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Smartphone Selection Using Structured User Reviews: A Hybrid Random Forest and Fuzzy DIBR II–WASPAS Approach

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ABSTRACT

One of the complex decision-making problems, which requires consideration of several criteria, is the choice of a smartphone. This paper presents an approach that combines user review analysis with machine learning and multi-criteria decision making (MCDM) methods to identify and evaluate alternatives. Based on the processed reviews, the Random Forest algorithm was used to identify the criteria that most influence the selection of smart phones. The weights of the criteria were determined using the Defining Interrelationships Between Ranked criteria II (DIBR II) method, improved by the application of triangular fuzzy numbers for better processing of the subjective and imprecise nature of the data. For the final selection of the optimal alternative, the Weighted Aggregated Sum Product Assessment (WASPAS) method was applied in a fuzzy environment, which enables the combination of additive and multiplicative approaches in ranking. The methodological justification of the proposed approach was confirmed by a sensitivity analysis, through 15 scenarios of changes in the weight coefficients of the criteria, which showed that small oscillations in the weights do not significantly affect the final ranking, especially not in the first two positions. The validation was additionally supported by a comparative analysis with four other decision-making methods in a fuzzy environment, which confirmed the stability and consistency of the results. The proposed approach provides an empirically grounded and methodologically robust framework for solving decision-making problems under conditions of multi-criteria evaluation and uncertainty, and can be applied to a wide range of similar problems in different fields.

Keywords: smartphone selection, Random Forest, Fuzzy DIBR II, Fuzzy WASPAS, MCDM

(MSC2020) Codes: 20F10, 28E10, 90B50

1 | INTRODUCTION

Smartphones have become an indispensable part of society today. In addition to basic functions such as calling and sending messages, their use has expanded to access the Internet, media, taking photos, recording video content, playing various games, participating in various social networks, and the like. The progress of smartphone capabilities is very rapid, and manufacturers are constantly improving their capabilities, developing different models with different features. All of the above creates a complex decision for potential buyers when choosing a smartphone.

When buying a smartphone, the buyer is required to consider various factors (criteria) to choose a smartphone that suits their needs and budget. Some of the key criteria that are considered when choosing include the operating system, processor performance, random-access memory (RAM) capacity, read-only memory (ROM) capacity, screen quality, battery capacity, camera quality, price, brand and other additional options.

In the modern digital environment, user reviews and ratings are of additional importance, which provide users with a direct insight into the experiences of other customers and thus significantly influence the final decision. User reviews are crucial when choosing a smartphone because they provide real user experiences and help with decision-making. In principle, they enable the assessment of reliability, quality, performance, price-value ratio, identify potential problems, which facilitate decision-making. They also allow comparisons of competing models and brands, offering transparency when shopping. In short, reviews are an irreplaceable source of information, helping users avoid bad choices and make a decision based on the real experiences of other users. The volume and variety of information that needs to be processed make this process time-consuming and cognitively taxing. In essence, the complexity of the choice comes from the need to balance personal preferences, budget and technological capabilities. Each user strives to find the ideal balance between these factors. Therefore, there is a need for a systematic and efficient approach that can support the user in making an informed and optimal decision. Considering that it is necessary to consider many different criteria that determine their choice, an optimal decision that becomes complex also requires a lot of time. Because of all this, it is necessary to define an approach that will solve this decision-making problem. The solution to this problem can be found in the application of various machine learning algorithms that process classification, regression and analysis of the significance of features and the application of multi-criteria decision-making methods (MCDM). Most researches use MCDM methods or machine learning separately, while their combination can improve the accuracy and objectivity of selection.

One way to determine the most significant criteria from a set of admissible ones that influence the final decision is the Random Forest machine learning algorithm. This algorithm is based on Bootstrap

Aggregating technique and Decision Trees [1]. Unlike individual decision tree models, Random Forest is more resistant to overfitting and can work better with uncertain data, which is useful in a fuzzy MCDM environment. Random Forest uses what is called random feature projection when building a stable decision [1]. The Random Forest algorithm is effective in analyzing large databases, including user reviews, technical specifications and market trends, which is suitable for smartphone selection. The combination of Random Forest with MCDM methods enables better analysis of user preferences and optimization of mobile phone selection.

MCDM methods enable the evaluation and ranking of alternative options based on multiple criteria, considering both quantitative and qualitative aspects, as is the problem of smartphone selection. Application of these methods allows users to make an optimal decision based on precisely defined preferences. To prove the previous claim, several studies that support it are given below. In order to select a highway restaurant site, i.e., to arrive at the optimal location, the authors in [2] use the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods in a fuzzy environment. To assess the efficiency of insurance companies, the authors in [3]use the TOPSIS method and Decision Theory. The authors in [4] perform selection of the optimal forklift, applying the Full Consistency Method (FUCOM) in a neutrosophic environment, a novel triangular neutrosophic score function and ranking function, as well as a novel single valued triangular neutrosophic numbers linear programming problem. They can be used individually [5] or in combination [6], [7], depending on the specific needs and requirements of the user.

The aim of this paper is to investigate the possibility of the combined application of the Random Forest algorithm and MCDM methods in the process of deciding on the purchase of a smartphone, based on user reviews. The paper aims to identify the key criteria that influence the customer's decision, to analyze the importance of each of them and to demonstrate how the available alternatives can be systematically ranked according to the individual preferences of the customer. In this way, the paper contributes to the development of intelligent recommendation systems in the field of e-commerce and provides a basis for future research in the field of personalized decision-making in the digital environment. The integration of the Random Forest algorithm with the aforementioned methods enhanced with triangular fuzzy numbers, which improves the handling of subjective user ratings and qualitative criteria, is a novelty in this field.

2 | LITERATURE REVIEW

Smartphone selection is a frequent subject of research. Researchers have used different approaches and methods in selection, as well as different theories that handle uncertainties in imprecision in input data well. They mainly use MCDM methods to make the final decision. The authors in [8] perform the subject selection using the Fuzzy AHP and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) methods, while the authors in [9] use a similar MCDM model, i.e., they do not use Fuzzy theory. The AHP or Fuzzy AHP method was used to determine the weights of the criteria, while the PROMETHEE or TOPSIS method was used to select the optimal alternative (smartphone). Also, for the selection of smartphones, both TOPSIS and Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) methods were used in [10]. The authors in [11] compare Simple Multi Attribute Rating Technique (SMART) and Fuzzy Multi Criteria Decision Making (FMCDM) methods for the decision-making process for choosing a smartphone. In their study, they conclude that Fuzzy methods are better because the results are closer to a predetermined standard of decision value, and that these methods can be applied to problems more complex ones that require a lot of data and criteria. Also, numerous and more recent studies are available in this area, or rather the subject of research [12], [13], etc.

The application of machine learning algorithms and MCDM approach for smartphone selection is not a frequently addressed research topic. Authors in [14] use the Mamdani approach, a traditional fuzzy inference tool (FLC) and a neuro-fuzzy system (ANFIS) to design a process with three inputs and one output. The application of the neuro-fuzzy system is based on the back-propagation algorithm. Two traditional fuzzy inference tools - artificial neural network (ANN) and neuro-fuzzy system - were used to achieve a more precise understanding of the process of choosing a mobile phone for personal use. In the study [15], the TOPSIS method and graph theory and matrix approach (GTMA) were used to select a smartphone and tariff plan.

The application of the Random Forest algorithm in combination with MCDM methods in various research subjects is represented in a large number of studies. In research related to various insurance models [16], the use of the TOPSIS method and the Random Forest algorithm was demonstrated. The authors in [17] apply the AHP method and the subject-matter machine learning algorithm for enhancing smartphone authentication. For Cybersecurity Risk Assessment, the authors in [18] use the Visekriterijumska Optimizacija i Kompromisno Resenje (VIKOR) method enhanced with a single-valued neutrosophic set and the following machine learning algorithms: Decision Tree, Random Forest, and Support Vector Machine. The authors in the paper [19] use methods such as Complex Proportional Assessment of Alternatives (COPRAS), and algorithms Logistic Regression, Improved Regression Tree, Random Forest and Frequency Ratio for spatial prediction of gully erosion. Also, the authors in the paper [20] apply MCDM methods such as Simple Additive Weighting (SAW), VIKOR, TOPSIS and the Condorcet algorithm based on game theory, as well as machine learning algorithms (MLAs), including K-nearest neighbors, Naive Bayes, Random Forest, simple linear regression and support vector machine, for spatial mapping of sediment formation potential.

All of the above and other research in this area point to the following:

1. Smartphone selection is a common and current area of research.
2. The most common approach of selection is to apply one or more MCDM methods.
3. Various decision-making problems are solved by applying machine learning algorithms such as Random Forest in combination with MCDM methods.
4. There is a small number of researches that deal specifically with the selection of smartphones using the Random Forest algorithm and the MCDM methods.
5. MCMD methods such as Defining Interrelationships Between Ranked criteria II (DIBR II) and Weighted Aggregated Sum Product Assessment (WASPAS), especially in a fuzzy environment, have not been used for subject selection so far.

Based on all of the above, a gap opens for the use of previously unused methods for smartphone selection, especially in a fuzzy environment, and often qualitatively exploited MCDM methods in other decision-making problems, in combination with the Random Forest machine learning algorithm.

3 | MATERIALS AND METHODS

The Random Forest machine learning algorithm was used to identify key criteria for smartphone selection. After the criteria that determine smartphone selection have been identified, it is necessary to define their weights. For this, the Fuzzy Defining Interrelationships Between Ranked Criteria II (DIBR II) method was used in this paper. The Fuzzy Weighted Aggregated Sum Product Assessment (WASPAS) method was used to select the optimal alternative (smarthphone). The mentioned methods in the fuzzy environment have proven to be methods that treat uncertainty and inaccuracies well, which certainly represents a problem of choosing a smartphone, due to the characteristics of the criteria that determine the choice. In particular, the application of triangular fuzzy numbers in the decision-making process enables effective treatment of uncertainty, subjectivity and imprecision, which are often present in real decision-making problems. Unlike classical approaches, triangular fuzzy numbers enable the expression of ratings (opinions) in the form of intervals with a lower, middle and upper value, which more reliably conveys the uncertain nature of human assessments. Due to their simple structure and mathematical apparatus, these numbers are easy to implement, while enabling better and more realistic decision-making. Their application is particularly useful in MCDM methods, where they enable more flexible expression of experts' opinions and more precise evaluation of alternatives. Using triangular fuzzy numbers reduces the risk of wrong decisions and improves the overall reliability of the decision-making process in conditions of complexity and uncertainty.

To check the consistency and validity of the methodology's output results, sensitivity and comparative analysis were performed. Figure 1 shows the algorithm of this research.

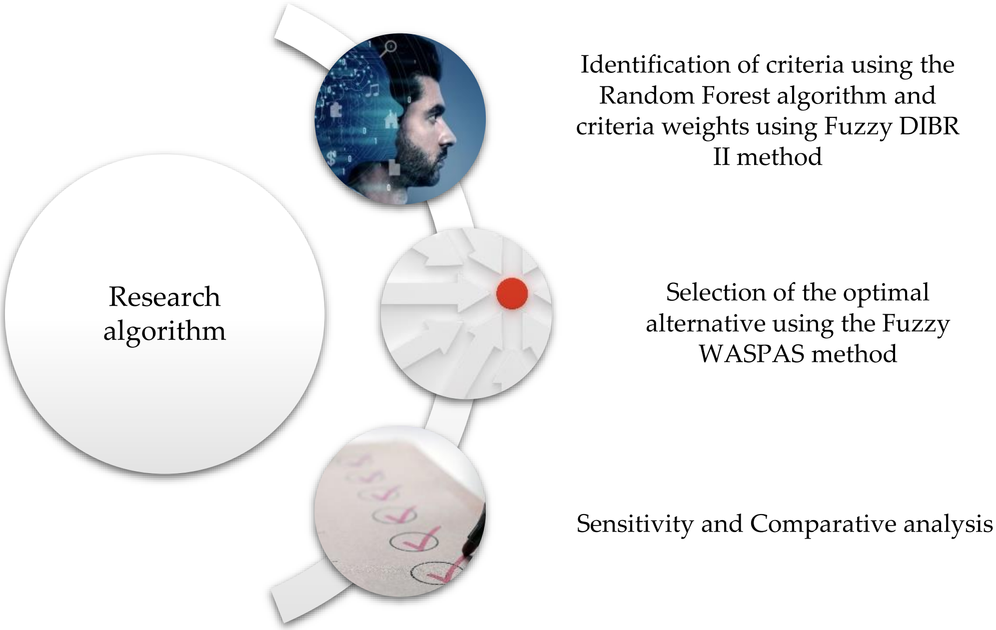

Figure 1. Proposed Research Model

The following text describes the algorithm used, as well as the methods.

3.1 | Random Forest Algorithm

Random Forest is a machine learning algorithm used for classification, regression and feature significance analysis. This algorithm is a method that combines multiple decision trees to reduce overfitting and improve the accuracy of the resulting data. The basic principles underlying the Random Forest algorithm are [21], [22]:

1) Creation of multiple decision trees;
2) Using random subsampling (Bootstrap aggregating - Bagging) [1];
3) Random selection of a subset of characteristics;
4) Majority voting or average prediction.

Random Forest is often used to analyze the importance of features (Feature Importance), which enables the selection of the most relevant criteria in the decision-making process [23], [24]. The algorithm assigns each feature a certain importance value based on how much it contributes to the accuracy of the prediction. This analysis is usually done using the following metrics [25], [26], [27], [28]:

1) Gini coefficient or Entropy - used to measure the impurity decrease in tree nodes when dividing data [1].

2) Permutation Importance of characteristics - measures how much the accuracy of the model decreases when the values of a certain characteristic are randomly permuted [29].

The above algorithm with the Feature Importance module is used in the orange data mining software (open-source software for machine learning and data visualization) [30]. In this research, Random Forest uses default preprocessing, as follows:

1) ʻʼremoves instances with unknown target values,
2) continues categorical variables (with one-hot-encoding),
3) removes empty columns
4) imputes missing values with mean valuesʼʼ [30].

In the context of choosing a smartphone, Random Forest can analyze customer rating data and identify the key criteria that have the greatest influence on the choice. This information can be very useful for applying MCDM methods to obtain optimal customer recommendations.

3.2 | Fuzzy DIBR II Method

The DIBR II method [31] represents an improved version of the DIBR method [32] that has found its application in numerous researches, both in its original form and modified [33], [34], [35], [36], [37]. This method is suitable for defining the weights of criteria when choosing a smartphone because it enables the precise determination of the importance of factors based on their mutual relationships, eliminating the subjective assessments present in traditional MCDM methods. It relies on a mathematical analysis of the relative importance of adjacent criteria, instead of a direct comparison of all factors, thus improving objectivity and reducing the cognitive load of the user. Its flexibility in working with uncertain data enables integration into a fuzzy environment. Due to these characteristics, the DIBR II method is suitable for the precise evaluation of key factors when choosing a smartphone. One of the modifications is the implementation of triangular fuzzy numbers in the DIBR II method, which is presented in [38]. The pseudocode of this method is presented in Figure 2, according to [39].

To determine the weights of criteria using this method, it is first necessary to identify the criteria, which is done using the Random Forest algorithm. Then, the significance of each criterion in relation to the neighboring criterion is determined. The number of comparisons is n-1 of the total number of criteria (n). After that, the weight of the most significant criterion is calculated, and then the others. Considering that the values of the criteria are obtained in the form of fuzzy numbers, they are de fuzzified and get crisp values. Finally, it is necessary to check the quality of the defined relationships. If the relationships are well defined, the obtained weight values are final. If the quality of the relationships is not satisfactory, it is necessary to redefine them. The detailed mathematical apparatus of the DIBR II method can be seen in [39].

```
# Method: Defining Interrelationships Between Ranked Criteria II

def defining_interrelationships_between_ranked_criteria_ii(criteria):

  # STEP 1: Identify criteria
  identified_criteria = identify_criteria(criteria)

  # STEP 2: Determine the importance of each criterion
  importance_fuzzy_values = determine_importance(identified_criteria)

  # STEP 3: Define relationships between criteria
  relationship_fuzzy_matrix = define_fuzzy_relationships(identified_criteria)

  # STEP 4: Find the most important criterion
  most_important_criterion = find_most_important(importance_values)

  # STEP 5: Calculate the weight of the most important criterion
  fuzzy_weight_most_important =
calculate_fuzzy_weight(most_important_criterion, relationship_fuzzy_matrix)

  # STEP 6: Calculate the weights of other criteria
  fuzzy_weight_other_criteria = calculate_weights(identified_criteria,
relationship_fuzzy_matrix, most_important_criterion)

  # STEP 7: Defuzzify the weight coefficients
  defuzzified_weights = defuzzify(fuzzy_weight_most_important,
fuzzy_weight_other_criteria)

  # STEP 8: Check the quality of the relationship
  relationship_quality = check_quality(defuzzified_weights)

  # If relationship quality is satisfactory
  if relationship_quality == "satisfactory":
    return "Relationships are good"
  else:
    return "Relationships are not good" # return to Step 2
```

Figure 2. Pseudocode of the Fuzzy DIBR II method

3.2 | Fuzzy WASPAS Method

The WASPAS method [40] is a widely used method for various MCDM problems [41], [42], [43]. The method has been improved so far by various theories and numbers that handle uncertainty and indeterminacy well [44], [45], [46]. The WASPAS method is suitable for smartphone selection because it combines the Weighted Sum Model (WSM) and the Weighted Product Model (WPM), enabling a more accurate ranking of alternatives with reduced oscillation of the results. This method offers better differentiation of phones based on key factors, reducing subjectivity in the evaluation. Unlike AHP or TOPSIS methods, WASPAS is more resistant to subjective evaluations, more efficient in analyzing large data sets and more flexible when working with uncertain data, especially in combination with fuzzy logic. Its ability to integrate criteria weights and relative relationships between alternatives makes it an ideal approach for optimizing smartphone choices. One of the modifications of this method is the implementation of triangular fuzzy numbers, presented in [47]. The method consists of six steps, according to [47], shown in Figure 3.

As with any other MCDM method, the first step in implementing the method is the formation of the initial decision matrix, in this case a Fuzzy matrix. For the purposes of evaluating alternatives by criteria, a fuzzy linguistic scale is formed. After that, the initial matrix is normalized in relation to the type of criterion (Benefit or Cost). The next step includes weighting the matrix using the weight coefficients of the criteria, while the next step is normalization. Then it is necessary to calculate the optimal and utility functions. Based on the value of the utility function, the alternatives are ranked (the highest value is the highest rank and vice versa). The detailed mathematical apparatus of the Fuzzy WASPAS method can be seen in the paper [47].

```
# Method: Fuzzy WASPAS

# STEP 1: Forming of fuzzy decision-making matrix
   fuzzy_decision_matrix = form_fuzzy_decision_matrix(decision_matrix)

# STEP 2: Normalize the initial values of all attributes
   normalized_matrix = normalize_matrix(fuzzy_decision_matrix)

# STEP 3a: Calculate the weighted normalized fuzzy decision matrix for WSM
   if type_of_aggregation == 'WSM':
      weighted_normalized_wsm =
calculate_weighted_normalized_matrix(normalized_matrix, weights)

# STEP 3b: Calculate the weighted normalized fuzzy decision matrix for WPM
   elif type_of_aggregation == 'WPM':
      weighted_normalized_wpm =
calculate_weighted_normalized_matrix(normalized_matrix, weights)

# STEP 4: Calculate fuzzy values of the optimality function and defuzzification
   fuzzy_optimality_values =
calculate_fuzzy_optimality(weighted_normalized_wsm if
type_of_aggregation == 'WSM' else weighted_normalized_wpm)
   defuzzified_values = defuzzify_fuzzy_values(fuzzy_optimality_values)

# STEP 5: Determine the integrated utility function
   utility_values = calculate_utility_function(defuzzified_values)

# STEP 6: Rank the preference order and choose the alternative with the maximal
utility function value
   ranked_alternatives = rank_alternatives(utility_values)
   optimal_alternative = choose_best_alternative(ranked_alternatives)

   return optimal_alternative
```

Figure 3. Pseudocode of the Fuzzy WASPAS method

4 | RESULTS

In the continuation of the text, the application of the proposed model is presented. Also, its validation was carried out.

4.1 | Identification of criteria and determination of their weights

Following the algorithm in Figure 1, it is first necessary to identify the key criteria. For the purposes of this research and demonstration of the application of the proposed model, the Amazon product phones (A Comprehensive Overview of Amazon's Mobile Phone Offerings) dataset from the Kaggle website was used [48], which contains a total of 4499 entries (different users who reviewed smartphones) for 35 different smartphone features. In the Orange software, the model presented in Figure 4 was formed.

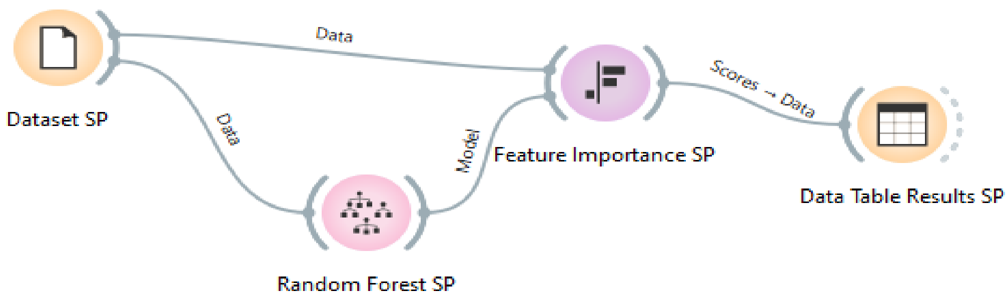

Figure 4. Model for identifying key criteria using the Random Forest algorithm

By applying the above model to the above dataset, where the target value was set to the category "Ratings", and the parameters were set to 10 trees and 8 permutations, the following 10 key criteria were obtained (Table 1):

Table 1. Key identified criteria

Criteria	Description [34]	Type of the criteria
C1 - Battery power	The power rating of the battery	Benefit
C2 - RAM	The amount of RAM in the phone	Benefit
C3 - CPU speed	The speed of the phone's CPU (in GHz)	Benefit
C4 - Screen size	Size of the display (in inches)	Benefit
C5 - Brand	The brand name of the phone	Benefit
C6 - ROM	Internal storage capacity of the phone	Benefit
C7 - OS	The operating system of the phone (e.g., Android, iOS and their versions)	Benefit
C8 - Processor	Processor model	Benefit
C9 - Charging time	Time taken to charge the phone fully	Cost
C10 - Price	The current price with USD of the phone	Cost

Criteria C5, C7 and C8 are qualitative, while the rest are quantitative. Potential weaknesses or limitations of the algorithm may appear here, such as the risk of overfitting in the Random Forest or the computational complexity of the approach when applied to larger datasets.

For the purposes of this research, a five-point fuzzy linguistic scale was used (Table 2), which is a tool that enables the conversion of qualitative, verbal ratings into quantitative values, thereby supporting decision-making under conditions of uncertainty and subjectivity. Each of these linguistic ratings is represented by a triangular fuzzy number, which allows for a more flexible and realistic analysis within MCDM methods. This approach allows participants in the decision-making process to express their opinions in an intuitive way, without the need for strictly defined numbers, while fuzzy logic allows for a more precise and objective analysis of different alternatives.

Table 2. Fuzzy linguistic scale

Linguistic descriptor	**Fuzzy value**
Absolutely satisfying (AS)	(5,5,5)
Satisfies (S)	(3,4,5)
Partially satisfying (PS)	(1,2,3)
It does not satisfy (NS)	(1,1,1)

The criteria from Table 1 are ranked by importance, from the most important (C1) to the least important (C10). For the purposes of this research, 12 potential buyers (B) were hired who evaluated the relationship between the defined criteria, in accordance with the principles of the DIBR II method. Figure 5 shows the relationships between criteria defined by potential buyers.

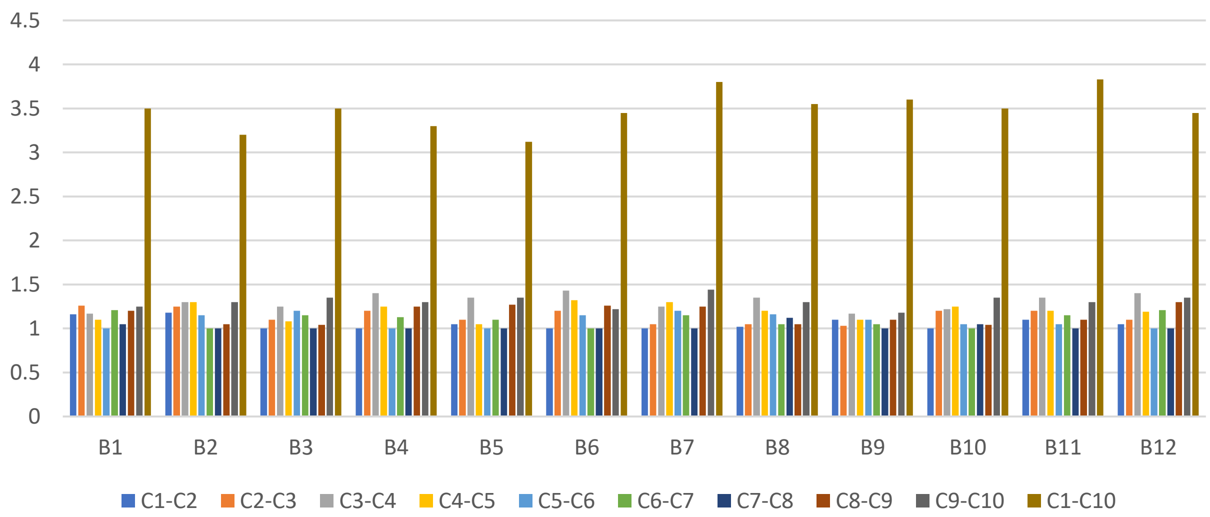

Figure 5. Defined relationships between criteria by potential customers

To form triangular fuzzy numbers of the relationship between the criteria and their implementation in the DIBR II method, the minimum value was taken for the left distribution, the maximum value for the right distribution, while for the value where the membership function of the triangular fuzzy number has the value 1, the average value assigned by potential customers was taken, for each of the observed relationships. In Table 3, the fuzzy values of the relationship between the criteria are given.

Table 3. Fuzzy values of the relationship between the criteria

Observed relationship between criteria	Fuzzy value of relationship
C1-C2	(1,1.055,1.16)
C2-C3	(1.03,1.145,1.26)
C3-C4	(1.17,1.303,1.43)
C4-C5	(1.08,1.195,1.32)
C5-C6	(1,1.088,1.1)
C6-C7	(1,1.1,1.21)
C7-C8	(1,1.018,1.12)
C8-C9	(1.04,1.159,1.27)
C9-C10	(1.18,1.308,1.44)
C1-C10	(3.13,3.483,3.83)

By implementing the defined fuzzy relationships between the criteria in the Fuzzy DIBR II method, the algorithm of the method is applied, and the final weight values are obtained. Figure 6 shows the final values of the weight coefficients of the criteria.

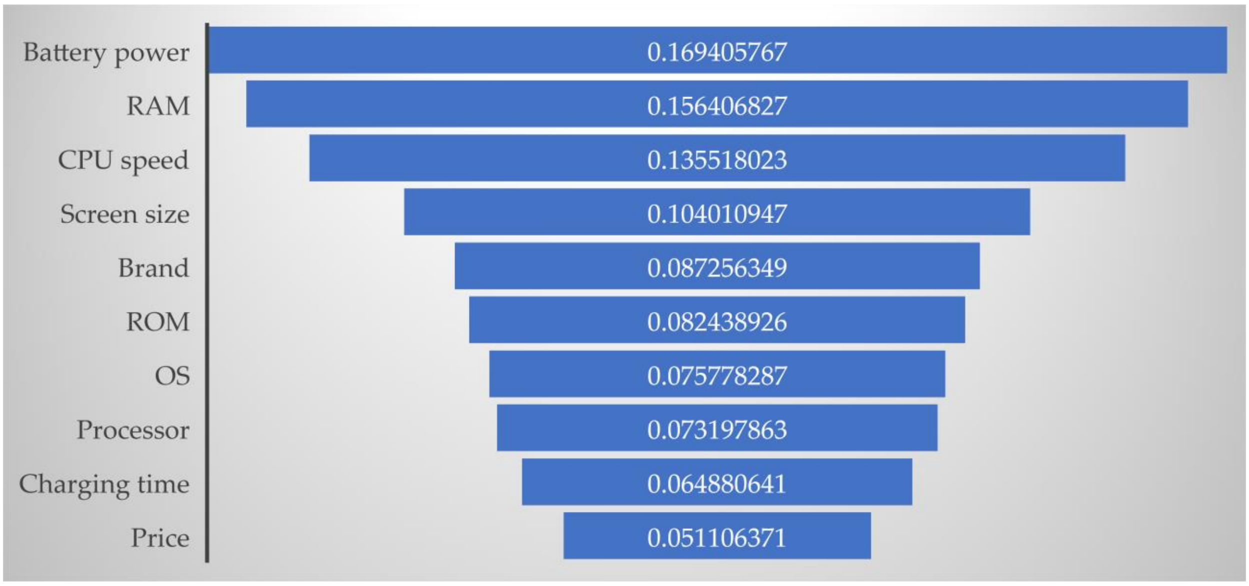

Figure 6. The final values of the criteria weights

4.2 | Selection of the Optimal Alternative

After obtaining the weight coefficients of the criteria, their values implementation in the Fuzzy WASPAS method is approached and the value of the alternatives is defined according to each of the criteria. To present the proposed model, ten existing alternatives (smarthphone) will be selected with their specifications (Table 4). Evaluations of alternatives according to quantitative criteria were entered in quantitative form, while qualitative ones were entered using linguistic scale (Table 2).

Table 4. Alternative Specifications - Initial Decision Matrix

		Criteria									
		C1 Battery power (mAh)	C2 RAM (GB)	C3 CPU speed (GHz)	C4 Screen size (inches)	C5 Brand	C6 ROM (GB)	C7 OS	C8 Processor	C9 Charging time (min)	C10 Price ($)
Alternative	A1	6000	16	3.2	6.7	S	512	AS	AS	82.5	888
	A2	5000	12	3.2	6.8	AS	512	PS	PS	59	783
	A3	4400	12	3	6.2	AS	1000	S	S	80	1499
	A4	5000	12	3	6.5	AS	512	S	AS	102	1598
	A5	5000	12	2.6	6.8	AS	512	AS	S	59	1125
	A6	4500	8	2.84	6.1	AS	128	PS	AS	30	798
	A7	4000	6	2.36	6	S	256	PS	PS	20	749
	A8	5000	12	2.85	7.6	PS	256	PS	PS	92	746
	A9	4700	12	3	6.7	PS	256	AS	S	55	728
	A10	6000	16	3.2	6.78	S	512	S	PS	42	699

After analyzing the data from Table 4 and fuzzifying the values from the table, the initial decision matrix is obtained (Table 5). As can be seen from the following table, the triangular fuzzy numbers for quantitative criteria were formed in such a way that all fuzzy number distributions have the same value, while the values for qualitative criteria were formed based on the linguistic scale (Table 2).

Table 5. Initial Fuzzy Decision Matrix

		Criteria									
		C1 Battery power (mAh)	C2 RAM (GB)	C3 CPU speed (GHz)	C4 Screen size (inches)	C5 Brand	C6 ROM (GB)	C7 OS	C8 Processor	C9 Charging time (min)	C10 Price ($)
Alternative	A1	(6000,6000,6000)	(16,16,16)	(3.2,3.2,3.2)	(6.7,6.7,6.7)	(3,4,5)	(512,512,512)	(5,5,5)	(5,5,5)	(82.5,82.5,82.5)	(888,888,888)
	A2	(5000,5000,5000)	(12,12,12)	(3.2,3.2,3.2)	(6.8,6.8,6.8)	(5,5,5)	(512,512,512)	(1,2,3)	(1,2,3)	(59,59,59)	(783,783,783)
	A3	(4400,4400,4400)	(12,12,12)	(3,3,3)	(6.2,6.2,6.2)	(5,5,5)	(1000,1000,1000)	(3,4,5)	(3,4,5)	(80,80,80)	(1499,1499,1499)
	A4	(5000,5000,5000)	(12,12,12)	(3,3,3)	(6.5,6.5,6.5)	(5,5,5)	(512,512,512)	(3,4,5)	(5,5,5)	(102,102,102)	(1598,1598,1598)
	A5	(5000,5000,5000)	(12,12,12)	(2.6,2.6,2.6)	(6.8,6.8,6.8)	(5,5,5)	(512,512,512)	(5,5,5)	(3,4,5)	(59,59,59)	(1125,1125,1125)
	A6	(4500,4500,4500)	(8,8,8)	(2.84,2.84,2.84)	(6.1,6.1,6.1)	(5,5,5)	(128,128,128)	(1,2,3)	(5,5,5)	(30,30,30)	(798,798,798)
	A7	(4000,4000,4000)	(6,6,6)	(2.36,2.36,2.36)	(6,6,6)	(3,4,5)	(256,256,256)	(1,2,3)	(1,2,3)	(20,20,20)	(749,749,749)

	A8	(5000,5000,5000)	(12,12,12)	(2.85,2.85,2.85)	(7.6,7.6,7.6)	(1,2,3)	(256,256,256)	(1,2,3)	(1,2,3)	(92,92,92)	(746,746,746)
	A9	(4700,4700,4700)	(12,12,12)	(3,3,3)	(6.7,6.7,6.7)	(1,2,3)	(256,256,256)	(5,5,5)	(3,4,5)	(55,55,55)	(728,728,728)
	A10	(6000,6000,6000)	(16,16,16)	(3.2,3.2,3.2)	(6.78,6.78,6.78)	(3,4,5)	(512,512,512)	(3,4,5)	(1,2,3)	(42,42,42)	(699,699,699)

Further application of the steps of the Fuzzy WASPAS method leads to the following rank of alternatives, shown in Figure 7.

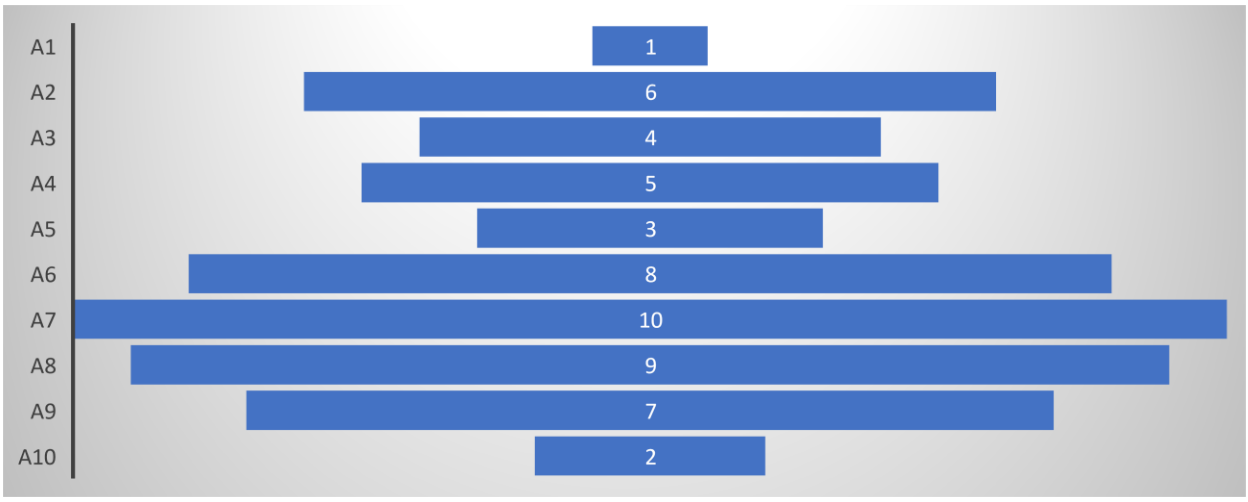

Figure 7. Alternative ranking

The applicability of the model is reflected in the criteria derived from user (customer) reviews, while the accuracy of the model's results will be confirmed through Comparative Analysis.

4.3 | Sensitivity Analysis

To check the consistency of the output results, a sensitivity analysis was performed on changes in the weight coefficients of the criteria [49], [50]. For this purpose, 15 different weight change scenarios were formed (Figure 8).

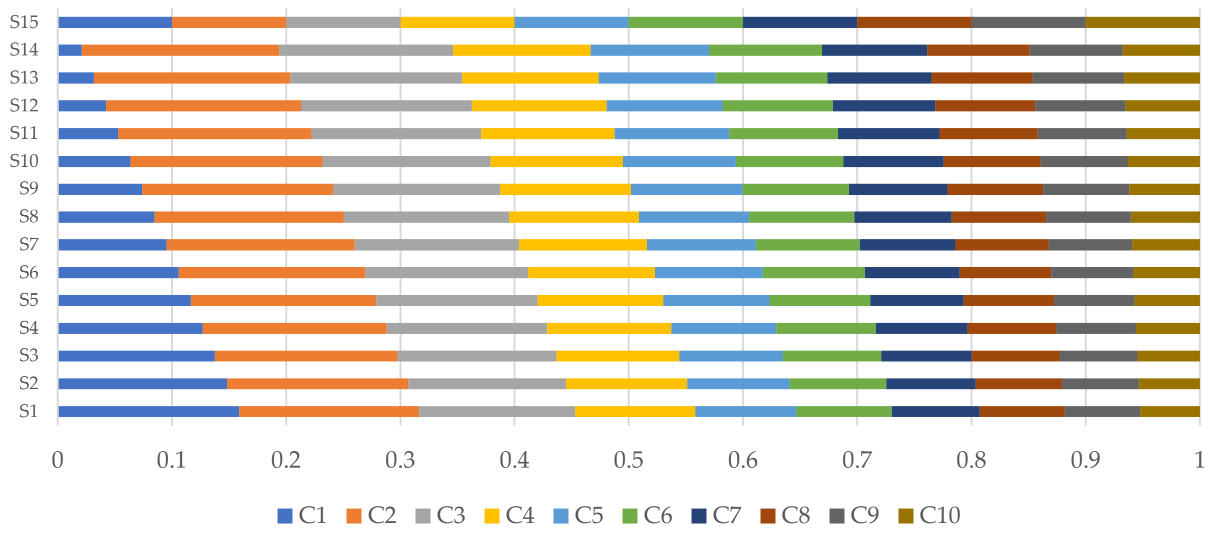

Figure 8. Scenarios of changing criteria weights

By applying the mentioned scenarios in the Fuzzy WASPAS method, the ranks of the alternatives are reached, shown in Figure 9.

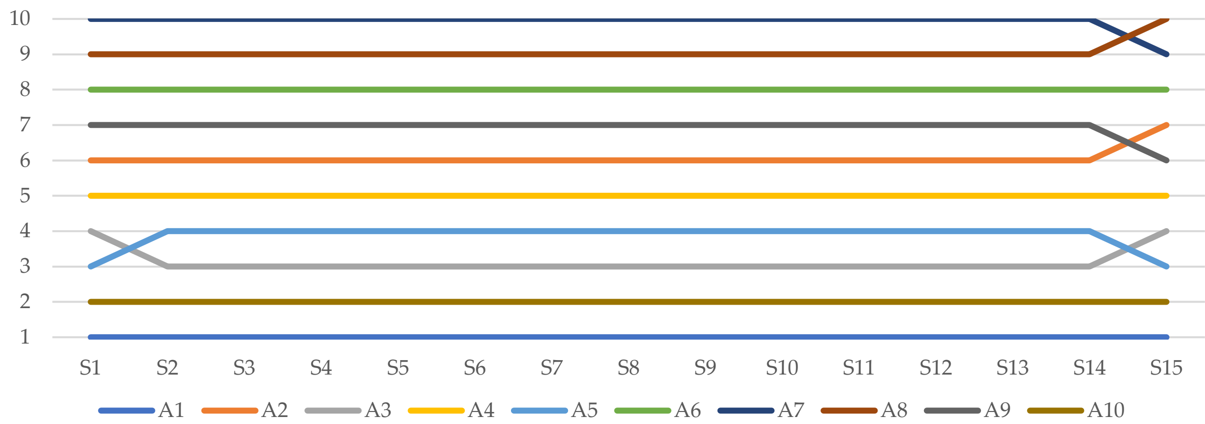

Figure 9. The rankings of alternatives obtained by applying different scenarios

4.4 | Comparative analysis

Comparative analysis is performed to ensure the accuracy, reliability and consistency of the decisions made [51], [52], [53]. Different MCDM methods often give different results, so their comparison is crucial to check the consistency of the ranking of alternatives and identify deviations [54]. This analysis enables the validation of the best alternatives, which is achieved by comparing the results - if a certain alternative consistently appears as the best in several methods, it is considered a reliable choice [55]. Comparative analysis contributes to making more robust decisions, because it allows combining the results of different methods to obtain a balanced and precise choice and provides a deeper understanding of mutual relationships and a more precise decision on the optimal alternative [56]. In this research, the results of the Fuzzy WASPAS method were compared with the results of the methods Fuzzy CoCoSo [57], Fuzzy SAW [58], Fuzzy COPRAS [59] and Fuzzy LMAW [60]. The results of the comparative analysis are shown in Figure 10.

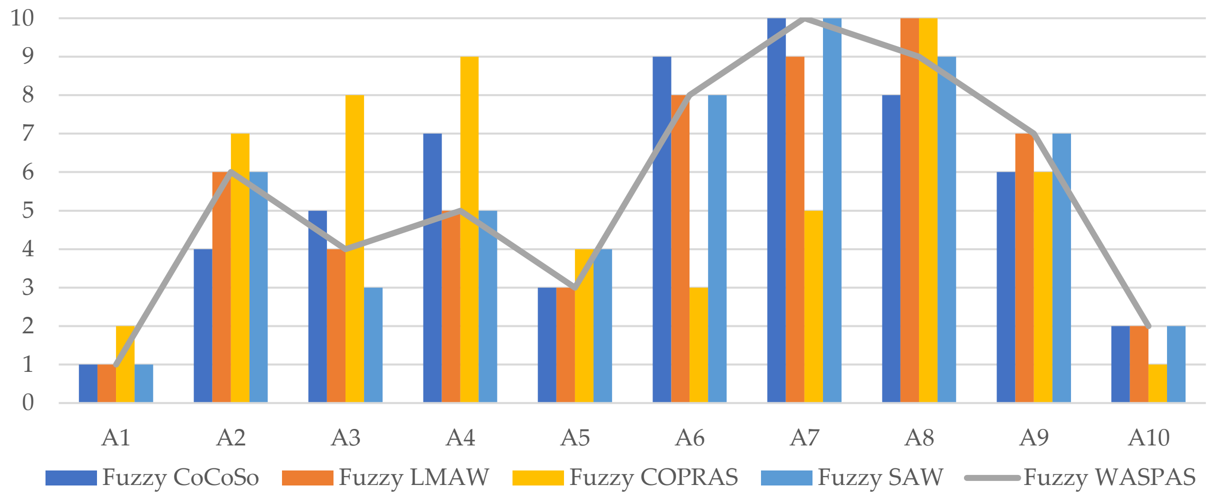

Figure 10. The results of the comparative analysis

5 | DISCUSSION

Based on the defined research algorithm, first the criteria that determine the choice of a smartphone based on user reviews were identified using the Random Forest algorithm. Then the weight coefficients of the identified criteria were determined using the Fuzzy DIBR II method. By implementing the obtained weights of the criteria and evaluating the alternatives for each criterion in the Fuzzy WASPAS method, the optimal alternative was determined. The best ranking alternatives according to the Fuzzy WASPAS method are A1 and A10, because they have the lowest values and are consistently ranked as optimal according to the other methods. These alternatives represent the most favorable choice because their values are stable and confirmed in all the methods analyzed. On the other hand, the worst rated alternatives are A6 and A7, which have the highest values according to the Fuzzy WASPAS method, and their poor ranking is also confirmed by other methods. This indicates that these alternatives are not suitable for selection, as they are consistently identified as unfavorable. When it comes to the remaining alternatives, A2, A3, A4, A5, A8 and A9 fall into the middle-ranked category. They show variations in ranking depending on the method used – some methods rate them as better, while others rank them closer to lower ranked options. The A5 stands out as slightly better than the other average alternatives, while the A8 and A9 are ranked slightly worse.

After that, a sensitivity analysis of the output results was performed based on the created 15 weight change scenarios. As can be seen from the Figure 10, the change in the ranking of the third ranked and fourth ranked alternatives occurred in scenario S1, while in scenario S15, where all criteria are of equal importance, there is a change in the listed alternatives, as well as in the sixth and seventh ranked alternatives and the last and penultimate ranked ones. In all cases, the first ranked remains as the optimal alternative. It can be concluded that minor changes in the weights of the criteria do not significantly affect the final ranking of the alternatives and especially do not affect the first and second ranked alternatives.

In order to validate the proposed methodology, a comparative analysis was performed, i.e., a comparison of the obtained results with the results of other methods (Fuzzy CoCoSo, Fuzzy SAW, Fuzzy COPRAS and Fuzzy LMAW). As can be seen from the Figure 10, and according to the Fuzzy WASPAS method, the alternatives A1 and A10 are the best-ranked smarthphones because they have the highest values on the green line. Conversely, the A6 and A7 have the lowest values, making them a poorer choice. Other alternatives (A2, A3, A4, A5, A8, A9) show a significant variation, which means that their position depends on the applied method and the specific weight of the criteria.

A more detailed analysis of the results of the comparative analysis indicates the following:

A1 and A10 - Fuzzy WASPAS ranks them as the best alternatives, which is consistent with the results of Fuzzy CoCoSo, Fuzzy SAW and Fuzzy COPRAS, with CoCoSo showing almost identical values. Fuzzy COPRAS shows larger oscillations, but A1 and A10 remain among the leading options in all methods.

A2, A4, A5, A8, A9 – These alternatives show moderate variation. Fuzzy WASPAS gives them more stable values compared to Fuzzy COPRAS, which for some alternatives, like A3, shows larger deviations. Fuzzy SAW keeps them within moderate limits, while Fuzzy LMAW has slightly lower values for A5 and A8.

A3 - In Fuzzy WASPAS, the alternative value is relatively balanced, while Fuzzy COPRAS shows a significantly larger jump, indicating the sensitivity of this method to the way data is aggregated.

A6 and A7 - Consistently rank as the worst alternatives across all methods, with Fuzzy WASPAS showing lower values in line with the trends of Fuzzy CoCoSo, SAW and COPRAS.

Finally, Fuzzy WASPAS provides stable results compared to other methods, with the best and worst alternatives consistently ranked across all methods. The largest oscillations occur with Fuzzy COPRAS, while Fuzzy SAW and CoCoSo provide more balanced values.

Variations in the results of MCDM methods arise from different algorithms and approaches to ranking alternatives, approaches of normalizing data, weighting criteria and applying fuzzy logic [61], [62]. Methods like Fuzzy WASPAS and Fuzzy CoCoSo use different techniques for data processing, with WASPAS combining additive and multiplicative approaches, while CoCoSo applies compromise solution. These differences affect the ranking, because the results are formed based on different mathematical models. Fuzzy SAW and Fuzzy COPRAS, although they show certain similarities, still have oscillations due to the way they handle criteria and alternative values. Fuzzy SAW provides more stable results with less variation, while Fuzzy COPRAS can generate more deviation in ranking, because certain alternatives are affected by a specific weighting structure. Fuzzy LMAW shows consistency with methods like SAW and COPRAS, but with smaller deviations. The application of fuzzy logic additionally introduces uncertainty when evaluating alternatives, which can cause fluctuations in the ranking.

6 | CONCLUSION

In this paper, a methodology for selecting the optimal smartphone was developed, which combines machine learning algorithms and MCDM methods. The selection process was started using the Random Forest algorithm, which identified the most important criteria when choosing a smartphone. Based on the results obtained and the engagement of potential customers, the weight coefficients of the criteria were determined using the Fuzzy DIBR II method, while the Fuzzy WASPAS method was used for the final selection of the optimal alternative. The application of the above methods enabled the definition of the relationship between the criteria and the priorities between the alternatives, while considering the uncertainty in the decision-making process.

To check the consistency and validity of the obtained results, sensitivity analysis and comparative analysis were performed. Sensitivity analysis showed the impact of changes in weight coefficients on the final choice, while comparative analysis confirmed that the proposed methodology provides reliable and stable results. The research results showed that the integration of machine learning and multi-criteria decision-making can significantly improve and enable a faster process of selecting smartphones, where imprecision and uncertainty in the input data are considered.

The proposed methodology can be used not only in smartphone selection, but also in other decision-making problems where it is necessary to consider multiple criteria. Future research could focus on expanding the set of criteria to include additional technical specifications, user experience factors, and novel smartphone features that influence decision-making. Furthermore, the application of other machine learning algorithms, such as deep learning models or ensemble techniques, could improve the accuracy of criterion selection and better capture complex relationships between attributes. In addition, the model could be further refined by integrating alternative or more advanced MCDM methods, such as hybrid approaches that combine Rayleigh-ite theories that handle uncertainty, discontinuity, and indeterminacy well (such as Rough, Gray, and other fuzzy numbers) and optimization techniques, to improve the stability and reliability of the rankings and deal with uncertainty more effectively. These improvements could lead to a more adaptable and comprehensive methodology, which would benefit not only smartphone selection but also broader applications in technology evaluation and consumer decision support systems. Also, future research may include the validation of the model using real-world data. Potential weaknesses or limitations of the algorithm may appear here, such as the risk of overfitting in the Random Forest or the computational complexity of the approach when applied to larger datasets. This paper provides significant practical implications for the smartphone industry, commerce and consumer decision-making, enabling a more accurate, faster and more personalized selection process through a combination of machine learning (Random Forest) and MCDM methods (Fuzzy DIBR II, Fuzzy WASPAS). By identifying key criteria and optimizing weighting coefficients, the methodology helps buyers make informed decisions, while manufacturers and sellers can better understand market needs and adapt their strategies. In addition, the approach can improve recommended systems in e-commerce, enable targeted advertising and support innovation in product design. Validation through sensitive and comparative analysis confirms the reliability of the results, while the concept can be extended to other areas, such as the automotive industry, health and construction, providing an efficient way of making decisions in conditions of uncertainty.

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