



# Decision Support System for Mobile Phone Selection Utilizing Fuzzy Hypersoft Sets and Machine Learning



Muhammad Tahir Hamid<sup>1\*</sup>, Muhammad Abid<sup>2</sup>

<sup>1</sup> Department of Mathematics, Garrison Post Graduate College for Men, Lahore Cantt, 54000 Lahore, Pakistan

<sup>2</sup> Department of Mathematics, North Carolina State University, 27695 NC Raleigh, USA

\* Correspondence: Muhammad Tahir Hamid ([tahirhameedch1@gmail.com](mailto:tahirhameedch1@gmail.com))

**Received:** 02-03-2024

**Revised:** 03-10-2024

**Accepted:** 03-26-2024

**Citation:** M. T. Hamid, and M. Abid, "Decision support system for mobile phone selection utilizing fuzzy hypersoft sets and machine learning," *J. Intell Manag. Decis.*, vol. 3, no. 2, pp. 104–115, 2024. <https://doi.org/10.56578/jimd030204>.



© 2024 by the author(s). Published by Acadlore Publishing Services Limited, Hong Kong. This article is available for free download and can be reused and cited, provided that the original published version is credited, under the CC BY 4.0 license.

**Abstract:** In the dynamic landscape of mobile technology, where a myriad of options burgeons, compounded by fluctuating features, diverse price points, and a plethora of specifications, the task of selecting the optimum mobile phone becomes formidable for consumers. This complexity is further exacerbated by the intrinsic ambiguity and uncertainty characterizing consumer preferences. Addressed herein is the deployment of fuzzy hypersoft sets (FHSS) in conjunction with machine learning techniques to forge a decision support system (DSS) that refines the mobile phone selection process. The proposed framework harnesses the synergy between FHSS and machine learning to navigate the multifaceted nature of consumer choices and the attributes of the available alternatives, thereby offering a structured approach aimed at maximizing consumer satisfaction while accommodating various determinants. The integration of FHSS is pivotal in managing the inherent ambiguity and uncertainty of consumer preferences, providing a comprehensive decision-making apparatus amidst a plethora of choices. The elucidation of this study encompasses an easy-to-navigate framework, buttressed by sophisticated Python codes and algorithms, to ameliorate the selection process. This methodology engenders a personalized and engaging avenue for mobile phone selection in an ever-evolving technological epoch. The fidelity to professional terminologies and their consistent application throughout this discourse, as well as in subsequent sections of the study, underscores the meticulous approach adopted to ensure clarity and precision. This study contributes to the extant literature by offering a novel framework that melds the principles of fuzzy set (FS) theory with advanced computational techniques, thereby facilitating a nuanced decision-making process in the realm of mobile phone selection.

**Keywords:** Fuzzy set (FS) theory; Decision-making; Ambiguity; Uncertainty; Fuzzy hypersoft set (FHSS); Mobile phone selection

## 1 Introduction

The purpose of this study is to examine the complexities involved in choosing a mobile phone, with a focus on the need for strong decision-support systems. Through an analysis of extant literature on decision-making models across multiple domains and an exploration of parallels with consumer difficulties in the mobile technology space, this study seeks to provide insights that improve consumer decision-making. The sections that follow will examine pertinent research, evaluate decision-support tools, and suggest methods for enhancing decision-making when choosing a mobile phone. Adopting new technology, like a cell phone, is a complex process that is impacted by several variables. A framework for comprehending the phases of technological adoption is provided by Rogers' Diffusion of Innovations hypothesis [1], which highlights the roles of innovators, early adopters, and the majority. When choosing a mobile phone model, consumers are heavily influenced by their impressions of innovative features, including trialability, observability, compatibility, relative advantage, and complexity [2]. The difficulty of choosing a mobile phone is influenced by several things. Kim and Forsythe [3]'s research emphasizes how important perceived value, design aesthetics, and brand loyalty are in swaying consumer decisions. Critical considerations also include pricing dynamics, performance criteria, and functionality [4]. A thorough decision-making process is needed to weigh these factors against personal preferences and financial limitations. To help consumers make educated selections, DSS has become more important resources. DSS incorporates cutting-edge technology like artificial

intelligence, machine learning, and data analytics in the context of choosing a mobile phone to offer customized suggestions based on customer preferences and past data [5]. Through the reduction of information overload and the provision of choices that are in line with user demands, these systems seek to improve the decision-making process. There are significant parallels when comparing decision-making in agriculture, where risk management techniques and optimization models play a critical role. To help farmers make the best choices possible when it comes to planting patterns and resource allocation, for example, optimization models have been presented [6]. These models consider factors like climate unpredictability. The idea of risk management, which is investigated in agriculture through crop diversification [7], is reflected in the range of choices customers consider when choosing a cell phone to reduce hazards [8]. Consumer decisions in the mobile technology space are influenced by factors such as ethical material sourcing, the impact of production on the environment, and electronic waste [9]. These factors represent an increasing interest in the adoption of sustainable technologies [10, 11].

Zadeh [12] proposed the FS theory and the idea of membership in 1965. Every item we use today for the convenience of our lives or the comfort we experience is founded on this principle, which is currently in vogue. According to this theory, the numbers we give membership to can be divided into four categories: single-valued fuzzy numbers, multiple-valued fuzzy numbers, bipolar fuzzy numbers, interval-valued fuzzy numbers, and rough sets. All of this leads to the suggestion of new set structures such as single-valued fuzzy set (SVFS), multiple-valued fuzzy set (MVFS), bi-polar fuzzy set (BPS), interval-valued fuzzy set (IVFS) by Turksen (Turksen IVFS), m-polar interval-valued fuzzy set (m-PIVFS), and fuzzy rough set (FRS) [13–18]. Since falsehood values must be taken into account for greater accuracy, Atanassov and Stoeva [19] expanded the FS idea in 1986 to include intuitionistic fuzzy sets (IFS), which have membership and non-membership values. Ejegwa [20] and Zhang and Xu [21] provided the Pythagorean fuzzy set (PFS) generalization of IFS and suggested its operational rules and decision-making methods to address Multiple Criteria Decision Making (MCDM) issues. A new theory was urgently needed to address inconsistencies. To deal with uncertain and inconsistent environments, Smarandache [22] developed a new idea in 1998. The mapping from attributes to the power set of the universal set is known as the "soft set," and it was inapplicable in situations where the bifurcation of the attributes was more pronounced [23–25]. Hypersoft set (HSS) is a new set structure that Smarandache [26] proposed in 2018. In essence, this set is the mapping from the product of attributes (which are further divided) to the power set of the universal set and the desire set of attributes. The concepts of FHSS, intuitionistic hypersoft set (IHSS), and neutrosophic hypersoft set (NHSS) were also put forth in the study of Maji et al. [27] to address truthiness, uncertainty, and indeterminacy. The definition of FHSS [26], aggregate operators, similarity measures, and distance measures were proposed by Jafar and Saeed [28], along with matrix notations, and using these definitions, the applications of the algorithms with case studies have been presented by Yolcu and Ozturk [29]. There are several HSS versions, each with unique decision-making processes. The definition of NHSS [30], the distance and similarity measures of NHSS, and its MCDM techniques along with their applications in decision-making problems [31–33]. The similarity measures based on NHSS along with the machine learning approach have been proposed by Saqlain et al. [34]. The concept has been further extended to fuzzy, fairly aggregate operators along with material selection applications by Saqlain et al. [35]. The concepts of linguistic hypersoft sets and fuzzy linguistic hypersoft sets were proposed by Saqlain et al. [36]. This review of the literature integrates findings from several research disciplines to offer a thorough overview of decision-making [37–40] in the selection of a mobile phone. A comprehensive viewpoint can be obtained by comprehending consumer behavior, ideas surrounding technology adoption, the function of DSS, and similarities to agricultural decision-making [41–43]. Future studies can examine the changing dynamics of mobile phone selection and the influence of developing technologies on decision-making processes as technology develops [42–45].

The research methodology combines the theoretical framework of FHSS with machine learning capabilities to develop a robust DSS for mobile phone selection. The process can be outlined as follows:

### 1.1 Data Preprocessing

- Collect data on various mobile phone alternatives and relevant selection criteria (e.g., performance, camera quality, battery life, storage capacity, price, user reviews, and brand reputation).
- Pre-process the data by handling missing values, encoding categorical variables, and normalizing numerical features.

### 1.2 FHSS Construction

- Define the universal set of mobile phone alternatives and the set of relevant selection criteria.
- Construct the FHS by mapping the product of criteria subsets to the power set of the universal set, representing the relationship between mobile phone alternatives and selection criteria.

It is crucial to note that the specific implementation details, such as the choice of programming language, libraries, and tools, should be provided in the methodology section. Additionally, any assumptions, limitations, or potential challenges associated with the proposed approach should be acknowledged and discussed.

### 1.3 Objective

- The goal of this research is to present a thorough model that effectively tackles relevant issues related to mobile selection. The Multi-Objective Optimization by Ratio Analysis (MULTIMOORA) decision-making strategy is used in this research as an effective way to streamline complex decision-making processes related to mobile phone selection.

- By investigating the uses of current approaches in successfully navigating the inherent uncertainties in mobile technology, it accomplishes noteworthy advancements in the field of decision-making. The MULTIMOORA model offers a novel and inventive approach to the context-dependent and abstract problems that arise throughout the mobile phone selection process.

- This study has broad implications for applications in natural language processing, sentiment analysis, and artificial intelligence, among other disciplines that depend on uncertainty-based decision-making.

This work's organization goes as follows: In Section 2, the fundamental concepts of the FHSS are thoroughly examined within the framework of choosing a cell phone. The MULTIMOORA approach is introduced in Section 3 with concise definitions, essential concepts, and examples that are relevant to the current state of mobile technology. A thorough framework for MCDM is presented in Section 4, with a focus on the uncertainty that customers encounter when choosing a mobile phone. Section 4 highlights the findings and highlights the advantages of the suggested algorithm through a thorough case study, emphasizing the algorithm's importance in the mobile choosing process. The paper is finally concluded in Section 5, which offers suggestions for future research directions aimed at improving decision-making in the rapidly changing field of mobile technology.

## 2 Preliminary Section

In this section, we go through some basic definitions that support the construction of the framework of this paper: HSS, FHSS, and decision-making approaches.

### Definition 2.1: HSS [27]

Assuming that the universal and power sets of universal set are given as  $\mu$  and  $P(\mu)$ . Considering  $(i^1, i^2, i^3, \dots, i^n)$  when  $n \geq 1$ , and supposing  $n$  be a well-defined attributive, whose corresponded attributive elements are sequentially, the set  $(\mathcal{F}^1, \mathcal{F}^2, \mathcal{F}^3, \dots, \mathcal{F}^n)$  with  $\mathcal{F}^i \cap \mathcal{F}^j = \emptyset$ , where  $i \neq j$  and  $i, j \in \{1, 2, 3 \dots n\}$ , then  $(\xi, \mathcal{F})$  is called a HSS:

$$\xi : (\mathcal{F} = \mathcal{F}^1 \times \mathcal{F}^2 \times \mathcal{F}^3 \times \dots \times \mathcal{F}^n) \rightarrow P(\mu) \quad (1)$$

### Definition 2.2: FHSS [26–28]

In Eq. (1), if we assign the values to each attribute in the form of truthiness  $\langle T \rangle$ , where  $\xi : T \rightarrow [0, 1]$ . Then there are each pair then  $(\xi, \mathcal{F})$  is called a FHSS.

### Definition 2.3: Decision-making methods/MCDM [38]

Methods for making decisions based on many criteria or objectives, such as MCDM, are useful tools for assessing and contrasting alternatives. By assisting decision-makers in considering a variety of variables and preferences, these tools provide a more thorough study of complicated decisions. The Analytic Hierarchy Process (AHP), TOPSIS, VIKOR, WSA, WPA, MULTIMOORA, and PROMETHEE are common MCDM methodologies for ranking based on resemblance to ideal solutions, and outranking analysis, respectively. MCDM techniques support well-informed and impartial decision-making across a range of areas by combining many viewpoints and managing uncertainty.

## 3 MCDM Algorithm (MULTIMOORA)

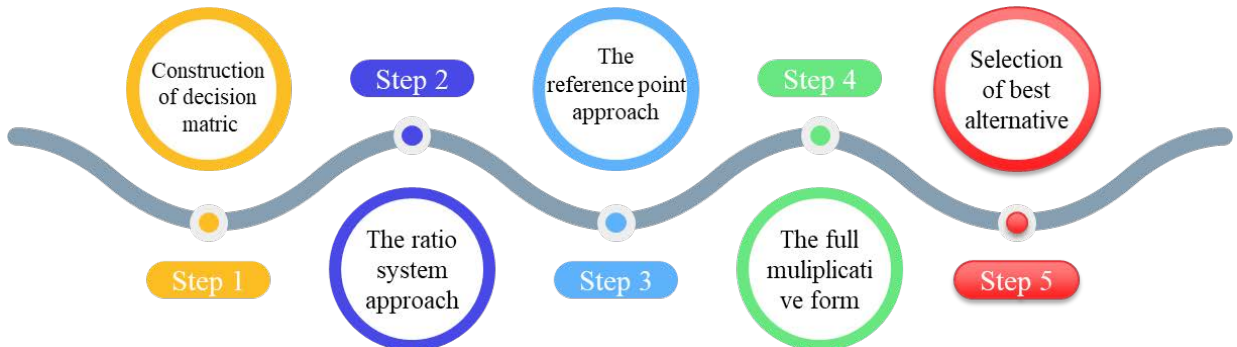


Figure 1. MCDM algorithm (MULTIMOORA)

Brauers and Zavadskas [37] established the MOORA technique. The full multiplicative form (FMF) was subsequently introduced in 2010 by Brauers and Zavadskas [37], who improved this strategy and created the MULTIMOORA technique. Three crucial steps make up the more reliable and effective MULTIMOORA method: the FMF, the reference point approach (RPA), and the ratio system approach (RSA). These steps are used to assess and prioritize the options under consideration. The theory of dominance, which finds the option with the highest overall ranking throughout all three stages, is used to make the final decision. Graphs illustrating the algorithm are shown in Figure 1.

**Step 1:** First, construct a decision matrix.

**Step 2:** The RSA approach. In this approach, the general standing of the alternative  $A_i$  can be measured as follows:

$$A_i = A_i^+ - A_i^-$$

where,

$$A_i^+ = \sum_{j \in \Omega_{\max}} \omega_j r_{ij}$$

$$A_i^- = \sum_{j \in \Omega_{\min}} \omega_j r_{ij}$$

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}$$

where,  $A_i$  stands for  $i$ th position of the alternative on the basis of all criteria;  $A_i^+$  and  $A_i^-$  denote the positions of the  $i$ th alternative according to benefit and cost criteria respectively;  $r_{ij}$  represents the normalized  $i$ th alternative under the  $j$ th criteria;  $x_{ij}$  denotes the  $i$ th alternative related to the  $j$ th criterion; the sets of benefit criteria are denoted by  $\max$ , and  $\min$  denotes the cost criteria where  $i = 1, 2, 3, \dots, m$  and  $j = 1, 2, 3, \dots, n$ . The associated alternatives are positioned depending on  $A_i$  in descending order so the alternative having the largest value of  $A_i$  is the best in this approach.

**Step 3:** The RPA approach.

Using this approach best alternative selection could be done as below:

$$B_i^{\max} = \max_j (\omega_j |r_j^* - r_{ij}|)$$

where,  $B_i^{\max}$  denotes the extreme distance of the alternative  $A_i$  with respect to the reference point and  $r_j^*$  represents the coordinate  $j$  of the reference point as follows:

$$r_j^* = \begin{cases} \max_i r_{ij}, & j \in \Omega_{\max} \\ \min_i r_{ij}, & j \in \Omega_{\min} \end{cases}$$

The final ranking in this approach is done by using the ascending order of  $B_i^{\max}$  and accordingly, the lowest  $B_i^{\max}$  value is the best one.

**Step 4:** FMF approach.

For this form, the total efficacy of the alternative could be obtained as follows:

$$C_i = \frac{\alpha_i}{\beta_i}$$

where,

$$\alpha_i = \prod_{j \in \Omega_{\max}} \omega_j r_{ij}$$

$$\beta_i = \prod_{j \in \Omega_{\min}} \omega_j r_{ij}$$

where,  $C_i$  means the overall efficacy of the  $i$ th alternative,  $\alpha_i$  and  $\beta_i$  indicate the product of the weighted performance ratings of the benefit and cost criteria of the  $i$ th alternative respectively. Like RSA, the associated alternatives are graded in descending order based on the value of  $C_i$  and the best alternative is selected, having maximum value of  $C_i$ .

**Step 5:** The final rank of alternatives established through the MULTIMOORA method.

Three ranking lists are produced for the alternatives that are being evaluated after the MULTIMOORA method is applied. Then, dominance theory is used, as study suggests [38], to identify the best-ranked alternative. This is done by looking at which alternative consistently ranks highest across all ranking lists.

#### 4 Case Study (Mobile Phone Selection)

In the constantly changing world of mobile phone technology, selecting the ideal device requires sifting through a wide range of options, all of which boast unique features and technical details. This case study examines the process of selecting a mobile phone from eight options while considering seven different criteria, each with a unique set of unknowns. This case study offers a methodical method for choosing a mobile phone while considering variable factors. In the constantly changing world of mobile technology, people can make well-informed decisions that suit their preferences and priorities by adhering to the decision-analysis process (Figure 2).



**Figure 2.** Mobile selection case study

##### 4.1 Challenges or Uncertainties

- **Performance:** The device's performance may be impacted by the timing and nature of upcoming software updates. A subpar update could cause the phone to lag or introduce bugs.

- **Camera Quality:** User experiences in different lighting scenarios may differ, and the camera's actual performance in low light may differ from the specifications advertised.

- **Battery:** Based on each user's distinct usage habits, there are uncertainties in predicting the phone's performance. Individual usage patterns have a significant impact on battery life.

- **Storage Capacity:** Pre-installed apps and system software may cause the actual usable space for files, media, and apps to differ from the stated storage capacity, creating ambiguity over the amount of storage that is available.

- **Cost:** There is uncertainty about possible extra expenses that may not be specified up front, like required subscriptions, service fees, or extra accessories.

- **User Reviews:** Opinions expressed in reviews may differ depending on personal experiences and preferences, making them subjective or biased. This can raise questions about the validity of user reviews.

- **Brand Reputation:** It is difficult to forecast how a brand's image will change over time because brand reputation is susceptible to shifting market perceptions. Users may differ in their preferences, and it can be difficult to determine how closely a brand corresponds with a person's unique expectations.

## 4.2 Decision-Making Process

• **Criteria Weighting:** Based on the priorities of the individual, give each criterion a certain weight. For instance, a higher weight should be given to camera quality if it is more significant than storage capacity.

• **Performance Evaluation:** Taking the uncertainties into account, assess each option in relation to the criteria. To measure the performance, apply a numerical scale or a scoring system.

• **Uncertainty Management:** Include uncertainty in the model used to make decisions. To comprehend how changes in uncertainty affect the choice, apply sensitivity analysis.

• **Decision Making:** Add up the points for every option, considering the weights and uncertainties pertaining to each criterion.

• **Final Decision:** Considering the person's preferences, priorities, and risk tolerance, present the suggested smartphone based on the decision analysis.

## 4.3 Construction of FHSS

• **Performance:** Assesses the general speed, processing power, and efficacy of the mobile phone.

• **Camera Quality:** Evaluates the resolution, features, and performance of the system.

• **Battery:** Determines how long the phone can operate on a single charge under normal use circumstances.

• **Storage Capability:** Determines how much internal storage space is available for programs, files, and media.

• **Price:** Represents the cost of the cell phone.

• **User Reviews:** Provides information and firsthand experiences from users who have already purchased and used the phone.

• **Brand Reputation:** Considers the brand's overall reputation and dependability in the mobile phone industry. The attributes for phone selection are presented in Table 1, and alternatives are presented in Table 2, respectively.

**Table 1.** List of criteria considered in crop production

$C_1$	Performance
$C_2$	Camera quality
$C_3$	Battery
$C_4$	Storage capacity
$C_5$	Price
$C_6$	User reviews
$C_7$	Brand reputation

**Table 2.** List of alternative phones in production

$A_1$	Apple
$A_2$	Samsung
$A_3$	Huawei
$A_4$	Google
$A_5$	Vivo
$A_6$	OnePlus
$A_7$	Sony

These attributes/criteria are further subdivided as:

$$C_1 = \text{Performance} = \{1.8\text{Ghz}, 2.0\text{Ghz}, 2.4\text{ghz}\}$$

$$C_2 = \text{Camera quality} = \{8\text{MP}, 12\text{MP}, 48\text{MP}\}$$

$$C_3 = \text{Battery} = \{< 4000\text{mAH}, 4500\text{mAH}, 5000\text{mAH}, > 6000\text{mAH}\}$$

$$C_4 = \text{Storage capacity} = \{64 \text{ GB}, 128 \text{ GB}, 256 \text{ GB}, 512 \text{ GB}\}$$

$$C_5 = \text{Price} = \{\$180, \$220, \$300, \$500\}$$

$$C_6 = \text{User reviews} = \{4, 5, 7, 9\}$$

$$C_7 = \text{Brand reputation} = \{ \text{low}, \text{medium}, \text{high} \}$$

Assuming that the relation for function  $\mathcal{F} : C_1 \times C_2 \times C_3 \times C_4 \times C_5 \times C_6 \times C_7 \rightarrow P(A)$  as  $F(C_1 \times C_2 \times C_3 \times C_4 \times C_5 \times C_6 \times C_7)$  and we get eight FHSSs as presented in Table 3. One decision-maker  $\{\mathbb{M}^1\}$  is intended

**Table 3.** FHSS decision matrix

Alternative/ Criteria	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>5</sub>	C <sub>6</sub>	C <sub>7</sub>
A <sub>1</sub>	0.081	0.031	0.135	0.351	0.122	0.264	0.143
A <sub>2</sub>	0.166	0.568	0.521	0.271	0.500	0.370	0.712
A <sub>3</sub>	0.147	0.875	0.356	0.409	0.177	0.651	0.892
A <sub>4</sub>	0.024	0.429	0.268	0.276	0.460	0.550	0.455
A <sub>5</sub>	0.043	0.412	0.588	0.267	0.266	0.631	0.298
A <sub>6</sub>	0.005	0.338	0.382	0.161	0.159	0.660	0.116
A <sub>7</sub>	0.010	0.520	0.311	0.171	0.840	0.970	0.781

to select the most suitable crop for his farm based on his/her facilities in terms of attributes. This decision-maker will give valuable opinion in the form of FHSSs, as follows:

The weights are calculated using the entropy method.

$$w_1 = 0.1927 \quad w_2 = 0.1073; \quad w_3 = 0.2110; \quad w_4 = 0.3990; \quad w_5 = 0.0110 \quad w_6 = 0.0119; \quad w_7 = 0.0791.$$

#### 4.4 Solution

**Step 1.** Construction of the decision matrix, which is the same as Table 1.

**Step 2.** The RSA approach.

Applying the method, we get RSA Scores: [9963.761311494107, 13.247435158651056, 10.659823109022922, 2.5970219934276653, 1.0699530480062045, 0.00013873874125029667, 0.22913624007062128].

**Step 3.** The RPA approach.

Using this approach, the alternative orders are:

RPA Scores:

- A<sub>1</sub> -0.364305
- A<sub>2</sub> -0.313404
- A<sub>3</sub> -0.394971
- A<sub>4</sub> -0.023071
- A<sub>5</sub> 0.023685
- A<sub>6</sub> 0.876638
- A<sub>7</sub> 0.308176

**Step 4.** The FMF approach.

Using this approach, the total efficacy of all alternatives is obtained.

FMF Scores:

- A<sub>1</sub> 1.729476 e<sup>-09</sup>
- A<sub>2</sub> 2.552206 e<sup>-06</sup>
- A<sub>3</sub> 3.021494 e<sup>-06</sup>
- A<sub>4</sub> 1.530178 e<sup>-07</sup>
- A<sub>5</sub> 2.201886 e<sup>-07</sup>
- A<sub>6</sub> 1.084033 e<sup>-09</sup>
- A<sub>7</sub> 2.175347 e<sup>-07</sup>

**Step 5.** Selection of best alternative.

The ranking of alternatives using all approaches has been obtained.

**Table 4.** Crop production economics ranking

	RSA	RPA	FMF
0	9963.761311	-0.364305	1.729476 e <sup>-09</sup>
1	13.247435	-0.313404	2.552206 e <sup>-06</sup>
2	0.659823	-0.394971	3.021494 e <sup>-06</sup>
3	2.597022	-0.023071	1.530178 e <sup>-07</sup>
4	1.069953	0.023685	2.201886 e <sup>-07</sup>
5	0.000139	0.876638	1.084033 e <sup>-09</sup>
6	0.229136	0.308176	2.175347 e <sup>-07</sup>

Brauers and Zavadskas [37] stated that dominance theory is used to identify the best-ranked option, which is the one that appears first in every ordered ranking. Table 4 illustrates that A<sub>1</sub> = **Apple** is the highest-ranked alternative,

with  $A_3 = \text{Huawei}$  coming in the second. When choosing a smartphone for Bryce,  $A_6 = \text{OnePlus}$  and  $A_1 = \text{Apple}$  take the second and the first place, respectively. By applying this strategy and generating a FHSS, Bryce has gained important insights into the process of choosing a mobile phone, allowing him to make more informed choices in the face of uncertainties brought on by scarce facilities and resources.

#### 4.5 Python Code for the Calculations and Ranking

The adoption of Python programming for the MULTIMOORA decision-making algorithm in this study is instrumental for several reasons, particularly given the complex nature of the calculations involved in FHSS and the potential scalability challenges associated with increasing the number of alternatives and attributes. First, Python provides a wide range of tools and libraries designed especially for activities involving data analysis, numerical computations, and machine learning. It is ideally suited for executing complicated algorithms and effectively managing large datasets because of its adaptability and simplicity of usage. This is especially helpful in situations where adding more options and attributes could make calculations more complex because Python's robustness can handle those kinds of challenges. In conclusion, by using Python programming and machine learning approaches in this study, we can successfully address the inherent complications involved in choosing a mobile phone. Using these technologies to their full potential will allow us to improve the scalability, accuracy, and efficiency of our analysis, finally giving decision-makers insightful information to help them navigate the ever-changing world of mobile technology. Second, machine learning algorithms offer strong instruments for pattern recognition, prediction, and decision-making process optimization. We can automate data analysis and produce insights that might not be immediately evident through manual methods by utilizing machine learning techniques. This improves our data's accuracy and dependability and makes it possible to investigate more complex decision-making models.

```
import pandas as pd
import seaborn as sns
import numpy as np
from matplotlib import pyplot as plt
def normalize(matrix):
    """
    Normalize a matrix by dividing each element by the sum of its column.
    """
    col_sum = matrix.sum(axis=0)
    # Check for zero column sums
    if np.any(col_sum == 0):
        raise ValueError("One or more columns have zero sum. Cannot normalize.")
    return matrix / col_sum
def rsa(benefit_matrix, cost_matrix):
    normalized_benefit = normalize(benefit_matrix)
    normalized_cost = normalize(cost_matrix)
    ratios = normalized_benefit / normalized_cost
    rsa_scores = np.prod(ratios, axis=1).tolist()
def rpa(reference_point, benefit_matrix, cost_matrix):
    normalized_benefit = normalize(benefit_matrix)
    normalized_cost = normalize(cost_matrix)
    reference_point = np.random.rand(benefit_matrix.shape[1])
    benefit_distances = np.abs(normalized_benefit-reference_point)
    cost_distances = np.abs(normalized_cost-reference_point)
    rpa_scores = np.sum(benefit_distances - cost_distances, axis=1)
def fmf(benefit_matrix, cost_matrix):
    normalized_benefit = normalize(benefit_matrix)
    normalized_cost = normalize(cost_matrix)
    fmf_scores = np.prod(normalized_benefit / (1 + normalized_cost), axis=1)
```

#### 4.6 Result Discussion and Comparison

Data analysis shows that, when it comes to mobile selection, the results obtained from the MULTIMOORA approach, and very interesting. The MULTIMOORA technique's determination of  $A_1 = \text{Apple}$  as the optimal

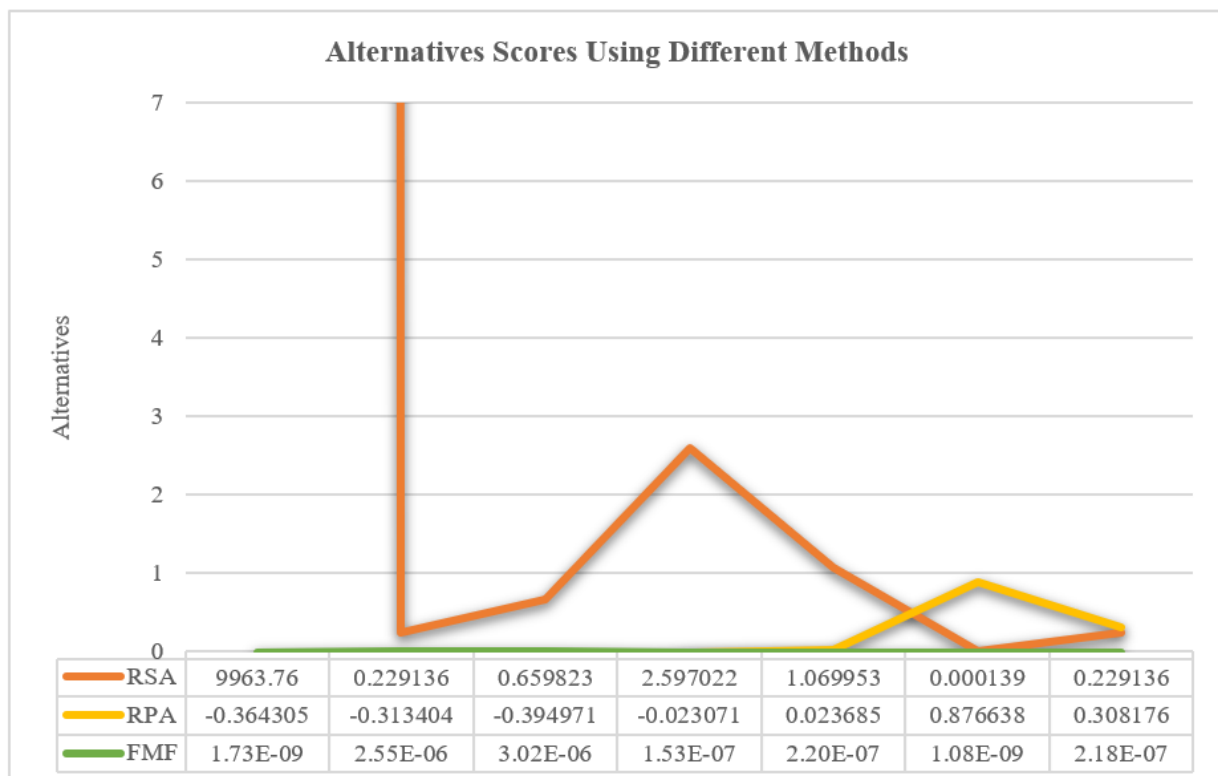


choice closely resembles the ideal preference. Moreover, the ranking of  $A_6 = \text{OnePlus}$  and  $A_1 = \text{Apple}$  take the second and the first place, respectively, corresponds to the MULTIMOORA approach. This notable convergence highlights the dependability and efficiency of the approach. It implies that even with the use of ensemble learning techniques, while MULTIMORA applies multi-objective decision-making principles, they can reliably determine which smartphone is the best. This consistency in outcomes supports the viability of both approaches and increases Bryce's confidence in her capacity to make well-informed decisions, especially considering the complexities of resource constraints and uncertainties in her mobile environment.

**Table 5.** Comparison with existing studies

Researcher	Approach	Alternative Rankings
Kumar and Singh [7]	RSA	$A_1 > A_2 > A_3 > A_4 > A_5 < A_7 < A_6$
	RPA	$A_6 > A_7 > A_5 > A_4 > A_2 < A_1 < A_3$
	FMF	$A_3 > A_2 > A_5 > A_4 > A_7 < A_1 < A_6$
Pérez et al. [11]	RSA	$A_6 > A_2 > A_4 > A_3 > A_5 < A_7 < A_1$
	RPA	$A_6 > A_7 > A_5 > A_4 > A_2 < A_1 < A_3$
	FMF	$A_6 > A_2 > A_4 > A_5 > A_1 < A_7 < A_3$
Proposed study	RSA	$A_1 > A_2 > A_3 > A_4 > A_5 < A_7 < A_6$
	RPA	$A_6 > A_7 > A_5 > A_4 > A_2 < A_1 < A_3$
	FMF	$A_6 > A_2 > A_5 > A_4 > A_7 < A_1 < A_3$

The results from the various study approaches are analyzed and compared with the proposed study; the tabular and graphical comparisons are presented in Table 5 and Figure 3. We assess how well FHSS using machine learning perform in comparison to other decision-making strategies or conventional techniques applied in comparable scenarios. We draw attention to important discoveries like the precision, effectiveness, and resilience of our suggested framework in comparison to other approaches.



**Figure 3.** Graphical representation of the results

Figure 3, which presents a graphical representation of the results obtained from the three different approaches (RSA, RPA, and FMF) of the MULTIMOORA algorithm. In Figure 3, the x-axis represents the different approaches, while the y-axis displays the scores or values obtained from each approach. The graph visualizes the relative performance or ranking of the mobile phone alternatives across the three approaches.

From the graph, we can observe the following:

1-RSA scores:

- The alternative A1 (Apple) has the highest RSA score, indicating its top ranking based on this approach.
- A2 (Samsung) and A3 (Huawei) have the next highest RSA scores, respectively.
- A7 (Sony) has the lowest RSA score among the alternatives.

2-RPA scores:

- A6 (OnePlus) has the highest RPA score, suggesting its top ranking based on this approach.
- A5 (Vivo) and A7 (Sony) have the next highest RPA scores, respectively.
- A1 (Apple) and A3 (Huawei) have the lowest RPA scores.

3-FMF scores:

- A3 (Huawei) has the highest FMF score, indicating its top ranking based on this approach.
- A2 (Samsung) and A5 (Vivo) have the next highest FMF scores, respectively.
- A1 (Apple) and A6 (OnePlus) have the lowest FMF scores.

The graphical representation highlights the differences in the rankings or scores obtained from the three approaches, reflecting the diverse perspectives and considerations involved in the MULTIMOORA algorithm. It visually demonstrates how the same set of mobile phone alternatives can yield varying rankings based on the different optimization criteria or objectives employed by each approach. This graphical representation allows for a quick and intuitive comparison of the results, enabling the decision-maker to identify the top-performing alternatives across multiple approaches. It also provides insights into the potential trade-offs or compromises that may need to be made when considering different aspects of the decision-making process. Furthermore, the graphical representation can facilitate further analysis, such as investigating the reasons behind the discrepancies in rankings between the approaches or exploring the sensitivity of the results to changes in the input data or weightings of the criteria. Overall, Figure 3 serves as a valuable visual aid in communicating the key findings of the research, enabling a more effective understanding and interpretation of the results obtained from the MULTIMOORA algorithm in the context of mobile phone selection.

## 5 Conclusion

In conclusion, this study has shown how well FHSS work with machine learning to handle the complexity involved in choosing a cell phone. Our framework provides a methodical approach to optimizing user interest by considering the variety of options offered and the dynamic nature of customer preferences. Applying FHSS gives consumers a strong DSS by efficiently managing ambiguity and uncertainty. Our approach, which makes use of complex Python scripts and algorithms, makes it easier for consumers to choose mobile phones in the ever-changing technological landscape by providing a more personalized and interesting experience. All things considered, this study helps consumers make better decisions when they are faced with a wide range of options for mobile phones.

The MULTIMOORA approach's practical relevance is highlighted by its demonstrated ability to consistently identify the best smartphone, even when ensemble learning approaches are being used. Such uniformity not only confirms the practicality of both strategies but also gives decision-makers like Bryce assurance that they can successfully negotiate resource limitations and unpredictability in a mobile environment.

Future studies in this field will focus on the following areas:

- Investigating different methods of generating decisions or machine learning algorithms to improve the precision and effectiveness of the framework.
- Assessing the methodology's suitability for use in other consumer-driven businesses.
- Investigating the possible integration of cutting-edge technology like blockchain and artificial intelligence.

## Data Availability

The data used to support the research findings are available from the corresponding author upon request.

## Acknowledgments:

The authors are thankful for anonymous reviewer for their comments who helped us to improve the quality of this paper.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## References

- [1] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Q.*, vol. 13, no. 3, pp. 319–340, 1989. <https://doi.org/10.2307/249008>
- [2] S. Ha and L. Stoel, "Consumer e-shopping acceptance: Antecedents in a technology acceptance model," *J. Bus. Res.*, vol. 62, no. 5, pp. 565–571, 2009. <https://doi.org/10.1016/j.jbusres.2008.06.016>
- [3] J. Kim and S. Forsythe, "Adoption of virtual try-on technology for online apparel shopping," *J. Interact. Mark.*, vol. 22, no. 2, pp. 45–59, 2008. <https://doi.org/10.1002/dir.20113>
- [4] P. Adamopoulos and A. Tuzhilin, "On unexpectedness in recommender systems: Or how to better expect the unexpected," *ACM Trans. Intell. Syst. Technol.*, vol. 5, no. 4, pp. 1–32, 2014. <https://doi.org/10.1145/2559952>
- [5] I. Perfecto and J. Vandermeer, "Biodiversity conservation in tropical agroecosystems: A new conservation paradigm," *Ann. N. Y. Acad. Sci.*, vol. 1134, no. 1, pp. 173–200, 2008. <https://doi.org/10.1196/annals.1439.011>
- [6] O. Mont *et al.*, "Sustainable consumer behavior: A collection of empirical studies," *J. Clean. Prod.*, vol. 9, no. 10, pp. 335–345, 2016.
- [7] R. Kumar and H. H. Singh, "Selection of mobile phone with multi criteria decision making approach: A case study," in *Future of Business through Innovations*. New Delhi, India: National Press Associates, 2020, pp. 121–125.
- [8] S. Mokhlis and A. Y. Yaakop, "Consumer choice criteria in mobile phone selection: An investigation of malaysian university students," *Int. J. Soc. Sci. Humanity Stud.*, vol. 2, no. 2, pp. 203–212, 2012.
- [9] B. Efe, M. A. Yerlikaya, and O. F. Efe, "Mobile phone selection based on a novel quality function deployment approach," *Soft Comput.*, vol. 24, pp. 15 447–15 461, 2020. <https://doi.org/10.1007/s00500-020-04876-x>
- [10] T. D. Juwaheer, I. Vencatachellum, S. Pudaruth, D. Ramasawmy, and Y. Ponnusami, "Factors influencing the selection of mobile phones in Mauritius," *Ijikmmena*, vol. 3, no. 1, 2014. <https://doi.org/10.47556/I.IJKMME.NA.3.1.2014.4>
- [11] I. J. Pérez, F. J. Cabrerizo, and E. Herrera-Viedma, "A mobile decision support system for dynamic group decision-making problems," *IEEE Trans. Syst. Man Cybern.: Syst.*, vol. 40, no. 6, pp. 1244–1256, 2010. <https://doi.org/10.1109/TSMCA.2010.2046732>
- [12] L. A. Zadeh, "Fuzzy sets," *Inf. Control.*, vol. 8, no. 3, pp. 338–353, 1965. [https://doi.org/10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X)
- [13] S. Miyamoto, "Remarks on basics of fuzzy sets and fuzzy multisets," *Fuzzy Sets Syst.*, vol. 156, no. 3, pp. 427–431, 2005. <https://doi.org/10.1016/j.fss.2005.05.040>
- [14] J. Chen, S. Li, S. Ma, and X. Wang, "Polar fuzzy sets: An extension of bipolar fuzzy sets," *Sci. World J.*, vol. 2014, 2014. <https://doi.org/10.1155/2014/416530>
- [15] W. R. Zhang, "Bipolar fuzzy sets and relations: A computational framework for cognitive modeling and multiagent decision analysis," in *NAFIPS/IFIS/NASA'94. Proceedings of the First International Joint Conference of The North American Fuzzy Information Processing Society Biannual Conference. The Industrial Fuzzy Control and Intelligence*, 1994, pp. 305–309. <https://doi.org/10.1109/IJCF.1994.375115>
- [16] I. B. Turksen, "Interval valued fuzzy sets based on normal forms," *Fuzzy sets syst.*, vol. 20, no. 2, pp. 191–210, 1986. [https://doi.org/10.1016/0165-0114\(86\)90077-1](https://doi.org/10.1016/0165-0114(86)90077-1)
- [17] C. Kahraman, S. C. Onar, and B. Oztaysi, "Fuzzy multicriteria decision-making: A literature review," *Int. J. Comput. Intell. Syst.*, vol. 8, no. 4, pp. 637–666, 2015. <https://doi.org/10.1080/18756891.2015.1046325>
- [18] V. Torra, "Hesitant fuzzy sets," *Int. J. Comput. Intell. Syst.*, vol. 25, no. 6, pp. 529–539, 2010. <https://doi.org/10.1002/int.20418>
- [19] K. T. Atanassov and S. Stoeva, "Intuitionistic fuzzy sets," *Fuzzy sets Syst.*, vol. 20, no. 1, pp. 87–96, 1986. [https://doi.org/10.1016/S0165-0114\(86\)80034-3](https://doi.org/10.1016/S0165-0114(86)80034-3)
- [20] P. A. Ejegwa, "Pythagorean fuzzy set and its application in career placements based on academic performance using max–min–max composition," *Complex Intell. Syst.*, vol. 5, no. 2, pp. 165–175, 2019.
- [21] X. Zhang and Z. Xu, "Extension of topsis to multiple criteria decision making with pythagorean fuzzy sets," *Int. J. Comput. Intell. Syst.*, vol. 29, no. 12, pp. 1061–1078, 2014. <https://doi.org/10.1002/int.21676>
- [22] F. Smarandache, *Neutrosophy: Neutrosophic Probability, Set, and Logic: Analytic Synthesis & Synthetic Analysis*. Rehoboth, NM: American Research Press, 1998.
- [23] M. Saqlain, S. Moin, N. Jafar, M. Saeed, and S. Broumi, "Single and multi-valued neutrosophic hypersoft set and tangent similarity measure of single valued neutrosophic hypersoft sets," *Neutros. Sets Syst.*, vol. 32, pp. 317–329, 2020.
- [24] D. Molodtsov, "Soft set theory—first results," *Comput. Math. Appl.*, vol. 37, no. 4-5, pp. 19–31, 1999. [https://doi.org/10.1016/S0898-1221\(99\)00056-5](https://doi.org/10.1016/S0898-1221(99)00056-5)
- [25] P. K. Maji, R. K. Biswas, and A. Roy, "Fuzzy soft sets," *J. Fuzzy Math.*, vol. 5, no. 9, pp. 589–602, 2001.

- [26] F. Smarandache, "Extension of soft set to hypersoft set, and then to plithogenic hypersoft set," *Neutrosophic Sets Syst.*, vol. 22, no. 1, pp. 168–170, 2018.
- [27] P. K. Maji, R. K. Biswas, and A. Roy, "An application of soft sets in a decision making problem," *Comput. Math. Appl.*, vol. 44, no. 8-9, pp. 1077–1083, 2002.
- [28] M. N. Jafar and M. Saeed, "Aggregation operators of fuzzy hypersoft sets," *Turk. J. Fuzzy Syst.*, vol. 11, no. 1, pp. 1–17, 2021.
- [29] A. Yolcu and T. Y. Ozturk, "Fuzzy hypersoft sets and its application to decision-making," *Theor. Appl. Hypersoft Set*, vol. 50, 2021.
- [30] S. Debnath, "Fuzzy hypersoft sets and its weightage operator for decision making," *J. Fuzzy. Ext. Appl*, vol. 2, no. 2, pp. 163–170, 2021. <https://doi.org/10.22105/jfea.2021.275132.1083>
- [31] M. Saqlain, M. Riaz, N. Kiran, P. Kumam, and M. S. Yang, "Water quality evaluation using generalized correlation coefficient for M-polar neutrosophic hypersoft sets," *Neutros. Sets Syst.*, vol. 55, pp. 58–89, 2023.
- [32] M. Riaz, A. Habib, M. Saqlain, and M. S. Yang, "Cubic bipolar fuzzy-VIKOR method using new distance and entropy measures and einstein averaging aggregation operators with application to renewable energy," *Int. J. Fuzzy Syst.*, vol. 25, no. 2, pp. 510–543, 2023.
- [33] M. Saqlain, M. Riaz, R. Imran, and F. Jarad, "Distance and similarity measures of intuitionistic fuzzy hypersoft sets with application: Evaluation of air pollution in cities based on air quality index," *AIMS Math.*, vol. 8, no. 3, pp. 6880–6899, 2023.
- [34] M. Saqlain, H. Garg, P. Kumam, and W. Kumam, "Uncertainty and decision-making with multi-polar interval-valued neutrosophic hypersoft set: A distance, similarity measure, and machine learning approach," *Alex. Eng. J.*, vol. 84, pp. 323–332, 2023. <https://doi.org/10.1016/j.aej.2023.11.001>
- [35] M. Saqlain, P. Kumam, W. Kumam, and S. Phiangsungnoen, "Proportional distribution based pythagorean fuzzy fairly aggregation operators with multi-criteria decision-making," *IEEE Access*, vol. 11, pp. 72 209–72 226, 2023. <https://doi.org/10.1109/ACCESS.2023.3292273>
- [36] M. Saqlain, P. Kumam, and W. Kumam, "Linguistic hypersoft set with application to multi-criteria decision-making to enhance rural health services," *Neutrosophic Sets Syst.*, vol. 61, pp. 28–52, 2023. <https://doi.org/10.5281/zenodo.10428591>
- [37] W. K. Brauers and E. K. Zavadskas, "The MOORA method and its application to privatization in a transition economy," *Control Cybern.*, vol. 35, no. 2, pp. 445–469, 2006.
- [38] H. Taherdoost and M. Madanchian, "Multi-criteria decision making (MCDM) methods and concepts," *Encyclopedia*, vol. 3, no. 1, pp. 77–87, 2023. <https://doi.org/10.3390/encyclopedia3010006>
- [39] Meharunnisa, M. Saqlain, M. Abid, M. Awais, and Z. Stevic, "Analysis of software effort estimation by machine learning techniques," *Ing. Syst. Inf.*, vol. 28, pp. 1445–1457, 2023. <http://doi.org/10.18280/isi.280602>
- [40] N. Rehman, M. Abid, and S. Qamar, "Numerical approximation of nonlinear and non-equilibrium model of gradient elution chromatography," *J. Liq. Chromatogr. Relat. Technol.*, vol. 44, no. 7-8, pp. 382–394, 2021. <http://doi.org/10.1080/10826076.2021.1947316>
- [41] G. A. Abdulaziz, M. K. A. Kaabar, S. Rashid, and M. Abid, "A novel numerical treatment of nonlinear and nonequilibrium model of gradient elution chromatography considering core-shell particles in the column," *Math. Probl. Eng.*, vol. 2022, p. 1619702, 2022. <http://doi.org/10.1155/2022/1619702>
- [42] M. Abid and M. Saqlain, "Utilizing edge cloud computing and deep learning for enhanced risk assessment in China's international trade and investment," *Int. J. Knowl. Innov. Stud.*, vol. 1, no. 1, pp. 1–9, 2023. <http://doi.org/10.56578/ijkis010101>
- [43] H. B. U. Haq, W. Akram, M. N. Irshad, A. Kosar, and M. Abid, "Enhanced real-time facial expression recognition using deep learning," *Acad. Trans. Mach. Learn.*, vol. 3, no. 1, pp. 24–35, 2024. <http://doi.org/10.56578/ataiml030103>
- [44] M. Abid and M. Saqlain, "Decision-making for the bakery product transportation using linear programming," *Spectr. Eng. Manag. Sci.*, vol. 1, no. 1, pp. 1–12, 2023. <http://doi.org/10.31181/sems1120235a>
- [45] M. Abid, M. Bibi, N. Yasin, and M. Shahid, "A novel computational analysis of boundary driven two-dimensional heat flow with the internal heat generation," *Comput. Algorithms Numer. Dimens.*, 2024. <http://doi.org/10.22105/cand.2024.443017.1090>