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A Multi-Criteria Decision-Making Approach to Compare the Maternal Healthcare Status of Indian States: An Application of Data Science

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Abstract

The health system of a nation influences the well-being of its citizens. Maternal health is about the contentment of women throughout pregnancy, childbirth, and the postpartum period. In a country with millions of people like India, there are still goals in the area of maternal healthcare that need to be met despite widespread concern by the authorities. Spatial quantification of maternal health is necessary to identify the regions of immediate concern. In light of the methods and the variables used- the result of the quantification techniques produces a range of possible outcomes. The paper builds Composite Indicators based on some parameters of maternal healthcare, using different weighting methods, namely- TOPSIS, Iyengar-Sudarshan, Principal Component Analysis, Data Envelopment Analysis, and Ordered Weighted Average. Eventually, the most robust weighting technique is identified. The study finds Lakshadweep, Kerala, and Goa have better maternal healthcare, while Bihar, Arunachal Pradesh, and Nagaland are poorly positioned.

Key words: Demography; Composite index; TOPSIS; Principal component analysis; Data envelopment analysis; Ordered weighted average; Robustness.

AMS Subject Classifications: 90B50, 91B42

1. Introduction

Health, education, and income are the essential aspects of human development Swain and Mohanty (2010). A healthy society results from a community's access to quality healthcare services. The WHO rightly emphasized that the main objective of a healthcare system is to deliver better health services appropriately WHO (2000). However, the performance of a health system in achieving its objectives is measured by the actual health outcomes. The primary health system undertakes several interventions for promotive and preventive care of mother and child, along with curative and referral services Mishra (2001).

The healthcare services have two divisions, as detailed in the seventh schedule of part XI of the Indian Constitution, which deals with dividing powers between the central and

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state governments. Some of the health services are under the Concurrent List [1] like All India Institutes of Medical Sciences (AIIMS), controlled by the central government under the jurisdiction of the Ministry of Health and Family Welfare (MoHFW), whereas Government Medical Colleges, Civil Hospitals, Community Health Centers (CHC), Primary Health Centers (PHC) and Sub Centers are under the control of Directorate of Health Services by state government comes under State List. 'The matter of public health belongs to state list and maternity benefits is under concurrent list so a state-wise variation in maternal healthcare is expected' Chakraborty and Bhattacharjee (2017). For example, *Janani Suraksha Yojana* (JSY) is a centrally sponsored scheme but the state governments implement it through civil hospitals, health centers, *etc.* The extent of implementation of such schemes varies depending upon the quality of governance at the state level.

Maternal Health refers to women's health during pregnancy, childbirth, and postpartum. It encompasses the healthcare dimensions of family planning, preconception, prenatal and postnatal care to reduce maternal morbidity and mortality Chakraborty and Bhattacharjee (2017).

With the safe motherhood initiative by the UN in the 1980s, India initiated the Reproductive and Child Health Policies in 1997, followed by the National Population Policy in 2000, the National Health Policy in 2002, and then the National Rural Health Mission (NRHM) in 2005 based on Global health commitments for Millennium Development Goals (MDGs) to enhance access to high-quality healthcare for women Mali (2018). It is estimated that about 21 million women benefited from this scheme between April 2005 to August 2009 Jain (2010). In the last three years, 28.223 million mothers benefitted from JSY, with an expenditure of 46.23 billion. In India, institutional delivery has increased to 78 percent Janani Suraksha Yojana (2017). According to Sunaina (2018) the fifth Millennium Development Goal (MDG) called for lowering the Maternal Mortality Ratio (MMR) by at least three-fourths by 2015, from 437 to 109 per 100,000 live births. The achievement by 2015 was 167, according to the country report for the MDG 2015 MDG (2015).

Recognizing the need for improved maternal health, the government of India came up with different schemes like the cash assistance program *Janani Suraksha Yojana* (JSY) in April 2005 to encourage institutional deliveries by providing cash incentives to pregnant women and *Accredited Social Health Activists* (ASHA) and thus to reduce the MMR, especially among the states with high maternal mortality. The *Janani Shishu Suraksha Karayakaram* (JSSK) provided free medical services such as nutritional supplements, antenatal check-ups, medical transportation, free admission to hospitals, *etc.*, during the period of pregnancy and with limited prenatal and post-natal healthcare through public healthcare institutions. According to Mali (2018) the *Indira Gandhi Matritva Sahyog Yojana* (IGMSY) provided cash to pregnant women to make up for the loss of income they experienced during pregnancy, subject to age and parity requirements. Another program, the *Pradhan Mantri Surakshit Matritva Abhiyan* (PMSMA) provides guaranteed, comprehensive, and high-quality antenatal care at no cost to all pregnant women on the ninth day of every month. PMSMA assures pregnant women a minimum package of antenatal care services in their *second/third* trimesters at assigned government health centers NHP (2016).

[1] A list of activities that both state and central government look after. Public Health is one such activity.

Pandey and Singh (2018) measured the frequency with which women utilize pregnancy and child health services using data from the National Family Health Survey (NFHS-III). Their work serves as an illustration of Andersen's Behavioural Model of healthcare usage. It was discovered that the quintile of home wealth and the mother's educational level were accurate indicators of the use of maternal healthcare services.

Obviously, better maternal healthcare namely, prenatal health, including antenatal check-ups, neo-natal tetanus protection, and pregnancy registration in suitable health centers shall lead to a decrease in maternal mortality. This study's primary goal is to investigate the maternal healthcare condition in different Indian states and Union Territories (UTs) to identify the maternal health services that need immediate attention. This shall help the government in policy-making to achieve uniform national growth.

Since many demographers are continually working on various issues relating to the health sector, there is a wealth of literature concerning maternal health in India. Blum and Fargues (1990) created a mechanism to predict maternal mortality when cause-of-death is insufficient. They provided two strategies: one based upon an extrapolation by smoothing the observed profile of deaths among women, which yields lower estimates, and another on the age-specific mortality ratio of men and women. By processing a few life tables, one can quickly determine the number, age pattern, and trend of maternal mortality regardless of the method. Bhat (2002) derived estimates of maternal mortality for India using the sisterhood technique and a regression method that took into account sex differences in adult mortality and compared those values to the values of the estimates from different sources.

Research on the disparity in maternal healthcare facilities in different regions is undertaken periodically using different approaches, leading to the classification of alternatives are abundant in the literature. Authors like Iyengar and Sudarshan (1982), Ram and Shekhar (2006), Mohanty and Ram (2001) developed different multivariate ranking techniques using various parameters to rank the districts/states of India. These studies mainly focused to calculate a single index and a conclusion is made based on the value of the index. In this study, some methods of computing maternal healthcare are considered, and the authors tried to reach a unique solution that gives the most robust result.

Robustness signifies the insensitivity of a result to minor deviations from the assumptions Huber and Ronchetti (2009). "In a broad informal sense, robust statistics is a body of knowledge, partly formalized into theories of robustness, relating to deviations from idealized assumptions in statistics" Hampel *et al.* (1986). For robust composite indices, minor changes in the values of the participating variables in the index should not change the values in ranking. Robustness analysis is required to limit the possibility of getting meaningless Composite Indicators. This kind of analysis can enhance the final results' accuracy, credibility, and interpretability OECD (2008).

Many studies are carried out by converging values from different relevant parameters into a single index using several different methods of aggregation and weighting Chakraborty and Bhattacharjee (2017), Iyengar and Sudarshan (1982), Mohanty and Ram (2001). Gang *et al.* (2012) ranked the alternatives using various Multi-Criteria Decision Making (MCDM) methods and later used Spearman's rank correlation coefficient to generate the final ranking to resolve the inconsistency. A significant value of Spearman's rank correlation coefficient indicates a good agreement between a given MCDM method with other MCDM methods.

In this study, different weighting techniques are visited to build Composite Indicators using parameters associated with maternal healthcare. This paper distinguishes itself from the previously mentioned papers by employing multiple weighting methods to construct Composite Indicators, rather than creating a single index. (Gang *et al.*, 2012, pp.198) claims that - applying various MCDM methods to a sorting problem is beneficial because the ranking agreed by several methods is more trustful than a single method. However, it is necessary to check the robustness of the various methods used for ranking the regions to identify the most reliable method of ranking.

In this paper, the researchers identified some parameters that influenced maternal healthcare. These parameters were then combined into a single index using different weighting methods, forming different indices. However, it should be noted that no single approach can be superior in all aspects, and the selection of the optimal method depends on its compatibility and robustness. Combining some scattered statistical tools, the researcher's aim is to determine the robust Composite Indicator (MCDM method) from the competing approaches.

2. Objectives of the study

Based on the research gap identified and the issues raised in the above discussion, this paper intends to attain the following objectives :

- Formulate Composite Indicators to measure the extent of maternal healthcare status of the states/UTs of India combining all the maternal healthcare parameters.
- Identifying the most robust composite index amongst the competing methods of weighting.
- Ranking the states/UTs according to maternal health care services and accordingly identifying the state-wise level of maternal healthcare attainments.

3. Data source

The study uses secondary data from 36 Indian states and union territories that can be found in factsheets for the National Family Health Survey (NFHS-4) (`http://rchiips.org/nfhs/factsheet_NFHS-4.shtml`). The following parameters for evaluating maternal healthcare are identified from the aforementioned data source:

- P_1 = Mothers who had an antenatal check-up in the first trimester (%)
- P_2 = Mothers who had at least 4 antenatal care visits (%)
- P_3 = Mothers whose last birth was protected against neonatal tetanus (%)
- P_4 = Mothers who consumed iron folic acid for 100 days or more when they were pregnant (%)
- P_5 = Mothers who had full antenatal care (%)

- P_6 = Registered pregnancies for which the mother received Mother and Child Protection (MCP) card (%)

- P_7 = Mothers who received postnatal care from a doctor/ nurse/ LHV/ ANM/ midwife/ other health personnel within 2 days of delivery (%)

- P_8 = Mothers who received financial assistance under *Janani Suraksha Yojana* (JSY) for births delivered in an institution (%)

4. Different steps of composite indicator building

A Composite Indicator (CI) is a multidimensional concept calculated based on two or more single indicators on the basis of an underlying model. It compares spatial performance and is increasingly recognized as a useful tool in policy analysis and public communication OECD (2008). Defining a composite index is an integral part of MCDM problem which looks into selecting, ranking, and evaluating a finite set of alternatives (in this case states/UTs) Singh and Pant (2021). A brief description of the various steps involved in building a composite index is provided in the subsequent Sub-sections.

4.1. Normalization of parameters

The first step of Composite Indicator (CI) building invites the normalization of the variables. By converting the data to pure, dimensionless numbers, the data collected for the variables under consideration are normalized to bring the indicators to the same standard. Although there are other normalizing methods, in the current work re-scaling approach is utilized which is commonly coined as the max-min approach of indicators. To know in detail about different normalization techniques, one may refer to (OECD, 2008, pp.29–32).

Let, x_{ij} represents the value of the i^{th} state of the j^{th} parameter. The normalized decision matrix y_{ij} is calculated as

$$y_{ij} = \frac{x_{ij} - \min\limits_i(x_{ij})}{\max\limits_i(x_{ij}) - \min\limits_i(x_{ij})}, \quad i = 1, 2, \ldots, n \quad \text{and} \quad j = 1, 2, \ldots, m \tag{1}$$

The normalization technique is fixed throughout the study only the weighing techniques are changed. The weights of the normalized parameters are computed using five different weighting techniques, then the weights and normalized score of a given state are combined as a sum-product (linear aggregation) to attain the value of the composite index of the state. As five weighting techniques are used so for each state five composite index values are obtained, one for each weighing technique.

4.2. Weighting of the indicators

As weights quantify the relative importance of the different factors in the composite index and also control the dominance of the parameters with higher variance, so different popular methods of weighting are identified from the available literature and different sets of weights w_j for each of the weighting methods are computed. The values of the Composite

Indicators are calculated using the method of linear aggregation. A brief description of the various weighting techniques is provided below:

(i) Technique for order preference by similarity to ideal solution

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach, developed by Hwang and Yoon (1981) is a mechanism for ranking alternatives based on a variety of factors by minimizing the distance to the ideal solution and maximizing the distance to the negative-ideal solution.

Let, x_{ij} represent the value of the i^{th} state of the j^{th} parameter; $L(i, IDR)$ and $L(i, NIDR)$ are two components of an ideal solution and negative-ideal solution, then

$$L(i, IDR)=\sqrt{\frac{\sum_{j=1}^{m}\left(x_{ij}-\max_i(x_{ij})\right)^2 w_j}{\sum_{j=1}^{m} x_{ij}^2}} \tag{2}$$

$$L(i, NIDR)=\sqrt{\frac{\sum_{j=1}^{m}\left(x_{ij}-\min_i(x_{ij})\right)^2 w_j}{\sum_{j=1}^{m} x_{ij}^2}} \tag{3}$$

The weight (w_j) is calculated using Shannon's entropy Wu *et al.* (2011), Chakraborty and Bhattacharjee (2017)

$$w_j=\frac{1-\phi_j}{\sum_j(1-\phi_j)};\quad 0<\phi_j<1 \quad \text{and} \quad \sum_{j=1}^{m} w_j=1 \tag{4}$$

The entropy of the j^{th} parameter is given by

$$\phi_j=-\sum_i \frac{p_{ij}ln(p_{ij})}{ln(n)} \tag{5}$$

$$\text{where,}\quad p_{ij}=\frac{d_{ij}}{\sum_j d_{ij}} \quad \text{and} \quad n=\text{total no of state/UT;}$$

$$d_{ij}=\frac{x_{ij}}{\max_j(x_{ij})} \quad \text{in case of positive indicators}$$

$$\text{and}\quad d_{ij}=\frac{x_{ij}}{\min_j(x_{ij})} \quad \text{in case of negative indicators}$$

Composite Indicator (CI_{TOP}) for the $TOPSIS$ method is given by:

$$CI_{TOP}=\frac{L(i, IDR)}{L(i, IDR)+L(i, NIDR)} \tag{6}$$

(ii) Iyengar-Sudarshan method

Iyengar and Sudarshan (1982) proposed a weighting technique where the weights vary inversely proportional to the variation in the respective variables. Here the weights act as variance stabilizers of the participating parameters.

Let, y_{ij} represents the normalized value of the i^{th} state of the j^{th} parameter, and w_j represents the weights of the j^{th} parameter, then,

$$w_j = \frac{k}{\sqrt{\underset{i}{var}(y_{ij})}} \quad \text{with} \quad \sum_j w_j = 1 \quad \text{and} \quad 0 < w_j < 1 \tag{7}$$

$$\text{and} \quad k = \left[\sum_{j=1}^{m} \frac{1}{\sqrt{var(y_{ij})}}\right] \tag{8}$$

These weights stabilize the variance of the normalized parameters and prevent any one of the variables from dominating the composite index. The choice of the weights in this manner would ensure that large variation in any one of the indicators would not unduly dominate the contribution of the rest of the indicators and distort the inter-state comparisons Bhattacharjee and Wang (2011).

Composite Indicator (CI_{IS}) for the $Iyengar - Sudarshan$ method is given by:

$$CI_{IS} = \sum_{j=1}^{m} w_j y_{ij} \tag{9}$$

(iii) Principal component analysis

The eigenvalues indicate the proportion of each variable's variance that can be explained by the primary component. The Eigenvalues of the parameters for maternal healthcare can be obtained using the *Principal Component Analysis* (PCA) method.

The term *Principal Component Analysis* (PCA) refers to a technique that employs complex mathematical principles to reduce a large number of variables that could be associated with one another into a smaller set. It rotates the data point cluster to highlight the maximum variance. Additionally, because the input variables are grouped in a particular way using the Principal component analysis, the least important variables can be eliminated while the most useful ones can be retained.

$$w_j = \frac{\text{Individual Eigen values}}{\text{Sum of all Eigen values}} \tag{10}$$

Composite Indicator (CI_{PCA}) for the *Principal Component Analysis* method is given by:

$$CI_{PCA} = \sum_{j=1}^{m} w_j y_{ij} \tag{11}$$

(iv) Data envelopment analysis

Data Envelopment Analysis (DEA) is a mathematical programming technique presented by Charnes *et al.* (1978). Its application has been focused mainly on efficiency assessment. An efficiency frontier that could be used as a benchmark to compare countries' relative performance is estimated using linear programming tools by DEA. This requires the development of a benchmark (the frontier) and the estimation of the distance between nations in a multi-faceted system OECD (2008).

The weighted composite index for the i^{th} state is given by,

$$CI_{DEA} = \frac{\sum_{j=1}^{m} w_j y_{ij}}{\sum_{j=1}^{m} w_j} \tag{12}$$

The weights are to be selected in such a way that CI is *maximized* for the i^{th} state. Thus, the objective function is

$$\text{M}axim ize \quad \text{C}I_{DEA} = \frac{\sum_{j=1}^{m} w_j y_{ij}}{\sum_{j=1}^{m} w_j} \tag{13}$$

$$\text{Constrained by the following relations} \quad \sum_{j=1}^{m} w_j = 1 \quad ; \quad a < w_j < b \quad \forall j$$

The values of a and b are fixed for a particular problem and it depends on the value of the number of parameters (m) in the composite index.

(v) Ordered weighted average

Yager (1988) introduced the concept of *Ordered Weighted Average* (OWA). The main objective of the technique is to determine the weights of the different components participating in the formation of the composite index.

The weighted composite index for the i^{th} state is given by,

$$CI_{OWA} = \sum_{j=1}^{m} w_j y_{ij} \tag{14}$$

where y_{ij} is the i^{th} largest observation of the normalized matrix and w_j are the corresponding weights with the ordered values of the component y_{ij} such that

$$w_j > 0, \quad \sum_{j=1}^{m} w_j = 1, \forall j$$

Accordingly, some OWA operators are defined as the entropy function explaining the dispersion in the weights,

$$Disp(w_j) = -\sum_{j=1}^{m} w_j ln(w_j) \tag{15}$$

and some OWA operators are called the orness and are defined as,

$$\alpha = Orness(w_j) = \frac{1}{n-1}\sum_{j=1}^{m}(n-j)w_j \tag{16}$$

The OWA weights are determined using the linear programming method minimax disparity rule proposed by Wang and Parkan (2005). The objective function is

$$\text{M}inimize \quad \delta \tag{17}$$

$$\text{such that} \quad \sum_{j=1}^{m}\Big(\frac{n-j}{n-1}\Big)w_j = \alpha, \quad \text{where} \quad \alpha \in [0,1], w_j > 0 \tag{18}$$

$$\sum_{j=1}^{m} w_j = 1, \forall j \quad \text{and} \quad |w_j - w_{j+1}| \leqslant \delta, \quad j = 1, 2, \ldots, j-1 \tag{19}$$

The ultimate value of the composite index shall lie between the highest and the lowest value of the participating components in the formation of the index.

5. Process of testing robustness of composite indicators

As such, no fixed method is available to check the robustness of composite indices. With the help of the available resources from the literature, combining some scattered statistical tools an algorithm is developed to identify the robust Composite Indicator/MCDM method from a set of competing approaches. The algorithm is provided in Table A.1 of the paper. However, before introducing the method one needs to know about some statistical tests detailed below:

The process of measuring the robustness of the ranks of the same set of subjects (alternatives) obtained from different processes discussed here is improvised notation-wise over the method explained by Saisana *et al.* (2005) and Saltelli *et al.* (2008). Here, R_{ij} denotes the rank of the i^{th} state/UT (alternative) obtained from the j^{th} method. Let there be n states/UTs and m competing methods.

5.1. Inter-rater agreement of subjective judgment

The method proposed by Tinsley and Weiss (1975) looks into the agreement in ranks of a common group of subjects provided by different raters. The method can be hired and designed into the current setup to compare the agreement of the rating (in this case the ranking) of states/UTs obtained from different weighting methods. From the ranks of the n competing states and m methods S and S_1 are computed, where,

$$S = mn\frac{(n^2-1)}{12}, \quad S_1 = \frac{1}{m}\sum_{i=1}^{n}\Big[(\sum_{j=1}^{m}R_{ij}) - (\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{m}R_{ij})\Big]^2 \text{and} \quad S_2 = S - S_1$$

The corresponding test statistic as defined by Tinsley and Weiss (1975) is

$$F = \frac{S_1/n-1}{S_2/nm-n} \sim F_(n-1, nm-n) \tag{20}$$

It can be applied to test the null-hypothesis of independence amongst the raters *i.e.*, the different methods in this case related to the ranking of states are independent of each other. The agreement between the raters takes place in case the null hypothesis is rejected.

5.2. Rank correlation matrix

The Rank correlation coefficient measures the degree of similarity between two rank sets of the same groups of subjects. A high value of the Rank correlation coefficient implies a better agreement between two rank sets and vice versa. The Rank correlation coefficient (R_{ij}) is defined as

$$R_{ij} = 1 - \frac{6\sum d_i jk^2}{n(n-1)} \tag{21}$$

where n is the number of alternatives (states/UTs) and d_{ijk} is the difference between ranks of k^{th} state in the i^{th} and j^{th} weighting technique.

The correlation between the various methods of ranking can be checked with the help of the rank correlation matrix. It gives the pairwise comparison of rank correlation with every method.

5.3. Distance between ranks across different methods

The aggregate absolute difference in rank of the i^{th} state across all the different methods is given by,

$$\sum_{j'=1, j'\neq j}^{m} \left| R_{ij} - R_{ij'} \right| \tag{22}$$

gives the sum of the absolute difference of the rank of the i^{th} state obtained through the j^{th} method with the rank of the same i^{th} state obtained from all the other $(j')^{th}$ methods *i.e.*, $j' = 1, 2, \ldots, j-1, j+1, \ldots, m$. More precisely, in (22) j is fixed but. j' is varying from 1 to m (assuming there are m methods) but, $j \neq j'$

Subsequently, the average $\bar{R}_j$, aggregating the difference of ranks of all the states across all the competing methods is defined as

$$\bar{R}_j = \frac{1}{n(m-1)} \sum_{i=1}^{n} \sum_{j'=1, j'\neq j}^{m} \left| R_{ij} - R_{ij'} \right| \tag{23}$$

The ideal situation when all the techniques are equally robust is that the value of $\bar{R}_j$ should be very close to $0 \,\forall\, j$ and accordingly the $Avg(\bar{R}_j)$, with average taken over all the different methods shall be close to 0 too. Accordingly, the one-sided Studentized t is proposed for testing the null-hypothesis that H_0 : Avg $\bar{R}_j = 0$ against the alternative hypothesis H_1 : Avg $\bar{R}_j > 0$, taking the values of $\bar{R}_j$ as $j = 1, 2, \ldots, m$ as the values of the test variable. Accepting the null hypothesis takes us to the conclusion that the methods are equally robust.

Another single measure for overall robustness is defined in OECD (2008) as,

$$\bar{R} = \sum_{j=1}^{m} \bar{R}_j = \frac{1}{nm(m-1)} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j'=1, j' \neq j}^{m} \left| R_{ij} - R_{ij'} \right| \tag{24}$$

High values of $\bar{R}$ indicate the need for robustness check or sensitivity analysis of the competing methods (OECD, 2008, pp.117–118). However, the existing body of literature is yet to define any test for the statistic $\bar{R}$ to be utilized to test the hypothesis H_0: $\bar{R} = 0$ against the alternative $H_1 : \bar{R} > 0$.

5.4. Kendall Tau distance

The Kendall Tau rank distance Kendall (1938) is a statistic originally used to compute the dissimilarity between two rank sets and can be extended to find the robust composite index out of the competing composite indices. Considering two rank-sets of the same set of subjects (alternatives) say τ_1 and τ_2, the distance is defined as

$$\begin{aligned} K(\tau_1, \tau_2) = &|\{(i, i') : i < i', [\tau_1(i) < \tau_1(i') \wedge \tau_2(i) > \tau_2(i')] \\ &\vee [\tau_1(i) > \tau_1(i') \wedge \tau_2(i) < \tau_2(i')]\}| \end{aligned} \tag{25}$$

where, $\tau_1(i)$ and $\tau_2(i')$ are the ranking of the i^{th} and $(i')^{th}$ subject in the rank set τ_1 and τ_2 respectively. The expression in (25) is summarized as

$$K(\tau_1, \tau_2) = \sum_{\substack{\{i,i'\} \in P \\ i < i'}} \hat{K}_{i,i'}(\tau_1, \tau_2) \tag{26}$$

where, P is the set of unordered pairs of all the distant subjects in the rank set τ_1 and τ_2 respectively, and

$$\begin{aligned} \hat{K}_{i,i'}(\tau_1, \tau_2) &= 0 \text{ if the } i^{th} \text{ and } (i')^{th} \text{ subject are in the same order in both the rank set } \tau_1 \text{ and } \tau_2 \\ &= 1, \text{ otherwise} \end{aligned}$$

Thus, the statistic $K(\tau_1, \tau_2)$ is a measure of the distance between the rank set τ_1 and τ_2 for the same set of subjects. Accordingly, the statistic for an aggregate distance of a rank set τ_j and τ_j with all other rank set $\tau_{j'}$ is defined as

$$K_j = \sum_{\substack{j'=1 \\ j' \neq j}}^{m} K(\tau_j, \tau_{j'}), \;\; j = 1, 2, \ldots, m \tag{27}$$

The rank set τ_j shall be considered as the most robust set of ranks of the subjects (alternatives) over any other rank set $\tau_{j'}$ if

$$K_j < K_{j'} \;\; \forall \; j' \;\; (\text{but} \neq j) \tag{28}$$

Eventually, the j^{th} method of ranking stands out to be the most robust technique of ranking the subjects given the dataset.

6. Analysis and result

As described in Section 4.1. the normalized values of the parameters for the different states/UTs are computed. The normalized values of the parameters are used to calculate the composite index with the use of five weighting techniques *viz*; TOPSIS, Iyengar-Sudarshan, Principal Component Analysis, Data Envelopment Analysis, and Ordered Weighted Average. The aggregation of the normalized score was done using the linear aggregation method. The normalization and aggregation method remains the same throughout the study only the weighting techniques varied. Based on the methods discussed in Section 4.2. above, 5 sets of composite indices along with their ranks are obtained and are given in Table A.2. From Table A.2, it can be seen that Kerala and Lakshadweep are the two states that are on the top list of ranking for all the methods. However, for other states, it can be seen that there is heterogeneity of ranking especially for ranks obtained by the TOPSIS method which has significant dissimilarity in ranking in comparison to the other four methods. Moving down the table one can find a lack of consensus on ranks among the different methods. This shows the relevance of the current study. Different method generates different ranking so one needs to check for the robustness of different competing approaches to reach a unique set of ranks.

The next step is to use the proposed algorithm (*c.f.* Table A.1) to check the robustness of the methods. All the steps of the algorithm are implemented in R-software.

Initially, the test proposed by Tinsley and Weiss (1975) is applied to look for consistency in the rankings obtained from several methods under

Null hypothesis H_0: There is independence in ranks obtained from different methods.

Alternative hypothesis H_1: the ranking methods are in agreement with each other.

After performing the test in R-software we have found that $Cal.F(42.3184) > Crit.F(1.5050)$ at 5% level of significance. Accordingly, the null hypothesis is rejected and it is concluded that there is an agreement between the ranking methods.

As agreement could be found between the rankings one can skip steps III and IV of the algorithm (*c.f.* Table A.1) and directly can move towards step V to check:

Null hypothesis H_0: All the ranking methods are equally robust.

Alternative hypothesis H_1: All the ranking methods are not equally robust.

From Table 1 we find that the p-value is $0.0024 < 0.05$, so, we shall conclude that all the methods are not equally robust. Hence, the next task is to determine the most robust ranking method out of the methods used (*c.f.* Table A.1). Kendall's distance measures the pairwise disagreement between two rankings. The lesser the distance, the more robust the method is. A detailed discussion on the same is available in Section 5.4.

Table 1: Result for robustness check

$\overline{R}_1$	$\overline{R}_2$	$\overline{R}_3$	$\overline{R}_4$	$\overline{R}_5$	$\overline{R}$	t-value	p-value
4.6389	2.2917	4.0278	2.1389	2	3.0389	5.646494	0.0024

Table 2 confirms that method *Ordered Weighted Average* (OWA) has the least score (190), *i.e.*, the lowest distance with all other methods. Hence, the composite index based on the OWA method of weighting is considered to be the most robust method for the said data. Accordingly, the composite index values obtained from OWA method are shown in Figure 1.

Table 2: Kendall's distance measurement

Sl no	Methods	Distance between rankings (S)	Rank
1	TOPSIS	422	5
2	I-S	215	3
3	PCA	398	4
4	DEA	199	2
5	OWA	190	1

*one with minimum score is ranked 1

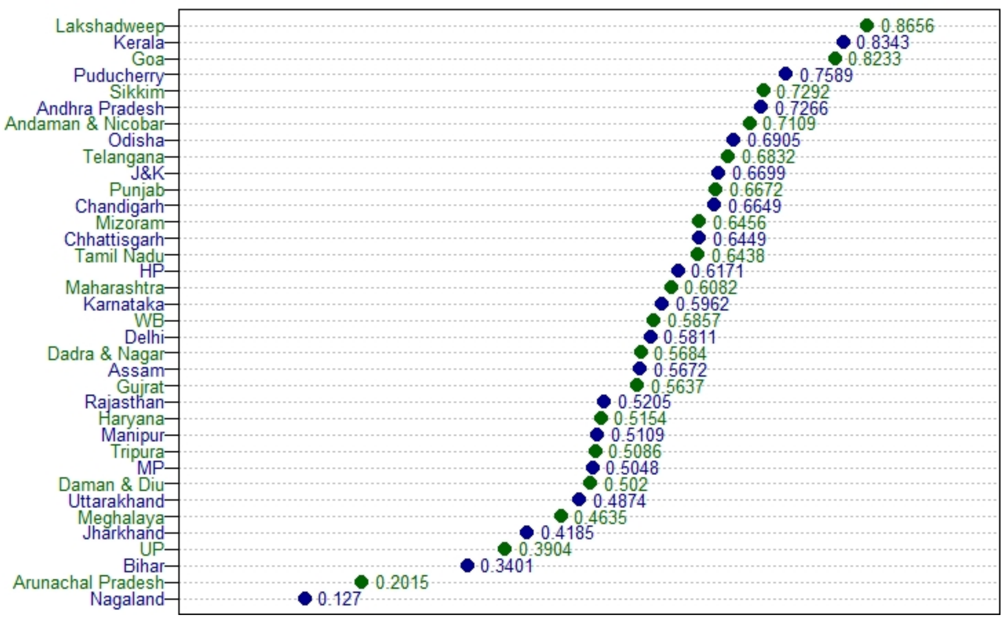

Figure 1: CI values of all the states/UTs using OWA method

7. Discussion and conclusion

Using several healthcare indicators, the article aimed to compare the situation of maternal healthcare in India's various states and UTs using the MCDM technique. In order to determine the most reliable weighting approach for merging multiple healthcare indicators, the study suggests a methodology incorporating a number of dispersed statistical methods. The states and UTs were rated in terms of their maternal healthcare facilities using the *Ordered Weighted Average* (OWA) technique, as this weighting tool posted itself as the most robust of the various weighting techniques. The states and UTs that do poorly in terms of maternal healthcare are identified, and pertinent discussion concerning those states is conducted.

According to the aforementioned survey, the top five performing states/UTs are Lakshadweep, Kerala, Goa, Puducherry, and Sikkim, whereas the bottom five states or UTs are Jharkhand, Uttar Pradesh, Bihar, Arunachal Pradesh, and Nagaland.

As per census 2011 data, it has been observed that the female literacy rate of all the top 5 states/UTs, namely Puducherry (81.2), Goa (81.8), Lakshadweep (88.3), Kerala (92), is very high (above 81 percent) except Sikkim (76.4 percent). Similarly, for the bottom five states, Jharkhand (56.2), Uttar Pradesh (59.3), Bihar (53.3), and Arunachal Pradesh (59.7), the female literacy rate is below 60 percent; the exception lies with Nagaland, where the female literacy is (76.7) percent which is same as Sikkim Ministry of Statistics and Program Implementation (2017). Thus, female literacy might be one of the major contributors to better maternal healthcare status as literature has evidence of the positive and significant influence of mother's schooling on maternal care utilization Govindasamy and Ramesh (1997). Nagaland ranks lowest in maternal healthcare despite having the same literacy rate as that of Sikkim. This might be due to Nagaland's remote location, restricted access to healthcare, and lack of proper medical facilities.

Among the top-ranked states/ UTs, Puducherry has a compact geographical area with a high literacy rate and better health facilities both in the public and private sectors. As per Kayaroganam *et al.* (2016) 78.6 percent of the mother avail full ANC. Paul and Chouhan (2020) suggested that Maternal mortality can be prevented by regular ANC visits, supervised deliveries, and postnatal care (PNC). According to Census 2011, in Puducherry, 87 percent of mothers consult an Obstetrician and prefer delivery at government hospitals, while 56 percent have good knowledge of nutrition during pregnancy. Additionally, 99 percent of mothers have adequate knowledge of breastfeeding and its benefits Ramaiah *et al.* (2022).

Goa, a coastal state with mountains on its western border, covers an area of 3702 square kilometers and has a population of 1.46 million. The state excels in protecting mothers against neonatal tetanus, with a rate of 96.2 percent surpassing the national average of 89 percent. Iron deficiency anemia among mothers is a major threat to safe motherhood and to the health and survival of infants, but Goa has achieved a consumption rate of 67.4 percent for Iron and Folic Acid (IFA), surpassing the national average of 30.3 percent Dehury *et al.* (2017).

Kerala, a state in South India is home to more than 33 million people "with females enjoying higher status compared to other states" Gupta and Mani (2022). This state is known for its remarkable achievements in education and health Mukherjee (2010). As per the report of the Department of Health, Govt of Kerala, the state has 1280 numbers of modern medicine Institutions including Hospitals, Community Health Centers (CHC), Public Health Center (PHC) *etc.*, with 38004 numbers of Beds with a population bed ratio of 879 per person Saritha (2018). As per the 2011 census, 92 percent of the women of Kerala are literate. The government's efforts to improve healthcare have positively impacted the state's socioeconomic development. Easy access to adequate medical facilities and the availability of such facilities to its stakeholders are significant contributors to maternal health issues. Access to quality obstetric care is a priority to prevent complications during and after delivery.

Sikkim is a mountainous state, with *Kangchenjunga* having the highest peak in India. It is one of the states of North-east India with a population of 6 million. Numerous studies concur that women's empowerment improves access to health and wellness. 95.3 percent of the women in Sikkim participate in household decision-making. Proper nutrition is crucial for women's health; inadequate nutrition can lead to anemia and health issues Dehury *et al.* (2017).

As derived, Nagaland has one of the worst maternal healthcare, preceded by Arunachal Pradesh, Bihar, Uttar Pradesh, and Jharkhand. Nagaland's maternal care and child immunization indicators are significantly below the national average Chakraborty and Bhattacharjee (2017). Geographic isolation, limited healthcare access, high medical costs, and inadequate health facilities contribute to the challenges faced by women in Nagaland. They often prefer home births assisted by traditional midwives to reduce expenses. A lack of encouragement to participate in seminars and awareness programs on maternal healthcare is observed, particularly in rural areas. Traditional midwives support childbirth and reduce family costs Humtso and Soundari (2019).

Arunachal Pradesh, the neighboring state of Nagaland, has the second lowest position in maternal healthcare status. Singh *et al.* (2009) points out that approximately 50 percent of women in Arunachal Pradesh do not make any prenatal visits. Prenatal visits are crucial for recognizing pregnancy complications and knowing when to seek emergency obstetric care, reducing the risk of maternal death.

The neighboring states Bihar, Uttar Pradesh, and Jharkhand located in eastern India, rank among the bottom five states. Under utilization of professional assistance during delivery may contribute to the poor conditions of maternal healthcare. Singh *et al.* (2009) stated that nearly 75 percent of women still give birth without any medical assistance in Uttar Pradesh and Bihar. Despite the fact that 56 percent of women are aware of the requirement for three ANC check-ups, 49 percent do not adhere to it because they are unaware of the hazards associated with pregnancy without these check-ups. Many people think that unless there are difficulties, a normal pregnancy doesn't need three ANC checks. Only 22 percent of pregnant women are advised to have a minimum of three ANC visits Khan *et al.* (2014).

Despite its abundant resources, Jharkhand faces issues in maternal healthcare, with high maternal mortality and low utilization of prenatal and secure delivery services IIPS (2010). In 2009, the maternal mortality rate in Jharkhand was 261 per 100,000 live births, higher than the national average of 212 Ogala *et al.* (2012). As per the guidelines developed by the Ministry of Health and Family Welfare (2010) and WHO (2006), complete ANC is one of the key factors of maternal healthcare utilization. Only 9 percent of women in Jharkhand used complete ANC services during 2007-2008, compared to 18.8 percent nationally. Socioeconomic disparities, caste, and media exposure influence the utilization of ANC services Kavitha and Audinarayan (1997), Pandey *et al.* (2004). Complete ANC services were provided to approximately 19 percent from other social groups, compared to 7 percent of SC and 6 percent of ST married women. All ANC services were utilized by 10 percent of Hindus and 27 percent of urban women Singh and Chaturvedi (2015). Women exposed to mass media were 65 percent more likely to use all ANC services Gupta *et al.* (2016). The coal mine industry in Jharkhand also contributes to the problem of an irregular visit to health centers with women not receiving paid leave and facing occupational hazards Dubey (2016), Bhanumathi (2002). It is essential to address these issues for improved maternity healthcare.

Governments must prioritize maternal healthcare as an investment in society. India needs a clear healthcare vision, emphasizing immunization, maternity care, primary health centers, committed doctors, and support staff. Public awareness campaigns can reduce disparities in ANC utilization. Spreading knowledge about prenatal screening and highlighting government health programs are essential.

Although the study is exploratory and indicative, it provides comparative information on the status of Indian states/UTs in terms of maternal health care. Policymakers should focus on lower-ranked states/UTs as they shall show a higher convergence rate. To identify such spatial black spots, further research is needed at the district level in such low-performing states. Various normalization and aggregation techniques can benefit the quantification of maternal healthcare. Incorporating other demographic and socioeconomic variables can generate an advanced composite score. Examining further the disadvantaged districts may offer focused insights and potential solutions. Timely ANC check-ups, preparedness for delivery, postnatal care, and family planning are crucial for improving maternal health Khan *et al.* (2014). This approach of identifying a reliable MCDM method from among the many choices available can also be applied to several other MCDM-related activities in other knowledge domains.

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References

Bhanumathi, K. (2002). The status of women affected by mining in India. In *Tunnel Vision: Women, Mining and Communities.*

Bhat, P. N. (2002). Maternal mortality in India: an update. *Studies in Family Planning*, **33**, 227–236.

Bhattacharjee, D. and Wang, J. (2011). Assessment of facility deprivation in the households of the north eastern states of India. *Demography India*, **40**, 35–54.

Blum, A. and Fargues, P. (1990). Rapid estimations of maternal mortality in countries with defective data: an application to Bamako (1974–85) and other developing countries. *Population Studies*, **44**, 155–171.

Chakraborty, A. and Bhattacharjee, D. (2017). Maternal health: which states are more caring? *Demography India*, **46**, 82–96.

Charnes, A., Cooper, W., and Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, **2**, 429–444.

Dehury, R. K., Samal, J., Desouza, N. V., and Dehury, P. (2017). Status of women's health in Goa and Sikkim: a comparative analysis of state fact sheets of NFHS-3 and 4. *International Journal of Medicine and Public Health*, **7**, 196–202.

Dubey, K. (2016). *Socio Economic Impact Study of Mining and Mining Polices on the Livelihoods of Local Population in the Vindhyan Region of Uttar Pradesh*. Technical Report, NITI Aayog.

Gang, K., Lu, Y., Peng, Y., and Shi, Y. (2012). Evaluation of classification algorithms using MCDM and rank correlation. *International Journal of Information Technology & Decision Making*, **11**, 197–225.

Govindasamy, P. and Ramesh, B. M. (1997). *Maternal Education and the Utilization of Maternal and Child Health Services in India*. Technical Report, International Institute for Population Sciences and Macro International Inc.

Gupta, A., Kumar, P., and Dorcas, O. A. (2016). Decomposing the socio-economic inequalities in utilization of full antenatal care in Jharkhand state, India. *International Journal of Population Studies*, **2**, 92–106.

Gupta, A. and Mani, S. S. (2022). Assessing mortality registration in Kerala: the MARANAM study. *Genus*, **78**.

Hampel, F., Rousseeuw, P., and Stahel, W. (1986). *Robust Statistics: The Approach Based on Influence Functions*. John Wiley & Sons, New York.

Huber, P. J. and Ronchetti, E. M. (2009). *Robust Statistics*. Wiley, Hoboken, 2nd edition.

Humtso, M. Y. and Soundari, M. H. (2019). Maternal health care practices of Lotha Naga tribal women in India. *PEOPLE: International Journal of Social Sciences*, **5**, 738–755.

Hwang, C. and Yoon, K. (1981). *Multiple Attribute Decision Making Methods and Applications*. Springer.

IIPS (2010). *District Level Household and Facility Survey (DLHS-3), 2007-08: Jharkhand*. Technical Report, International Institute for Population Sciences.

Iyengar, N. and Sudarshan, P. (1982). A method of classifying regions from multivariate data. *Economic and Political Weekly*, **17**, 2047–2052.

Jain, A. K. (2010). Janani suraksha yojana and the maternal mortality ratio. *Economic and Political Weekly*, **45**, 15–16.

Janani Suraksha Yojana (2017). National health portal of India. Retrieved August 7, 2017, from `https://www.nhp.gov.in/janani-suraksha-yojana-jsy-_pg`.

Kavitha, N. and Audinarayan, N. (1997). Utilisation and determinates of selected maternal and child health care in rural areas of Tamil Nadu. *Health and Population: Perspectives and Issues*, **20**, 112–125.

Kayaroganam, R., Saya, G. K., and Kar, S. S. (2016). Utilization of maternal health services among janani suraksha yojana beneficiaries in Puducherry, India. *International Journal of Advanced Medical and Health Research*, **3**, 73–77.

Kendall, M. (1938). A new measure of rank correlation. *Biometrika*, **30**.

Khan, M. E., Agarwal, P. K., Hazra, A., Dixit, A., Bhatnagar, I., Ahmad, J., and Ahmad, D. (2014). *Maternal and Newborn Health Behaviors in Rural Uttar Pradesh: Findings from Learning Phase Baseline Survey 2013*. Population Council, New Delhi.

Mali, N. V. (2018). A comparative assessment of maternal health and maternal health policies in India and the US: need to transition from a biomedical model to a biopsychosocial model for maternal health policies. *Journal of Health and Human Services Administration*, **40**, 462–498.

MDG (2015). *Millennium Development Goals (MDG) India Country Report 2015*. Technical Report, MoSPI.

Ministry of Statistics and Program Implementation (2017). *Women & Men in India-2017*. Technical Report, MoSPI.

Mishra, R. K. (2001). *Utilisation of Maternal Child Health and Family Planning Services Through Primary Health Centres in Rural Rajasthan*. Ph.D. Thesis, Jawaharlal Nehru University.

Mohanty, S. and Ram, F. (2001). *District at a Glance: India*. Mimeograph, IIPS, Mumbai.

Mukherjee, S. (2010). State of health and health care in West Bengal: a study in comparative perspective with Kerala and Tamil Nadu. *Demography India*, **39**, 259–276.

NHP (2016). Pradhan mantri surakshit matritva abhiyan. Retrieved October 13, 2022, from `https://pmsma.nhp.gov.in/about-scheme/`.

OECD (2008). *Handbook on Constructing Composite Indicators: Methodology and User Guide*. OECD, Paris.

Ogala, V., Avan, B., and Roy, I. (2012). Women's Level of Satisfaction with Maternal Health Services in Jharkhand. Technical Report, United States Agency International Development. Retrieved from `http://pdf.usaid.gov/pdf_docs/PA00JDGP.pdf`.

Pandey, A., Roy, N., Sahu, D., and Acharya, R. (2004). Maternal health care services observations from Chhattisgarh, Jharkhand and Uttaranchal. *Economic and Political Weekly*, **39**, 713–720.

Pandey, K. and Singh, R. (2018). Accessing maternal and child health care services utilization: an application of andersen's behaviour model. *Elixir International Journal*, **118**, 50646–50655.

Paul, P. and Chouhan, P. (2020). Socio-demographic factors influencing utilization of maternal health care services in India. *Clinical Epidemiology and Global Health*, **8**, 666–670.

Ram, F. and Shekhar, C. (2006). *Ranking and Mapping of Districts Based on Socio-economic and Demographic Indicators*. Technical Report, International Institute of Population Sciences, Mumbai.

Ramaiah, C. K., Raju, S., Chennupati, D., and Prakash, G. S. (2022). Maternal healthcare information requirements of first-time mothers in Puducherry: a survey.

Saisana, M., Saltelli, A., and Tarantola, S. (2005). Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators. *Journal of the Royal Statistical Society Series A: Statistics in Society*, **168**, 307–323.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., and Tarantola, S. (2008). *Global Sensitivity Analysis: The Primer*. John Wiley & Sons.

Saritha, R. (2018). *Health at a Glance 2018*. Technical Report, Department of Health Services. Kerala: Directorate of Health Services. Retrieved January 07, 2022, from `https://dhs.kerala.gov.in/wp-content/uploads/2020/03/health_25022019.pdf`.

Singh, K. J. and Chaturvedi, H. K. (2015). Factors influencing the skilled birth attendant utilization of non-institutional delivery in empowered action group states, India. *American International Journal of Research in Humanities, Arts and Social Sciences*, **12**, 54–62.

Singh, M. and Pant, M. (2021). A review of selected weighing methods in MCDM with a case study. *International Journal of Systems Assurance Engineering and Management*, **12**, 126–144.

Singh, S., Ramez, L., Ram, U., Moore, A. M., and Audam, S. (2009). Barriers to Safe Motherhood in India. Technical Report, IIPS.

Sunaina, P. (2018). *Inequalities in Maternal Health Care in Kerala.* Ph.D. Thesis, Mahatma Gandhi University.

Swain, A. and Mohanty, B. (2010). Socio-demographic disparities in Orissa-maternal and child health and welfare perspectives. *Demography India*, **39**, 129–131.

Tinsley, H. E. and Weiss, D. J. (1975). Inter-rater reliability and agreement of subjective judgments. *Journal of Counseling Psychology*, **22**, 358–376.

Wang, Y.-M. and Parkan, C. (2005). A minimax disparity approach for obtaining OWA operator weights. *Information Sciences*, **175**, 20–29.

WHO (2000). World health report 2000 health systems: improving performance. Retrieved January 07, 2022, from https://apps.who.int/iris/bitstream/handle/10665/42281/WHR_2000-eng.pdf?sequence=1&isAllowed=y.

Wu, J., Sun, J., Liang, L., and Zha, Y. (2011). Determination of weights for ultimate cross efficiency using shannon entropy. *Expert Systems with Applications*, **38**, 5162–5165.

Yager, R. R. (1988). On ordered weighted averaging aggregation operators in multicriteria decision making. *IEEE Transactions on Systems, Man, and Cybernetics*, **18**, 183–190.

Appendix A

Table A.1: Algorithm for robustness check

Step I	Compute rank of all the subjects (alternatives) based on the composite index developed from all the methods i.e., rank of the n-subjects for the m-different methods.
Step II	Perform test for Inter-rater agreement of subjective judgment (different methods in this exercise) as defined in Tinsley and Weiss (1975). Null hypothesis: H_0: There is independence in ranks (of subjects) obtained from different methods tested against the alternative H_1: The ranking methods are in agreement to each other If H_0 is rejected go to Step V else go to step III.
Step III	Rank correlation Matrix taking all the methods in pairs are computed
Step IV	Look for insignificant rank correlations if any. Identify the method(s) which is (are) insignificant from the other methods and drop it from further analysis. Repeat step II else GO TO Step V
Step V	Compute $\bar{R}_j$ (Eqn. 23) for each of the methods ($j = 1, 2, \ldots, m$). Test if Avg ($\bar{R}_j$) is significantly greater than 0. If Avg ($\bar{R}_j$) is significantly close to zero conclude that "All the methods are equally robust"- GOTO Step VIII ELSE – "All methods are not equally robust and there is a need of Robustness study"- GOTO Step VI
Step VI	Compute Kendall Tau distance of a method (j, say) with all the other methods (except j) and add the distances. Call it K_j Compute K_j for all the methods ($j = 1, 2, \ldots, m$). The method with a minimum value of K_j is the most robust technique.

Table A.2: Rank & CI values of states/UTs of maternal healthcare parameters

State/UTs	Methods				
	TOPSIS	**I-S**	**PCA**	**DEA**	**OWA**
Andaman & Nicobar	13 (0.5200)	7 (0.7277)	10 (0.7178)	7 (0.7179)	7 (0.7109)
Andhra Pradesh	11 (0.5410)	6 (0.7439)	4 (0.8158)	5 (0.7315)	6 (0.7266)
Arunachal Pradesh	36 (0.1836)	35 (0.2381)	35 (0.1505)	35 (0.2089)	35 (0.2015)
Assam	12 (0.5264)	23 (0.5857)	28 (0.469)	21 (0.576)	22 (0.5672)
Bihar	32 (0.3582)	34 (0.3578)	34 (0.1955)	34 (0.352)	34 (0.3401)
Chandigarh	20 (0.4566)	11 (0.6908)	14 (0.6513)	11 (0.6686)	12 (0.6649)
Chhattisgarh	10 (0.5607)	15 (0.6574)	15 (0.6473)	13 (0.6526)	14 (0.6449)
Daman & Diu	25 (0.4237)	27 (0.5257)	18 (0.6178)	29 (0.5088)	29 (0.502)
Delhi	21 (0.4428)	20 (0.5983)	20 (0.6034)	20 (0.5863)	20 (0.5811)
Dadra & Nagar Haveli	26 (0.4148)	21 (0.5902)	19 (0.6039)	22 (0.5752)	21 (0.5684)
Goa	7 (0.5828)	3 (0.8373)	3 (0.8811)	3 (0.8280)	3 (0.8233)
Gujarat	28 (0.4032)	22 (0.5859)	12 (0.6774)	23 (0.5703)	23 (0.5637)
Haryana	34 (0.3256)	24 (0.5454)	25 (0.5465)	25 (0.5219)	25 (0.5154)
Himachal Pradesh	16 (0.4678)	16 (0.6411)	13 (0.6579)	16 (0.6218)	16 (0.6171)
Jammu & Kashmir	8 (0.5719)	12 (0.6797)	8 (0.7225)	10 (0.6746)	10 (0.6699)
Jharkhand	33 (0.336)	32 (0.442)	32 (0.3954)	32 (0.4282)	32 (0.4185)
Karnataka	18 (0.466)	18 (0.6136)	17 (0.6208)	18 (0.6011)	18 (0.5962)
Kerala	2 (0.6353)	2 (0.8383)	1 (0.9744)	2 (0.8373)	2 (0.8343)
Lakshadweep	1 (0.6453)	1 (0.8789)	2 (0.9404)	1 (0.8669)	1 (0.8656)
Madhya Pradesh	19 (0.4596)	28 (0.5256)	31 (0.4198)	28 (0.5147)	28 (0.5048)
Maharashtra	23 (0.4262)	17 (0.6294)	16 (0.6439)	17 (0.609)	17 (0.6082)

Table A.2: Continued

State/UTs	**Method**				
	TOPSIS	**I-S**	**PCA**	**DEA**	**OWA**
Manipur	15 (0.4728)	31 (0.4866)	11 (0.6982)	26 (0.5179)	26 (0.5109)
Meghalaya	29 (0.3916)	30 (0.4895)	29 (0.4259)	31 (0.4624)	31 (0.4635)
Mizoram	4 (0.6189)	13 (0.6634)	22 (0.5931)	15 (0.6485)	13 (0.6456)
Nagaland	35 (0.2122)	36 (0.151)	36 (0.0122)	36 (0.1333)	36 (0.127)
Odisha	6 (0.6034)	8 (0.7034)	21 (0.6032)	8 (0.6959)	8 (0.6905)
Punjab	17 (0.4667)	10 (0.6914)	9 (0.7194)	12 (0.6682)	11 (0.6672)
Puducherry	3 (0.6215)	4 (0.7758)	6 (0.7918)	4 (0.7644)	4 (0.7589)
Rajasthan	22 (0.4359)	25 (0.5442)	25 (0.5076)	24 (0.5251)	24 (0.5205)
Sikkim	9 (0.5644)	5 (0.7487)	7 (0.7624)	6 (0.7291)	5 (0.7292)
Tamil Nadu	5 (0.6103)	14 (0.6609)	24 (0.5866)	14 (0.6508)	15 (0.6438)
Telangana	14 (0.5074)	9 (0.7015)	5 (0.7948)	9 (0.6882)	9 (0.6832)
Tripura	31 (0.3582)	26 (0.5259)	23 (0.5923)	27 (0.5165)	27 (0.5086)
Uttar Pradesh	30 (0.3605)	33 (0.4084)	33 (0.313)	33 (0.3999)	33 (0.3904)
Uttarakhand	27 (0.4082)	29 (0.5129)	30 (0.4206)	30 (0.497)	30 (0.4874)
West Bengal	24 (0.4257)	19 (0.6058)	26 (0.5434)	19 (0.5912)	19 (0.5857)