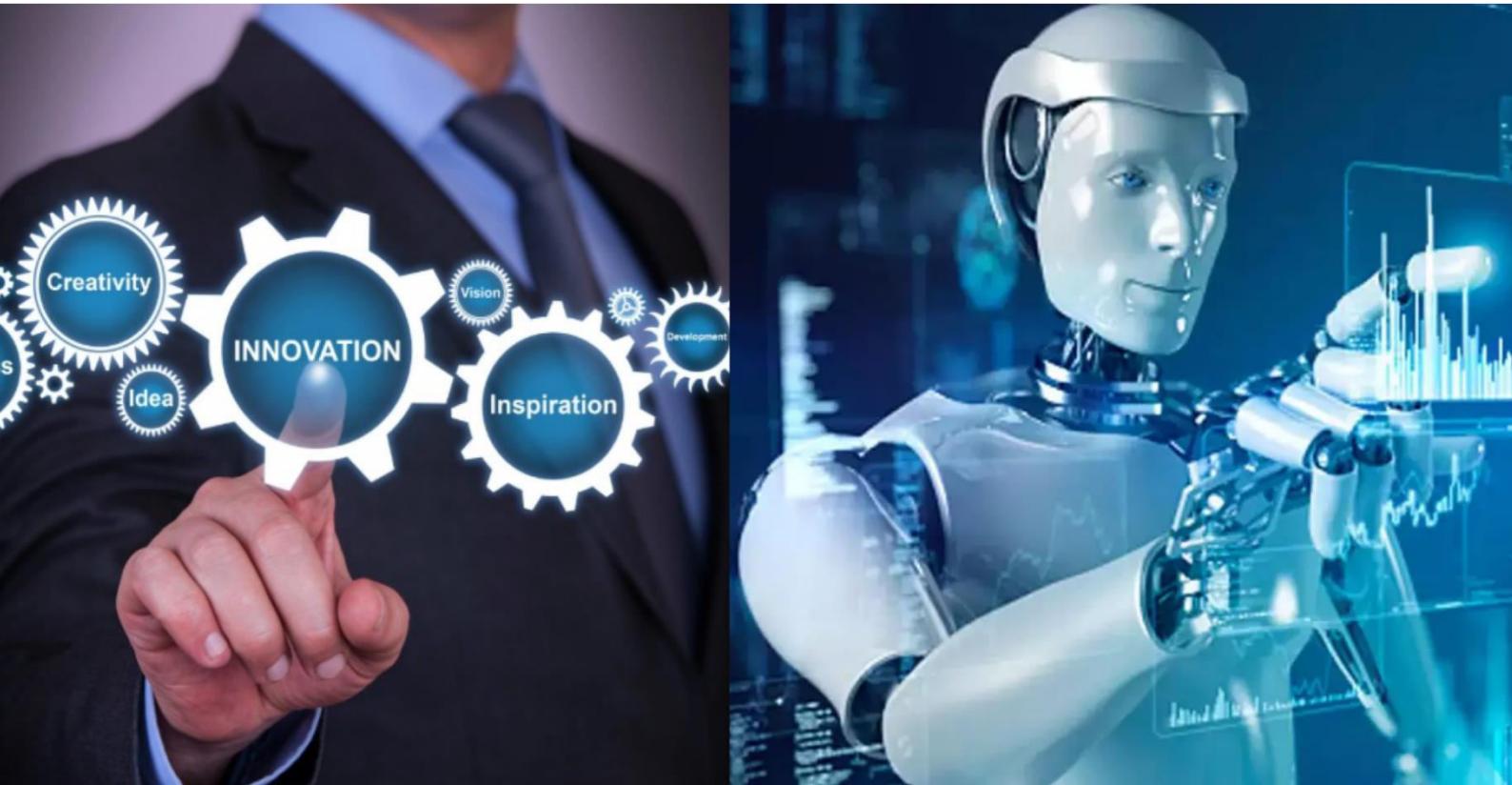




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# **Fuzzy Cognitive PDUS-MOORA Decision Model for Prioritizing Women's Safety using Perceptual -Dynamic Uncertainty Set**

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**ABSTRACT:** Women's safety has become a crucial concern in social environments. Identifying and prioritizing safety measures based on perception and contextual factors is essential for effective policy-making. This study introduces a fuzzy-based decision model to evaluate women's safety using the PDUS MOORA (Perceptual Dynamic Uncertainty Set Multi-Objective Optimization on the Basis of Ratio Analysis) method. A structured survey was conducted to collect data from female participants using perceptual dynamic uncertainty variables to represent subjective judgments on various safety criteria. The fuzzy model translates imprecise human opinions into meaningful numerical representations. The PDUS-MOORA method is then applied to rank these safety alternatives by normalizing and comparing their performance scores across multiple dimensions. The integration of fuzzy logic with the PDUS-MOORA technique ensures a balanced, data-driven, and context-sensitive decision-making process. The outcome provides a prioritized list of effective safety measures in enhancing women's security in a practical and informed manner.

**KEYWORDS:** Fuzzy logic, MOORA method, decision-making, women safety.

## **I. INTRODUCTION**

Women's safety has emerged as one of the most critical social concerns in recent years. Due to the increasing number of safety-related incidents in public and semi-public environments, there is a growing need to design appropriate measures that ensure security, comfort, and freedom of movement for women. In reality, the perception of safety is influenced by multiple dynamic factors such as environment, time, location type, previous experiences, and external events. These perceptions are often uncertain, imprecise, and subjective, making the evaluation of women's safety a challenging multi-criteria decision-making task.

Traditional methods of decision-making struggle to handle human opinions because they are rarely crisp or fully certain. To address this challenge, recent research has focused on fuzzy logic, neutrosophic systems, Pythagorean fuzzy sets, and other uncertainty-based mathematical tools. These approaches help convert vague human judgments into mathematically meaningful structures. Building upon these developments, the concept of the Perceptual Dynamic Uncertainty Set (PDUS) provides a more realistic way of representing human perception.

Uncertainty in human thinking and real-world systems is rarely stable. As situations change, the level of confidence, doubt, or disagreement also shifts, creating a moving boundary of perception. Traditional models capture uncertainty at a single point in time, but they do not reflect how it grows, reduces, or transforms with new experiences or information. To bridge this gap, the Dynamic Uncertainty Set (DUS) was developed as a modern framework that represents uncertainty as a flexible and evolving entity.

The DUS framework recognizes that truth, hesitation, and false belief are not static quantities. Instead, they interact with each other and change depending on context, learning, and external triggers. By integrating components that measure both the present state of uncertainty and its possible direction of change, the Dynamic Uncertainty Set provides a richer and more adaptive mathematical structure. This makes it possible to observe how certainty stabilizes, how confusion emerges, or how opinions drift over time.

In essence, the Dynamic Uncertainty Set offers a realistic way to model uncertainty as a living process rather than a fixed value. Its ability to capture continuous transformation makes it an essential foundation for modern decision-making and intelligent analysis.

To prioritize safety measures effectively, this study integrates the PDUS framework with the MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) technique. MOORA is a powerful and computationally simple multi-criteria decision-making method capable of ranking alternatives by evaluating their performance across several dimensions. By normalizing PDUS-based scores and analyzing benefit and cost criteria, the PDUS-MOORA model identifies which safety measures or locations offer the highest level of perceived safety.

The proposed Fuzzy Cognitive PDUS-MOORA Decision Model therefore achieves two major objectives:

1. It captures the dynamic psychological perceptual of safety using PDUS.
2. It prioritizes safety measures or places using MOORA in a transparent, data-driven manner.

The integration of PDUS with MOORA ensures a balanced evaluation considering subjective (fuzzy) and objective (quantitative) components. This makes the decision-making process more realistic, context-sensitive, and applicable for policymakers, urban planners, and security departments. Ultimately, the outcome of this model is a ranked list of environments or safety measures, highlighting which ones are most effective for enhancing women's safety.

The remaining sections of this work are structured as follows: Section II deals with the review of literature followed by preliminary concepts in Section III. In section IV, we have introduced the new Fuzzy Cognitive Perceptual Dynamic Uncertainty Set and its operators. In section V, we have proposed the algorithm for the PDUS-MOORA followed by a real life example based on survey data in section VI. Section VII summarizes the conclusions and implications of the proposed model.

## II. LITERATURE SURVEY

The foundations of handling uncertainty were laid by Zadeh [18] in 1965, who transformed classical crisp data into fuzzy representations using membership degrees bounded within [0,1]. This initial framework captured only the degree of truth. To better characterize imprecision, Zadeh [19] later expanded his theory by introducing interval-valued fuzzy sets in 1975, allowing membership values to vary within an interval rather than a single point. Building on these developments, Atanassov [3] presented intuitionistic fuzzy sets in 1986, incorporating both membership and non-membership values to reflect hesitation in decision-making scenarios. A major conceptual shift occurred with the introduction of neutrosophic sets by Florentin Smarandache [13], [10], [13–14] in 1995, where uncertainty was modeled through three independent components-truth, indeterminacy, and falsity each taking values in the real unit interval. This richer structure enabled a more comprehensive representation of vague and inconsistent information.

Studies by Abdel Basset et al. [1,2] utilized trapezoidal neutrosophic numbers within a neutrosophic AHP-Delphi framework, illustrating their effectiveness for group-based decision-making in MADM environments. Similarly, the work of Deli and Subas [5,6] applied single-valued neutrosophic numbers to multi-attribute decision-making and presented ranking strategies that are well suited for problems with multiple interacting criteria.

Yager [15,16,17] introduced the Pythagorean fuzzy set model, an extension of classical fuzzy theory that offers enhanced flexibility in expressing uncertainty. Building on this concept, Zhang and Xu [21] adapted the TOPSIS method to operate under Pythagorean fuzzy conditions, allowing alternatives to be evaluated through their distance from an ideal solution. Garg's extension [8] further strengthened the TOPSIS technique for uncertain environments, improving its precision in sectors such as public health where expert consensus is vital.

MOORA and MULTIMOORA have also gained strong relevance within MADM due to their computational simplicity and adaptability. Setyono and Sarno [12] applied MOORA and COPRAS for supplier evaluation, while Pérez Domínguez et al. [11] implemented MULTIMOORA for assessing industrial maintenance systems. Geetha et al [9] demonstrated the usefulness of these methods in the context of healthcare waste management. Additionally, Zaitun et al [20] employed the MOORA framework to identify beneficiaries of the Smart Indonesia Program. Zhi-Hui Li [22]

further advanced the MULTIMOORA approach by integrating hesitant fuzzy sets, improving its capability for complex group decision-making tasks.

Recent studies emphasize the need for dynamic uncertainty modeling, as human perception evolves over time due to incidents, social awareness, and situational contexts. Current fuzzy and neutrosophic frameworks do not explicitly incorporate components such as stability or perception drift, which are crucial for realistically evaluating safety environments.

To address these gaps, our work proposes the Perceptual Dynamic Uncertainty Set (PDUS) and integrates it with the MOORA ranking method. This approach enables a more accurate and context-aware analysis of women's safety alternatives by combining multi-dimensional perception factors with a robust decision-making framework.

### III. METHODOLOGY

**Definition 3.1[7]: Fuzzy set**

A Fuzzy set  $F$  in universe  $P$  is characterized by a membership function  $\mu_F(x): P \rightarrow [0,1]$

Where  $\mu_F(P)$  represents the degree of membership of an element  $P$  in the set  $F$ .

**Definition 3.2[3]: Intuitionistic Fuzzy Set**

An intuitionistic fuzzy set  $A$  in  $X$  is defined as:  $A = \{(x, \mu_A(x), v_A(x)): x \in X\}$  with the condition  $0 \leq \mu_A(x) + v_A(x) \leq 1$ .

Here,

- $\mu_A(x)$  – membership
- $v_A(x)$  – nonmembership

**Definition 3.3[13]: Neutrosophic set**

A Neutrosophic set  $P$  in  $X$  expressed as  $P(x) = \{(T_x, I_x, F_x) | x \in X\}$  where  $T_x, I_x$ , and  $F_x$  represents the truth, indeterminacy, and falsity membership function respectively where,

$$0 \leq T_x + I_x + F_x \leq 3$$

**Definition 3.4[14]: Single Valued Neutrosophic Set**

A single valued neutrosophic set  $A$  on  $X$  is written as  $A = \{x, T_A(x), I_A(x), F_A(x): x \in X\}$  where  $X$  be a space of discourse.  $T_A(x): X \rightarrow [0,1]$ ,  $I_A(x): X \rightarrow [0,1]$ ,  $F_A(x): X \rightarrow [0,1]$  with  $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$

**Definition 3.5[4]: Uncertainty Set**

An Uncertainty Set is a mathematical representation of all possible values that an uncertain parameter can assume. It defines the boundaries within which the uncertain data may vary, allowing decision-makers to create solutions that remain effective under different conditions.

The general mathematics form of an uncertainty set is:

$$u = \{x \in \mathbb{R}^n: g_i(x) \leq 0, i = 1, 2, \dots, m\}$$

$u$  = uncertainty set

$x$  = uncertain parameter

$g_i(x) \leq 0$  = constraints describing all possible values  $x$  that can take

$m$  = number of defining conditions

**Definition 3.6[7]: Decision matrix**

Let there be  $m$  alternatives  $P_i = (1, 2, \dots, m)$  and  $n$  attributes  $R_j = (1, 2, \dots, n)$ . The decision matrix is constructed as  $M = [S_{ij}]_{m \times n}$  for each pair  $(P_i, R_j)$  and the assessment is represented by a element  $S_{ij} = [T_{ij}, I_{ij}, F_{ij}]$ .

### IV. PROPOSED METHODOLOGY

#### PERCEPTUAL DYNAMIC UNCERTAINTY SET (PDUS)

**Definition 4.1:**

Perceptual Dynamic Uncertainty Set (PDUS): Let  $X$  be a finite set of alternatives under evaluation. A  $PDUS(x)$  in  $X$  is defined as

$$P = \{(T_x, I_x, F_x, S_x, D_x) | x \in X\}$$

Where  $T_x, I_x, F_x, S_x, D_x$  denote the truth degree, indeterminacy, falsity, stability, and drift factors, each taking values in  $[0,1]$ .

The PDUS Set:

T – Truth degree

I – Indeterminacy degree

F – Falsity degree

S – degree of Stability

D – Drift factor

These variables reflect real-world dynamic perceptions, making PDUS ideal for analyzing decision making where opinions may change based on time, context, or recent incidents.

**Definition 4.2:** PDUS Complement

The complement of a PDUS element  $x$ . is defined as

$PDUS(x) = \langle F_x, 1 - I_x, T_x, S_x, 1 - D_x \rangle$  where the truth and falsity components are reversed, indeterminacy and drift factors change, while stability remains unchanged.

**Definition 4.3:**

Let  $A = (T_1, I_1, F_1, S_1, D_1)$  and  $B = (T_2, I_2, F_2, S_2, D_2)$  be two PDUS number The operations

$A+B = (T_1 + T_2, I_1 + I_2, F_1 + F_2, S_1 + S_2, D_1 + D_2)$

$A-B = (T_1 - T_2, I_1 - I_2, F_1 - F_2, S_1 - S_2, D_1 - D_2)$

$kA = (k T_1, k I_1, k F_1, k S_1, k D_1)$  ( $k > 0$ )

**Fuzzy Cognitive Perceptual Dynamic Uncertainty Set and it's operators**

**Definition 4.4:**

Let  $P = \{< x, [T_P, I_P, F_P, S_P, D_P] >\}$  and

$S = \{< r, [T_S, I_S, F_S, S_S, D_S] >\}$  be two Perceptual Dynamic Uncertainty Sets, then

$P+S = \{< x+r, [T_P + T_S - T_P T_S], [I_P I_S], [F_P F_S], [S_1 + S_2 - S_1 S_2], [D_1 + D_2 - D_1 D_2] >\}$

$P.S = \{< x r, [T_P T_S], [I_P + I_S - I_P I_S], [F_P + F_S - F_P F_S], [S_P S_S], [D_P D_S], >\}$

**Definition 4.5:**

The Score function(sc) of a perpetual dynamic uncertainty value is defined as

$$Sc(P) = \frac{T_P(x) \cdot S_P(x) (1 - D_P(x))}{1 + I_P(x) + F_P(x) + D_P(x)}$$

**Definition 4.6:**

Let  $P_1, P_2$  be Perceptual Dynamic Uncertainty Sets then their operators are defined as follows:

$$P_1 = \{T_1, I_1, F_1, S_1, D_1\}, P_2 = \{T_2, I_2, F_2, S_2, D_2\}$$

$$1. \quad P_1 \cup P_2 = \left\{ < \begin{array}{l} x, [\max(T_1(x), T_2(x))], \\ [\min(I_1(x), I_2(x))], \\ [\min(F_1(x), F_2(x))], \\ [\max(S_1(x), S_2(x))], \\ [\min(D_1(x), D_2(x))] \end{array} > / x \in X \right\}$$

$$2. \quad P_1 \cap P_2 = \left\{ < \begin{array}{l} x, [\min(T_1(x), T_2(x))], \\ [\max(I_1(x), I_2(x))], \\ [\max(F_1(x), F_2(x))], \\ [\min(S_1(x), S_2(x))], \\ [\max(D_1(x), D_2(x))] \end{array} > / x \in X \right\}$$

$$3. P_1 \oplus P_2 = \left\{ \begin{array}{l} x, [T_1 + T_2 - T_1 T_2], \\ [I_1 I_2], \\ [F_1 F_2], \\ [S_1 + S_2 - S_1 S_2], \\ [D_1 + D_2 - D_1 D_2] \end{array} \right\} / x \in X$$

$$4. P_1 \otimes P_2 = \left\{ \begin{array}{l} x, [T_1 T_2], \\ [I_1 + I_2 - I_1 I_2], \\ [F_1 + F_2 - F_1 F_2], \\ [S_1 S_2], \\ [D_1 D_2] \end{array} \right\} / x \in X$$

$$5. \alpha P = \left\{ \begin{array}{l} x, [(T_P(x))^\alpha], \\ [1 - (1 - (I_P(x))^\alpha)], \\ [1 - (1 - (F_P(x))^\alpha)], \\ [(S_P(x))^\alpha], \\ [(D_P(x))^\alpha] \end{array} \right\} / x \in X$$

$$6. P^\alpha = \left\{ \begin{array}{l} x, [1 - (1 - (T_P(x))^\alpha)], \\ [(I_P(x))^\alpha], \\ [1 - (1 - (F_P(x))^\alpha)], \\ [1 - (1 - (S_P(x))^\alpha)], \\ [1 - (1 - (D_P(x))^\alpha)] \end{array} \right\} / x \in X$$

## V. ALGORITHM FOR PDUS-MOORA

### Step 1: Define the Decision Matrix

- Identify the alternatives  $P_1, P_2, P_3, \dots, P_n$
- Identify the criteria /attributes  $C_1, C_2, C_3, \dots, C_m$
- Construct a matrix  $X = [X_{ij}]$  where  $X_{ij}$  is the performance value of alternatives  $i$  under attributes  $j$

$$P_{ij} = \begin{bmatrix} P_{11}P_{12}P_{13} \dots \dots \dots P_{1n} \\ P_{21}P_{22}P_{23} \dots \dots \dots P_{2n} \\ P_{31}P_{32}P_{33} \dots \dots \dots P_{3n} \\ \vdots \\ \vdots \\ P_{m1}P_{m2}P_{m3} \dots \dots \dots P_{mn} \end{bmatrix}$$

### Step 2: Score Function

The perpetual dynamic uncertainty values are reduced to the PDUS score matrix using the score function.

$$Sc(P) = \frac{T_P(x) \cdot S_P(x) \cdot (1 - D_P(x))}{1 + I_P(x) + F_P(x) + D_P(x)}$$

### Step 3: Normalize the Decision Matrix

Normalize each PDUS t value to bring values into a comparable range

$$S_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{j=1}^n (x_{ij})^2}}$$

For PDUS, normalization is applied separately for  $T, I, F, S$  and  $D$ .

### Step 4: Apply Weights to the Criteria

- Assign a weight  $w_j$  to each criterion  $c_j$  based on its importance.
- Multiply normalized values by their respective weights

$$v_{ij} = w_j \times r_{ij}$$

**Step 5: Apply PDUS MOORA Ratio Analysis**

Compute the PDUS MOORA ratio.  $(\hat{y}_i) = \frac{1}{n} \sum_{j=1}^n (\mathcal{S}_{ij}^* - \mathcal{S}_j^{ref})$

Here, favourable criteria are added and non-favourable criteria are subtracted.

The reference point represents the ideal value for each criterion after normalization. It is obtained by taking the maximum for favourable criteria and the minimum for non-favourable criteria.

$(\hat{y}_i)$  = Final score for alternatives  $P_i$

$n$  = Number of criteria

$\mathcal{S}_{ij}^*$  = Normalized value

$\mathcal{S}_j^{ref}$  = Reference point

**Step 6: Ranking of Alternatives**

- Rank all alternatives based on the descending order of  $y_i$ .
- The alternative with the highest score is the best choice.

**Step 7: Decision Making**

Choose the best alternative considering the PDUS–MOORA scores and decision-maker's preference.

**VI. CASE STUDY**

In this research work, PDUS values are generated based on a structured survey collected from women across different environments such as public transport, educational institutions, workplace areas, and residential surroundings. Since human judgments are imprecise, these PDUS values are converted into fuzzy numerical representations, enabling systematic comparison of safety-related alternatives.

To evaluate women's safety across different urban environments, a PDUS–MOORA decision-making framework is applied. The objective of this case study is to identify which location provides better safety conditions and which safety measures contribute most effectively to overall protection.

**Three distinct locations are considered as alternatives:**

P<sub>1</sub>: College, P<sub>2</sub>: Bus Stand, P<sub>3</sub>: IT Company

P<sub>1</sub>: College

A semi-secure educational zone where students frequently move between classrooms and common areas. Safety depends on campus discipline, awareness programs, and the presence of trained staff. It reflects a balanced environment with both controlled and open-access regions.

P<sub>2</sub>: Bus Stand

An open public hub with unpredictable crowd patterns throughout the day. Safety varies widely due to changing lighting, temporary gatherings, and public access. It is a sensitive area where surveillance and timely interventions are crucial.

P<sub>3</sub>: IT Company

A professional workplace supported by structured security protocols and restricted entry. Most movements are monitored, offering consistent safety conditions. The environment benefits from organized infrastructure and corporate safety policies.

**The assessment is based on three critical safety factors as criteria:**

C<sub>1</sub>: Self-defence Training, C<sub>2</sub>: CCTV Surveillance, C<sub>3</sub>: Helpline Services

C<sub>1</sub>: Self-defence Training

Builds personal resilience and prepares individuals to face sudden risks. Gives women the confidence to navigate unsafe situations independently. Serves as a proactive measure that reduces vulnerability.

C<sub>2</sub>: CCTV Surveillance

Creates a monitored environment that discourages unsafe behaviour. Helps authorities trace incidents quickly and maintain accountability. Improves the visibility of hidden or sensitive locations.

C<sub>3</sub>: Helpline Services

Acts as an emergency contact point for immediate support. Ensures faster coordination with safety personnel during crises. Provides reassurance that help is accessible at any moment.

Data for each criterion are collected through a PDUS-based safety perception survey, where respondents express their safety belief using the five components (Truth, Indeterminacy, Falsity, Stability, and Drift factor). These PDUS values are then transformed into a decision matrix, which captures the perceived safety level at each location.

Using the PDUS-MOORA method, the normalized and aggregated PDUS values are processed to determine a final ranking of the three locations. This ranking indicates the comparative safety performance of each place and helps identify which safety interventions need improvement.

The results of this case study demonstrate how PDUS, combined with multi-criteria decision-making techniques, provides a dynamic and perception-based evaluation of women's safety in real-world environments.

**Step 1:** The Table 6.1, represents the Perceptual Dynamic Uncertainty Set (PDUS) values for different alternatives  $P_1, P_2, P_3$  under criteria  $C_1, C_2, C_3$ . Each alternative is evaluated in terms of truth (T), indeterminacy (I), falsity (F), stability (S), and drift factor (D), where the values are normalized between 0 and 1 to capture uncertainty in the decision-making process.

Alt/Crit	$C_1$	$C_2$	$C_3$
$A_1$	[(0.816), (0.636), (0.682), (0.842), (0.662)]	[(0.8), (0.426), (0.382), (0.828), (0.612)]	[(0.794), (0.506), (0.4), (0.746), (0.598)]
$A_2$	[(0.764), (0.568), (0.476), (0.686), (0.574)]	[(0.78), (0.508), (0.49), (0.636), (0.638)]	[(0.692), (0.552), (0.456), (0.678), (0.674)]
$A_3$	[(0.776), (0.566), (0.494), (0.692), (0.652)]	[(0.818), (0.574), (0.436), (0.68), (0.596)]	[(0.712), (0.69), (0.466), (0.664), (0.628)]

Table 6.1 PDUS values as Decision metrix

**Step 2:** The PDUS decision values is converted using the score function and tabulated in Table 6.2

Alt/Crit	$C_1$	$C_2$	$C_3$
$A_1$	0.07790	0.10620	0.09510
$A_2$	0.08530	0.06810	0.05700
$A_3$	0.06890	0.08620	0.06320

Table 6.2 Score values of PDUS

**Step 3:** Normalization of the PDUS score values for the favourable criteria are calculated and given in Table 7.3

Alt/Crit	$C_1$	$C_2$	$C_3$
$A_1$	0.5790	0.6949	0.7457
$A_2$	0.6341	0.4457	0.4470
$A_3$	0.5122	0.5642	0.4956

Table 6.3 Normalized values

**Step 4:** The Weighted Normalized PDUS values is obtained by using the weight allotted for the criteria which are 0.4,0.3,0.3.

Alt/Crit	$C_1$	$C_2$	$C_3$
$A_1$	0.2316	0.2085	0.2237
$A_2$	0.2536	0.1337	0.1341
$A_3$	0.2049	0.1693	0.1487

Table 6.4 Weighted Normalized values

**Step 5:** PDUS MOORA Analysis thus provides the ratio values.

Alternatives	$P_i$
$A_1$	0.6638
$A_2$	0.5214
$A_3$	0.5229

Table 6.5 PDUS-MOORA Analysis

**Step 6:** Rank all alternatives based on the descending order. The alternative with the highest score is the best choice.

Alternatives	$P_i$	Rank
$A_1$	0.6638	1
$A_2$	0.5214	3
$A_3$	0.5214	2

Table 6.6 Ranking of alternatives

$A_1 > A_3 > A_2$ .

**Step 7:** In the PDUS-MOORA method, the alternative which gets the highest overall score after all calculations is given the best rank (Rank 1). Here the alternative  $A_1$  is considered the most optimal choice among all the options evaluated.

After applying the PDUS-MOORA method, the college was ranked best, proving it to be the safest and most effective option.

## VII. CONCLUSION

This study proves that women's safety cannot be measured by a single factor it requires a balanced view of training, technology, and support systems. By applying the PDUS-MOORA framework, the three locations (College, Bus Stand, and IT Company) were evaluated through an unbiased, mathematical process rather than assumptions or general opinions. The PDUS-MOORA ranking clearly reveals how each environment transforms safety from a concept into a practical system. More importantly, the analysis shows that even small variations in self-defence awareness, surveillance quality, or responsiveness of helpline services can significantly shift the overall safety index of a location. This highlights that improving women's safety is not just about adding resources, but aligning them effectively. In essence, the study demonstrates that structured decision-making tools like MOORA do more than rank locations they expose hidden strengths, bring clarity to gaps, and provide a roadmap for focused improvements. This approach can guide institutions, transport authorities, and workplaces to build safer, more reliable spaces for women in a measurable and accountable manner.

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