**Project Report**

**On**

# FUZZY LOGIC IN MULTI-CRITERIA DECISION MAKING

***Submitted***

***in partial fulfilment of the requirements for the degree of***

**BACHELOR OF SCIENCE**

***in***

**MATHEMATICS**

*by*

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ST. TERESA'S COLLEGE (AUTONOMOUS), ERNAKULAM

# CERTIFICATE

This is to certify that the dissertation entitled, **FUZZY LOGIC IN MULTI-CRITERIA DECISION MAKING** is a bonafide record of the work done by **ELIZABETH LIJO, under my guidance as partial fulfillment of the award of the degree of Bachelor of Science in Mathematics at St. Teresa's College (Autonomous), Ernakulam affiliated to Mahatma Gandhi University, Kottayam. No part of this work has been submitted for any other degree elsewhere.**

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# DECLARATION

I hereby declare that the work presented in this project is based on the original work done by me under the guidance of Ms. Anna Sheethal V S, Assistant Professor, Department of Mathematics and Statistics, St. Teresa's College(Autonomous), Ernakulam and has not been included in any other project submitted previously for the award of any degree.

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# Contents

*CERTIFICATE* . . . . . ii
*DECLARATION* . . . . . iii
*ACKNOWLEDGEMENT* . . . . . iv
*CONTENT* . . . . . v

**1 INTRODUCTION** **1**
1.1 Background : The challenge of decision making . . . . . 1
1.2 Soft computing . . . . . 1
1.3 Introduction to fuzzy logic . . . . . 2
1.4 Problem statement:The need for a Fuzzy solution . . . . . 2
1.5 Objective . . . . . 2

**2 FUNDAMENTALS OF FUZZY LOGIC AND MCDM** **4**
2.1 Multi criteria decision making(MCDM) . . . . . 4
2.2 Fuzzy sets - Introduction and basic concepts . . . . . 4
2.3 Fuzzy logic . . . . . 5
2.4 Fuzzy Multi criteria decision making . . . . . 6
2.5 Types of membership functions . . . . . 6
2.5.1 Triangular membership function . . . . . 7
2.6 Linguistic variable . . . . . 7
2.7 Fuzzification . . . . . 8
2.8 Defuzzification . . . . . 8
2.9 Ranking of fuzzy sets and fuzzy numbers . . . . . 9

**3 FUZZY MCDM APPROACH** **10**
3.1 Problem statement . . . . . 10
3.2 Data preparation and loading . . . . . 10

3.3 Weight assignment . . . . . 11
3.4 Fuzzification . . . . . 12
3.4.1 Dynamic triangular points . . . . . 12
3.4.2 Triangular membership function . . . . . 14
3.5 Centroid values( representative) for each fuzzy term . . . . . 15
3.6 Defuzzification( weighted average method) . . . . . 15
3.7 Weighted aggregation and finding weighted scores . . . . . 17
3.7.1 Aggregation across all people ( per phone) . . . . . 17
3.8 Ranking . . . . . 17

**4 EXPERIMENTAL RESULTS AND ANALYSIS 19**

4.1 Overview of analysis . . . . . 19
4.2 Survey data used . . . . . 19
4.3 Application of FMCDM . . . . . 19
4.4 Final rankings and survey results . . . . . 20
4.5 Comparison with market ratings . . . . . 21
4.6 Future scope and conclusion . . . . . 23
4.7 Conclusion . . . . . 23
*REFERENCES* . . . . . 24

# Chapter 1

# INTRODUCTION

## 1.1 Background : The challenge of decision making

The concept of sets is as ancient as the concept of numbers.All known mathematical concepts can be reduced to the ideas of set and membership in a set. Uncertainty has been a part of our everyday life.The study of uncertainty can be dated back to as early as the sixteenth century.In mid seventeenth century, Blaise Pascal's Wager is also one of the earliest instances to use uncertainty and decision theory which also marked the evolution of probability theory. Statistical models are the first models of uncertainty in the literature.

Decision making is a cognitive process to identify or choose a final choice among several alternative possibilities based on the situation, values and preferences of the decision maker. So many real world problems which include factors like good quality, long lasting and high performance cannot be easily measured by simple binary logic . In order to tackle these ambiguous problems, the field of soft computing was developed.

## 1.2 Soft computing

In contrast to traditional hard computing, which demands precise inputs and yields precise outputs, soft computing is a subfield of computational intelligence that is designed to handle imprecision, uncertainty, and approximation . The main idea is that it can handle ambiguity and uncertainty in a flexible way by using approximate reasoning and data-driven learning. To deal with such uncertainty, soft computing—which includes fuzzy sets, neural networks, and soft set

theory—expands the traditional ideas of sets and membership. Soft computing focuses on addressing real world problems like a human does. Soft computing broadly consist of : Neural network, Fuzzy logic, Genetic Algorithm

## 1.3 Introduction to fuzzy logic

In this chapter, the concept of fuzzy sets ,fuzzy logic ,operations and its membership functions are discussed.Classical sets are also called 'crisp' sets so as to distinguish them from fuzzy sets. In fact, the Crisp sets can be taken as special cases of fuzzy sets. Let A be a crisp set defined over Universe X. Then for any element x in X, either x is a member of A or not. Therefore, in a fuzzy set, it is not necessary that x is a full Member of the set or not a member. It can be a partial member of the sets.

How does fuzzy set theory differ from classical set theory?
For eg : Is an apple red ? For a crisp set the answer is either true (1) or false (0),here membership value is either 1 or 0. And according to fuzzy logic the answer would be different like slightly red , not red, perfectly red etc. So the membership value can be any value in $[0 \ldots\ldots 1]$.

## 1.4 Problem statement:The need for a Fuzzy solution

In this study the problem addressed is ranking consumer products - specifically , smartphones based on multiple criterias. A simple numerical rating (eg 4.4) can't capture the vagueness of human judgement. So here we use multi-criteria decision making which helps in choosing the best one out of all the available criterias by evaluating all factors ( camera, battery, storage, price - in our problem ). In our problem we asked 10 people to rate 4 top ranked phones and the importance of each parameter in a 1-5 scale which is an imprecise representation. So we used fuzzy logic to model this human ambiguity. So we incorporated multi-criteria decision making with fuzzy logic to solve this problem.

## 1.5 Objective

This study aims to create a fuzzy multi-criteria decision-making (MCDM) framework for smartphone ranking according to user preferences. Traditional numerical

scores are unable to capture the uncertainty in judgment because human ratings on features like camera, battery, storage and price are frequently ambiguous and imprecise. The study intends to integrate consumer preferences and multiple evaluation criteria to generate a fair, realistic, and trustworthy ranking of smartphones by gathering participant ratings and modeling this uncertainty using fuzzy logic.

# Chapter 2

# FUNDAMENTALS OF FUZZY LOGIC AND MCDM

## 2.1 Multi criteria decision making(MCDM)

Multi-criteria decision making (MCDM) is a process of expressing real life problems in terms of preference values of decision-maker in order to obtain the best choice. It is of the fastly developing branches in decision science. MCDM is a process of choosing the best one out of all available criteria or alternatives . It depends on the preferences of the decision maker or expert's opinion. The multi-criteria decision making involving more than one decision maker is called multicriteria group decision making.(MCGDM). It has many applications in the fields of decision theory , Artificial Intelligence , pattern recognition ,optimization theory, supplier selection method etc.

## 2.2 Fuzzy sets - Introduction and basic concepts

The word "fuzzy" means "vagueness (ambiguity)". Fuzziness occurs when the boundary of a piece of information is not clear-cut. Fuzzy set theory is an extension of classical set theory where elements have degree of membership. A Fuzzy Set is any set that allows its members to have different degrees of membership, called membership function, having interval [0,1] that is ,it assigns grades of membership between 0 and 1 to objects within its universe of discourse. Fuzzy Logic is derived from fuzzy set theory.

Fuzzy Set Theory was formalized by Professor Lofti Zadeh at the University of

California in 1965 which is a powerful tool for modelling various events , especially those with imprecise uncertainties. The motive for the idea of fuzzy sets has come from the fact that the conventional approaches could not adequately handle certain kinds of uncertainties, especially those inherent in human cognitive processes. According to classical set theory, if an element belongs to the set it is assigned to 1 and if the element does not belong to the set it is assigned to 0. But in case of fuzzy set theory it is different ,ie if it is a membership function it is assigned 1 ,if it is not a membership function it is assigned 0 and partial membership function is assigned to 0 to 1 .So in case of fuzzy set theory each element is assigned to a membership function that denotes the level of closeness to the condition

The membership function $\mu_A$(x) of a fuzzy set A is a function $\mu_A$ : X $\rightarrow$[0,1] So, every element x in X has membership degree: $\mu_A$(x) $x \in$ [0,1]

If X is an universe of discourse and x is a particular element of X, then a fuzzy set A defined on X and can be written as a collection of ordered pairs A = {(x, $\mu_A$(x)), $x \in$ X}

Example • Let X = {g1, g2, g3, g4, g5} be the reference set of students. Let A be the fuzzy set of "smart" students, where "smart" is a fuzzy term. A = {(g1 ,0.4) (g2 ,0.5) (g3 ,1) (g4 ,0.9) (g5 ,0.8)} , here A indicates that the smartness of g1 is 0.4 and so on .

There are 2 types of fuzzy set type 1 and type2. Type 1 fuzy set is characterised by a single membership function that maps from universal set to a value between 1 and 0 which represent the degree of membership, while in type 2 fuzzy system the membership function is fluctuating.

## 2.3 Fuzzy logic

The study of human reasoning's foundations and techniques is known as fuzzy logic. A statement in classical logic can only be true (1) or false (0);it cannot be partly true or partly false. As a generalization of classical logic, fuzzy logic allows a statement's truth to be represented by any number between 0 and 1, denoting degrees of truth as opposed to merely true or false.

## 2.4 Fuzzy Multi criteria decision making

The fields of probability and game theories serve as the foundation for traditional decision-making techniques. Fuzzy sets were later used to modify the earlier decision-making techniques in order to effectively address ambiguity, uncertainty, and information gaps. Alternatives or objectives are assessed in fuzzy multi criteria decision making based on a set of ambiguous or fuzzy criteria, or perhaps more accurately, ambiguous or fuzzy constraints.

## 2.5 Types of membership functions

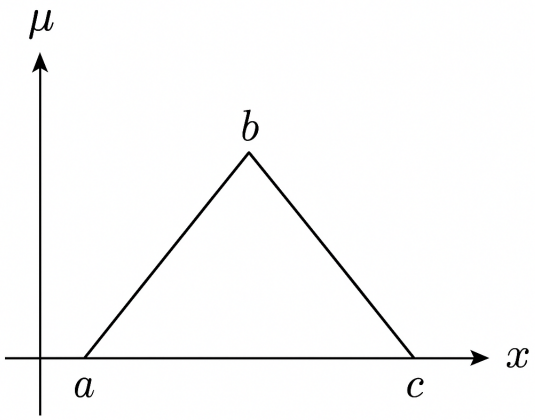
Depending on how the degree of membership is defined, various membership function (MF) types can be used to create fuzzy sets. Lotfi A. Zadeh divided membership functions into two primary categories: Calculating linear (straight) functions is easy and quick. Nonlinear (curved) functions are more complicated, but they occasionally increase accuracy.

Because they save computation time, linear membership functions are frequently chosen. Types of membership functions include the following:

Exponential, Quadratic, Gamma, Quasi-Gaussian, Trapezoid, Gaussian, Triangular, Quasi-Exponential, Singleton, L-Function, S Function, etc.,

Each type has a unique shape and is selected according to the fuzzy system's particular need In our case we are using triangular membership function

### 2.5.1 Triangular membership function




$$\mu_A(x) = \begin{cases} 0 & x \leq a \\ \dfrac{x-a}{b-a} & a < x \leq b \\ \dfrac{c-x}{c-b} & b < x < c \\ 0 & x \geq c \end{cases}$$

Fig 2.5.1: This figure shows triangular membership function

In a triangular membership function we assign a membership value between 0 and 1. If the input value is less than a or is greater than c then the membership value is 0 . The membership value rises from 0 to 1 from a to b and falls from 1 to 0 from b to a

## 2.6 Linguistic variable

A linguistic variable is defined as one whose value is a word or a sentence rather than a precise number in a natural language. A variable was made up of multiple expressions that have a similar level of membership. A language expression (one or more words) that assigns a label to specific data is called a language variable. For example, the linguistic variable “student education level” has the following

values: “very poor,” “poor,” “medium,” “good,” “very good,” “very very good,” etc.

Membership functions are used to represent linguistic values. The meanings of linguistic concepts are ambiguous and nearly context-dependent.

## 2.7 Fuzzification

The process of turning a clear value into a fuzzy one is called ”fuzzification.” Even though they are measured precisely, many real-world quantities are ambiguous, imprecise, or uncertain. Membership functions can be used to represent such variables, enabling fuzzy modeling of otherwise clear data. In this case, triangular fuzzy numbers are used in this study to fuzzify numbers, and each element is given a membership grade.

## 2.8 Defuzzification

The process of converting a fuzzified output into a single crisp value with respect to a fuzzy set .The defuzzified value represents the action to be taken in controlling the process. There are different methods of defuzzification :

Centroid of Area: This method is also known as Center of gravity or Center of area. This technique was developed by Sugeno in 1985. This is the most commonly used technique.

$$z^* = \frac{\int \mu(z)\, z\, dz}{\int \mu(z)\, dz}$$

Bisector method:The bisector is the vertical line that divides the region into two sub-regions of equal area. It is sometimes, but not always coincident with the centroid line.

$$\int_{\alpha}^{z_{BOA}} \mu(z)\, dz = \int_{z_{BOA}}^{\beta} \mu(z)\, dz$$

Weighted Average method :This method can only be used for symmetric output membership functions. Formed by weighting each function in the output by its respective maximum membership value.

$$z^* = \frac{\sum \mu(\bar{z}) \cdot \bar{z}}{\sum \mu(\bar{z})}$$

Where $\bar{z}$ is the centroid of each symmetric membership function

Mean of Maximum: In this method, the defuzzified value is taken as the element with the highest membership values. When there are more than one element having maximum membership values, the mean value of the maxima is taken.

- First of Maxima Method (FOM): This method determines the smallest value of the domain with maximum membership value
- Last of Maxima Method (LOM): Determine the largest value of the domain with maximum membership value.

## 2.9 Ranking of fuzzy sets and fuzzy numbers

The center of gravity, the area covered by the membership function, or the points where fuzzy sets intersect are some examples of features that can be used to order fuzzy quantities. Using multiple ranking methods can yield different rankings from the same fuzzy data because each method focuses on a different aspect.

Ranking fuzzy numbers is crucial for decision-making because the majority of real-world issues are fuzzy rather than strictly probabilistic or deterministic. Prior to making any decisions, fuzzy numbers must be ranked in fuzzy risk analysis and optimization. In order to facilitate ranking, Dr. M. L. Jain initially suggested using fuzzy sets to represent uncertain quantities.Since fuzzy numbers can overlap and are imprecise, they cannot be ranked directly; instead, defuzzification is utilized.

# Chapter 3

# FUZZY MCDM APPROACH

## 3.1 Problem statement

Our problem is to apply fuzzy multi-criteria decision making in ranking phones to get the best choice.Here we are taking Vivo X200,Xiomi 15 ultra,I phone 16 and Samsung S24. This is done on the basis of a small sample survey in which people rated each phone in a 1-5 scale based on the parameters camera,battery storage, and price. So we have a dataset containing these ratings and we use this to get the final ranking and the implementation is carried out in python which involves all the fuzzy logic processes.

This methodology involves several key stages like data preparation, fuzzification, defuzzification,and finally a weighted scoring and ranking system.

## 3.2 Data preparation and loading

The first step involves loading a data set containing user ratings for different phones based on the criterias camera, storage ,battery and price.The data set is in an excel file format.

| PHONES | IPHONE 16 | | | | XIAOMI 15 ULTRA | | | | SAMSUNG S24 | | | | VIVO X 200 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CAMERA | BATTERY | STORAGE | PRICE | CAMERA | BATTERY | STORAGE | PRICE | CAMERA | BATTERY | STORAGE | PRICE | CAMERA | BATTERY | STORAGE | PRICE |
| P1 | 5 | 3 | 1 | 3 | 4 | 4 | 3 | 2 | 4 | 2 | 3 | 3 | 4 | 3 | 3 | 2 |
| P1 | 4 | 4 | 4 | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 3 | 4 | 3 | 4 | 3 | 3 |
| P3 | 4 | 3 | 3 | 3 | 4 | 3 | 4 | 3 | 3 | 4 | 4 | 3 | 5 | 3 | 3 | 3 |
| P4 | 5 | 3 | 4 | 3 | 5 | 4 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 4 | 4 |
| P5 | 4 | 3 | 3 | 3 | 2 | 4 | 4 | 4 | 3 | 4 | 4 | 4 | 3 | 5 | 5 | 4 |
| P6 | 4 | 3 | 3 | 3 | 4 | 5 | 5 | 5 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 5 |
| P7 | 4 | 3 | 2 | 3 | 5 | 5 | 4 | 3 | 4 | 3 | 3 | 4 | 5 | 5 | 3 | 3 |
| P8 | 5 | 4 | 4 | 3 | 3 | 5 | 5 | 4 | 5 | 5 | 4 | 4 | 5 | 5 | 5 | 4 |
| P9 | 4 | 3 | 3 | 3 | 5 | 4 | 5 | 4 | 5 | 5 | 5 | 3 | 5 | 5 | 5 | 5 |
| P10 | 3 | 3 | 4 | 4 | 4 | 5 | 5 | 5 | 4 | 3 | 5 | 5 | 5 | 5 | 5 | 5 |

Table 3.2.1 The above table shows the data from sample survey

## 3.3 Weight assignment

Weights used are the one we got from the sample survey and then these weights are then normalized by python ,so that their sum equals one.

Normalized weight = raw weight / sum of all weights. Weights can be survey-based , expert -based,or equal if unknown. Let the set of criteria be

$$C = \{C_1, C_2, \ldots, C_m\}$$

In our data set $C_i =$ camera, battery, storage, price Each criterion $C_j$ can be assigned $w_j \geq 0$ which reflects its importance in the decision making process.

$\sum_{j=1}^{m} w_j = 1$

| Person | Camera | Battery | Storage | Price |
|---|---|---|---|---|
| P1 | 5 | 4 | 3 | 4 |
| P2 | 4 | 5 | 5 | 4 |
| P3 | 5 | 4 | 4 | 4 |
| P4 | 5 | 3 | 4 | 4 |
| P5 | 4 | 5 | 5 | 3 |
| P6 | 4 | 5 | 4 | 4 |
| P7 | 5 | 5 | 3 | 3 |
| P8 | 5 | 5 | 5 | 4 |
| P9 | 4 | 5 | 5 | 1 |
| P10 | 5 | 5 | 5 | 5 |

Table 3.3.1

This Table shows the importance of each criteria ( weights) rated by individuals in our sample survey.

Then the average of camera ,battery ,storage,price is evaluated. Camera - 4.6 , battery - 4.6 , storage - 4.3 , price - 3.6

| Criterion | Normalized Weight |
|---|---|
| Camera | 0.269005848 |
| Battery | 0.269005848 |
| Storage | 0.251461988 |
| Price | 0.210526316 |

Table 3.3.2

The above table shows normalized weights

## 3.4 Fuzzification

In our data set each rating is given on a 1-5 scale. In fuzzification crisp values are converted into fuzzy sets (low ,med,high) using triangular membership function (TMF).

### 3.4.1 Dynamic triangular points

For each criterion $C_j$ , the triangular points are calculated dynamically from data . We define three triangular membership functions:

- Low (a,b,c) = min, min, mean

- medium( a,b,c) =min,mean,max
- High (a,b,c)= mean, max , max

In fuzzy logic the researcher or the algorithm defines the membership functions.Either it is expert driven or data driven. So in this python itself sets the low, medium, high based on our data. This can work for any datasets that is why python code uses it .The triangular membership functions for this problem were constructed dynamically from the dataset using min, mean, and max values of each criterion. This makes fuzzy sets adapt to the data range.

- In low we want values near min and towards mean
- Medium means average ,so b= mean and with boundaries min and max
- High means we want value near the maximum .

For eg. camera ratings across all phones is taken and its min,mean,max value is determined.

| | Criterion | Fuzzy Set | a | b | c |
|---|---|---|---|---|---|
| 0 | Camera | Low | 2.00000 | 2.000 | 3.65000 |
| 1 | Camera | Medium | 2.55000 | 4.200 | 4.80000 |
| 2 | Camera | High | 4.40000 | 5.000 | 5.00000 |
| 3 | Battery | Low | 2.00000 | 2.000 | 3.42500 |
| 4 | Battery | Medium | 2.47500 | 3.900 | 4.72500 |
| 5 | Battery | High | 4.17500 | 5.000 | 5.00000 |
| 6 | Storage | Low | 1.00000 | 1.000 | 3.11875 |
| 7 | Storage | Medium | 1.70625 | 3.825 | 4.70625 |
| 8 | Storage | High | 4.11875 | 5.000 | 5.00000 |
| 9 | Price | Low | 2.00000 | 2.000 | 3.21875 |
| 10 | Price | Medium | 2.40625 | 3.625 | 4.65625 |
| 11 | Price | High | 3.96875 | 5.000 | 5.00000 |

Table 3.4.1(a)

This table shows triangular membership function parameters (a,b,c) for each criterion. Using these a,b,c values for each parameter the $\mu$ values are calculated .

### 3.4.2 Triangular membership function

The 'trimf' function calculates the degree to which a given value belongs to each of the fuzzy sets (low,medium,high). In the 'trimf ' function as written in the code, the very first check performed is x $\leq$ a or x$\geq$ $c$. So after the initial check for the outer boundaries ( $\leq$ a or $\geq$ c.), the code then checks if the value is on the left slope (a $<$ $x$ $\leq$ b) or the right slope (b $<$ x $<$c) and then calculates the membership degree accordingly for more efficiency.

This conditional structure (if/elif/else) is a common way to implement piecewise functions in programming. The elif and else blocks naturally handle the remaining cases (the slopes) after the simple 0-membership cases are excluded.

- If x $\leq$ a or x$\geq$ $c$ membership is 0
- If a$<$ $x$ $\leq$ b, membership is (x-a)/(b-a)
- If b $<$ x $<$c membership is (c-x)/(c-b)

In some cases , ratings might fall outside a category,which gives membership value 0 . To solve this we made sets to overlap,so a rating can partially belong to two sets at the same time.This ensures that no value falls outside. When taking i phone camera rating of the first person , 5 that is , x=5

- For camera low: a=2 , b=2,c= 3.65

$x$ $>$c so $\mu$ =0

- Medium : a=2.55, b=4.2, c=4.80

$x$ $>$c, $\mu$ =0

- High : a=4.4 , b=5 , c= 5

x=b=c $\mu$ =1 Apply the membership function to individual ratings and find all $\mu$ values.

```python
# ==============================
# 5 Triangular membership function
# ==============================
def trimf(x, a, b, c):
    x = float(x)
    if x < a or x > c:
        return 0.0
    elif a <= x <= b:
        return (x - a)/(b - a) if b!=a else 1.0
    else: # b < x <= c
        return (c - x)/(c - b) if c!=b else 1.0


def fuzzify_dynamic(value, criterion):
    memberships = {}
    # Use abc_dict and trimf for triangular fuzzification
    for k,(a,b,c_val) in abc_dict[criterion].items():
        memberships[k] = trimf(value,a,b,c_val)
    return memberships
```

Fig:3.4.2 This shows the python code used to calculate the triangular membership function.

## 3.5 Centroid values( representative) for each fuzzy term

For each triangular fuzzy set a numeric representative r is used for defuzzification. In a triangle(a,b,c) the centroid is $\frac{a+b+c}{3}$

Our code dynamically computes for each criterion and each term ( low ,medium,high)

Taking camera , fuzzy sets for camera are: Low - ( 2,2,3.65) Medium - ( 2.55 ,4.2, 4.80) High - (4.4,5,5) Then, representative values or (centroids)$r_k = \frac{a+b+c}{3}$

r( low) = ( 2+2+3.65) / 3 = 2.55 r( med) = (2.55+4.2+4.80) / 3 = 3.85 r(high) = ( 4.4+5+5) / 3 = 4.8

| criterion | Low | Medium | High |
|---|---|---|---|
| Camera | 2.55 | 3.85 | 4.8 |
| Battery | 2.475 | 3.7 | 4.725 |
| Storage | 1.70625 | 3.4125 | 4.70625 |
| Price | 2.40625 | 3.5625 | 4.65625 |

Table 3.5 This table shows the cetroid values

## 3.6 Defuzzification( weighted average method)

Defuzzification converts these fuzzy values back to a crisp numeric score for each criterion. So we get the membership values $\mu_k(x)$ and the representative values

$r_k$,then the defuzzified value Here for one criterion camera we have low , med, high with membership values $\mu_{\text{low}}, \mu_{\text{med}}, \mu_{\text{high}}$. Each fuzzy set has a representation value $r_k$. Here memberships act as weight because it represents how strongly the input belongs to each fuzzy category.

$$z^* = \frac{\sum_k \mu_k \cdot r_k}{\sum_k \mu_k}$$

$$= \frac{(0 \cdot 2.55) + (0 \cdot 3.85) + (1 \cdot 4.8)}{0 + 1 + 1} = 4.8$$

this is the camera defuzzified score for an individual when that person rated 5. Here defuzzification is done per person, per phone. So in this case taking first person we evaluate a defuzzified score for each criterion camera, battery, storage and price.

```
        # Defuzzification (weighted average method)
        # Fallback to original value if sum of memberships is 0
        defuzz_val = sum(mu[k]*rep_values_dict[c][k] for k in mu)/sum(mu.values()) if sum(mu.values())>0 else val


        # Save original, mu values, defuzzified
        row_data[c+"_Original"] = val # Store the original individual rating
        row_data[c+"_LowMu"] = round(mu.get('Low', 0.0),3)
        row_data[c+"_MediumMu"] = round(mu.get('Medium', 0.0),3)
        row_data[c+"_HighMu"] = round(mu.get('High', 0.0),3)
        row_data[c+"_Defuzz"] = round(defuzz_val,3)

        weighted_sum += defuzz_val * weights[c]

    # This WeightedScore is for the individual rating entry
    row_data["WeightedScore"] = round(weighted_sum,3)
    final_rows.append(row_data)

# The final_df now contains one row per ORIGINAL rating entry
final_df = pd.DataFrame(final_rows)
```

Fig:3.6(a) This shows the python code implementation of defuzzification and weighted score calculation.

| | Phone | Camera_Original | Camera_LowMu | Camera_MediumMu | Camera_HighMu | Camera_Defuzz | Battery_Original | Battery_LowMu | Battery_MediumMu | Battery_HighMu | .. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | I phone16 | 5 | 0.0 | 0.000 | 1.0 | 4.80 | 3 | 0.298 | 0.368 | 0.0 | .. |
| 1 | I phone16 | 4 | 0.0 | 0.879 | 0.0 | 3.85 | 4 | 0.000 | 0.879 | 0.0 | .. |
| 2 | I phone16 | 4 | 0.0 | 0.879 | 0.0 | 3.85 | 3 | 0.298 | 0.368 | 0.0 | .. |
| 3 | I phone16 | 5 | 0.0 | 0.000 | 1.0 | 4.80 | 3 | 0.298 | 0.368 | 0.0 | .. |
| 4 | I phone16 | 4 | 0.0 | 0.879 | 0.0 | 3.85 | 3 | 0.298 | 0.368 | 0.0 | .. |
| 5 | I phone16 | 4 | 0.0 | 0.879 | 0.0 | 3.85 | 3 | 0.298 | 0.368 | 0.0 | .. |
| 6 | I phone16 | 4 | 0.0 | 0.879 | 0.0 | 3.85 | 3 | 0.298 | 0.368 | 0.0 | .. |
| 7 | I phone16 | 5 | 0.0 | 0.000 | 1.0 | 4.80 | 4 | 0.000 | 0.879 | 0.0 | .. |
| 8 | I phone16 | 4 | 0.0 | 0.879 | 0.0 | 3.85 | 3 | 0.298 | 0.368 | 0.0 | .. |
| 9 | I phone16 | 5 | 0.0 | 0.000 | 1.0 | 4.80 | 3 | 0.298 | 0.368 | 0.0 | .. |

Table 3.6(b) This table shows the $\mu$ values and defuzzified scores

## 3.7 Weighted aggregation and finding weighted scores

In this step we multiply each defuzzified score with the corresponding weight of that criteria and then take its sum to get the weighted score for each person's rating for each phone. So we will get 10 weighted scores for each of 10 people who rated i phones and then take its average to get a single score for Iphone. W =$\sum$D . $w_c$

$w_c$ is the weights of each criterion W = (camera defuzzified score). (0.26900) + (battery defuzzified score ) . (0.26900) ..........

### 3.7.1 Aggregation across all people ( per phone)

And then , average the weighted scores of all people for the same phone to get the overall phone score: Phone score =$\sum_{i=1}^{n} \frac{W}{N}$ N = number of people, in our case it is 10 . The python code groups the 'final_df' by the phone name (phonec_ol). So, all the rows in 'final_df' that correspond to "I phone16" are grouped together.Then, for each group (each phone), it calculates the mean (average) of the WeightedScore values within that group.So, if there are 10 rows in 'final_df' for "I phone16", the code will take those 10 WeightedScore values and calculate their average. This average WeightedScore is then considered the overall score for "I phone16".

## 3.8 Ranking

The ranking 'DataFrame' contains each phone and its corresponding overall fuzzy score. Then ranking is done by sorting this ranking 'data frame' based on the

weighted score in descending order that is from highest to lowest.

# Chapter 4

# EXPERIMENTAL RESULTS AND ANALYSIS

## 4.1 Overview of analysis

In this chapter the results of a mobile selection problem based on fuzzy multi-criteria decisions are presented . We took 4 latest phones and the criterias considered are battery , camera, storage and price.

## 4.2 Survey data used

The primary data for this study was collected through a small survey in which people were asked to rate 4 phones( iPhone 16, Vivo X200, Xiaomi 15 Ultra, Samsung S24) on a 1-5 scale based on the criteria camera , battery ,storage and price. This data set was used as input for the FMCDM analysis to determine the overall ranking of the phones.

## 4.3 Application of FMCDM

Survey Ratings → Fuzzification → Centroid Calculation → Defuzzification → Weighted Aggregation → Aggregation Across Respondents → Final Ranking

## 4.4 Final rankings and survey results

| Rank | Phone | Weighted score rounded |
|---|---|---|
| 1 | Vivo X200 | 4.063 |
| 2 | Xiaomi 15 ultra | 3.896 |
| 3 | Samsung S24 | 3.687 |
| 4 | I Phone 16 | 3.474 |

Table 4.4.1 This table shows the final ranking of smart phones based on the sample survey

So here, Vivo X200 is ranked top among other phones.

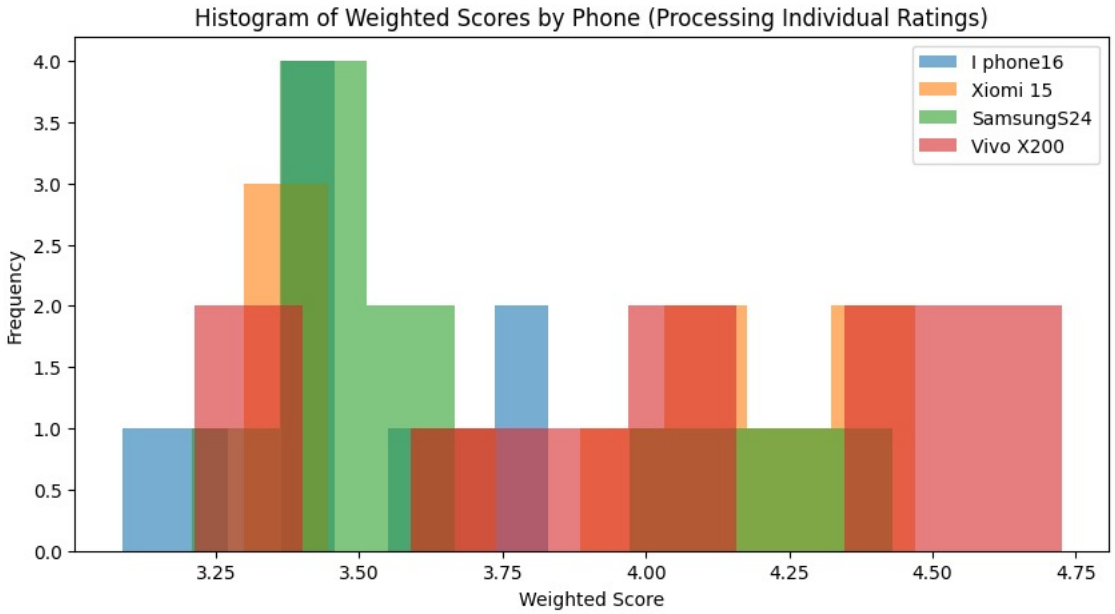



Fig:4.4.1

In this graph the y-axis is labeled as frequency which is the height of each coloured bar. Along the x-axis is the weighted score. The height of the bar tells us how many individual rating entries of a phone resulted in a weighted score within that particular range.

- Vivo X200 (red bars) : from the graph it is understood that most of the individual ratings of Vivo X200 consistently resulted in high weighted scores. This appears to be the highest overall.

- Xiaomi 15 (orange bars) : Xiaomi also shows its individual scores are generally in the highest score ranges,although there is a slight shift to left compared to Vivo X200 .

- Samsung S24 (green bars) : the individual scores of Samsung S24 are in the mid - high range. Though many scores are higher ,they are not as high as Vivo X200 and Xiaomi 15.

- I phone16 ( blue bars) : Its individual scores are the most spread out, with most of the bars in the lower score ranges compared to other phones. While it has some higher scores, the presence of lower scores pulls it down. It has the lowest score and is ranked 4.

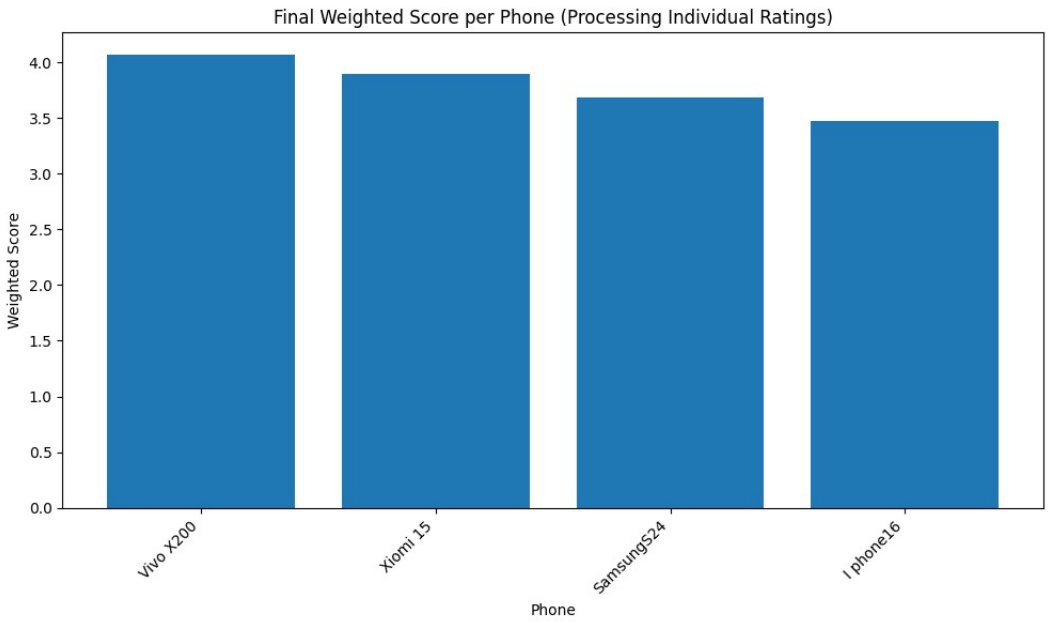



Fig:4.4.2

This graph shows a single bar for each phone. The height of the bar gives the average weighted score for that phone. It directly represents the final ranking based on the average weighted scores per phone.

## 4.5 Comparison with market ratings

Additional information was gathered from Flipkart, which offers user ratings for the chosen mobile phones based on factors including battery, camera, storage, and

cost, in order to verify the outcomes of the survey-based fuzzy MCDM model. This dataset was subjected to the same fuzzy assessment procedure (fuzzification, defuzzification, aggregation, and ranking) using Python.

It's interesting to note that the Flipkart dataset's results and our survey-based findings agreed that Vivo X200 was the best-performing smartphone out of all the options taken into consideration. This consistency shows that the fuzzy decision-making model created in this study is consistent with market ratings.

| Rank | Phone | Weighted score rounded |
|---|---|---|
| 1 | Vivo X200 | 4.625 |
| 2 | I Phone 16 | 4.531 |
| 3 | Xiaomi 15 Ultra | 4.503 |
| 4 | Samsung S24 | 4.48 |

Table 4.5.1 This table shows the final ranking of smartphones based on flipkart data

This shows the final ranking of phones using the flipkart data. We can see that flipkart ratings show that all 4 phones somewhat have equal preference,but Vivo X200 stands slightly above all.

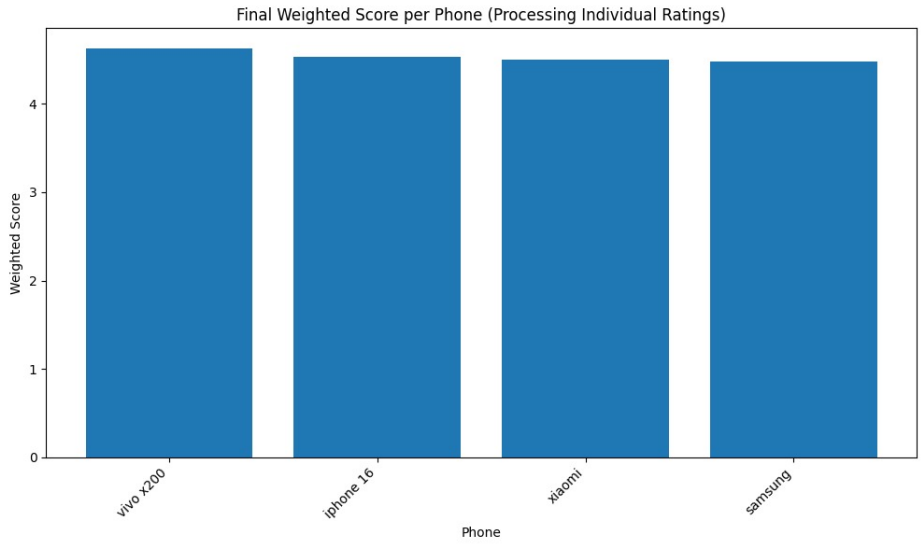



Fig:4.5.1 This figure shows the bar graph of the final weighted score per phone

On comparing survey result and flipkart results:

- Survey result -

Vivo X200> Xiaomi 15 ultra > Samsung S24> iPhone 16

- Flipkart result -

Vivo X200 >iPhone 16 > Xiaomi 15 ultra > Samsung S24

Even though the order of ranking is different , both methods identified Vivo X200 as the top-ranked phone. Flipkart data showed very close scores among all phones. In contrast, the survey data reflected clearer preferences, with Xiaomi and Samsung performing better compared to iPhone 16.

## 4.6 Future scope and conclusion

We can expand this sample survey and use this python code to a large data set of different phones from several brands and by considering a wide range of parameters like camera ,battery, storage, display, performance,design etc for more large-scale decision making. Personalized Recommendation system. We can use this for suggesting the best phone for individual users based on their personal preferences. The fuzzy MCDM we used here can be applied to other areas like selection of laptops, cars,education etc.

## 4.7 Conclusion

This study used a Fuzzy Multi-Criteria Decision-Making (FMCDM) approach to evaluate and rank mobile phones based on various parameters. A survey considered criteria such as battery, storage, camera, and price. Additionally, Flipkart public ratings gave market-based data for comparison. The fuzzy logic framework involved fuzzification, defuzzification, weighted aggregation, and final ranking using Python. From the survey data, Vivo X200 was the top-ranked mobile phone. It was followed by Xiaomi, Samsung, and iPhone. When processing Flipkart market ratings through the same fuzzy model, Vivo X200 again ranked as the best phone, although the order of the other phones changed slightly. The consistent results between the survey data and market ratings confirm the effectiveness and reliability of the fuzzy MCDM method. Overall, the project shows that fuzzy logic can effectively address vagueness and subjectivity in decision-making problems like mobile phone selection. It produces results that match both consumer perceptions and real-world market trends.

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