterion for evaluating alternatives leads to choosing alternative P6 as the fifth priority. Meanwhile, as shown in Fig. 5, the alternative P31 is on average better than the alternative P6.

Finally, it can be concluded that to achieve a robust-reliable decision, all alternatives must be evaluated in all positions occupied, and in this evaluation, standard deviation and the mean of position numbers occupied by each alternative should be considered as the evaluation criteria.

Conclusion:

The present study is to achieve a desirable decision that is robust to the uncertainties of human judgments to select the five most proper automotive platforms as benchmarks for the development of an automotive family. For this purpose, SAW, KDD, simulation of possible scenarios of expert judgments and stakeholder expectations, statistical analysis and sensitivity assessment methods has been used. Each of these techniques and tools has contributed to achieving the desired and robust decision, which is summarized as follows:

- As the most widely used and oldest multi-attribute decision-making method, the SAW decision-making method has reduced the level of computational complexity for problems with a large number of decision options.

- Collecting the database of previous products and the use of KDD techniques instead of relying solely on the expert judgments will lead to smart determination of decision space and reduce the level of uncertainty and lack of knowledge in determining the values of attributes based on the knowledge contained in previous product data as the output of the efforts of other designer and decision-making teams.
- Simulation of possible scenarios for expert judgments and stakeholder expectations (human judgments) led to a comprehensive view of the range of changes in the priority of alternatives over changes in the relative importance of the attributes.
- Statistical analysis and sensitivity assessment have been used as tools to determine the most robust-reliable alternatives.

Finally using a combination of these tools and techniques has led to the selection of five platforms of P34 (VW MQB), P25 (Renault-Nissan B), P30 (Toyota TNGA), P29 (Toyota MC), P31 (VW A) as the most robust-reliable decision for benchmark platforms. This approach can be used in other decision-making problems. Recommendations for continuing this research line and improving the performance of the proposed approach are:

- Simulation of expert judgments and stakeholder expectations based on real data and different probability distribution functions
- Development of knowledge-based decision support tools for selecting benchmarking platforms

Declarations:

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Figures

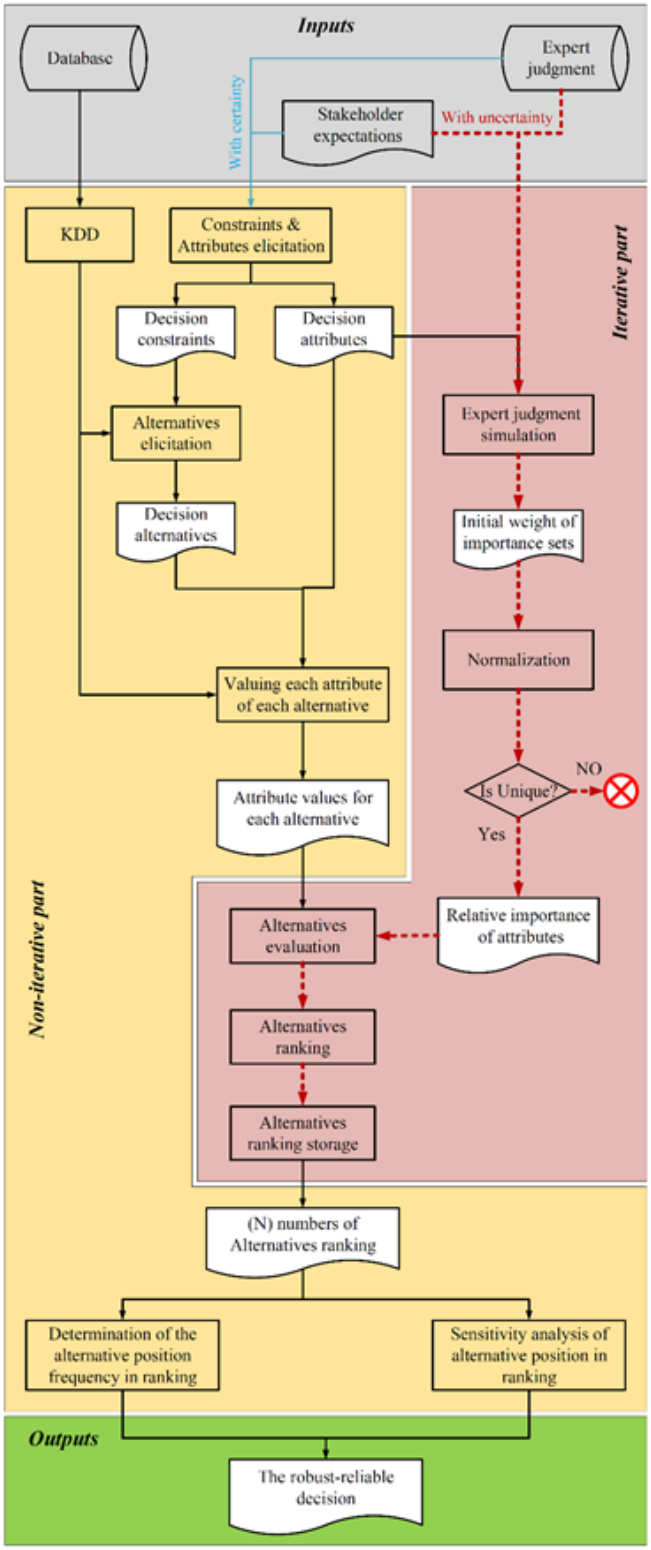

Figure 1

Steps required for achieving a robust-reliable decision

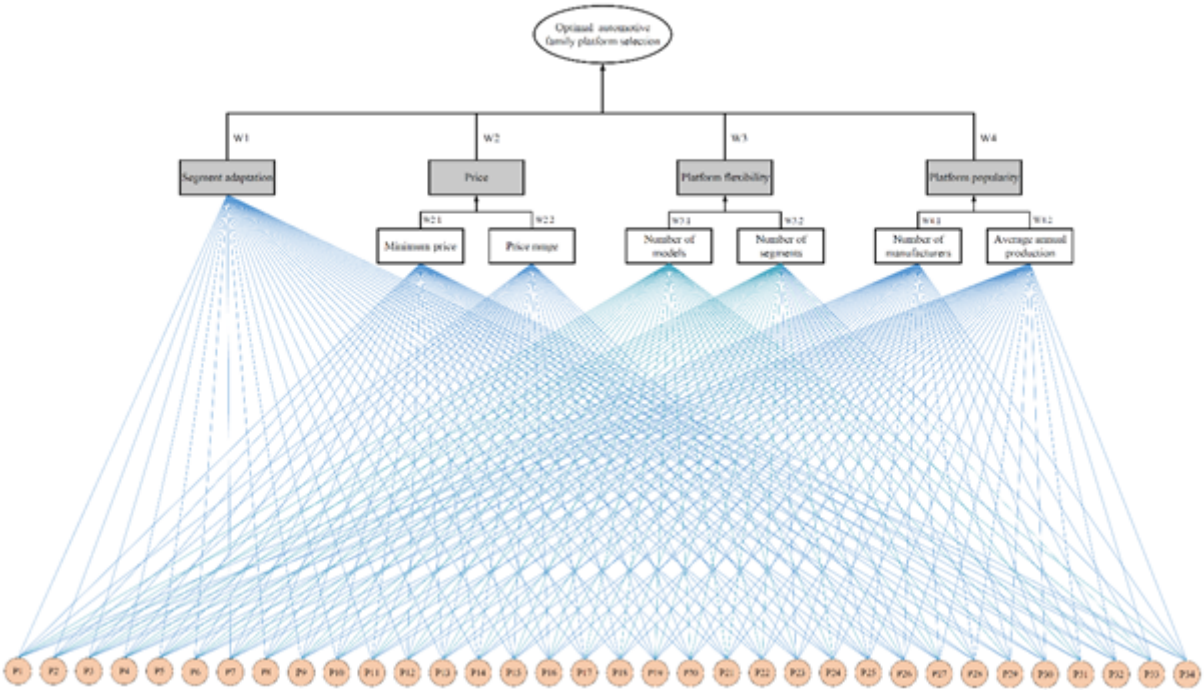

Figure 2

Hierarchical system for the MADM problem

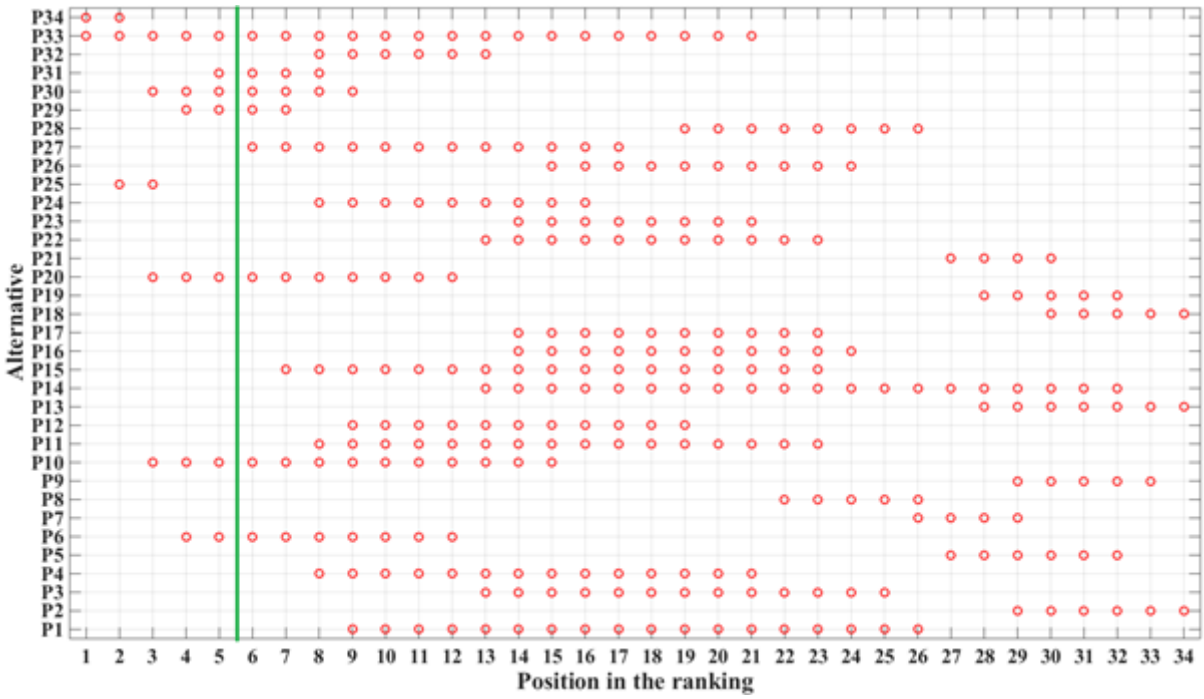

Figure 3

The positions occupied by each alternative during the 6223 times of solving the decision-making problem

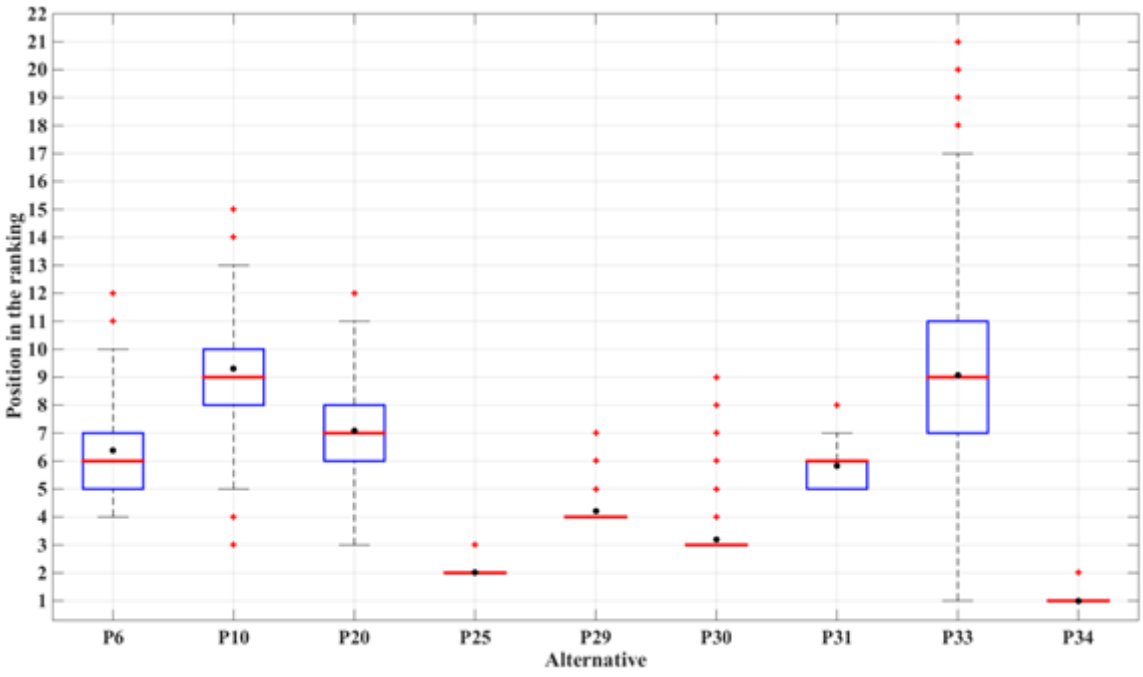

Figure 4

Box diagram of the positions occupied by the alternatives in 6223 times of solving the decision problem

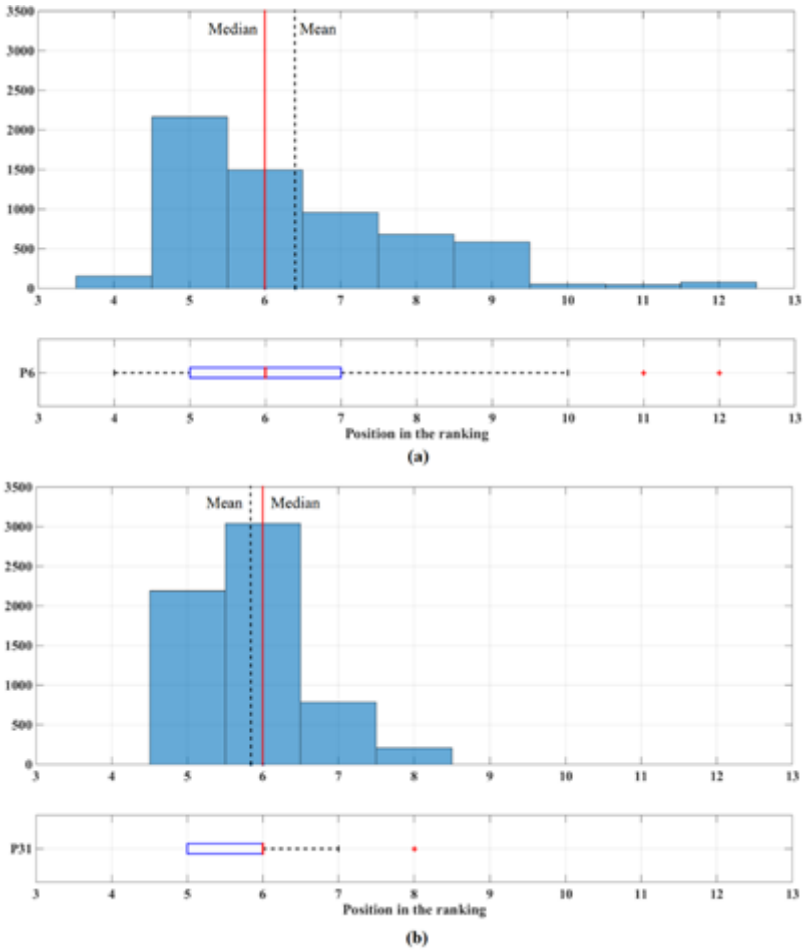

Figure 5

Statistical comparison of (a) alternative P6 and (b) alternative P31