District-level Study of Uttar Pradesh Based on the MCDM Approach

Sumedha Sharma[1], Jitendra Kumar[2,*], Niraj Kumar Singh[1] and Anup Kumar[3]

[1] *Department of Statistics, AIAS, Amity University, Noida, Uttar Pradesh*
[2] *Vellore Institute of Technology, Vellore, Tamil Nadu, India*
[3] *Department of Biostatistics and Health Informatics, SGPGIMS, Lucknow, Uttar Pradesh*
E-mail: sumedhasharma18@gmail.com; jitendra.kumar@vit.ac.in
[*] *Corresponding Author*

Received 07 February 2024; Accepted 14 July 2024

Abstract

Development and population are two crucial and complex areas of study for the researchers. They depend on many variables such as demography, economic status, nutritional status of the child and women, etc. This research aims to determine the best districts by evaluating them against eight specific criteria that reflect the demographic composition of women and children in Uttar Pradesh (UP).

The identification of the criteria of the variables is determined by various factors such as education, security & threat, gender equality, and health dimensions within the districts of UP, India. To achieve this we attempted to implement the multiple criteria decision-making (MCDM) methods comprehensibly. This study has presented an impartial assessment of the performance of 75 districts in UP. The methodology included a technique for order preference by similarity to ideal solution (TOPSIS) and multi-objective optimization based on ratio analysis (MOORA). Data on demographic and educational parameters were collected from the most recent published report

Journal of Reliability and Statistical Studies, Vol. 17, Issue 1 (2024), 191–222.
doi: 10.13052/jrss0974-8024.1718

of the national family health survey (NFHS-5) and various online portals & platforms of the government of UP. Also, we made an attempt to validate the techniques using a non-parametric statistical test known as Wilcoxon sign rank test. TOPSIS and MOORA were identified as two most popular MCDM techniques for demography research. Interestingly, we found districts namely, (Agra, Kanpur Nagar, Moradabad), Lucknow and Shrawasti as outliers with respect to variables area(A_3), CAW(A_5) and TFR(A_6) respectively that need to be dealt with careful attention and effective measures has to be taken. The study provides useful information on the demographic characteristics of districts in UP and possibly provide the basis to our policymakers for designing the targeted interventions to improve the social and economic indicators of the State.

Keywords: MCDM, TOPSIS, MOORA, Wilcoxon signed-rank test, CAW, TFR.

1 Introduction

Government policy and planning are designed to create conditions for sustainable, inclusive, and intelligent growth goals. To achieve this, it is important for planning strategies to consider the preferences of the public before implementation. One way to obtain public preferences, which has recently attracted researchers, is to rank available resources.

MCDM is a field of study that deals with making decisions when multiple criteria need to be considered. Howard and Coat 1960 et al. have established the MCDM technique as a field of study. Their studies helped establish the principles of MCDM and played a key role in its development. In the 21st century, MCDM has continued to evolve with the advent of new techniques such as fuzzy logic, genetic algorithms, and neural networks [1, 2]. Knowledge about the dynamics of demographic composition is almost a requirement for balanced planning to develop a State. The study has considered district-level observations on various demographic characteristics to understand the problem and its nature at the grassroots level. The MCDM approach is a decision-making tool that is widely used in social and economic analyses. Various fields of study applied the MCDM approach, such as the financial performance of fourteen large-scale conglomerates listed on the ISE (Istanbul Stock Exchange) between 2009 and 2011 using the Criteria Importance through Intercriteria Correlation (CRITIC)-TOPSIS method [3]. The CRITIC method has consistently been a popular tool for examining the robustness of various MCDM methods. It established their potential for stable criteria weights and ranks with larger decision matrices, while also pioneered the use of a distance correlation test to compare different weighting methods [4]. To analyse the data, their study used TOPSIS, a method of analysis that involves multiple criteria for decision-making. The study has evaluated and ranked the relative performance of competing companies considering multiple financial ratios as criteria [5]. Saxena et al. worked on an integrated CRITIC-TOPSIS approach to illustrate two real-time failure data sets. They compared the result with another MCDM method, namely Additive Ratio Assessment (ARAS) [6]. These techniques allow decision-makers to tackle even more complex problems and make more informed decisions in a wider range of contexts. The TOPSIS, MOORA, and VIKOR methods are used for the evaluation of the Nomenclature of Units for Territorial Statistics (NUTS) [7].

The present study has employed this approach to identify the key factors that influence the demographic characteristics of each district in the UP. The district-level study of UP based on the MCDM approach is a comprehensive analysis of various indicators across districts. As the most populous State in India, UP have significant implications for the overall demographic patterns of the country.

The study provides insight into the demographic trends and patterns of districts, highlighting the factors that contribute to these trends. The level of health of women and children in a particular district can be indicated by demographic characteristics such as the total fertility rate (TFR) and the infant mortality rate (IMR). Additionally, the gender ratio at birth and female education can reflect changes in societal development in that district.

The security parameters can be measured by the number of police stations and incidents of crime against women. The infrastructure of the district may be influenced by its total population and area. These demographic characteristics have been classified into two criteria: endogenous variables and exogenous variables. To select endogenous and exogenous variables, the availability of data and the 17 sustainable development goals were considered, with a focus on good health and well-being, quality education, and gender equality. Data from the NFHS-5 and official district websites was used to gather this information. This information's may be helpful for policy makers and planners to develop targeted strategies and address the demographic challenges faced by different districts in the State. The study also assesses the relative performance of each district based on different demographic indicators, providing a comparative analysis of demographic conditions throughout the State.

Overall, this study provides a valuable resource for researchers, policymakers, and practitioners interested in understanding the demographic characteristics of various districts and developing evidence-based strategies to promote sustainable demographic development in the State.

1.1 Objectives

We are aiming at the following objectives:

(i) Develop an understanding of demographic characteristics in the UP.
(ii) Develop a district-wise consistency ranking based on demographic attributes.
(iii) Perform a descriptive analysis of various attributes under the study.
(iv) Derive inferences for highlighting the current demographic scenarios in the UP.

Our basic goal is to understand the intrinsic and extrinsic pattern of the basic demographic bedrock because understanding the basic demographic structure is important for a State or country's holistic growth. Here, by development, we mean social, cultural, and economic progress.

1.2 Review of the Literature

The district-level study of UP based on the MCDM approach in demography has been a topic of interest for researchers in recent years. However, there has been a scarcity of research conducted in the field of demography using the MCDM approach. The purpose of this review of the literature is to provide a comprehensive overview of the existing literature on this technique. To rank districts according to their characteristics, various methods may be employed, viz. TOPSIS, VIKOR, SWOT AHP, PROMETHEE, MOORA, and ELECTER, drawing from recommendations in the literature. For instance, (Esangbedo and Wei et al., 2023) [8] addressed the issue of uncertainty in multi-criteria decision-making, specifically focusing on the normalization process. Although previous research has examined uncertainty in aspects such as performance values and weighting criteria, the impact of different normalization methods has not been thoroughly explored. TOPSIS methodology used and reviewed an up-to-date analysis of the existing literature, to design and develop the taxonomies for the current and emerging topics. They examined 266 academic papers and published them in 103 different journals [9]. For implementation of TOPSIS methodology they attempted to assign unique ranks for alternative phase change materials and provided entropy weights to the selected materials [10]. An attempt has been made for streamlining the progress of EU (European Union) members during EU-2020 and various strategies using TOPSIS and VIKOR methods has been experimented to achieve the success [11]. Also, we observe that a combination of CRITIC-TOPSIS and CRITIC-GRA methodology being adopted to analyse the performance of Indian private sector banks. To verify the ranks obtained, the Wilcoxon signed rank test was performed [12]. The research investigation was conducted to assess the efficacy of the machinery through the utilization of the MOORA technique, leading to the determination that it is a viable option for experimental scenarios [13, 14]. Some integrated techniques have been used based on TOPSIS and CRITIC method to determine the optimal software reliability growth model and an attempt has been made to compare the computed results with additive ratio assessment values [6]. Meanwhile, in yr. 2021 TOPSIS and entropy methodology were used to rank smart cities in the context of energy/ power distribution across the world except the continent of Africa [15]. With the entropy and TOPSIS integrated approach, the study ranked software reliability growth models (SRGMs) and underscored the challenges associated with selecting suitable SRGMs [16].

A separate study, employed Kaiser Criteria and principle factor analysis (PCA) based on Eigen-vectors and Eigen-value to rank 640 districts and 36 States / UTs in India [17]. The present work aimed at developing the district-wise consistency ranking based on existing demographic parameters in the State of UP, using MCDM methods to assess the comparative status of various districts, whereas, TOPSIS and MOORA methods are used to develop respective rankings. Achieving this goal we will be able to frame suitable policies and directed to design an effective strategy for its successful implementation within a given timeline.

Meshram et al. (2017) [18] Aims to evaluate the ranking of districts in Andhra Pradesh based on health and nutritional indicators using the TOPSIS method, which can serve as a tool to evaluate the development of the district regarding maternal health indicators in the State. MCDM methods have become increasingly popular in modelling COVID-19 problems owing to the multidimensionality of this crisis and the complexity of health and socioeconomic systems [19]. We found that MCDM involves AHP (Analytical Hierarchy Process) including fuzzy AHP as one of the most preferred and widely popular methods followed by TOPSIS and VIKOR. (Saleh et al., 2023) [20] Analysed to determine the optimal supplier of medical equipment according to the standards set by the Emergency Care Research Institute

(ECRI). This analysis involved the use of the SAW (Simple Additive Weighting), TOPSIS, and MOORA methods, in conjunction with three distinct approaches for weighting criteria.

The district-level study of UP based on the MCDM approach in demography has been an active area of research. The review of the study demonstrates the usefulness of the MCDM approach in evaluating demographic performance and development of districts in UP. The findings of these studies can provide valuable insight to policymakers and programme implementers in formulating viable policies and evolving suitable strategies to improve the demographic indicators for further success.

2 Methodology

2.1 Study Area

India is a country that consists of a wide array of variations such as socioeconomic, cultural, linguistic, geological, lifestyle's, and genetic diversity within its population. Among its States, UP is recognized as the State having the largest population and the fourth largest in area. As per the 2011 Census, UP represents 75 districts out of 707 districts of India, and encompassed a significant portion of India's geographical landscape, serving 17% of its total population, located in the north-central region of the country. As such, UP signifies a pivotal position in India.

2.2 Data Source

The data sets used in this analysis were obtained from the NFHS-5 (https://dhsprogram.com), which was conducted by the International Institute of Population Sciences between 2019 and 2021 [21]. The data covers 707 districts in 28 States and 8 union territories in India and is representative of the main demographic characteristics. The sampling frame for the selection of villages and households in each district was based on the 2011 census. All women between the ages of 15 and 49 years of age, who lived in the selected households, were invited to participate in the survey. The total sample size was 101,839 for men and 724,115 for women. The higher number of women respondents reflects the focus of the NFHS-5 on maternal and child health. Computer-Assisted Personal Interviewing (CAPI) was used to collect data on mini notebook computers by trained interviewers, which ensures better data quality, fewer inconsistencies, and missing cases. The fieldwork for NFHS-5 in some States/UTs was split into two halves due to the COVID-19 pandemic and lockdowns. In UP, for example, the fieldwork was conducted by the Academy of Management Studies (AMS) and Research and Development Initiative (RDI) Pvt. Ltd., in all 75 districts of the State from 13 January 2020 to 21 March 2020 before the lockdown and from 28 November 2020 to 19 April 2021 after the lockdown. Information was collected from 12,043 males, 93,124 women and 70,710 families.

2.3 CRITIC Method

The CRITIC method is a problem-solving approach used in decision-making and problem-solving that involves evaluating potential solutions or decisions based on their feasibility and desirability [22]. One of the most prevalent approaches to computing the weight of criteria is the CRITIC method. Criteria-weighting approaches are classified into three types: objective methods, subjective methods, and integrated methods [23].

2.3.1 The CRITIC method involves the following steps

Step 1. To normalize the decision matrix we use Equation (1) as shown below

$$\overline{Y}_{ij} = \frac{y_{ij} - y_j^{worst}}{y_j^{best} - y_j^{worst}}; \quad j = 1, 2, 3 \ldots m \tag{1}$$

Where, y_{ij} denote decision matrix of observations and y_j denote the attributes.

For exogenous variables, the minimum value is the best value and the maximum value is the worst. Similarly, for endogenous variables, the maximum value is the best value and the minimum value is the worst.

Step 2. Calculate the standard deviation σ_j; $(j = 1, 2, \ldots m)$.

Step 3. Determine the symmetric matrix of $n \times n$ with r_{jk}, where r_{jk} is the linear correlation coefficient between the vectors, P_j and P_k.

$$r_{jk} = \frac{\sum_{i=1}^{m} (y_{ij} - \overline{y}_j)(y_{jk} - \overline{y}_k)}{\sqrt{\sum_{i=1}^{m} (y_{ij} - \overline{y}_j)^2 (y_{jk} - \overline{y}_k)^2}} \tag{2}$$

Step 4. Calculate the measure of the conflict created by criterion j for the decision situation defined by the rest of the criteria as shown in Equation (3)

$$\textit{Measure of conflict} = \sum_{k=1}^{m} (1 - r_{jk}) \tag{3}$$

Step 5. Determine the amount of information about each criterion.

$$C_j = \sigma_j \sum_{k=1}^{m} (1 - r_{jk}) \tag{4}$$

Where, C_j denote the amount of information about each criterion.

Step 6. Determine the objective weights

$$w_j = \frac{C_j}{\sum_{i=1}^{m} C_j}; \quad i = 1, 2 \ldots m \tag{5}$$

Where, w_j denote the objective weights.

2.3.2 TOPSIS method

TOPSIS is a method used to evaluate and rank a set of alternatives based on a set of attributes. This study has considered various demographic characteristics mentioned below as our attributes [24].

TOPSIS is a multiple-criterion method for identifying solutions from a finite collection of alternatives based on the simultaneous minimization of distance from an ideal point and maximisation of distance from a nadir point. The TOPSIS method is based on the idea that the best alternative is the one that has the shortest distance to the positive ideal solution (PIS) and the longest distance to the negative ideal solution (NIS). The PIS is the alternative that has the best performance for each attribute, and NIS is the alternative that has the worst performance for each attribute.

2.3.3 Steps involved in TOPSIS methods:

Step 1: Construct a decision matrix where each row represents an alternative and each column represents attributes. The matrix (m x n), contains the performance scores of each alternative for each attribute.

$$Y_{ij} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1j} \\ \vdots & & \ddots & \vdots \\ y_{i1} & y_{i2} & \cdots & y_{ij} \end{bmatrix}$$

Step 2: Normalize the matrix to eliminate the effects of different units and scales as shown by Equation (6)

$$N_{ij} = \frac{Y_{ij}}{\sqrt{\sum_{i=1}^{m} Y_{ij}^2}}; \ (i = 1, 2 \ldots m; j = 1, 2, \ldots n). \tag{6}$$

Where, N_{ij} denote normalized matrix.

Step 3: Multiply the normalized matrix by the weights assigned to each criterion as shown in Equation (7)

$$\gamma_{ij} = N_{ij} * W_j \tag{7}$$

Where, $\gamma_{ij} =$ *Weighted normalized matrix*, $W_j =$ *Weights of the criteria*

Step 4: Calculate the PIS and NIS for the weighted normalized decision matrix.

$$\begin{aligned} PIS(\gamma^+) &= \{\gamma_1^+, \gamma_2^+, \gamma_3^+, \ldots \gamma_n^+\};\ v_j^+ \\ &= \{(max(\gamma_{ij}),\ j \in J); (min(\gamma_{ij}), j \in J^{|})\} \\ NIS(\gamma^-) &= \{\gamma_1^-, \gamma_2^-, \gamma_3^-, \ldots \gamma_n^-\}; v_j^- \\ &= \{(min(\gamma_{ij}), j \in J); (max(\gamma_{ij}), j \in J^{|})\}, \end{aligned} \tag{8}$$

Where, J is related to endogenous criteria/attribute, $J^{|}$ is related to exogeneous attributes.

Step 5: Calculate the Euclidean distance between each alternative and the PIS and NIS as shown by S_i^+ and S_i^-.

$$\begin{aligned} where,\ S_i^+ &= \sqrt{\sum_{j=1}^{n} (\gamma_{ij} - \gamma_j^+)^2};\ i = 1, 2, \ldots, m; \\ S_i^- &= \sqrt{\sum_{j=1}^{n} (\gamma_{ij} - \gamma_j^-)^2};\ i = 1, 2, \ldots, m. \end{aligned} \tag{9}$$

Step 6: Calculate the relative closeness of each alternative to the PIS by dividing the distance to the NIS by the sum of the distances from the PIS and the NIS.

$$RC_i = \frac{S_i^-}{S_i^- + S_i^+};\ 0 \le RC_i \le 1. \tag{10}$$

where, RC_i denote relative closeness

Step 7: Rank the alternatives based on their relative closeness to the PIS.

2.4 MOORA Method

The MOORA method is a decision-making technique used to evaluate alternatives that are characterized by multiple criteria. It is a popular multi-criteria decision-making method. The MOORA method uses ratio analysis to convert the evaluation criteria into a common unit, and finally, we calculate a score for each alternative based on how well it performs on each criterion. The scores are then combined to produce an overall ranking of the alternatives. A superior alternative receives the maximum score; while the worst alternative receives the lowest score [25].

2.4.1 The MOORA method involves the following steps

Step 1: Identify the criteria that will be used to evaluate the alternatives in the form of a decision matrix.

$$Y_{ij} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1j} \\ \vdots & & \ddots & \vdots \\ y_{i1} & y_{i2} & \cdots & y_{ij} \end{bmatrix}$$

Step 2: Normalize the data for each criteria to bring it to a common scale, using either the Min-Max method or the sum-of-squares method.

$$y_{ij}^{*} = y_{ij} \bigg/ \left[\sum_{i=1}^{m} y_{ij}^{2}\right]^{1/2} \; ; \; (j = 1, 2 \ldots, n) \tag{11}$$

Where, y_{ij}^{*} denotes the normalized value computed using MOORA method.

Step 3: Multiply each score of the criteria by its weight to get the weighted score for each alternative.

Step 4: Estimation of Assessment values (z_i), where z_i is computed using Equation (12)

$$z_i = \sum_{j=1}^{g} w_j y_{ij}^{*} - \sum_{j=g+1}^{n} w_j y_{ij}^{*}; \; (j = 1, 2, \ldots, n) \tag{12}$$

Step 5: Rank the alternatives according to their total weighted scores.

2.5 Spearman Rank Correlation (ρ)

Spearman's rank correlation coefficient (ρ), as shown in Equation (13), is a non-parametric measure of linear association between two ranked variables.

It estimates the relationship between the ranks assigned by both methods (TOPSIS and MOORA). This method is even suitable for variables that may not have a linear relationship but still exhibit a monotonic relation.

$$\rho = 1 - \frac{6 \times \sum d_i^2}{n(n^2 - 1)};\ -1 \leq \rho \leq 1 \tag{13}$$

Where, $d_i =$ difference between the two ranks assigned by two different aforesaid methods, and n denote the number of districts in UP.

2.6 Demographic Characteristics

A_1 = Female literacy rate (endogenous variable)
A_2 = Female ratio at birth (endogenous variable)
A_3 = Area of districts (endogenous variable)
A_4 = Number of police stations in a district (endogenous variable)
A_5 = Crime against women per district (exogenous variable)
A_6 = Total fertility rate (exogenous variable)
A_7 = Infant mortality rate (exogenous variable)
A_8 = Total population (exogenous variable)

2.7 Hypothesis Testing

The Wilcoxon signed-rank test, a non-parametric test, was utilized to validate the results obtained from the TOPSIS and MOORA analysis methods. The formulation and setting of null and alternative hypotheses is shown below:

H_0: $R_T = R_M$; There is no significant difference between the individual ranks obtained by TOPSIS and MOORA analysis, against
H_1: $R_T \neq R_M$; There is a significant difference between the individual ranks obtained by TOPSIS and MOORA analysis.

Where, R_T and R_M denotes respective ranks used for TOPSIS and MOORA.

2.8 Flow Diagram

Figure 1, presents the organisational flow diagram of the methodology being implemented.

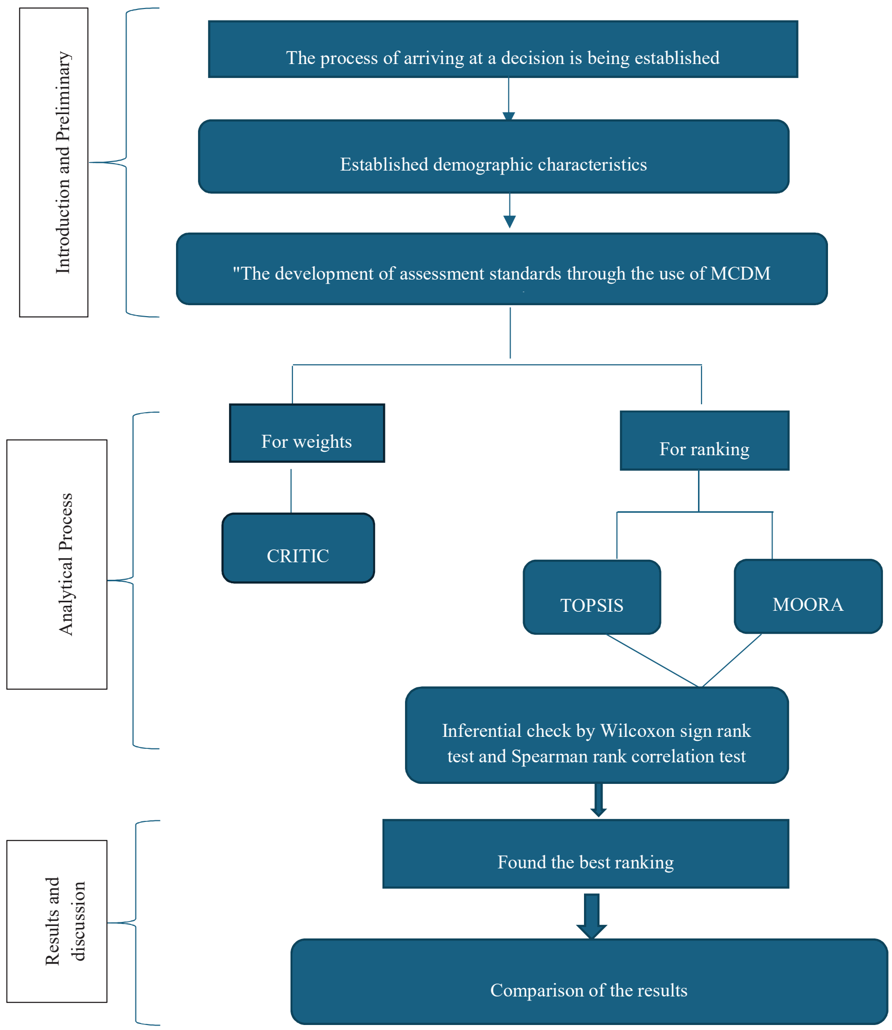

Figure 1 Methodology of the study.

3 Result and Discussion

3.1 Descriptive Statistics

Table 1 presents tabulated summary statistics providing valuable insights into the nature of data distribution, its degree of symmetricity, variable characteristics and degree of sharpness of the curve generated for analytical purposes. The mean literacy rate (A_1) across districts under study is 65.10

Table 1 Summary statistics of attributes

Statistics	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
Mean	65.10	935.80	3541.89	20.1	658.11	2.39	48.32	2643447.65
Median	65.70	930.00	3021	20.0	574.00	2.37	50.78	2496970.00
Standard Deviation	9.53	92.19	2008.77	7.87	437.08	0.44	18.94	1145907.16
Coefficient of Variation	14.64	9.85	56.71	39.1	66.41	18.37	39.20	43.35
Kurtosis	0.27	−0.17	5.34	1.03	7.69	1.59	−0.34	−0.28
Skewness	−0.67	0.47	2.02	0.86	2.14	0.90	0.03	0.39
Minimum	38.69	786.00	1015	7.00	88.00	1.62	10.17	127988.00
Maximum	81.48	1191.0	10863	43.0	2847.0	3.75	93.96	5954000.00
Confidence Level	2.19	21.21	462.18	1.81	100.56	0.10	4.36	263649.29

per cent. The average sex ratio (A_2) across the State is 936 females per 1000 males. Each district has an average of approximately 20 police stations (A_4) per district. The mean number of Crimes against Women (CAW) as denoted by (A_5) per district is approximately 658. The average TFR (A_6) is recorded at 2.39 children per woman. The mean IMR (A_7) is approximately 48 deaths per 1000 live births. The average population (A_8) in the districts is approximately 2,643,447.

Most attributes exhibit medians that closely align with their means, indicating a relatively symmetrical distribution, except the variable area (A_3) and CAW (A_5), which display positively skewed nature. The high standard deviations reflect district wise variability suggesting possible heterogeneity in the State. The Coefficient of Variation (CV) assesses the consistency in the performance of variables within the study. A consistency ranking has been assigned to assess the prevalent volatility among the variables. Attributes such as CAW (A_5) and Area (A_3) demonstrate relatively higher ranking indicating the significant disparities across various districts of the State.

The high kurtosis observed in Area (A_3) (5.34) and CAW (A_5) (7.69) indicates heavy tails, implying a prevalence of more extreme values compared to a normal distribution.

Narrow confidence intervals for literacy rate (A_1) (2.19) and TFR (A_6) (0.10) indicate reliable average estimates, while wider intervals for Area (A_3) (462.18) and CAW (A_5) (100.56) reflect increased uncertainty in these averages due to high variability.

The substantial variation in area size and crime rates highlights an unequal distribution of resources and the challenges encountered by districts. The raw data has been processed to be normalized using z-score as shown in Appendix 4, to identify the outlier's presence in the data set and ensure the smoothness of available information's.

Table 2 Correlation coefficient of attributes

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
A_1	1.0000	−0.1522	−0.1397	0.2432	−0.1571	0.7601	0.2476	−0.1314
A_2	−0.1522	1.0000	0.0766	0.1721	−0.2140	−0.1042	−0.1117	−0.2889
A_3	−0.1397	0.0766	1.0000	0.5498	−0.3666	0.0196	−0.1332	−0.4738
A_4	0.2432	0.1721	0.5498	1.0000	−0.7423	0.3217	0.0880	−0.8388
A_5	−0.1571	−0.2140	−0.3666	−0.7423	1.0000	−0.2047	0.1409	0.6741
A_6	0.7601	−0.1042	0.0196	0.3217	−0.2047	1.0000	0.4542	−0.1498
A_7	0.2476	−0.1117	−0.1332	0.0880	0.1409	0.4542	1.0000	−0.0074
A_8	−0.1314	−0.2889	−0.4738	−0.8388	0.6741	−0.1498	−0.0074	1.0000

Table 3 Weights

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
C_j	1.40952	1.73495	1.52317	1.57561	1.24672	1.21528	1.42928	1.61598
W_j	0.11995	0.14765	0.12963	0.13409	0.10610	0.10342	0.12164	0.13752

It is important to highlight the names of certain computed outliers districts for different variables and requires special investigation to find the underlying causes for each of the variables under the study as shown in Appendix 4.

3.2 CRITIC Method

Appendix 1 represents the normalized decision matrix. In the process of min-max normalization, the data points undergo linear scaling to be accommodated within the interval [0, 1] using a specific mathematical expression. The normalization is achieved by adjusting the original values concerning the minimum and maximum values in the dataset. The outcome of the correlation coefficient matrix reveals that literacy rates (A_1) and TFR (A_6) are significantly correlated, with a correlation coefficient of 0.7601, suggesting a robust positive correlation. Similarly, the correlation coefficient for number of police station (A_4) and Total population (A_8) is -0.8388, indicating a strong negative correlation. The correlation coefficient between gender ratio at birth (A_2) and CAW (A_5) is -0.2140, signifying a weak negative correlation.

The CRITIC method is used to determine the weights of each attribute, and the results are presented in Table 3. It can be inferred from Table 3 that the attributes A_5 and A_6 have the least weights with the same value, while A_5 and A_6 hold the least significance. The criteria weights are then calculated using Equations (4) and (5).

Table 4 Positive and negative ideal solutions

Ideal solution type	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
V+	0.0170	0.0215	0.0397	0.0306	0.0014	0.0079	0.0026	0.0007
V–	0.00809	0.0142	0.0037	0.0049	0.0442	0.0184	0.0254	0.0328

3.3 TOPSIS Method

The TOPSIS method analyses and ranks the data based on positive and negative ideal solutions. Then, positive and negative ideal solutions were determined based on the results.

3.4 MOORA Method

We have attempted to normalize the data at hand using Equation (11) and multiply them by the weights to obtain the weighted normalized matrix. The assessed values will range between 0 and 1, with higher values indicating better performance. Based on the assessed values, we ranked the alternatives or attributes from highest to lowest. The alternative with the highest value is considered the best choice. According to this method, districts such as Kanpur Nagar, Lalitpur, Jalaun, Sonbhadra, Agra and Hamirpur are top performers with relatively higher ranking scores.

3.5 Comparative Analysis

Annexure-4 provides an intriguing presentation that reveals a robust correlation coefficient $\rho = 0.87$ between two sets of rankings. Consequently, one can postulate that an elevated MOORA ranking of a certain district is associated with a corresponding higher ranking anticipated through the TOPSIS methodology. The two methods produced almost identical results with more or less similar rankings for best performing districts. We used the Wilcoxon signed rank test to evaluate the similarity between the rankings generated by TOPSIS and MOORA as presented in Table 5.

Table 5, presents the output of the Wilcoxon signed rank test, implemented at $\alpha = 0.50$ level of significance. The results indicate that the difference between the ranks obtained by the two methods appears to be statistically insignificant (Z = -0.379, p = 0.705). Therefore, we do not find enough evidence against the null hypothesis and subsequently, we fail to reject the null hypothesis H_0 as illustrated in sub-section 2.7. Thus, it can

Table 5 Wilcoxon signed ranks test

	N	Mean Rank	Sum of Ranks	TOPSIS-MOORA
Negative Ranks	33[a]	37.77	1246.50	Z −0.379[b]
Positive Ranks	39[b]	35.42	1381.50	Asymp. Sig. (2-tailed) 0.705
Ties	3[c]			a. Wilcoxon signed ranks test
Total	75			b. Based on negative ranks

be inferred that there is no significant difference between the ranks obtained by TOPSIS and MOORA methods in this particular study. In other words, the ranks obtained by these two methods seem to be unidirectional.

3.6 Visualization of Ranked Districts

It is interesting to observe that MCDM methods provide almost similar ranking for top twenty districts, there is a significant variation is being observed in the ranking of remaining districts. It might be because of the fact that different tools emphasises different criteria. This study found that the Spearman rank correlation coefficient for various pairs of tools is statistically significant with a value of $\rho = 0.8$. This implies the relevance of both approaches of ranking. This means the two methods of ranking are highly significant.

Figures 2(a) and 2(b) shows the visualization map of rank districts using the aforesaid methods TOPSIS and MOORA.

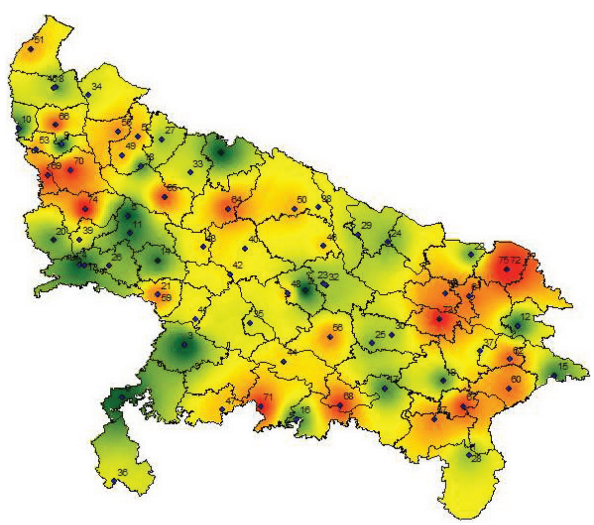

Figure 2(a) TOPSIS method ranking visualization map.

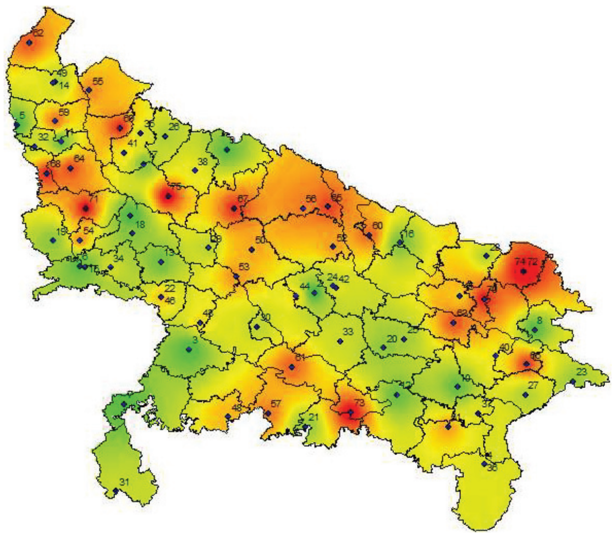

Figure 2(b) MOORA method ranking visualization map.

In the above figures, red colour indicates higher ranked and relatively more vulnerable districts, orange colour indicates districts with moderate vulnerability, yellow colour indicates districts with relatively weaker vulnerability and green colour indicates districts with almost no vulnerability (safe zone).

4 Conclusion

By considering demographic characteristics such as district-wise population, area, female literacy rate, female birth rate and health indicators based on child mortality rate and fertility rates, we motivated to assess the overall performance of different districts in UP and particularly aimed at identifying the districts with significant rankings to bring future improvements. We found the following top ten districts with relatively higher order namely, Sonbhadra, Lalitpur, Jaluan, Agra, Kanpur Nagar, Jhansi, Moradabad, Mirzapur and Hamirpur and the following districts with relatively poorer rankings namely, Bareilly, Sitapur, Allahbad, Aligarh and Lucknow. Though, the TOPSIS method is expected to identify the best-performing districts, whereas, the MOORA method enables us to determine the districts' optimal ranking based on multiple objectives, in the present scenario both tools become unidirectional. The study revealed that certain districts in UP have excelled in terms of these criteria, while others lag behind. It also highlights the need for targeted interventions and policies in lagging dis to address the underlying challenges and promote inclusive development. It is important to highlight the name of computed outlier's districts for each of the variables under study as shown in Appendix 4, and requires special investigation to find the underlying causes. In this paper, we statistically evaluated the progress of districts using various demographic indicators filtered through TOPSIS and MOORA methods. It is essential to emphasize the identification of specific outlier districts calculated for different variables under the study, necessitating a thorough examination to uncover the root causes of variability, as depicted in Appendix 4. (Agra, Kanpur Nagar, Moradabad), Lucknow, Shrawasti and are the districts declared outliers in respect to variables like, area(A_3), CAW(A_5), and TFR (A_6) respectively. It is interesting to present our researchers, policy and decision-makers and all related stakeholders including common people of the State to bring focused attention and timely intervention to reduce the heterogeneity that persists across all seventy-five districts of UP that is one of the fastest evolving States of India in terms of increasing investment destination, improving laws and order State, a hotspot of religious tourism, and witnessed as one of the fastest growing States of India.

5 Limitations

However, it is important to acknowledge the limitations of the study. The first notifiable limitation is the secondary data source, which was acquired deliberately to ensure the authenticity and reliability of the data set. But, at the same, it didn't provide us enough scope for survey-based experimentation. The second limitation refers to the methods using TOPSIS and MOORA. As the number of criteria and alternatives increases, there is a corresponding escalation in the computational intricacy and time needed to conduct the analysis. TOPSIS and MOORA approaches necessitate a substantial volume of data to ensure precision in the analysis, a resource that may not be consistently accessible or effortlessly procured.

6 Future Scope

The present work may provide good insight and show the roadmap to future researchers for carrying out the micro-level analysis that consists of relatively smaller geographical units of research namely, sub-divisions, blocks and villages for bringing in-depth investigation and achieving relatively higher precisions. The present work provides a unique understanding of challenges, threats and opportunities in each district of UP. Furthermore, MCDM methodologies such as CRITIC, AHP, MOORA and TOPSIS implementations to evaluate district-specific factors need to be investigated at micro geographical units (sub-divisions, blocks, and villages) of research. Employ information derived from the Census of India, the National Sample Survey Office (NSSO), and various other governmental sources to access current demographic and socio-economic data. In the future, additional demographic variables sourced from existing data could potentially be integrated. As UP is the most populous state of India, the assurance of data availability and reliability at the district level may present challenges arising from discrepancies or deficiencies in data collection and reporting. The varied geographical terrain of UP could potentially give rise to logistical hurdles in the process of data collection and fieldwork.

7 Competing Interests and Funding

The authors declare that they have no conflict of interest and that there is no funding for this research article.

Appendix

Appendix 1 Weighted Normalized Matrix by TOPSIS method

S.N.	Districts	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
1	Saharanpur	0.01496	0.01844	0.01347	0.01566	0.01182	0.01111	0.01442	0.01909
2	Bijnor	0.01525	0.01716	0.01479	0.01566	0.01403	0.01066	0.01346	0.02027
3	Rampur	0.01193	0.01747	0.00864	0.01210	0.00656	0.01309	0.01866	0.01286
4	Jyotiba Phule Nagar	0.01276	0.01552	0.00821	0.00926	0.00658	0.01307	0.01434	0.01013
5	Meerut	0.01629	0.01671	0.00946	0.02136	0.01218	0.01194	0.01366	0.01896
6	Baghpat	0.01591	0.01476	0.00482	0.00783	0.00622	0.01165	0.01158	0.00717
7	Gautam Buddha Nagar	0.01655	0.01619	0.00527	0.01495	0.01203	0.00792	0.01577	0.00907
8	Bulandshahr	0.01473	0.01518	0.01590	0.02065	0.01969	0.01257	0.01823	0.01926
9	Aligarh	0.01374	0.01859	0.01333	0.02136	0.02483	0.01215	0.01626	0.02022
10	Mahamaya Nagar	0.01376	0.01785	0.00672	0.00783	0.00708	0.01117	0.01576	0.00861
11	Mathura	0.01335	0.01678	0.01220	0.01566	0.01744	0.01266	0.01468	0.01402

(*Continued*)

Appendix 1 Continued

S.N.	Districts	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
12	Agra	0.01288	0.01628	0.03967	0.02848	0.01578	0.01158	0.01890	0.02432
13	Firozabad	0.01493	0.01572	0.00863	0.01495	0.01417	0.01173	0.02004	0.01375
14	Mainpuri	0.01543	0.01510	0.01008	0.00997	0.00891	0.01136	0.02273	0.01197
15	Bareilly	0.01105	0.01956	0.01504	0.02065	0.01837	0.01041	0.01375	0.02449
16	Pilibhit	0.01126	0.01469	0.01278	0.01068	0.01054	0.00982	0.01039	0.00070
17	Shahjahanpur	0.01190	0.01920	0.01671	0.01638	0.01348	0.01570	0.02367	0.01655
18	Kheri	0.01186	0.01626	0.02804	0.01638	0.01805	0.01205	0.02015	0.02214
19	Sitapur	0.01122	0.01824	0.02097	0.02065	0.01873	0.01362	0.02162	0.02468
20	Hardoi	0.01153	0.01980	0.02187	0.01780	0.00959	0.01455	0.02327	0.02253
21	Unnao	0.01341	0.01732	0.01664	0.01495	0.01417	0.01088	0.01555	0.01711
22	Lucknow	0.01602	0.01770	0.00923	0.03061	0.04418	0.00798	0.00681	0.02527
23	Farrukhabad	0.01321	0.01424	0.00796	0.00997	0.00568	0.01345	0.01653	0.01038
24	Kannauj	0.01363	0.01873	0.00764	0.00641	0.00776	0.01365	0.01761	0.00757
25	Etawah	0.01605	0.01442	0.00844	0.01495	0.00459	0.01166	0.01577	0.00871
26	Auraiya	0.01566	0.01588	0.00736	0.00783	0.00712	0.01086	0.01548	0.00759
27	Kanpur Dehat	0.01472	0.01853	0.01103	0.01210	0.01156	0.01068	0.01524	0.00989
28	Kanpur Nagar	0.01704	0.01473	0.03967	0.02990	0.02385	0.00818	0.00739	0.02522
29	Jalaun	0.01385	0.01438	0.01659	0.01566	0.00566	0.00898	0.00405	0.00930
30	Jhansi	0.01459	0.01673	0.01667	0.01851	0.01016	0.00807	0.01145	0.01100
31	Lalitpur	0.01157	0.01801	0.01840	0.01068	0.00171	0.01021	0.00275	0.00672
32	Hamirpur	0.01456	0.01592	0.01505	0.00997	0.00481	0.01027	0.01408	0.00608
33	Mahoba	0.01369	0.01906	0.01053	0.00712	0.00321	0.01196	0.01158	0.00482
34	Banda	0.01203	0.01752	0.01610	0.01282	0.00763	0.01194	0.01591	0.00991
35	Chitrakoot	0.01167	0.01604	0.01155	0.00712	0.00331	0.01175	0.01222	0.00546
36	Fatehpur	0.01301	0.01606	0.01516	0.01424	0.00953	0.01301	0.01409	0.01449
37	Pratapgarh	0.01552	0.01866	0.01362	0.01566	0.01578	0.01048	0.01211	0.01767
38	Kaushambi	0.01228	0.01754	0.00650	0.00997	0.00585	0.01336	0.01242	0.00881
39	Allahabad	0.01383	0.02149	0.02002	0.02919	0.02711	0.01154	0.01528	0.03278
40	Bara Banki	0.01173	0.01716	0.01421	0.01638	0.01136	0.01309	0.01509	0.01795
41	Faizabad	0.01538	0.01597	0.00921	0.01282	0.01212	0.01054	0.00809	0.01360
42	Ambedkar Nagar	0.01591	0.01476	0.00858	0.01353	0.00711	0.00851	0.00940	0.01320
43	Bahraich	0.00814	0.01530	0.01715	0.01638	0.01424	0.01784	0.01653	0.01920
44	Shrawasti	0.00809	0.01752	0.00711	0.00498	0.00436	0.01836	0.01167	0.00614
45	Balrampur	0.00881	0.01866	0.01223	0.01139	0.00542	0.01800	0.01648	0.01183
46	Gonda	0.01201	0.01754	0.01462	0.01210	0.00934	0.01202	0.00926	0.01890
47	Siddharthnagar	0.01010	0.01538	0.01057	0.01282	0.00537	0.01520	0.00449	0.01409
48	Basti	0.01325	0.01615	0.00982	0.01210	0.00523	0.01134	0.00907	0.01357
49	Sant Kabir Nagar	0.01282	0.01507	0.00601	0.00641	0.00447	0.01160	0.00722	0.00940
50	Mahrajganj	0.01287	0.01684	0.01078	0.01424	0.00650	0.01048	0.00814	0.01478
51	Gorakhpur	0.01427	0.01617	0.01272	0.01994	0.01390	0.01019	0.01148	0.02445

(*Continued*)

Appendix 1 Continued

S.N.	Districts	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
52	Kushinagar	0.01309	0.01949	0.01061	0.01353	0.00784	0.01216	0.00814	0.01962
53	Deoria	0.01490	0.01808	0.00928	0.01638	0.00137	0.00985	0.00457	0.01707
54	Azamgarh	0.01593	0.01514	0.01480	0.01851	0.01182	0.01071	0.01318	0.02539
55	Mau	0.01498	0.01693	0.00626	0.00854	0.00808	0.00965	0.01444	0.01214
56	Ballia	0.01461	0.01916	0.01089	0.02207	0.00574	0.00948	0.00560	0.01783
57	Jaunpur	0.01598	0.01621	0.01475	0.01994	0.00791	0.01010	0.00385	0.02474
58	Ghazipur	0.01510	0.01754	0.01233	0.01922	0.01080	0.01051	0.00559	0.01993
59	Chandauli	0.01473	0.01583	0.00907	0.01139	0.00362	0.01123	0.00814	0.01075
60	Varanasi	0.01644	0.01597	0.00561	0.01994	0.01680	0.00866	0.00558	0.02024
61	Bhadohi	0.01439	0.01514	0.00371	0.00641	0.00304	0.01259	0.00814	0.00869
62	Mirzapur	0.01460	0.01465	0.01651	0.01353	0.00445	0.01156	0.01132	0.01375
63	Sonbhadra	0.01275	0.01758	0.02479	0.01566	0.00427	0.01381	0.01161	0.01025
64	Etah	0.01405	0.01812	0.01624	0.01282	0.00622	0.01252	0.01562	0.00977
65	Kanshiram Nagar	0.01186	0.01799	0.00728	0.00783	0.01165	0.01535	0.01900	0.00791
66	Amethi	0.01323	0.01523	0.00851	0.01068	0.00486	0.01250	0.02543	0.01028
67	Budaun	0.01018	0.01570	0.01546	0.01566	0.00948	0.01325	0.01600	0.01722
68	Ghaziabad	0.01667	0.02133	0.00378	0.01495	0.00919	0.00872	0.00997	0.01875
69	Hapur	0.01544	0.01418	0.00408	0.00783	0.00286	0.01177	0.01631	0.00737
70	Moradabad	0.01365	0.01844	0.03967	0.01424	0.01724	0.01100	0.01595	0.01875
71	Muzaffarnagar	0.01519	0.01561	0.01092	0.01495	0.00704	0.01037	0.00418	0.01558
72	Rae Bareli	0.01310	0.01572	0.01476	0.01353	0.01088	0.01046	0.00947	0.01598
73	Sambhal	0.01073	0.01696	0.00896	0.00926	0.00757	0.01397	0.01815	0.01207
74	Shamli	0.01361	0.01857	0.00426	0.00570	0.00433	0.01220	0.01492	0.00723
75	Sultanpur	0.01494	0.01799	0.00976	0.01353	0.00967	0.01045	0.01132	0.01339

Appendix 2 Normalized Matrix for MOORA

S.N.	Districts	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
1	Saharanpur	0.12559	0.12551	0.10478	0.11762	0.11160	0.10784	0.11860	0.13911
2	Bijnor	0.12800	0.11679	0.11501	0.11762	0.13240	0.10343	0.11071	0.14775
3	Rampur	0.10014	0.11888	0.06723	0.09089	0.06195	0.12707	0.15351	0.09371
4	Jyotiba Phule Nagar	0.10711	0.10561	0.06388	0.06950	0.06210	0.12690	0.11798	0.07383
5	Meerut	0.13671	0.11372	0.07357	0.16039	0.11497	0.11593	0.11239	0.13817
6	Baghpat	0.13353	0.10045	0.03752	0.05881	0.05873	0.11309	0.09527	0.05228
7	Gautam Buddha Nagar	0.13892	0.11016	0.04096	0.11227	0.11351	0.07687	0.12970	0.06612
8	Bulandshahr	0.12358	0.10328	0.12364	0.15504	0.18586	0.12205	0.14993	0.14039
9	Aligarh	0.11533	0.12649	0.10367	0.16039	0.23433	0.11795	0.13379	0.14740
10	Mahamaya Nagar	0.11550	0.12145	0.05226	0.05881	0.06679	0.10837	0.12960	0.06278

(*Continued*)

Appendix 2 Continued

S.N.	Districts	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
11	Mathura	0.11204	0.11421	0.09487	0.11762	0.16462	0.12285	0.12075	0.10219
12	Agra	0.10809	0.11077	0.30855	0.21385	0.14895	0.11242	0.15547	0.17728
13	Firozabad	0.12531	0.10696	0.06709	0.11227	0.13372	0.11382	0.16482	0.10023
14	Mainpuri	0.12948	0.10279	0.07840	0.07485	0.08407	0.11030	0.18693	0.08726
15	Bareilly	0.09276	0.13312	0.11702	0.15504	0.17341	0.10101	0.11307	0.17847
16	Pilibhit	0.09451	0.09996	0.09939	0.08019	0.09945	0.09533	0.08549	0.00513
17	Shahjahanpur	0.09991	0.13066	0.12995	0.12296	0.12727	0.15238	0.19474	0.12062
18	Kheri	0.09956	0.11065	0.21814	0.12296	0.17033	0.11691	0.16575	0.16133
19	Sitapur	0.09414	0.12416	0.16312	0.15504	0.17678	0.13217	0.17787	0.17990
20	Hardoi	0.09679	0.13472	0.17011	0.13366	0.09051	0.14120	0.19141	0.16421
21	Unnao	0.11250	0.11789	0.12947	0.11227	0.13372	0.10560	0.12788	0.12471
22	Lucknow	0.13448	0.12047	0.07181	0.22989	0.41697	0.07743	0.05605	0.18415
23	Farrukhabad	0.11087	0.09689	0.06195	0.07485	0.05360	0.13055	0.13597	0.07563
24	Kannauj	0.11435	0.12747	0.05945	0.04812	0.07323	0.13250	0.14486	0.05520
25	Etawah	0.13469	0.09812	0.06564	0.11227	0.04335	0.11321	0.12971	0.06346
26	Auraiya	0.13141	0.10807	0.05726	0.05881	0.06722	0.10538	0.12735	0.05535
27	Kanpur Dehat	0.12358	0.12612	0.08581	0.09089	0.10911	0.10364	0.12534	0.07206
28	Kanpur Nagar	0.14302	0.10021	0.30855	0.22454	0.22511	0.07936	0.06082	0.18380
29	Jalaun	0.11621	0.09788	0.12907	0.11762	0.05346	0.08719	0.03335	0.06780
30	Jhansi	0.12244	0.11384	0.12966	0.13900	0.09593	0.07833	0.09417	0.08018
31	Lalitpur	0.09711	0.12256	0.14313	0.08019	0.01611	0.09913	0.02265	0.04901
32	Hamirpur	0.12220	0.10831	0.11705	0.07485	0.04540	0.09970	0.11586	0.04430
33	Mahoba	0.11493	0.12968	0.08192	0.05346	0.03032	0.11606	0.09527	0.03514
34	Banda	0.10098	0.11924	0.12521	0.09623	0.07206	0.11591	0.13084	0.07219
35	Chitrakoot	0.09791	0.10917	0.08987	0.05346	0.03120	0.11406	0.10056	0.03979
36	Fatehpur	0.10916	0.10930	0.11793	0.10693	0.08993	0.12632	0.11588	0.10563
37	Pratapgarh	0.13022	0.12698	0.10595	0.11762	0.14895	0.10174	0.09962	0.12875
38	Kaushambi	0.10308	0.11937	0.05056	0.07485	0.05521	0.12970	0.10215	0.06418
39	Allahabad	0.11603	0.14626	0.15571	0.21920	0.25586	0.11202	0.12570	0.23888
40	Bara Banki	0.09842	0.11679	0.11053	0.12296	0.10721	0.12702	0.12410	0.13082
41	Faizabad	0.12908	0.10868	0.07164	0.09623	0.11438	0.10231	0.06651	0.09914
42	Ambedkar Nagar	0.13356	0.10045	0.06675	0.10158	0.06708	0.08263	0.07732	0.09620
43	Bahraich	0.06831	0.10414	0.13341	0.12296	0.13445	0.17314	0.13600	0.13993
44	Shrawasti	0.06790	0.11924	0.05534	0.03742	0.04115	0.17823	0.09600	0.04472
45	Balrampur	0.07391	0.12698	0.09513	0.08554	0.05111	0.17466	0.13557	0.08621
46	Gonda	0.10081	0.11937	0.11370	0.09089	0.08817	0.11666	0.07616	0.13777
47	Siddharthnagar	0.08475	0.10463	0.08223	0.09623	0.05067	0.14756	0.03697	0.10268
48	Basti	0.11122	0.10991	0.07635	0.09089	0.04936	0.11010	0.07464	0.09888
49	Sant Kabir Nagar	0.10759	0.10254	0.04675	0.04812	0.04218	0.11258	0.05937	0.06847
50	Mahrajganj	0.10804	0.11458	0.08385	0.10693	0.06137	0.10168	0.06695	0.10773

(*Continued*)

Appendix 2 Continued

S.N.	Districts	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
51	Gorakhpur	0.11977	0.11003	0.09893	0.14970	0.13123	0.09894	0.09440	0.17817
52	Kushinagar	0.10984	0.13263	0.08254	0.10158	0.07396	0.11805	0.06695	0.14301
53	Deoria	0.12501	0.12305	0.07215	0.12296	0.01289	0.09564	0.03757	0.12441
54	Azamgarh	0.13365	0.10303	0.11515	0.13900	0.11160	0.10392	0.10841	0.18504
55	Mau	0.12568	0.11519	0.04866	0.06416	0.07631	0.09366	0.11874	0.08847
56	Ballia	0.12262	0.13042	0.08467	0.16574	0.05419	0.09198	0.04607	0.12998
57	Jaunpur	0.13415	0.11028	0.11470	0.14970	0.07469	0.09806	0.03163	0.18031
58	Ghazipur	0.12672	0.11937	0.09592	0.14435	0.10194	0.10200	0.04600	0.14524
59	Chandauli	0.12364	0.10770	0.07058	0.08554	0.03412	0.10899	0.06695	0.07835
60	Varanasi	0.13799	0.10868	0.04360	0.14970	0.15861	0.08409	0.04591	0.14752
61	Bhadohi	0.12074	0.10303	0.02883	0.04812	0.02871	0.12215	0.06695	0.06332
62	Mirzapur	0.12254	0.09972	0.12841	0.10158	0.04203	0.11216	0.09311	0.10018
63	Sonbhadra	0.10701	0.11961	0.19281	0.11762	0.04028	0.13404	0.09551	0.07473
64	Etah	0.11789	0.12330	0.12628	0.09623	0.05873	0.12154	0.12846	0.07119
65	Kanshiram Nagar	0.09951	0.12244	0.05661	0.05881	0.10999	0.14903	0.15625	0.05764
66	Amethi	0.11105	0.10365	0.06616	0.08019	0.04584	0.12132	0.20922	0.07493
67	Budaun	0.08544	0.10684	0.12027	0.11762	0.08949	0.12856	0.13165	0.12554
68	Ghaziabad	0.13989	0.14516	0.02937	0.11227	0.08670	0.08461	0.08203	0.13665
69	Hapur	0.12961	0.09652	0.03170	0.05881	0.02695	0.11422	0.13414	0.05368
70	Moradabad	0.11456	0.12551	0.30855	0.10693	0.16272	0.10677	0.13122	0.13665
71	Muzaffarnagar	0.12744	0.10623	0.08496	0.11227	0.06649	0.10069	0.03440	0.11353
72	Rae Bareli	0.10995	0.10696	0.11484	0.10158	0.10267	0.10153	0.07786	0.11649
73	Sambhal	0.09003	0.11544	0.06968	0.06950	0.07147	0.13556	0.14927	0.08798
74	Shamli	0.11423	0.12637	0.03316	0.04277	0.04086	0.11841	0.12274	0.05270
75	Sultanpur	0.12541	0.12244	0.07592	0.10158	0.09124	0.10141	0.09311	0.09755

Appendix 3 Presents a normalized matrix evaluated using Equation (11)

S.N.	Districts	TOPSIS	MOORA
1	Agra	4	6
2	Aligarh	74	71
3	Allahabad	73	63
4	Ambedkar Nagar	25	20
5	Amethi	55	69
6	Auraiya	41	43
7	Azamgarh	59	46
8	Baghpat	37	40
9	Bahraich	65	75
10	Ballia	10	5
11	Balrampur	29	60

(*Continued*)

Appendix 3 Continued

S.N.	Districts	TOPSIS	MOORA
12	Banda	15	23
13	Bara Banki	46	52
14	Bareilly	71	57
15	Basti	23	24
16	Bhadohi	33	38
17	Bijnor	58	45
18	Budaun	34	55
19	Bulandshahr	70	64
20	Chandauli	18	17
21	Chitrakoot	16	21
22	Deoria	12	8
23	Etah	11	18
24	Etawah	21	22
25	Faizabad	43	29
26	Farrukhabad	44	61
27	Fatehpur	26	34
28	Firozabad	69	68
29	Gautam Buddha Nagar	53	32
30	Ghaziabad	60	27
31	Ghazipur	24	16
32	Gonda	31	39
33	Gorakhpur	63	47
34	Hamirpur	9	11
35	Hapur	40	50
36	Hardoi	39	54
37	Jalaun	3	3
38	Jaunpur	19	10
39	Jhansi	6	7
40	Jyotiba Phule Nagar	42	53
41	Kannauj	54	58
42	Kanpur Dehat	35	30
43	Kanpur Nagar	5	1
44	Kanshiram Nagar	68	73
45	Kaushambi	32	42
46	Kheri	50	56
47	Kushinagar	36	31
48	Lalitpur	2	2
49	Lucknow	75	74

(*Continued*)

Appendix 3 Continued

S.N.	Districts	TOPSIS	MOORA
50	Mahamaya Nagar	47	48
51	Mahoba	14	13
52	Mahrajganj	20	19
53	Mainpuri	62	66
54	Mathura	66	59
55	Mau	57	51
56	Meerut	52	35
57	Mirzapur	8	14
58	Moradabad	7	9
59	Muzaffarnagar	17	12
60	Pilibhit	13	15
61	Pratapgarh	56	33
62	Rae Bareli	27	26
63	Rampur	51	62
64	Saharanpur	49	41
65	Sambhal	61	70
66	Sant Kabir Nagar	28	36
67	Shahjahanpur	64	67
68	Shamli	45	49
69	Shrawasti	38	65
70	Siddharthnagar	22	28
71	Sitapur	72	72
72	Sonbhadra	1	4
73	Sultanpur	30	25
74	Unnao	48	44
75	Varanasi	67	37

Appendix 4 Z-Scores of the variables

S.N.	District	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
1	Saharanpur	0.677	0.935	0.073	0.237	0.238	−0.276	0.261	0.719
2	Bijnor	0.821	0.165	0.252	0.237	0.563	−0.487	0.074	0.907
3	Rampur	−0.845	0.349	−0.585	−0.398	−0.538	0.646	1.088	−0.268
4	Jyotiba Phule Nagar	−0.428	−0.822	−0.644	−0.906	−0.536	0.638	0.246	−0.701
5	Meerut	1.342	−0.106	−0.474	1.254	0.290	0.112	0.114	0.699
6	Baghpat	1.152	−1.278	−1.106	−1.160	−0.588	−0.024	−0.292	−1.170
7	Gautam Buddha Nagar	1.474	−0.421	−1.045	0.110	0.267	−1.760	0.524	−0.869
8	Bulandshahr	0.557	−1.028	0.404	1.126	1.398	0.405	1.003	0.747

(*Continued*)

Appendix 4 Continued

S.N.	District	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
9	Aligarh	0.063	1.022	0.054	1.254	2.155	0.209	0.621	0.899
10	Mahamaya Nagar	0.074	0.577	−0.847	−1.160	−0.462	−0.250	0.522	−0.941
11	Mathura	−0.133	−0.063	−0.101	0.237	1.066	0.443	0.312	−0.084
12	**Agra**	−0.369	−0.367	**3.645**	2.524	0.821	−0.056	1.135	1.549
13	Firozabad	0.660	−0.703	−0.587	0.110	0.583	0.011	1.356	−0.127
14	Mainpuri	0.910	−1.072	−0.389	−0.779	−0.192	−0.158	1.881	−0.409
15	Bareilly	−1.286	1.608	0.288	1.126	1.203	−0.603	0.130	1.575
16	Pilibhit	−1.181	−1.321	−0.021	−0.652	0.048	−0.875	−0.524	−2.195
17	Shahjahanpur	−0.858	1.391	0.514	0.364	0.483	1.859	2.066	0.317
18	Kheri	−0.880	−0.378	2.060	0.364	1.155	0.159	1.379	1.202
19	Sitapur	−1.204	0.816	1.096	1.126	1.256	0.890	1.666	1.606
20	Hardoi	−1.045	1.749	1.218	0.618	−0.092	1.323	1.987	1.265
21	Unnao	−0.105	0.263	0.506	0.110	0.583	−0.383	0.481	0.406
22	**Lucknow**	1.209	0.490	−0.505	2.905	**5.008**	−1.733	−1.222	1.699
23	Farrukhabad	−0.203	−1.592	−0.677	−0.779	−0.668	0.812	0.673	−0.662
24	Kannauj	0.005	1.109	−0.721	−1.414	−0.362	0.906	0.883	−1.106
25	Etawah	1.221	−1.484	−0.613	0.110	−0.828	−0.018	0.524	−0.926
26	Auraiya	1.025	−0.605	−0.760	−1.160	−0.456	−0.394	0.468	−1.103
27	Kanpur Dehat	0.557	0.989	−0.259	−0.398	0.199	−0.477	0.421	−0.739
28	**Kanpur Nagar**	1.719	−1.300	**3.645**	2.778	2.011	−1.640	−1.109	1.691
29	Jalaun	0.116	−1.506	0.499	0.237	−0.671	−1.265	−1.760	−0.832
30	Jhansi	0.489	−0.095	0.509	0.745	−0.007	−1.690	−0.318	−0.563
31	Lalitpur	−1.026	0.675	0.745	−0.652	−1.254	−0.693	−2.014	−1.241
32	Hamirpur	0.474	−0.584	0.288	−0.779	−0.796	−0.666	0.196	−1.343
33	Mahoba	0.040	1.304	−0.328	−1.287	−1.032	0.118	−0.292	−1.542
34	Banda	−0.795	0.382	0.431	−0.271	−0.380	0.111	0.551	−0.737
35	Chitrakoot	−0.978	−0.508	−0.188	−1.287	−1.018	0.022	−0.167	−1.441
36	Fatehpur	−0.306	−0.497	0.304	−0.017	−0.101	0.610	0.196	−0.009
37	Pratapgarh	0.954	1.065	0.094	0.237	0.821	−0.568	−0.189	0.494
38	Kaushambi	−0.669	0.393	−0.877	−0.779	−0.643	0.772	−0.129	−0.911
39	Allahabad	0.105	2.768	0.966	2.651	2.491	−0.076	0.429	2.889
40	Bara Banki	−0.948	0.165	0.174	0.364	0.169	0.643	0.391	0.539
41	Faizabad	0.885	−0.551	−0.508	−0.271	0.281	−0.541	−0.974	−0.150
42	Ambedkar Nagar	1.153	−1.278	−0.593	−0.144	−0.458	−1.484	−0.718	−0.214
43	Bahraich	−2.748	−0.952	0.575	0.364	0.595	2.854	0.673	0.737
44	**Shrawasti**	−2.772	0.382	−0.793	−1.669	−0.863	**3.097**	−0.275	−1.334
45	Balrampur	−2.413	1.065	−0.096	−0.525	−0.707	2.926	0.663	−0.432
46	Gonda	−0.805	0.393	0.230	−0.398	−0.128	0.147	−0.745	0.690
47	Siddharthnagar	−1.765	−0.909	−0.322	−0.271	−0.714	1.628	−1.674	−0.073
48	Basti	−0.182	−0.443	−0.425	−0.398	−0.735	−0.167	−0.781	−0.156

(*Continued*)

Appendix 4 Continued

S.N.	District	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
49	Sant Kabir Nagar	−0.399	−1.093	−0.944	−1.414	−0.847	−0.049	−1.143	−0.817
50	Mahrajganj	−0.373	−0.030	−0.294	−0.017	−0.547	−0.571	−0.964	0.037
51	Gorakhpur	0.329	−0.432	−0.029	0.999	0.544	−0.702	−0.313	1.569
52	Kushinagar	−0.265	1.564	−0.317	−0.144	−0.350	0.213	−0.964	0.804
53	Deoria	0.642	0.718	−0.499	0.364	−1.304	−0.860	−1.660	0.399
54	Azamgarh	1.159	−1.050	0.255	0.745	0.238	−0.464	0.019	1.718
55	Mau	0.682	0.024	−0.910	−1.033	−0.314	−0.955	0.264	−0.382
56	Ballia	0.499	1.369	−0.279	1.381	−0.659	−1.036	−1.459	0.520
57	Jaunpur	1.188	−0.410	0.247	0.999	−0.339	−0.744	−1.801	1.615
58	Ghazipur	0.744	0.393	−0.082	0.872	0.087	−0.556	−1.460	0.852
59	Chandauli	0.560	−0.638	−0.526	−0.525	−0.973	−0.221	−0.964	−0.603
60	Varanasi	1.418	−0.551	−0.999	0.999	0.972	−1.414	−1.462	0.902
61	Sant Ravidas Nagar (Bhadohi)	0.387	−1.050	−1.258	−1.414	−1.057	0.410	−0.964	−0.930
62	Mirzapur	0.495	−1.343	0.487	−0.144	−0.849	−0.069	−0.343	−0.128
63	Sonbhadra	−0.434	0.414	1.616	0.237	−0.877	0.980	−0.287	−0.681
64	Etah	0.217	0.740	0.450	−0.271	−0.588	0.381	0.495	−0.758
65	Kanshiram Nagar	−0.882	0.664	−0.771	−1.160	0.213	1.698	1.153	−1.053
66	Amethi	−0.192	−0.996	−0.604	−0.652	−0.790	0.370	2.409	−0.677
67	Budaun	−1.723	−0.714	0.345	0.237	−0.108	0.717	0.570	0.424
68	Ghaziabad	1.532	2.671	−1.248	0.110	−0.151	−1.389	−0.606	0.666
69	Hapur	0.917	−1.625	−1.208	−1.160	−1.085	0.030	0.629	−1.139
70	**Moradabad**	0.018	0.935	**3.645**	−0.017	1.036	−0.327	0.560	0.666
71	Muzaffarnagar	0.788	−0.768	−0.274	0.110	−0.467	−0.619	−1.735	0.163
72	Rae Bareli	−0.258	−0.703	0.249	−0.144	0.098	−0.578	−0.705	0.227
73	Sambhal	−1.449	0.046	−0.542	−0.906	−0.389	1.053	0.988	−0.393
74	Shamli	−0.002	1.011	−1.182	−1.541	−0.867	0.231	0.359	−1.160
75	Sultanpur	0.666	0.664	−0.433	−0.144	−0.080	−0.584	−0.343	−0.185

References

[1] A. W., and P. D. Coat, "Decision analysis: A Bayesian approach, Journal of the Royal Statistical Society," *Journal of the Royal Statistical Society*, 29(2), 207–224, 1960.

[2] C. A. Howard, "Dynamic programming and Markov processes," John Wiley, 1960.

[3] H. Kazan and O. Ozdemir, "Financial Performance Assessment of Large Scale Conglomerates Via Topsis and Critic Methods," *International*

Journal of Management and Sustainability, vol. 3, no. 4, pp. 203–224, Mar. 2014, doi: 10.18488/journal.11/2014.3.4/11.4.203.224.
[4] A. R. Krishnan, M. M. Kasim, R. Hamid, and M. F. Ghazali, "A modified critic method to estimate the objective weights of decision criteria," *Symmetry (Basel)*, vol. 13, no. 6, Jun. 2021, doi: 10.3390/sym13060973.
[5] H. Deng, C.-H. Yeh, and R. J. Willis, "Inter-company comparison using modified TOPSIS with objective weights," 2000.
[6] P. Saxena, V. Kumar, and M. Ram, "A novel CRITIC-TOPSIS approach for optimal selection of software reliability growth model (SRGM)," *Qual Reliab Eng Int*, vol. 38, no. 5, pp. 2501–2520, Jul. 2022, doi: 10.1002/qre.3087.
[7] O. Önay and B. Fatih Yıldırım, "Evaluation of NUTS Level 2 Regions of Turkey by TOPSIS, MOORA and VIKOR 1," 2016. [Online]. Available: www.ijhssnet.com.
[8] M. O. Esangbedo and J. Wei, "Grey hybrid normalization with period based entropy weighting and relational analysis for cities rankings," *Sci Rep*, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-40954-4.
[9] M. Behzadian, S. Khanmohammadi Otaghsara, M. Yazdani, and J. Ignatius, "A state-of the-art survey of TOPSIS applications," *Expert Systems with Applications*, vol. 39, no. 17. Elsevier Ltd, pp. 13051–13069, Dec. 01, 2012. doi: 10.1016/j.eswa.2012.05.056.
[10] C. Oluah, E. T. Akinlabi, and H. O. Njoku, "Selection of phase change material for improved performance of Trombe wall systems using the entropy weight and TOPSIS methodology," *Energy Build*, vol. 217, Jun. 2020, doi: 10.1016/j.enbuild.2020.109967.
[11] H. Ture, S. Dogan, and D. Kocak, "Assessing Euro 2020 Strategy Using Multi-criteria Decision Making Methods: VIKOR and TOPSIS," *Soc Indic Res*, vol. 142, no. 2, pp. 645–665, Apr. 2019, doi: 10.1007/s11205-018-1938-8.
[12] H. R. Sama, S. V. K. Kosuri, and S. Kalvakolanu, "Evaluating and ranking the Indian private sector banks—A multi-criteria decision-making approach," *J Public Aff*, vol. 22, no. 2, May 2022, doi: 10.1002/pa.2419.
[13] L. Pérez-Domínguez, K. Y. Sánchez Mojica, L. C. Ovalles Pabón, and M. C. Cordero Diáz, "Application of the MOORA method for the evaluation of the industrial maintenance system," in *Journal of Physics: Conference Series*, Institute of Physics Publishing, Dec. 2018. doi: 10.1088/1742-6596/1126/1/012018.
[14] L. Pérez-Domínguez, L. A. Rodríguez-Picón, A. Alvarado-Iniesta, D. Luviano Cruz, and Z. Xu, "MOORA under Pythagorean Fuzzy Set for

Multiple Criteria Decision Making," *Complexity*, vol. 2018, Apr. 2018, doi: 10.1155/2018/2602376.

[15] S. Hajduk and D. Jelonek, "A decision-making approach based on topsis method for ranking smart cities in the context of urban energy," *Energies (Basel)*, vol. 14, no. 9, May 2021, doi: 10.3390/en14092691.

[16] V. Kumar, P. Saxena, and H. Garg, "Selection of optimal software reliability growth models using an integrated entropy–Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) approach," in *Mathematical Methods in the Applied Sciences*, John Wiley and Sons Ltd, 2021. doi: 10.1002/mma.7445.

[17] "Population Dynamics and Health Issues in India-Final 20-6-22 GO Print ke liye (1)." [Online]. Available: https://www.researchgate.net/publication/362018745.

[18] I. I. Meshram, N. Kumar Boiroju, V. Kodali, and N. B. Kumar, "Ranking of districts in Andhra Pradesh using women and children nutrition and health indicators by topsis method Corresponding Author Citation Article Cycle," 2017.

[19] A. Sotoudeh-Anvari, "The applications of MCDM methods in COVID-19 pandemic: A state of the art review," *Applied Soft Computing*, vol. 126. Elsevier Ltd, Sep. 01, 2022. doi: 10.1016/j.asoc.2022.109238.

[20] N. Saleh, M. N. Gaber, M. A. Eldosoky, and A. M. Soliman, "Vendor evaluation platform for acquisition of medical equipment based on multi-criteria decision-making approach," *Sci Rep*, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-38902-3.

[21] "National Family Health Survey (NFHS), 2021, https://dhsprogram.com."

[22] D. Diakoulaki, G. Mavrotas, and L. Papayannakis, "Determining Objective Weights in Multiple Criteria Problems: The Critic Method," 1995.

[23] Hongtao Shi, Yifan Li, Zhongnan Jiang, and Jia Yan, "Comprehensive Evaluation of Power Quality for Microgrid Based on CRITIC Method," in *International Conference on Power Electronics and Motion Control (IPEMC)*, Nanjing, China.

[24] C. L. Hwang and K. Yoon, "Methods for Multiple Attribute Decision Making. In: Multiple Attribute Decision Making," *Economics and Mathematical Systems*.

[25] A. Alinezhad and J. Khalili, "International Series in Operations Research & Management Science New Methods and Applications in Multiple Attribute Decision Making (MADM)." [Online]. Available: http://www.springer.com/series/6161.

Biographies

Sumedha Sharma is pursuing Ph. D. in Statistics from Amity University Uttar Pradesh (AUUP), Noida and also working as a visiting faculty of statistical sciences in the same department. She had rendered services to ICMR Community Cervical Cancer project named “Screening for Cancer of Cervix by Aided-Visual and HPV Tests in a Rural Community” as Assistant Statistician and worked with MoHUPA as a Research Analyst. She gave training with DES, State/UTs on building permit data.

Jitendra Kumar [PhD(Statistics), M.Sc.(Statistics), M. Tech. CSE(AI & ML), FRSS(UK)] is the Associate Professor of Mathematical Statistics, Statistical Sciences and Computational Intelligence (Scientific Computing, Artificial Intelligence, Machine Learning & Quantum Computing), in the Department of Mathematics, School of Advanced Sciences (SAS), Vellore Institute of Technology, Vellore, Tamil Nadu, India(Since Nov 30, 2018 till date). He has been credited to have over 25 years of experiences in academics, research and industry. He had served various organizations namely Prophecy Technology, Gurugram, Datanet India Pvt. Ltd., New Delhi, CSC Pvt. Ltd., New Delhi, Bio Informatics Institute of India, Noida, Caechet Pharmaceutical Pvt. Ltd, Bhiwadi, Rajasthan and some other establishments as Consultant Technical Analyst and Statistician. He had served Amity University Uttar

Pradesh (AUUP), Noida (ABS & AIAS) for 13 years (From Jan 13, 2006 to Nov 27, 2018) including Amity University, Dubai Campus (in Yr. 2013) as Assistant Professor (Gr. III.). Dr. Kumar has authored and co-authored few books & contributed many book chapters, over 50 publications, guided over 200 students dissertations & master thesis, supervising six research scholars, reviewed more than 100 research article's published in reputed Scopus indexed journals, delivered over hundred talks besides being the members of many national and international organizations.

Niraj Kumar Singh has received his Ph. D. in Statistics from Banaras Hindu University in 2012. Presently he is working in Amity University, Noida as an Assistant Professor. He has been credited with 30 publications in mathematical demography and applied statistics. He has served as a reviewer for many peers reviewed and reputed journals.

Anup Kumar had pursued Ph. D. in Statistics from Banaras Hindu University, Varanasi, India. He has worked in Stochastic Modelling of Human fertility (Mathematical Demography). After teaching in the core department of Statistics at Central University of Rajasthan and Allahabad University, switched to Biostatistics Department, SGPGIMS, Lucknow. Dr. Anup has published more than 30 research articles in the area of Mathematical demography and Biostatistics. He has served as reviewer for many peer reviewed and reputed journals.