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Progress in Child Nutrition in India, 2015-2024: Evidence from National Family Health Survey

Aalok R Chaurasia

Abstract

This paper analyses the progress in child nutrition in India during the period 2015-2024 based on the data available from the latest, 2023-2024, round of the National Family Health Survey. The analysis is based on the concept of child nutrition surface and associated composite index of child nutrition proposed by Chaurasia (2025). The analysis reveals that progress towards child nutrition in the country remains slow and the progress is inconsistent across states/Union Territories and there is high degree of imbalance in the progress in different dimensions of child nutrition in the country and in different states and Union Territories of the country. Nearly all the progress in child nutrition in recent years has been confined to the linear growth dimension of child nutrition. The analysis emphasises the need of a decentralised approach to planning, implementing and monitoring child nutrition improvement efforts to address the local context of child nutrition which is quite pervasive to hasten the progress in child nutrition.

Introduction

The most recent, 2023-2024 round of the National Family Health Survey (NFHS-6) in India suggests that child nutrition continues to be the Achilles heel in the development diaspora of the country. According to the first hand estimates available from the survey, almost 30 per cent children below 5 years of age in the country were low height-for-age (Stunted), close to one third were low weight-for-age (underweight) and around 19 per cent were low weight-for-height (wasted) circa 2024 (Government of India, 2026) despite almost five decades of efforts from the launch of the Integrated Child Development Services (ICDS) in 1975 through the expansion of the Mid-Day Meal/PM Poshan Scheme to the launch of the ambitious Poshan Abhiyaan in 2018. Although the prevalence of stunting, underweight and wasting has decreased over time yet, in terms of absolute numbers, the challenge of under nutrition in the country remains mindboggling. According to the projections prepared by the United Nations, there were around 114 million children below 5 years of age in India in 2024 (United Nations, 2024). This means that an estimated 33.3 million children under 5 years of age in the country were stunted, 36.1 million were underweight, and 21.6 million were wasted. During the 8 years between 2015-2016 and 2023-2024, the number of stunted children in the country decreased by around 14.5 million, number of underweight children decreased by around 8.7 million, but number of wasted children decreased by only around 4.5 million.

There is, however, no single metric to measure child nutrition that can be used to monitor the progress and rank populations in terms of the nutritional status of children. The three indicators of child under nutrition widely used to assess the nutritional status of children – prevalence of stunting, prevalence of underweight and prevalence of wasting – depict the three different dimensions of child nutrition. Stunting reflects linear growth faltering and is a marker of chronic under nutrition (Isanaka et al, 2019; Benjamin-Chung, 2023). Wasting reflects ponderal growth faltering and is a marker of acute under nutrition (Mertens et al, 2023). Underweight reflects faltering in body mass growth which reflects both linear growth faltering and ponderal growth faltering but fails to distinguish between the two. Underweight also reflects thinness, which is also a marker of poor nutritional status, although a thin child may not necessarily be under nourished (Chaurasia, 2017). However, neither stunting nor underweight nor wasting fully captures the multidimensional nature of child nutrition (Svedberg, 2000; Gausman et al, 2022). In India, progress in the three dimensions of child nutrition has been different as the evidence available from different rounds of the National Family Health Survey show. The decrease in the prevalence of stunting has been relatively the fastest but the decrease in the prevalence of wasting has been only marginal. This means that choice of the indicator decides the progress in child nutrition.

In an attempt to construct a single metric of child under nutrition, Svedberg (2000) has proposed the composite index of anthropometric failure (*CIAF*) which has been further modified by Nandy et al (2005). Chaurasia (2017) has shown that classification approaches adopted by Svedberg (2000) and by Nandy et al. (2005) are special cases of the more general classification approach. *CIAF* has widely been used to measure and monitor nutritional status of children, but it lacks specificity as it does not reveal how linear growth faltering, ponderal growth faltering and body mass growth faltering influence *CIAF* (Bose and Mandal, 2010; Al-Sadeeq et al, 2018). *CIAF* assigns equal weight to the three dimensions of child growth – linear growth, ponderal growth and body mass growth – in its construction which is not appropriated as the prevalence of faltering in the three dimensions are different. Ideally, a higher weight should be assigned to that dimension of child growth which has a higher prevalence of faltering. Another problem of *CIAF* is that it is also not possible to estimate the contribution of the change in any of the three dimensions of child growth to the change in *CIAF*. Calculation of *CIAF* requires multidimensional classification of every child in terms of its weight and height relative to the weight and height of the reference child. It cannot be calculated from the prevalence rates of stunting, underweight and wasting that are commonly available through household surveys such as the National Family Health Survey in India or the Demographic and Health Surveys that have been carried out in more than 85 countries. Since *CIAF* cannot tell the relative dominance of stunting, wasting and underweight in deciding the burden of child under nutrition in the population, it is hardly used in tracking the progress in child nutrition and in ranking populations.

Recently Chaurasia (2025) has proposed a composite index of child nutrition (*CICN*) that addresses many of the shortcomings of *CIAF*. The *CICN* is based on the concept of child nutrition surface which recognises that child nutrition is at least a three-dimensional construct which can be described by a three-dimensional vector with linear growth, ponderal growth and body mass growth its three dimensions. The *CICN* proposed by Chaurasia (2025) is based on the area of the child nutrition surface. An advantage of *CICN* is that it is decomposable so that it is possible to ascertain the dominance of the three

dimensions of child nutrition in deciding the nutritional status of the population. It is also possible to decompose the change over time or difference across populations in *CICN* to the change or the difference attributed to the three dimensions of child nutrition. Using the data from the second, third, fourth and fifth rounds of the National Family Health Survey, Chaurasia (2025) estimated that the progress towards child nutrition in India has been slow as the *CICN* in the country increased from 0.609 during 1998-1999 to 0.708 during 2019-2021 and the progress has varied markedly across states and Union Territories of the country. There are four states/Union Territories where *CICN* has decreased during this period. It has also been observed that most of the progress in child nutrition in the country has been confined to the linear growth dimension while there has been little progress in the ponderal growth dimension of child nutrition.

This paper has four objectives. The first is to estimate *CICN* for India and its states and Union Territories for the period 2023-2024 based on the estimates of the prevalence of stunting, underweight and wasting available from the latest, round of the National Family Health Survey, 2023-2024 (NFHS-6). The second objective is to analyse the change in the rank of states/Union Territories in *CICN* during 2023-2024 compared to the rank during 2019-2021 and 2015-2016. The third objective is to decompose the change in *CICN* between 2015-2016 and 2023-2024 in terms of the change in the proportion of children who are not stunted, proportion who are not underweight and proportion who are not wasted. Finally, the fourth objective of the paper is to analyse how rural-urban difference in the proportion of children not stunted, not underweight and not wasted contributes to rural-urban difference in *CICN* in India and states. The analysis has been carried out for the country and for its states and Union Territories except Manipur as data for the state are not available from NFHS-6. District level estimates of the prevalence of stunting, underweight and wasting are also currently not available from NFHS-6 so that district level analysis is not possible at the moment.

Prevalence of Stunting, Underweight and Wasting

Estimates of the proportion of children under 5 years of age who are low height-for-age (stunted), low weight-for-age (underweight) and low weight-for-height (wasted) in India and in its 36 states and Union Territories are given in table 1 for the period 2015-2016, 2019-2021 and 2023-2024. Estimates the prevalence of stunting, underweight and wasting for Manipur are not available for the period 2023-2024 as the 2023-2024 round of the National Family Health Survey (NFHS-6) could not be conducted in the state. The proportion of children under 5 years of age who are low height-for-age decreased in the country from 38.4 per cent during 2015-2016 to 29.3 per cent during 2023-2024 while the proportion of children under 5 years of age who are low weight-for-age decreased from 35.8 per cent to 31.8 per cent during this period. The proportion of children under 5 years of age who are low weight-for-height, however, decreased from 21 per cent to 19 per cent between 2015-2016 and 2023-2024 because of only a marginal decrease from 19.3 per cent to 19 per cent between 2019-2021 and 2023-2024. The progress in child nutrition in the country has been different in terms of linear growth, body mass growth and ponderal growth. It has been relatively the fastest in the linear growth dimension while there has been near stagnation in the progress in the ponderal growth dimension of child nutrition.

Table 1: Proportion of children under 5 years of age who were low height-for-age (stunted), low weight-for-age (underweight) and low weight-for-height (wasted) in India and states/Union Territories, 2015-2024.

Country/State/Union Territory	Proportion (per cent) of children under 5 years of age who are								
	Low height-for-age (Stunted)			Low weight-for-age (Underweight)			Low weight-for-height (Wasted)		
	2023-2024	2019-2021	2015-2016	2023-2024	2019-2021	2015-2016	2023-2024	2019-2021	2015-2016
India	29.3	35.5	38.4	31.8	32.1	35.8	19.0	19.3	21.0
Andaman & Nicobar Islands	26.7	22.5	23.3	19.3	23.6	21.6	11.1	16.0	18.9
Andhra Pradesh	24.6	31.2	31.4	23.2	29.6	31.9	12.3	16.1	17.2
Arunachal Pradesh	24.1	28.0	29.4	18.2	15.4	19.4	16.1	13.1	17.3
Assam	30.3	35.3	36.4	30.7	32.8	29.8	21.4	21.7	17.0
Bihar	35.6	42.9	48.3	35.7	41.0	43.9	19.0	22.9	20.8
Chandigarh	19.0	25.3	28.7	31.6	20.6	24.5	19.5	8.4	10.9
Chhattisgarh	27.5	34.6	37.6	34.7	31.3	37.7	21.1	18.9	23.1
Dadra & Nagar Haveli Daman & Diu	37.1	39.4	31.9	41.3	38.7	27.0	24.2	21.6	15.9
Delhi	21.4	26.9	37.2	14.5	21.0	35.8	10.6	19.0	26.7
Goa	19.4	25.8	20.1	19.9	24.0	23.8	16.3	19.1	21.9
Gujarat	35.3	39.0	38.5	35.5	39.7	39.3	20.2	25.1	26.4
Haryana	25.9	27.5	34.0	28.9	21.5	29.4	16.6	11.5	21.2
Himachal Pradesh	20.6	30.8	26.3	16.8	25.5	21.2	10.4	17.4	13.7
Jammu & Kashmir	21.4	26.9	27.4	14.5	21.0	16.6	10.6	19.0	12.2
Jharkhand	35.0	39.6	36.2	41.1	39.4	35.2	22.3	22.4	26.1
Karnataka	26.5	35.4	19.7	27.8	32.9	16.1	18.7	19.5	15.7
Kerala	20.1	23.4	30.9	17.8	19.7	18.7	10.9	15.8	9.3
Ladakh	26.0	30.5	26.8	14.5	20.4	23.6	10.6	17.5	13.7
Lakshadweep	34.1	32.0	42.0	25.9	25.8	42.8	12.4	17.4	25.8
Madhya Pradesh	31.4	35.7	34.4	39.7	33.0	36.0	23.8	18.9	25.6
Maharashtra	29.5	35.2	28.9	31.4	36.1	13.8	19.9	25.6	6.8
Manipur		23.4	28.9		13.3	13.8		9.9	6.8
Meghalaya	36.8	46.5	43.8	25.3	26.6	28.9	13.2	12.1	15.3
Mizoram	26.1	28.9	28.1	14.5	12.7	12.0	8.1	9.8	6.1
Nagaland	25.1	32.7	28.6	12.2	26.9	16.7	8.9	19.1	11.3
Odisha	26.8	31.0	34.1	31.6	29.7	34.4	22.1	18.1	20.4
Puducherry	26.4	30.9	23.7	27.4	21.8	22.0	15.0	11.2	23.6
Punjab	20.4	24.5	25.7	23.7	16.9	21.6	18.0	10.6	15.6
Rajasthan	29.6	31.8	39.1	33.3	27.6	36.7	19.8	16.8	23.0
Sikkim	20.1	22.3	29.6	11.2	13.1	14.2	9.4	13.6	14.2
Tamil Nadu	20.7	25.0	27.1	23.2	22.0	23.8	17.4	14.6	19.7
Telangana	27.0	33.1	28.0	27.8	31.8	28.4	16.9	21.7	18.1
Tripura	21.9	33.3	24.3	25.7	25.6	24.1	18.4	18.2	16.8
Uttar Pradesh	31.5	39.7	46.3	34.5	32.1	39.5	19.2	17.3	17.9
Uttarakhand	20.0	27.0	33.5	19.6	21.0	26.6	11.0	13.2	19.5
West Bengal	22.4	33.8	32.5	28.5	32.2	31.6	20.3	20.3	20.3

Remarks: NFHS-6 was not conducted in Manipur.

Source: Government of India (2017; 2022; 2026a).

Among different states and Union Territories of the country, the progress in all the three dimensions of child nutrition varies widely. The prevalence of stunting was relatively the highest in Bihar but relatively the lowest in Karnataka during 2015-2016 but in Meghalaya and Sikkim respectively during 2019-2021 and respectively in Dadra & Nagar Haveli and Daman & Diu and Chandigarh during 2023-2024. The prevalence of underweight, on the other hand, was relatively the highest in Bihar but relatively the lowest in Mizoram during 2015-2016 and 2019-2021 but respectively in Dadra & Nagar Haveli and Daman & Diu and Sikkim during 2023-2024. Finally, the prevalence of wasting was relatively the highest in Delhi but relatively the lowest in Mizoram during 2015-2016 but respectively in Maharashtra and Chandigarh during 2019-2021 and Dadra & Nagar Haveli and Daman & Diu and Mizoram during 2023-2024. Dadra & Nagar Haveli and Daman & Diu has the dubious distinction of having relatively the highest prevalence of stunting, underweight and wasting in children under 5 years of age across the states and Union Territories during the period 2023-2024. The across states/Union Territories variation in all the three prevalence rates decreased during 2019-2021 relative to 2015-2016 but increased during 2023-2024 relative to 2019-2021.

Composite Index of Child Nutrition

Details of the construction of *CICN* are given elsewhere (Chaurasia, 2025).*CICN* is based on the concept of child nutrition surface and is defined as

$$CICN = \frac{\sqrt{ns \times nu} + \sqrt{nu \times nw} + \sqrt{nw \times ns}}{3} \quad (1)$$

where *ns* is the proportion of children under 5 years of age who are not low height-for-age, *nu* is the proportion not low weight-for-age and *nw* is the proportion not low weight-for-height. *CICN* ranges from 0 to 1 and the higher the *CICN* the better the nutritional status of children and vice versa. When there is no child who is either stunted or underweight or wasted, *CICN* is equal to 1. *CICN* serves as a convenient metric for monitoring the progress and ranking populations in child nutrition. It is a composite population-level metric constructed from the prevalence of children who are low height-for-age, low weight-for-age and low weight-for-height. It is not a direct measure of the nutritional status of a child. It also does not capture the joint occurrence different forms of undernutrition in the same child. The appropriate index for assessing the nutritional status of a child is the *CIAF* proposed by Svedberg (2000), its modification (Nandy et al, 2005) or its generalization (Chaurasia, 2017). However, application of *CIAF* requires child-specific data. When only prevalence rates of three forms of under-nutrition are available *CICN* a broad, macro, perspective of the challenge of undernutrition among children in the population that can be used for ranking populations, for comparing populations and for monitoring progress towards child nutrition. Being a composite metric, *CICN* has some limitations. Ranking of populations, comparison across populations and monitoring progress based on *CICN* may be different from ranking, comparison and monitoring in terms of the three dimensions of child nutrition. It is, therefore, necessary that the change over time or the difference across populations in *CICN* is decomposed in terms of the change or the difference in the three dimensions of child nutrition to fully understand the complex dynamics of the nutrition status of children in the population.

CICN is a mathematical transformation of *ns*, *nu* and *nw*. The uncertainty or the error in the estimation of *CICN*, therefore, is determined by the uncertainty or the error in the estimation of *ns*, *nu* and *nw* or in *s*, *u* and *n* and may be estimated through the application of the law of the propagation of uncertainty (Taylor and Kuyatt, 1994). Assuming that *ns*, *nu* and *nw* are mutually independent, the uncertainty or the error associated in the estimation of *CICN* may be estimated as

$$\sigma_{CICN} = \sqrt{\frac{\left(\sqrt{nu}+\sqrt{nw}\right)^2}{36\times ns} \times \sigma_{ns}^2 + \frac{\left(\sqrt{ns}+\sqrt{nw}\right)^2}{36\times nu} \times \sigma_{nu}^2 + \frac{\left(\sqrt{ns}+\sqrt{nu}\right)^2}{36\times nw} \times \sigma_{nw}^2} \quad (2)$$

Assuming that σ_{CICN} is a reliable estimate of the standard deviation of *CICN*, the upper and lower confidence limits of *CICN* may be obtained. Calculation of the confidence interval of *CICN*, therefore, requires measurement of the uncertainty in the estimation of *ns*, *nu* and *nw*. If estimates of uncertainty associated with *ns*, *nu* and *nw* are not available, confidence limits of *CICN* may not be calculated, although confidence limits are important testing the rank robustness of *CICN*. If confidence limits overlap, then variation in *CICN* is usually noise. It is therefore customary to construct categories rather than relying entirely on exact value of *CICN*.

The change or the difference in *CICN* may be decomposed into the change or the difference in *ns*, *nu* and *ns* following the logarithmic mean divisia index (LMDI) decomposition approach (Ang and Liu, 1998; Ang, 2015). This approach is based on the logarithmic mean (Carlson, 1972) instead of the arithmetic mean. Unlike the arithmetic mean, logarithmic means is more balanced proportional middle ground and is more suitable when the indicator being decomposed is a proportion variable as is the case here. The logarithmic mean of two numbers is greater than their geometric mean but less than their arithmetic mean. The change or the difference in *CICN* may be written as

$$\nabla_{CICN} = CICN_2 - CICN_1 = \frac{\sqrt{ns_2*nu_2}+\sqrt{nu_2*nw_2}+\sqrt{nw_2*ns_2}}{3} - \frac{\sqrt{ns_1*nu_1}+\sqrt{nu_1*nw_1}+\sqrt{nw_1*ns_1}}{3}$$

or

$$\nabla_{CICN} = \frac{\sqrt{ns_2*nu_2}-\sqrt{ns_1*nu_1}}{3} + \frac{\sqrt{nu_2*nw_2}-\sqrt{nu_1*nw_1}}{3} + \frac{\sqrt{nw_2*ns_2}-\sqrt{nw_1*ns_1}}{3} \quad (3)$$

Using the logarithmic mean, we can write

$$\sqrt{ns_2*nu_2} - \sqrt{ns_1*nu_1} = \frac{\sqrt{ns_2*nu_2}-\sqrt{ns_1*nu_1}}{ln\left(\frac{\sqrt{ns_2*nu_2}}{\sqrt{ns_1*nu_1}}\right)} * ln\left(\frac{\sqrt{ns_2*nu_2}}{\sqrt{ns_1*nu_1}}\right) = L_{lb} * ln\left(\frac{\sqrt{ns_2*nu_2}}{\sqrt{ns_1*nu_1}}\right)$$

or

$$\sqrt{ns_2*nu_2} - \sqrt{ns_1*nu_1} = \frac{L_{lb}}{2} * ln\left(\frac{ns_2}{ns_1}\right) + \frac{L_{lb}}{2} * ln\left(\frac{nu_2}{nu_1}\right) \quad (4)$$

where

$$L_{lb} = \frac{\sqrt{ns_2*nu_2}-\sqrt{ns_1*nu_1}}{ln\left(\frac{\sqrt{ns_2*nu_2}}{\sqrt{ns_1*nu_1}}\right)} \quad (5)$$

is the logarithmic mean of $\sqrt{ns_2*nu_2}$ and $\sqrt{ns_1*nu_1}$ (Carlson, 1972). Similarly, we can also write

$$\sqrt{nu_2 * nw_2} - \sqrt{nu_1 * nw_1} = \frac{L_{bp}}{2} * ln\left(\frac{nu_2}{nu_1}\right) + \frac{L_{bp}}{2} * ln\left(\frac{np_2}{np_1}\right) \quad (6)$$

and

$$\sqrt{nw_2 * ns_2} - \sqrt{nw_1 * ns_1} = \frac{L_{pl}}{2} * ln\left(\frac{nw_2}{nw_1}\right) + \frac{L_{pl}}{2} * ln\left(\frac{ns_2}{ns_1}\right) \quad (7)$$

so that

$$\nabla_{CICN} = \frac{(L_{lb}+L_{pl})}{6} * ln\left(\frac{ns_2}{ns_1}\right) + \frac{(L_{lb}+L_{bp})}{6} * ln\left(\frac{nu_2}{nu_1}\right) + \frac{(L_{pl}+L_{bp})}{6} * ln\left(\frac{nw_2}{nw_1}\right) \quad (8)$$

$$\nabla_{CICN} = C_{ns} + C_{nu} + C_{nw} \quad (9)$$

where C_{ns} is the contribution of the change in the proportion of children not stunted to the change in *CICN*. Similarly, C_{nu} is the contribution of the change in the proportion of children who are not underweight and C_{nw} is the contribution of the change in the proportion of children who are not wasted to the change in *CICN*.

Notice that if prevalence rates are available for more than two points in time, say at three points in time, then

$$ln\left(\frac{ns_3}{ns_1}\right) = ln\left(\frac{ns_3}{ns_2}\right) + ln\left(\frac{ns_2}{ns_1}\right)$$

so that the change in *CICN* between time 1 and time 3 can be decomposed into the change between time 1 and time 2 and the change between time 2 and time 3 as

$$\nabla_{CICN} = \frac{(L_{lb}+L_{pl})}{6} * ln\left(\frac{ns_3}{ns_2}\right) + \frac{(L_{lb}+L_{pl})}{6} * ln\left(\frac{ns_2}{ns_1}\right) +$$
$$\frac{(L_{lb}+L_{bp})}{6} * ln\left(\frac{nu_3}{nu_2}\right) + \frac{(L_{lb}+L_{bp})}{6} * ln\left(\frac{nu_2}{nu_1}\right) +$$
$$\frac{(L_{pl}+L_{bp})}{6} * ln\left(\frac{nw_3}{nw_2}\right) + \frac{(L_{pl}+L_{bp})}{6} * ln\left(\frac{nw_2}{nw_1}\right) \quad (10)$$

One problem with the LMDI decomposition approach is the handling zero values in the data as the logarithm of zero is undefined, and division by zero creates mathematical errors (Wood and Lenzen, 2006). Although, in surveys based on large samples, it is rare that the prevalence of under nutrition in any dimension of child nutrition is zero, yet this may be a problem in small scale surveys or in small geographical areas and in subgroups of population. Two alternatives have been suggested to address the zero-value problem in the LMDI decomposition approach. The first is the analytical limits approach while the second is the small-value substitution approach (Ang and Liu, 2007). The analytical limits approach is a mathematically robust approach. It uses the mathematical limits of the LMDI function as data points approach zero. When one value is zero, the logarithmic mean weight becomes zero and, even though the log-ratio tends toward infinity, the product of the weight and the log-ratio mathematically converges to exactly zero (Wood and Lenzen, 2006). The small-value substitution approach is the numerical approach. It suggests replacing all zero values in the dataset with a tiny positive number. The first approach is recommended because if the dataset contains a large number of zero values or very small real values, replacing zero by a tiny positive number may lead to significant calculation errors (Wood and Lenzen, 2006).

Child Nutrition in India, 2015-2024

Table 2 gives estimates of *CICN* for India and for its states and Union Territories for the period 2015-2016, 2019-2021 and 2023-2024. These estimates are based on the prevalence of stunting, underweight and wasting obtained from different rounds of the National Family Health Survey given in table 1. Based on the *CICN*, the nutritional status of children in a population may be termed as very good if $CICN \geq 0.850$; good if $0.800 \leq CICN < 0.850$; average if $0.750 \leq CICN < 0.800$; poor if $0.700 \leq CICN < 0.750$; and very poor if $CICN < 0.700$. These cutoff points have been arrived at on the basis of quantiles of the distribution of proportion of children not stunted, proportion of children not underweight, and proportion of children not wasted across states and Union Territories of the country during the period 2023-2024 as obtained from NFHS-6. For India as a whole, *CICN* is estimated to be 0.731 during the period 2023-2024 which means that nutritional status of children in India remains poor.

CICN varies widely across states and Union Territories. Sikkim with a $CICN > 0.850$ is the only state/Union Territory where the nutritional status of children may be termed as very good. In 11 states/Union Territories, nutritional status of children may be termed as good as $0.800 \leq CICN < 0.850$ in these states/Union Territories and average ($0.750 \leq CICN < 0.800$) in 11 states/Union Territories. There are 12 states/Union Territories where the nutritional status of children may be termed as either poor or poor as *CICN* is less than 0.750 in these states/Union Territories. There are 5 states/Union Territories which may be termed as hotspot states/Union Territories of the country in terms of child nutrition as *CICN* is below 0.700 in these states/Union Territories.

Table 2 shows the trend in *CICN* in India and its constituent states and Union Territories during the period 2015-2024. The annual rate of increase in *CICN* has been faster during the period 2019-2024 compared to the period 2015-2021 which implies that the progress in child nutrition in the country accelerated during the period 2019-2024 compared to the period 2015-2021. Among different states and Union Territories, the progress in child nutrition as reflected through the trend in *CICN* has been mixed. In 14 states/Union Territories, annual rate of increase in *CICN* during 2019-2024 was slower than that during 2015-2021 and in 9 states/Union Territories, *CICN* decreased, instead increased, during this period, indicating a deterioration in the nutritional status of children. During 2015-2021 also *CICN* decreased in 14 states/Union Territories. However, in 13 of these states/Union Territories, *CICN* increased during 2019-2024. Dadra & Nagar Haveli and Daman & Diu is the only state/Union Territory in the country in which *CICN* decreased during 2015-2021 as well as during 2019-2024.

The pace of increase in *CICN* has also been different in different states and Union Territories the country during 2019-2024 and during 2015-2021. During 2019-2024, the increase in *CICN* has been the most rapid in Nagaland followed by Delhi and Himachal Pradesh. During 2015-2021, the increase in *CICN* was the most rapid in Lakshadweep followed by Delhi. Combining the two period, the increase in *CICN* during 2015-2024 has been the most rapid in Delhi. On the other hand, the decrease in *CICN* has been the most rapid in Chandigarh during 2019-2024 and in Maharashtra during 2015-2021. During 2015-2024, the decrease in *CICN* has been the most rapid in Maharashtra because of the very rapid decrease during 2015-2021.

Table 2: *CICN* in India and states/Union Territories, 2015-2024.

Country/State/Union Territory	*CICN*			Average annual change (per cent)		
	2023-2024	2019-2021	2015-2016	2019-2024	2015-2021	2015-2024
India	0.731	0.708	0.680	0.675	0.629	0.649
Andaman & Nicobar Islands	0.808	0.792	0.787	0.383	0.132	0.258
Andhra Pradesh	0.798	0.741	0.729	1.422	0.302	0.862
Arunachal Pradesh	0.805	0.810	0.778	-0.161	0.627	0.331
Assam	0.724	0.699	0.719	0.639	-0.513	0.063
Bihar	0.696	0.639	0.615	1.409	0.611	1.010
Chandigarh	0.765	0.817	0.784	-1.737	0.662	-0.238
Chhattisgarh	0.721	0.715	0.669	0.191	0.911	0.641
Dadra & Nagar Haveli Daman & Diu	0.655	0.664	0.748	-0.224	-2.111	-1.168
Delhi	0.844	0.776	0.666	2.255	2.200	2.220
Goa	0.815	0.770	0.781	1.115	-0.265	0.425
Gujarat	0.694	0.651	0.651	1.063	0.019	0.541
Haryana	0.761	0.796	0.717	-1.188	1.595	0.552
Himachal Pradesh	0.840	0.753	0.795	2.176	-1.048	0.564
Jammu & Kashmir	0.844	0.776	0.811	1.691	-0.857	0.417
Jharkhand	0.669	0.658	0.674	0.339	-0.308	-0.065
Karnataka	0.756	0.705	0.828	1.276	-3.084	-0.904
Kerala	0.837	0.803	0.800	0.836	0.081	0.459
Ladakh	0.828	0.770	0.785	1.431	-0.360	0.535
Lakshadweep	0.755	0.748	0.628	0.180	2.993	1.587
Madhya Pradesh	0.681	0.705	0.679	-0.796	0.527	0.031
Maharashtra	0.729	0.676	0.831	1.340	-3.882	-1.271
Manipur		0.843	0.831		0.303	
Meghalaya	0.744	0.705	0.699	0.978	0.146	0.562
Mizoram	0.835	0.825	0.842	0.245	-0.417	-0.086
Nagaland	0.844	0.736	0.809	2.692	-1.819	0.436
Odisha	0.731	0.736	0.701	-0.159	0.684	0.368
Puducherry	0.769	0.784	0.769	-0.492	0.299	0.002
Punjab	0.793	0.825	0.790	-1.082	0.713	0.040
Rajasthan	0.723	0.744	0.668	-0.712	1.522	0.684
Sikkim	0.863	0.836	0.804	0.688	0.793	0.740
Tamil Nadu	0.795	0.794	0.764	0.054	0.591	0.390
Telangana	0.760	0.710	0.751	1.245	-1.014	0.116
Tripura	0.780	0.741	0.782	0.962	-1.025	-0.031
Uttar Pradesh	0.714	0.698	0.646	0.510	1.044	0.844
Uttarakhand	0.831	0.795	0.733	1.202	1.230	1.220
West Bengal	0.762	0.710	0.717	1.290	-0.166	0.562

Remarks: NFHS-6 was not conducted in Manipur.
Source: Author

Table 3: Rank of states/Union Territories in terms of *CICN* in 2015-2016, 2019-2021 and 2023-2024.

State/Union Territory	Rank in *CICN*			
	2023-2024	2019-2021	2015-2016	
Andaman & Nicobar Islands	11	10	10	Decreased
Andhra Pradesh	13	19	21	
Arunachal Pradesh	12	5	15	Decreased
Assam	27	29	22	
Bihar	31	35	35	
Chandigarh	18	4	12	Decreased
Chhattisgarh	29	23	29	Decreased
Dadra & Nagar Haveli Daman & Diu	35	32	19	Decreased
Delhi	2	12	31	
Goa	10	15	14	
Gujarat	32	34	32	
Haryana	20	7	24	Decreased
Himachal Pradesh	5	16	8	
Jammu & Kashmir	2	12	4	
Jharkhand	34	33	28	Decreased
Karnataka	22	28	3	
Kerala	6	6	7	
Ladakh	9	14	11	
Lakshadweep	23	17	34	Decreased
Madhya Pradesh	33	27	27	Decreased
Maharashtra	26	31	2	
Meghalaya	24	26	26	
Mizoram	7	2	1	Decreased
Nagaland	4	21	5	
Odisha	25	22	25	Decreased
Puducherry	17	11	16	Decreased
Punjab	15	3	9	Decreased
Rajasthan	28	18	30	Decreased
Sikkim	1	1	6	
Tamil Nadu	14	9	17	Decreased
Telangana	21	25	18	
Tripura	16	20	13	
Uttar Pradesh	30	30	33	
Uttarakhand	8	8	20	
West Bengal	19	24	23	

Remarks: Ranks are based on 35 states/Union Territories as NFHS-6 was not conducted in Manipur.
Source: Author

Because of differential pace of change, rank of a state/Union Territory vis-a-vis other states/Union Territories in terms of *CICN* has been different in 2023-2024 as compared to that in 2019-2021 and 2015-2016 (Table 3). The rank of 15 states/Union Territories in terms of *CICN* decreased during 2023-2024 compared to the rank during 2019-2021 while

rank of 18 states/Union Territories improved. Sikkim, Kerala, Uttar Pradesh and Uttarakhand are the only four states/Union Territories where the rank in *CICN* during 2019-2021 and during 2023-2024 has remained the same. In some states/Union Territories, the change in the rank has been very marked. For example, Chandigarh ranked 4 in terms of *CICN* during 2019-2021 but only 18 during 2023-2024. Similarly, Similarly, Haryana ranked 7 during 2019-2021 but 20 during 2023-2024 in terms of CICN. On the other hand, Nagaland ranked 21 during 2019-2021 in terms of *CICN* but the rank of the state jumped to 4 during 2023-2024. In Delhi and Jammu & Kashmir also, the rank in *CICN* improved substantially between 2019-2021 and 2023-2024. The decrease in rank of a state/Union Territory indicates that the progress has been slower as compared to other states/Union Territories. Similarly, an increase in the rank of a state/Union Territory in *CICN* indicates a faster progress in child nutrition relative to the progress in other states and Union Territories.

Decomposition of the Change in *CICN*

Table 4 shows how decrease in the proportion of stunted children, underweight children and wasted children has contributed to the increase in *CICN* in India during the period 2015-2024. The evidence available from the latest round of the National Family Health Survey suggests that more than 60 per cent of the increase in *CICN* in the country between 2015-2016 and 2023-2024 is attributed to the decrease in the proportion of stunted (low weight-for-age) children while around 27 per cent is attributed to the decrease in the proportion of underweight (low weight-for-age) children. On the other hand, the decrease in the proportion of wasted (low weight-for-height) children accounted for an increase of around 12 per cent in *CICN*. Table 4 suggests that the main driver of the improvement in the nutritional status of children in the country during the 8 years between 2015-2016 and 2023-2024 has been the decrease in the proportion of stunted children while the decrease in the proportion of wasted children contributed only marginally to the increase in *CICN*.

The contribution of the decrease in the proportion of stunted children, underweight children and wasted children to the increase in *CICN* has, however, been different during the period 2015-2021 and the period 2019-2024. During the period 2015-2021, more than 45 per cent of the increase in *CICN* was attributed to the decrease in the proportion of underweight children while the decrease in the proportion of stunted children accounted for an increase of almost 37 per cent. The rest of the increase in *CICN* was the result of the decrease in the proportion of wasted children. During the period 2019-2024, however, more than 90 per cent of the increase in *CICN* was accounted by the decrease in the proportion of stunted children while the decrease in the proportion of underweight children and the decrease in the proportion of wasted children contributed only marginally to the increase in *CICN*. Unlike the period 2015-2021, the improvement in the nutritional status of children in the country during the period 2019-2024 has almost entirely been because of the decrease in the proportion of stunted (low height-for-age) children. The proportion of underweight children and the proportion of wasted children decreased in the country during this period but the progress in these two dimensions of child nutrition contributed only marginally to the improvement in the nutritional status of children as reflected through the increase in *CICN*.

Table 4: Decomposition of the change in *CICN* during 2015-2024 in India and states/Union Territories.

Country/State/Union Territory	2015-2024				2019-2024				2015-2021			
	Change in *CICN*	Change in CICN due to			Change in *CICN*	Change in CICN due to			Change in *CICN*	Change in CICN due to		
		Change in *ns*	Change in *nu*	Change in *nw*		Change in *ns*	Change in *nu*	Change in *nw*		Change in *ns*	Change in *nu*	Change in *nw*
India	0.052	0.032	0.014	0.006	0.023	0.021	0.001	0.001	0.029	0.011	0.013	0.005
Andaman & Nicobar Islands	0.021	-0.012	0.008	0.025	0.015	-0.015	0.015	0.015	0.005	0.003	-0.007	0.009
Andhra Pradesh	0.069	0.024	0.030	0.015	0.056	0.023	0.022	0.012	0.013	0.001	0.008	0.003
Arunachal Pradesh	0.026	0.019	0.004	0.004	-0.005	0.014	-0.009	-0.009	0.031	0.005	0.013	0.013
Assam	0.005	0.022	-0.003	-0.013	0.026	0.018	0.007	0.001	-0.021	0.004	-0.010	-0.014
Bihar	0.081	0.046	0.029	0.005	0.055	0.025	0.018	0.011	0.026	0.021	0.011	-0.006
Chandigarh	-0.019	0.033	-0.025	-0.027	-0.051	0.021	-0.038	-0.034	0.032	0.012	0.013	0.007
Chhattisgarh	0.051	0.034	0.011	0.006	0.006	0.024	-0.012	-0.007	0.046	0.011	0.022	0.013
Dadra & Nagar Haveli Daman & Diu	-0.093	-0.018	-0.050	-0.025	-0.010	0.009	-0.010	-0.008	-0.084	-0.027	-0.040	-0.017
Delhi	0.178	0.055	0.072	0.051	0.063	0.018	0.020	0.025	0.115	0.037	0.052	0.026
Goa	0.034	0.002	0.013	0.018	0.045	0.022	0.014	0.009	-0.011	-0.020	-0.001	0.009
Gujarat	0.043	0.011	0.013	0.019	0.042	0.013	0.015	0.015	0.001	-0.002	-0.001	0.004
Haryana	0.044	0.028	0.002	0.014	-0.034	0.005	-0.024	-0.015	0.078	0.023	0.026	0.029
Himachal Pradesh	0.045	0.020	0.015	0.010	0.089	0.037	0.030	0.023	-0.044	-0.017	-0.015	-0.012
Jammu & Kashmir	0.033	0.021	0.007	0.005	0.069	0.020	0.022	0.028	-0.036	0.002	-0.015	-0.023
Jharkhand	-0.005	0.004	-0.021	0.012	0.010	0.016	-0.006	0.000	-0.016	-0.012	-0.015	0.011
Karnataka	-0.072	-0.023	-0.039	-0.010	0.056	0.034	0.019	0.003	-0.128	-0.057	-0.059	-0.012
Kerala	0.037	0.039	0.003	-0.005	0.033	0.011	0.006	0.016	0.003	0.027	-0.003	-0.021
Ladakh	0.043	0.003	0.030	0.010	0.058	0.016	0.019	0.022	-0.015	-0.014	0.011	-0.012
Lakshadweep	0.127	0.029	0.059	0.040	0.007	-0.007	0.000	0.014	0.120	0.036	0.059	0.026
Madhya Pradesh	0.002	0.010	-0.013	0.006	-0.023	0.015	-0.023	-0.014	0.026	-0.005	0.010	0.020
Maharashtra	-0.102	-0.002	-0.059	-0.040	0.059	0.021	0.018	0.020	-0.161	-0.024	-0.078	-0.060
Meghalaya	0.045	0.027	0.012	0.006	0.039	0.038	0.004	-0.003	0.006	-0.011	0.008	0.009
Mizoram	-0.007	0.007	-0.008	-0.006	0.010	0.010	-0.006	0.005	-0.017	-0.003	-0.002	-0.012
Nagaland	0.035	0.013	0.015	0.008	0.113	0.029	0.051	0.033	-0.078	-0.016	-0.036	-0.026
Odisha	0.029	0.025	0.010	-0.005	-0.005	0.014	-0.006	-0.012	0.034	0.011	0.016	0.007

Country/State/Union Territory	2015-2024				2019-2024				2015-2021			
	Change in *CICN*	Change in CICN due to			Change in *CICN*	Change in CICN due to			Change in *CICN*	Change in CICN due to		
		Change in *ns*	Change in *nu*	Change in *nw*		Change in *ns*	Change in *nu*	Change in *nw*		Change in *ns*	Change in *nu*	Change in *nw*
Puducherry	0.000	-0.009	-0.018	0.028	-0.014	0.016	-0.019	-0.011	0.014	-0.025	0.001	0.039
Punjab	0.003	0.018	-0.007	-0.008	-0.032	0.014	-0.022	-0.023	0.035	0.004	0.015	0.015
Rajasthan	0.055	0.033	0.012	0.010	-0.020	0.007	-0.019	-0.009	0.075	0.026	0.031	0.018
Sikkim	0.059	0.034	0.010	0.015	0.027	0.008	0.006	0.013	0.032	0.027	0.004	0.002
Tamil Nadu	0.031	0.022	0.002	0.007	0.002	0.014	-0.004	-0.009	0.030	0.007	0.006	0.016
Telangana	0.009	0.003	0.002	0.004	0.051	0.022	0.014	0.015	-0.042	-0.018	-0.012	-0.012
Tripura	-0.003	0.008	-0.005	-0.005	0.040	0.041	0.000	-0.001	-0.042	-0.033	-0.005	-0.004
Uttar Pradesh	0.068	0.054	0.018	-0.004	0.015	0.028	-0.008	-0.005	0.053	0.026	0.026	0.002
Uttarakhand	0.098	0.047	0.024	0.027	0.035	0.023	0.005	0.007	0.063	0.024	0.019	0.020
West Bengal	0.045	0.034	0.011	0.000	0.052	0.039	0.013	0.000	-0.007	-0.005	-0.002	0.000

Remarks: NFHS-6 was not conducted in Manipur.
Source: Author

The relative contribution of the improvement in the three dimensions of child nutrition to the improvement in the nutritional status of children during the period under reference has varied across the states and Union Territories of the country. There are only 23 states/Union Territories in which the nutritional status of children improved in all three dimensions of child nutrition. In 12 states/Union Territories, progress reversed in at least one dimension of child nutrition so that in 7 states/Union Territories, progress in the nutritional status of children reversed as reflected through the decrease in *CICN*. The progress in child nutrition has been the most rapid in Delhi increase in *CICN* in Delhi where *CICN* increased from 0.666 during 2015-2016 to 0.844 during 2023-2024. More than 40 per cent of the increase in *CICN* in the state was due to the decrease in the proportion of stunted children, and rest of the increase is attributed to the decrease in the proportion of underweight children and the proportion of wasted children. On the other hand, *CICN* decreased, instead increased, the most rapidly in Maharashtra because of the reversal in progress in all the three dimensions of child nutrition. The progress in all the three dimensions of child nutrition also reversed in Dadra & Nagar Haveli and Daman & Diu and Karnataka. In all the three states/Union Territories, more than half of the decrease in *CICN* was due to the increase in the proportion of underweight children. However, the contribution of the increase in the proportion of stunted children and the proportion of wasted children to the decrease in *CICN* was different. In Maharashtra, almost 40 per cent of the decrease in *CICN* is attributed to the increase in the proportion of wasted children while this proportion is around 27 per cent in Dadra & Nagar Haveli and Daman & Diu but only around 13 per cent in Karnataka. On the other hand, almost one third of the decrease in *CICN* in Karnataka is attributed to the increase in the proportion of stunted children but this proportion is only about 20 per cent in Dadra & Nagar Haveli and Daman & Diu. In Maharashtra, on the other hand, increase in the proportion of stunted children accounted for only around 2 per cent of the decrease in *CICN*.

During the period 2019-2024, the progress in child nutrition reversed in 9 states/Union Territories as *CICN* decreased in these states/Union Territories. There is, however, no state/Union Territory where progress reversed in all the three dimensions of child nutrition. This is quite contrast to the period 2015-2021 when progress towards child nutrition was reversed in 14 states/Union Territories and there were 8 states/Union Territories progress reversed in all the three dimensions of child nutrition. The progress in child nutrition during the period 2019-2024 has been the most rapid in Nagaland where *CICN* increased from 0.736 during 2019-2021 to 0.844 during 2023-2024 whereas *CICN* decreased the most rapidly in Chandigarh from 0.817 during 2019-2021 to 0.765 during 2023-2024 because of the increase in the proportion of underweight children and the proportion of wasted children as the proportion of the stunted children decreased in the Union Territory during this period. The decrease in *CICN* during this period has also been quite rapid in Haryana and Punjab because of the increase in the proportion of underweight children and the proportion of wasted children as the proportion of stunted children decreased in both states. Chandigarh, Haryana and Punjab constitute a geographical contiguous region which is known for its prosperity and wealth and an advanced standard of living. It is surprising that despite the prosperity and advanced standard of living the proportion of underweight children and the proportion of wasted children in the region increased, instead decreased in the recent past.

Urban-Rural Difference

The proportion of children low height-for-age, low weight-for-height and low weight-for-height has been found to be low in the urban areas of the country as compared to its rural areas so that *CICN* is higher in the urban areas which implies that the nutritional status of children is better in the urban areas as compared to rural areas (Table 5). This is, however, not the case in four states – Nagaland, Puducherry, Punjab and Sikkim – where nutritional status of children appears to be better in the rural areas than in urban areas as *CICN* is higher in the rural areas compared to that in urban areas in these states and Union Territories. In states and Union Territories where *CICN* is higher in the urban areas, the urban-rural difference in *CICN* is found to be the widest in Dadra & Nagar Haveli and Daman & Diu followed by Jharkhand, Gujarat, Karnataka and Mizoram. But the narrowest in Tamil Nadu followed by Uttarakhand. Tamil Nadu is the only state/Union Territory in the country where there appears virtually little difference in the nutritional status of urban and rural children as reflected through the marginal difference in *CICN* between urban children and rural children of the state. In Sikkim, on the other hand, the nutritional status of rural children is markedly better than that of urban children as *CICN* is estimated to be substantially higher in the rural children as compared to the urban children of the state.

Table 6 decomposes the urban-rural difference in *CICN* into the urban-rural difference in the proportion of children who are not stunted, not underweight and not wasted. In most of the states/Union Territories, the urban-rural difference in all the three dimensions of child nutrition is the same as the urban-rural difference in *CICN*, although the relative contribution of the urban-rural difference in any dimension to the urban-rural difference in *CICN* varies across states/Union Territories. In Andhra Pradesh and Uttarakhand, around two third of the urban-rural difference in *CICN* is attributed to the urban-rural difference in the proportion of children who are not stunted. In Andhra Pradesh, there is no urban-rural difference in the proportion of children who are not wasted while there is no urban-rural difference in the proportion of children who are not underweight. In Bihar, Kerala and Dadra & Nagar Haveli and Daman & Diu, more than half of the urban-rural difference in *CICN* is attributed to the urban-rural difference in the proportion of children who are underweight. In Goa, on the other hand, more than 60 per cent of the urban-rural difference in *CICN* is due to the urban-rural difference in the proportion of children who are not low weight-for-height (wasted).

There are nine states/Union Territories in which the direction of the urban-rural difference in one of the three dimensions of child nutrition is not the same as the direction in the urban-rural difference in *CICN*. In seven states/Union Territories, the direction of the urban-rural difference in the proportion of children who are not wasted is opposite to the direction of urban-rural difference in *CICN*. In Lakshadweep, the direction of the urban-rural difference in the proportion of children who are not underweight is opposite to the direction of the urban-rural difference in *CICN* whereas the direction of the urban-rural difference in the proportion of children not stunted is opposite to the direction of the urban-rural difference in *CICN*. In four of these nine states/Union Territories, rural *CICN* is higher than the urban *CICN* which indicates that the nutritional status of rural children is relatively better than the nutritional status of urban children.

Table 5: Proportion of children who are low height-for-age, low weight-for-age, low weight-for-height and *CICN* in urban and rural areas of India and States/Union Territories, 2023-2024.

Country/State/Union Territory	Urban				Rural			
	Proportion of children who are low			CICN	Proportion of children who are low			CICN
	Height-for-age	Weight-for-age	Weight-for-height		Height-for-age	Weight-for-age	Weight-for-height	
India	23.9	25.3	16.5	0.780	30.9	33.8	19.8	0.716
Andaman & Nicobar Islands	20.4	15.3	13.6	0.835	32.0	22.8	9.0	0.783
Andhra Pradesh	21.7	21.8	12.3	0.813	25.8	23.8	12.3	0.792
Arunachal Pradesh	23.5	16.0	14.2	0.820	24.4	19.3	17.1	0.797
Assam	21.7	20.1	17.4	0.803	31.0	31.6	21.8	0.718
Bihar	32.7	27.3	16.2	0.744	35.8	36.5	19.3	0.691
Chandigarh	18.7	31.4	19.4	0.767				
Chhattisgarh	21.7	29.3	19.3	0.765	28.5	35.6	21.4	0.713
Dadra & Nagar Haveli Daman & Diu	28.7	29.3	19.2	0.742	45.0	52.8	28.9	0.571
Delhi	19.3	11.6	8.2	0.869	21.9	15.1	11.1	0.839
Goa	18.8	19.5	14.7	0.823	20.0	20.5	18.3	0.804
Gujarat	28.2	27.2	15.5	0.762	39.5	40.5	23.0	0.653
Haryana	23.8	25.0	14.4	0.788	26.9	30.8	17.6	0.747
Himachal Pradesh	16.4	11.8	4.4	0.890	20.9	17.3	11.0	0.835
Jammu & Kashmir	19.3	11.6	8.2	0.869	21.9	15.1	11.1	0.839
Jharkhand	20.3	29.4	20.4	0.765	37.4	43.1	22.6	0.652
Karnataka	19.0	20.2	16.3	0.815	32.0	33.4	20.5	0.712
Kerala	18.8	15.6	10.5	0.850	21.3	19.8	11.3	0.824
Ladakh	22.1	12.3	8.2	0.856	26.7	15.0	11.1	0.822
Lakshadweep	31.0	26.6	10.6	0.769	37.6	25.1	14.4	0.738
Madhya Pradesh	24.5	30.5	19.3	0.751	33.2	42.0	24.9	0.664
Maharashtra	24.9	26.5	18.3	0.767	32.2	34.3	20.9	0.707

Country/State/Union Territory	Urban				Rural			
	Proportion of children who are low			CICN	Proportion of children who are low			CICN
	Height-for-age	Weight-for-age	Weight-for-height		Height-for-age	Weight-for-age	Weight-for-height	
Meghalaya	26.0	23.6	15.6	0.782	38.2	25.5	12.9	0.739
Mizoram	18.3	8.1	6.5	0.889	32.6	19.8	9.5	0.789
Nagaland	25.4	13.5	8.4	0.840	25.0	11.8	9.0	0.845
Odisha	18.5	22.1	22.6	0.789	28.0	32.9	22.1	0.722
Puducherry	26.4	27.4	15.1	0.769	28.5	26.6	10.3	0.779
Punjab	23.0	23.7	17.2	0.787	18.9	23.6	18.4	0.797
Rajasthan	21.8	22.5	14.8	0.802	31.4	35.8	20.9	0.704
Sikkim	18.2	21.0	8.0	0.841	17.8	8.6	9.8	0.879
Tamil Nadu	20.2	22.5	17.9	0.798	21.0	23.6	17.1	0.794
Telangana	22.3	24.3	15.2	0.793	28.6	28.9	17.4	0.749
Tripura	18.5	23.7	16.9	0.803	22.4	26.0	18.7	0.776
Uttar Pradesh	28.8	32.0	18.7	0.733	32.1	35.0	19.4	0.709
Uttarakhand	17.7	19.6	9.7	0.843	20.7	19.6	11.4	0.827
West Bengal	19.3	21.9	14.2	0.815	23.3	30.3	22.0	0.747

Remarks: NFHS-6 was not conducted in Manipur.
Source: Author

Table 6: Decomposition of the urban-rural difference in *CICN*, 2023-2024.

Country/State/Union Territory	Urban-rural difference in *CICN*	Urban-rural difference in *CICN* attributed to the urban-rural difference in the proportion of children not low		
		Height-for-age	Weight-for-age	Weight-for-height
India	0.064	0.024	0.030	0.010
Andaman & Nicobar Islands	0.052	0.041	0.025	-0.014
Andhra Pradesh	0.021	0.014	0.007	0.000
Arunachal Pradesh	0.023	0.003	0.011	0.009
Assam	0.085	0.032	0.039	0.014
Bihar	0.052	0.011	0.032	0.009
Chhattisgarh	0.052	0.022	0.022	0.007
Dadra & Nagar Haveli Daman & Diu	0.170	0.056	0.085	0.029
Delhi	0.030	0.009	0.012	0.009
Goa	0.019	0.004	0.003	0.012
Gujarat	0.109	0.040	0.047	0.023
Haryana	0.041	0.011	0.020	0.010
Himachal Pradesh	0.055	0.016	0.018	0.021
Jammu & Kashmir	0.030	0.009	0.012	0.009
Jharkhand	0.113	0.057	0.049	0.007
Karnataka	0.103	0.044	0.045	0.013
Kerala	0.025	0.009	0.014	0.003
Ladakh	0.035	0.017	0.009	0.009
Lakshadweep	0.031	0.024	-0.005	0.011
Madhya Pradesh	0.088	0.029	0.041	0.017
Maharashtra	0.060	0.025	0.027	0.008
Meghalaya	0.042	0.044	0.006	-0.008
Mizoram	0.100	0.052	0.038	0.009
Nagaland	-0.005	-0.001	-0.006	0.002
Odisha	0.067	0.031	0.037	-0.002
Puducherry	-0.010	0.007	-0.003	-0.015
Punjab	-0.010	-0.014	0.000	0.004
Rajasthan	0.098	0.033	0.046	0.019
Sikkim	-0.037	-0.001	-0.042	0.006
Tamil Nadu	0.004	0.003	0.004	-0.003
Telangana	0.044	0.022	0.016	0.007
Tripura	0.027	0.013	0.008	0.006
Uttar Pradesh	0.024	0.011	0.011	0.002
Uttarakhand	0.016	0.010	0.000	0.005
West Bengal	0.068	0.013	0.029	0.025

Remarks: There is no rural population in Chandigarh.
NFHS-6 was not conducted in Manipur.

Source: Author

Discussion and Conclusion

This paper has followed the concept of child nutrition surface and the associated composite metric of child nutrition (*CICN*) first proposed by Chaurasia (2025) to measure and monitor the progress in child nutrition in India and in its 35 states and Union Territories during 2015-2024. The concept of child nutrition surface recognises that nutritional status of children is a multi-dimensional construct with linear growth, ponderal growth and body mass growth its three core dimensions. A metric based on the child nutrition surface, therefore, is more appropriate to rank and compare populations and to monitor the progress in child nutrition than metrics which capture nutritional status of children in the population in individual dimensions of child nutrition only. *CICN* presents a broad, macro perspective of child nutrition in the population that reflects progress in the three dimensions of child nutrition simultaneously.

Assessing the nutritional status of children in terms of *CICN* using the evidence available from the latest round of the National Family Health Survey (NFHS-6) suggests that the problem of child undernutrition in India continues to be a challenge in the development discourse of the country. Although, the survey reveals progress in child nutrition in the country, yet the progress remains slow. If the improvement in *CICN* observed during the period 2019-2024 is any indication, then it will take at least three decades for the country to achieve a satisfactory level of the nutritional status of its children. Even more intriguing is the findings of the present analysis that progress in child nutrition has been inconsistent within the country, across states/Union Territories. Child nutrition has not improved in all states and Union Territories during the period under reference. The evidence from the latest NFHS indicates that the progress in child nutrition appears to have reversed in the recent past in many states and Union Territories. Another intriguing revelation of the present analysis is that states/Union Territories in which progress in child nutrition reversed during the period 2015-2021 are different from states/Union Territories in which progress reversed during the period 2019-2024. There is only one state/Union Territory – Dadra & Nagar Haveli and Daman & Diu – where progress in child nutrition reversed throughout the period 2015-2024. The inconsistency in the progress in child nutrition in many states and Union Territories of the country raises questions about the appropriateness, efficiency and effectiveness of the efforts directed towards improving the nutritional status of children.

The evidence available from different rounds of NFHS also suggests that the progress in the three dimensions of child nutrition in the country is highly imbalanced. In India and in most of its states and Union Territories, progress in child nutrition has been limited to the linear growth dimension of child nutrition whereas there has been little progress in other dimensions of child nutrition. The analysis suggests that more than 90 per cent of the progress in child nutrition in the country during 2015-2024 as capture through the increase in *CICN* is attributed to the increase in the proportion of children who are not low height-for-age or stunted, although there are many states and Union Territories in which progress reversed in this dimension of child nutrition also. This highly imbalanced progress in different dimensions of child nutrition appears to be a factor behind the slow progress in improving the nutritional status of children. It also indicates that efforts to address the challenge of child undernutrition in the country has, at best, been lop-sided. Linear growth faltering is an indicator of chronic undernutrition while ponderal growth faltering is an indicator of acute undernutrition and the strategies and approaches required

to address linear growth faltering and ponderal growth faltering are essentially different. It appears that the focus of efforts directed towards improving the nutritional status of children is on preventing linear growth faltering while efforts necessary to check ponderal growth faltering have received a neglected attention. The marginal progress in the ponderal growth dimension has also contributed to the marginal progress in the body mass growth dimension of child nutrition in the country.

Efforts to address the challenge of child undernutrition in India are currently being organised under the National Nutrition Mission, also known as the Poshan Abhiyaan or Nutrition Movement. This Mission was launched by the Government of India as a centrally sponsored programme in 2018 (Government of India, 2018). The Mission has the ambitious goal of improving nutritional outcomes among adolescent girls, pregnant and lactating women, and children under six years of age through technology, convergence, and community involvement. The evidence available from the latest round of the National Family Health Survey (NFHS-6), however, indicates that the Mission appears to have overlooked the local context of child nutrition so that the progress in child nutrition varies widely across states and Union Territories of the country. Since the local context of child nutrition varies widely across states and Union Territories and even across districts within states and Union Territories, it is imperative that a decentralised approach should have been adopted by the Mission to plan, implement and monitor the progress efforts directed towards improving the nutritional status of children. There is a need to examine the needs effectiveness and capacity efficiency of the National Nutrition Mission in addressing the local context of child nutrition. Such an exercise may preferably be carried out at the district level where all child nutrition related activities are actually implemented. District level estimates of the proportion of children below five years of age who are low height-for-age (stunted), low weight-for-age (underweight) and low height-for-weight (wasted) based on NFHS, 2023-2024 have recently been released (Government of India, 2026). These estimates may be used for ranking districts and for exploring the factors responsible for inter-district variation in child undernutrition in the country.

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Infrastructure Gaps, Functional Disparities, and Policy Implementation in Water and Sanitation: Assessing Progress towards SDG-6 in Manipur

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Abstract

Sustainable Development Goal 6 (SDG 6) targets universal availability and sustainable management of water and sanitation by 2030. This study evaluates sub-national progress across 16 districts of Manipur, India, utilizing secondary data from the Jal Jeevan Mission (JJM), National Family Health Survey (NFHS-5), and NITI Aayog SDG India Index reports. The analysis reveals marked spatial disparities in both universal availability and operational management of water infrastructure between hill and valley districts. While macro-level toilet access has reached near-saturation, actual functional household tap connection (FHTC) rates exhibit severe vulnerabilities in mountainous regions. Addressing these structural breakdowns requires localized Village Water and Sanitation Committee (VWSC) capacity building, dedicated funding for operations and maintenance (O&M), underground water protection, revival of traditional water rejuvenation systems, and terrain-appropriate faecal sludge management.

Introduction

Sustainable Development Goal 6 (SDG 6) of the United Nations 2030 Agenda for Sustainable Development (United Nations, 2015) has called for establishing a global framework to ensure universal availability and sustainable management of water and sanitation facilities. Access to clean water, safe sanitation, and adequate hygiene (WASH) constitutes a fundamental human necessity directly tied to public health, human dignity, and socioeconomic development (United Nations, 2018). Globally, accelerating population growth, rapid urbanisation, changing industrial footprints, and intensive agricultural requirements continue to generate water demands that outpace natural replenishment rates (UNESCO, 2023).

In India, sub-national localised execution drives macro programmatic targets for universal availability and sustainable management of water (Government of India, 2021). Central to this philosophy is the Jal Jeevan Mission (JJM) which was launched in 2019 with the aim to deliver safe and adequate drinking water through functional household tap connections (FHTCs) to every rural household at a standard service level of 55 litres per capita per day (LPCD) (Government of India, 2019). This flagship program is supplemented by the Swachh Bharat Mission and the 10-year National Rural Sanitation Strategy (2019–

2029). Through these combined policies, Manipur has successfully expanded its macro footprint by providing baseline access to improved drinking water sources to more than 79 per cent of the households of the state (Government of India, 2020). In the rural areas of the state, however, the proportion of households with tap water connections is still lower than the national average (Figure 1).

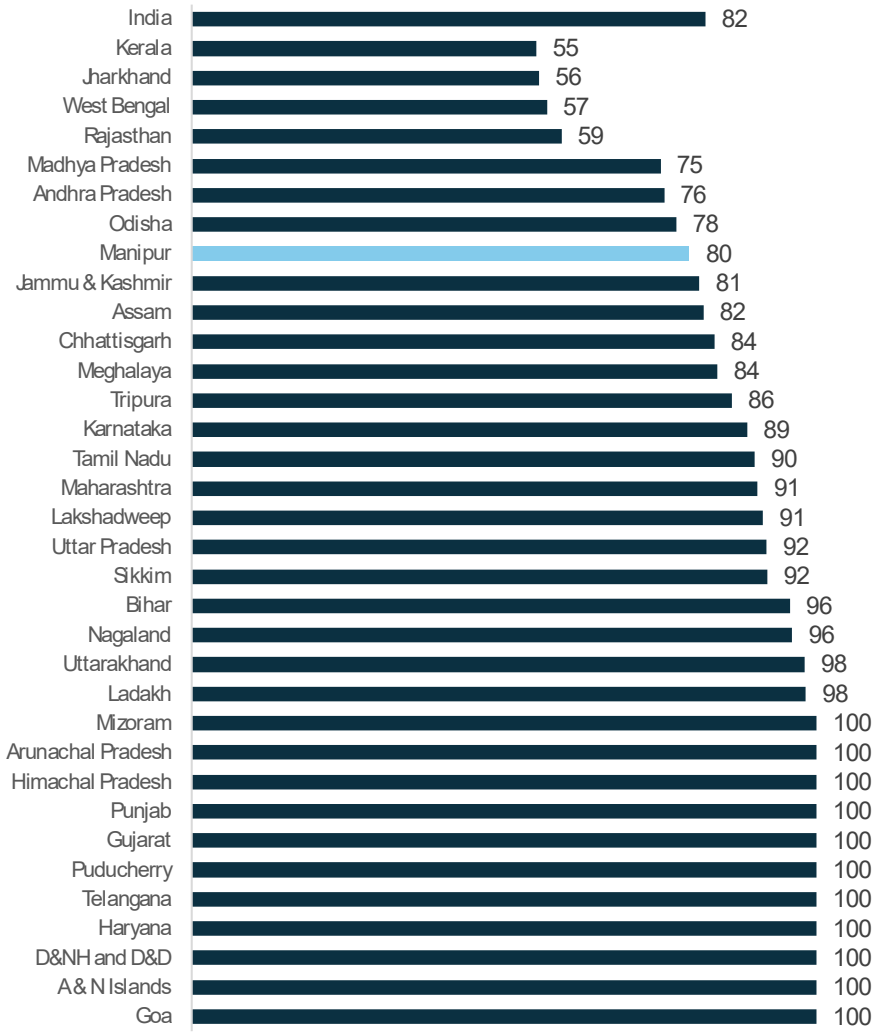

Figure 1: Proportion of rural households with tap water connection.
Source: Government of India.

The objective of this paper is to analyse the spatial distribution, physical coverage, and functionality of household drinking water and sanitation infrastructure across the districts of the state. The paper also analyses efficacy of urban waste water management system, water quality monitoring system, and local river rejuvenation initiatives to address

environmental degradation and service delivery gaps. Finally, the paper proposes an evidence-based policy framework for decentralising water governance in the state with the objective of securing operational financing and mitigating topographically driven infrastructure disparities in water and sanitation facilities to achieve the targets set under the SDG-6 of the United Nations 2030 Agenda for Sustainable Development.

Literature Review

The literature highlights a profound structural contradiction across WASH landscape in India, particularly in topographically complex regions like Manipur. The aggressive state and central programmatic drives such as the Jal Jeevan Mission and Swachh Bharat Mission have achieved high macro-level coverage in physical asset installations and basic sanitation coverage; sub-national data reveal sharp spatial inequalities and infrastructural stagnation that need attention at both policy and programme levels.

Mountainous terrain imposes steep capital, energy, and maintenance demands on piped water distribution system (Wester et al, 2019). Studies across high-altitude regions indicate that physical elevation and rugged topography drive systemic disparities in water delivery between centralised lowlands and decentralised hill settlements (Wester et al, 2019). The micro-level household survey conducted by Oinam and Ningombam (2021) within Imphal East district confirms a steep gap between baseline sanitation ownership and regular clean water delivery. Although up to 98 per cent of the surveyed households possessed toilet assets, less than 20 per cent maintained reliable tap access. Safe water handling remains heavily dependent on maternal education, highlighting the need for community governance alongside physical pipes.

Biswas et al (2022) have constructed a sub-national index to tracking progress across Indian states. The index highlights significant regional variation in achieving the targets set under SDG 6.1 and 6.2. While baseline valley zones achieve rapid asset saturation, northeastern states experience intermediate classification. These regional bottlenecks stem from deep historical pipeline deficits and geographic vulnerabilities, emphasising the necessity of decentralised interventions. Achieving long-term operational durability requires decentralising management while maintaining municipal technical support (Kohlitz et al, 2020).

Hansda and Ghosh (2025) highlight that while central programmes like Jal Jeevan Mission scale up physical infrastructure, real-world progress hinges on local government capacity, decentralised governance, and community-led maintenance identifying persistent rural-urban and top-ecological gaps as critical barriers to achieving universal water security.

Prakash et al (2022) have found out that urban households have more safely managed sanitation services than their rural counterparts. This means that there is a need to create more awareness at the village level on the health benefits of using improved sanitation facilities, along with providing them sanitation facilities.

It has also been stressed that without adequate operational funding and capacity-building at the local level, rural water supply infrastructure experiences rapid functional degradation (Kohlitz et al, 2020).

Rajapakse et al (2023) have evaluated progress towards SDG 6 globally. The study highlights severe rural-urban infrastructure disparities and noted that safely managed sanitation facilities require fourfold increase in the investment by the year 2030 in the developing regions of the world. Empirical evidence shows that rugged terrain, fragile hydrogeological constraints, and communication or governance gap at the grassroots level directly trigger severe functional tap water disruptions. Converting structural pipeline conduits into sustained safe water security system requires shifting from basic engineering metrics to decentralised, community-led institutional maintenance system.

Material and Methods

Empirical metrics for the present study on regional water governance, district-wise tap water allocation, and infrastructure operational performance are extracted from different secondary data sources including Jal Jeevan Mission (JJM) of the Government of India and NITI Aayog. On the other hand, district-level data covering baseline tap access, actual functional connections (FHTC), and establishment of Village Water and Sanitation Committees (VWSC) are taken from the state level reports of the Jal Jeevan Mission.

The functional household tap connection (FHTC) coverage rate is defined as the proportion of households provided a minimum of 55 litres per capita per day (LPCD) of potable tap water. To arrive at the quantity of water received by households, the flow rate was measured using the bucket method in one household per hamlet/habitation in each village. The quantity of water supplied per minute was measured using a graduated bucket to capture the volume of water supplied and a stopwatch to measure time. Daily water quantity was calculated by multiplying flowrate to the supply duration. If households in a village reported that the tap water was not supplied daily, then LPCD was calculated using weekly estimate. Based on the estimated LPCD, the availability of the potable water, household are categorised into three categories: 1) households having adequate level of water availability (LPCD$\geq$55 LPCD), 2) households having partially adequate water availability (40$\leq$LPCD$<$55), and 3) households having inadequate water availability ($<$40 LPCD). Based on the data on LPCD in each hamlet/habitation of the district, the LPCD for the district was calculated as the mean and median of the distribution of LPCD across hamlets/habitations of the district.

On the other hand, the local governance readiness was measured in terms of the formation of Village Water and Sanitation Committee (VWSC) in the village. Under JJM GUIDELINES, local governance readiness reflects a community's institutional capacity for bottom-up, decentralized water management. It is calculated at the district level as the percentage of targeted villages that have formally constituted a Village Water and Sanitation Committee (VWSC or *Pani Samiti*) as a sub-committee of the Gram Panchayat.

Topographical factors play an important role in the availability of water and sanitation facilities and their management. In this context, districts of Manipur can be divided into two categories - valley districts and hill districts. Out of the 16 districts of the state, six districts are categorised as valley districts – Bishnupur, Imphal West, Imphal East, Thoubal, Jiribam and Kakching. On the other hand, 10 districts – Chandel, Churachandpur, Kamjong, Kangpokpi, Noney, Pherzawl, Senapati, Tamenglong, Tengnoupal, and Ukhrul –

are categorised as hill districts. Valley districts are characterised by flat alluvial plains, high population density, and high ground water/perennial rivers. This geography allows for low-cost, centralised piped networks and standard sewer infrastructure. The hill districts, on the other hand, are characterised by rugged high-altitude mountain terrain, dispersed ridge-line hamlets, and heavy reliance on fragile mountain springs. Infrastructure, in these districts, requires expensive multi-stage high-lift pumps or vulnerable gravity-fed pipelines. However, these upland areas serve as primary water catchments, hosting forested watersheds and natural mountain springs that feed the state's major river basins.

Distinguishing hill districts from valley districts are essential because rugged topography imposes steep capital, energy, and maintenance demands on piped distribution systems. Mountain pipelines are vulnerable to seasonal landslide damage and monsoon silting. Consequently, hill districts exhibit severe operational deficits and low Functional Household Tap Connection (FHTC) coverage despite physical tap installations. Furthermore, remote hill settlements depend heavily on active Village Water and Sanitation Committees (VWSCs) to execute local repairs, and steep terrain restricts standard vacuum desludging trucks, requiring terrain-appropriate faecal sludge management to prevent groundwater contamination

Socio-hydrological frameworks suggest core targets to secure SDG 6 compliance by 2030 include achieving equitable access to safe and affordable drinking water (Target 6.1); ending open defecation and providing adequate sanitation (Target 6.2); improving water quality by eliminating dumping and hazardous discharge; minimising waste water generation; and implementing integrated water resources management (IWRM) across all levels (Garrick et al, 2017). However, nearly one-third of the human population globally lacks safely managed water and sanitation facilities to prevent waterborne morbidity and mortality (WHO/UNICEF, 2021). Capital investment in water and sanitation primarily focusses on laying physical supply conduits, but the systemic management of sewage and localized hygiene infrastructure lags behind (UN-Water, 2021). Manipur also reflects this contrast, although NITI Aayog classifies majority of the districts of the state as "Front Runners" in baseline water-sanitation parameters (Government of India, 2020). Capital-intensive projects like Imphal Sewerage Project Phase I & II attempt to stabilise urban indicators, but seasonal vulnerabilities, high cost-to-delivery realities across rugged mountain terrain, and socio-political factors limit the conversion of structural assets into sustained public utility (Wester et al, 2019) so that severe operational deficits persist.

Results and Discussion

Safe Drinking Water and Sanitation Infrastructure

Manipur exhibits asymmetric progress in terms of safe drinking water and sanitation infrastructure. Macro indicators show high cumulative coverage, but severe structural disparities separate rural and urban distribution networks. According to the NFHS-5, 2019-2021, more than 77 per cent households in the state had baseline access to improved drinking water resources. However, this macro average conceals a steep geographic gap – baseline access was more than 90 per cent in urban centres but less than 70 per cent in rural communities. However, only about 20 per cent households in the state

had direct piped water access inside residential premises, pointing to a heavy reliance on community supply points and private mobile water tankers, although NITI Aayog has rated Manipur as a top-tier improving state in 2023-2024, registering an 8-point increase in the composite score since 2020–2021 baselines. Official data indicate that rural household tap installations in the state have scaled up from around 17 per cent at the launch of JJM to a commanding almost 80 per cent by 2024-25 (Government of Manipur, 2024). However, rural piped sanitation infrastructure continues to lag behind the national baseline, displaying sharp inter-district variations. While valley districts such as Bishnupur, Imphal East, and Kakching, have achieved high functional tap coverage (>70 per cent) and improved sanitation facility access (>75 per cent), remote hill districts exhibit severe structural deficits. For instance, functional tap coverage drops drastically in hill districts like Ukhrul (10.3 per cent) and Kangpokpi (19.0 per cent).

On the other hand, according to NFHS-5, around 65 per cent of households in the state were having improved sanitation facilities in 2019-2021 and, interestingly, this proportion was higher in the rural areas of the state as compared to its urban areas (Government of India, 2022). In terms of recent progress, rural sanitation under Swachh Bharat Mission-Gramin (SBM-G) Phase II has accelerated significantly, moving beyond basic latrine coverage toward ODF Plus status. Similar to the rapid expansion in drinking water tap connections, rural sanitation initiatives have focused on solid and liquid waste management (SLWM), greywater management, and community sanitary complexes. Between 2019 and 2024, hundreds of villages across the state were declared ODF Plus, driven by high community-level participation and localized pit-toilet adoption in rural areas. Nevertheless, inter-district disparities remain pronounced: valley districts maintain near-universal sanitation coverage and superior liquid waste processing, whereas high-altitude hill districts face critical challenges in faecal sludge management due to steep gradients and poor road accessibility for vacuum desludging vehicles (Ministry of Jal Shakti, 2024).

Village Water and Sanitation Committee

The operational sustainability of decentralised water schemes depends directly upon the formation and functionality of Village Water and Sanitation Committees (VWSCs). These local bodies are responsible for collecting tariffs, performing water-quality tests, and handling minor structural repairs. In Manipur, VWSCs have been constituted in 84.6 per cent of the villages, and in 42.3 per cent of villages, VWSCs are functional in the sense that they are actively managing the village-level water system (Government of Manipur, 2024).

Specifically, functionality metrics indicate that while local committees exist on paper across many habitations, less than half actively execute their mandated duties. Field testing via Field Test Kits (FTKs) is routinely conducted by trained women members in only about 38 per cent of constituted VWSCs. Furthermore, formal operation and maintenance and tariff collection mechanisms are found to be systematically operational in less than 30 per cent of hill villages, creating a persistent revenue deficit for localised repairs. This gap between formal constitution and operational capability highlights that committee formation alone does not guarantee decentralised governance without sustained capacity-building and financial empowerment.

In 11 districts, VWSC has been formed in all villages, but in 5 districts, the proportion of villages in which VWSC has been constituted ranges from around 76 per cent

in district Noney to just around 33 per cent in districts Kangpokpi and Ukhrul. In Chandel and Kamjong districts also, VWSC has been constituted in around half of the villages only. All these five districts are hill districts of the state (Government of Manipur, 2024). The importance of VWSC in ensuring universal availability of safe drinking water lies in the fact that they play a crucial role in decentralised water governance, routine operation of water systems, and infrastructure maintenance at the local level. A strong administrative push is, therefore, required to form VWSC in in those districts which are lagging in their formation, alongside targeted training modules for existing committees.

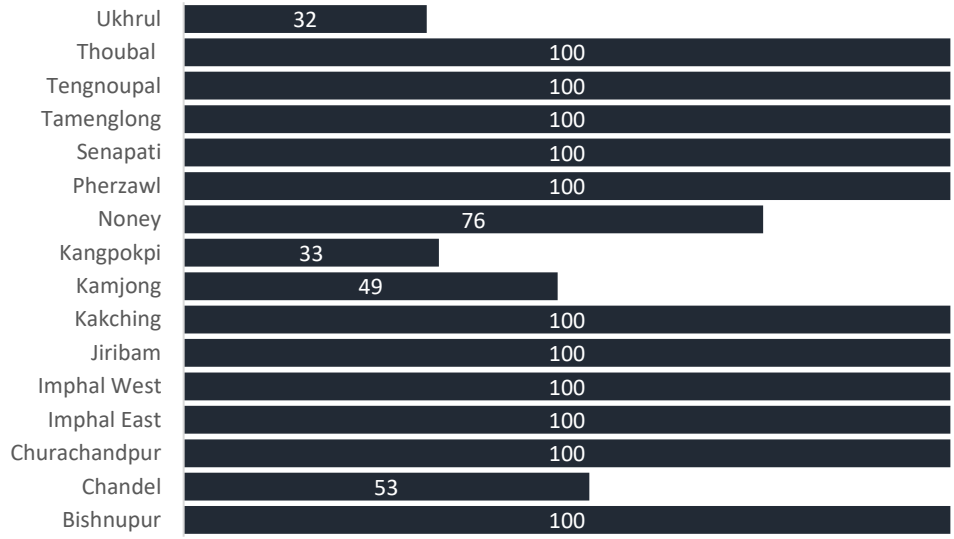

Figure 2: Proportion (Per cent) of villages having Village Water and Sanitation Committee.
Source: Government of Manipur (2024).

Households with Tap Water Supply

Around 80 per cent of the households in Manipur are now having tap water supply. This proportion is, however, lower than the national average of more than 82 per cent. There is a wide gap between urban (54.2 per cent) and rural (84.8 per cent) areas of the state in terms of the proportion of households with tap water supply. Similarly, there is a big difference in the proportion of households with tap water supply in valley districts compared to hill districts because of topological factors.

The proportion of households with tap water varies widely across districts. There is no district in which all households have tap water supply. District Thoubal is the only district where almost 90 per cent households have tap water supply while this proportion is less than 60 per cent in districts Jiribam and Pherzawl.

Availability of Potable Water

More than 80 per cent of the households in the state have access to potable water. This proportion is 93.3 per cent in the urban areas of the state but only 76.2 per cent in the rural areas. The proportion of households having access to potable water is relatively higher

in valley districts (86.4 per cent) compared to hill districts (70.8 per cent). There are still around 20 per cent households in the state where potable water is not available and this remains a major development challenge (Government of India, 2022).

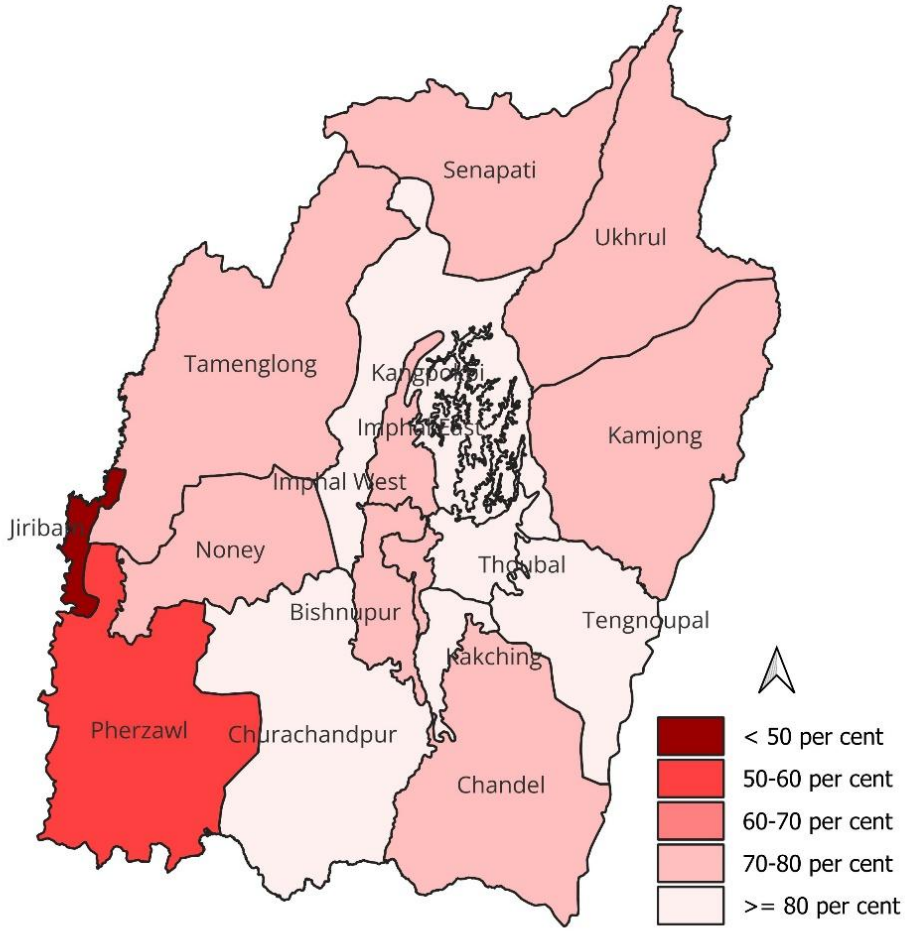

Figure 3: Proportion of households having tap water supply in districts of the state.
Source: Government if Manipur (2024).

The availability of potable water varies widely across the districts of the state. There are six districts where 100 per cent availability of potable water at the household level has been achieved. These districts serve as the benchmark for water security in the state. In two other districts, potable water availability at the household level is at least 90 per cent. These districts are expected to achieve 100 per cent potable water availability at the household level in the near future. There are, however, two districts where availability of potable water remains a critical issue as the proportion of households having access to potable water is less than 60 per cent. One of these two districts is a hill district while the other is a valley district. There may be district-specific reasons for poor availability of

potable water in these districts. In Manipur particularly across the hill districts, a tap connection does not guarantee potable water availability. While central hardware initiatives have rapidly scaled tap installations, operational challenges such as monsoonal pipeline bursts, seasonal depletion of mountain springs (spring-shed), and untreated surface runoff mean that many piped connections yield intermittent, untreated, or zero flow. Therefore, evaluating water security requires measuring functional flow and water safety rather than relying solely on physical coverage metrics.

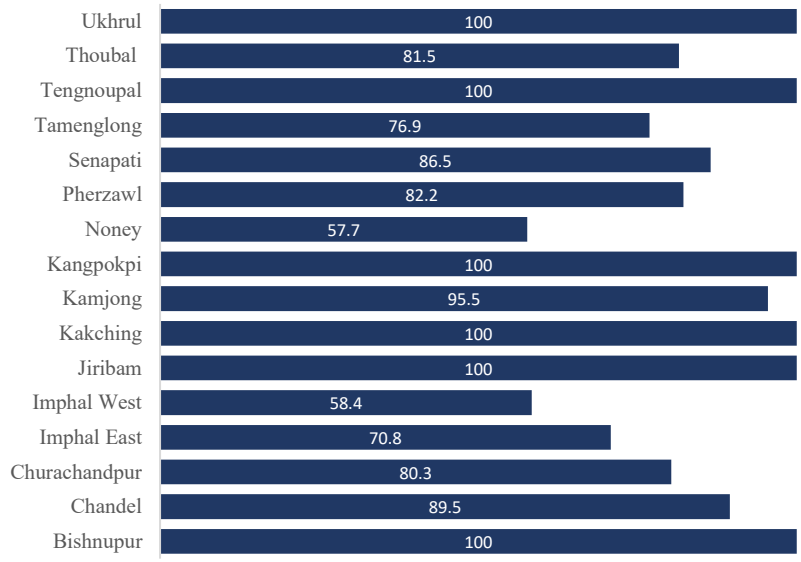

Figure 4: Availability of potable water in households
Source: Government of Manipur (2024).

Functional Household Tap Connection (FHTC)

Functional Household Tap Connection (FHTC) coverage in Manipur is around 80 per cent up significantly from less than 6 per cent in 2019. There are villages in the state and only 711 villages have achieved full FHTC coverage while in another 618 villages, FHTC coverage is at least 90 per cent. There are, however, villages where FHTC coverage is still less than 70 per cent (Figure 5). In 38 villages of the state, there is not a single household which has functional household tap connection. In another 150 villages, the FHTC coverage is less than 20 per cent. These villages may be termed as hotspot villages of the state in the context of full FHTC coverage.

Villages where FHTC coverage is 100 per cent are unevenly distributed across the districts of the state ranging from just around 6 per cent in Bishnupur district to more than 42 per cent in Churachandpur district. On the other hand, out of 38 villages where FHTC coverage is zero, 26 villages are in two districts – Jiribam and Kangpokpi – alone. On the other hand, out of 150 villages in which FHTC coverage is less than 20 per cent, 37 villages are in Kangpokpi district and 19 in Imphal West district. This means that there are 50 villages in Kangpokpi district where FHTC coverage is either zero or less than 20 per cent.

By contrast, Kakching is the only district where there is no village where FHTC coverage is either zero or less than 50 per cent. In all other districts, there is at least one village where the FHTC coverage is either zero or less than 20 per cent.

Low Functional Household Tap Connection (FHTC) coverage across these districts stems from a combination of geographical, infrastructure, and administrative challenges. In hilly and remote regions like Kangpokpi, rugged terrain, dense forest cover, and dispersed settlements make laying distribution pipelines and maintaining water pressure extremely difficult and expensive. Transporting construction materials to isolated villages is further complicated by poor road connectivity, while the seasonal drying of local natural springs compromises the reliability of water sources. Additionally, local socio-political instability, law and order issues, and execution delays by contractors significantly slow down infrastructure development and service delivery.

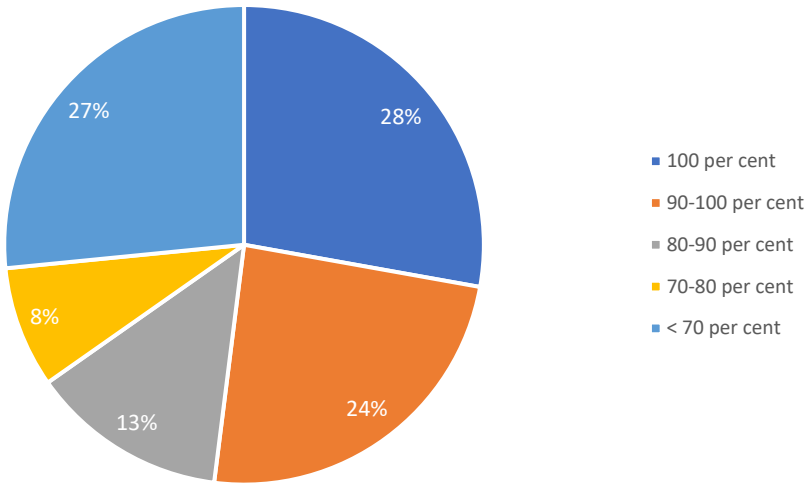

Figure 5: Distribution of villages according to FHTC coverage.
Source: Government of Manipur (2024).

Working Tap Connection in Households

A salient feature of household tap connections in the state is that more than 90 per cent of the household tap connections are operational. There are less than 10 per cent of the households in which there is a tap connection, but the connection is not operational or not functional. The proportion of households facing operational issues or disruptions in tap water supply is marginal.

Adequacy of Water Supply

Ensuring adequate water supply to all households remains a challenge in Manipur. There are only around 75 per cent households in the state in which the water supply is adequate (> 55 LPCD). In about 6 per cent households, adequacy of water supply is partially

adequate (40≤LPCD<55) whereas in around 18 per cent households, the water supply is inadequate (LPCD<40). Across the districts, adequacy of water availability varies widely. There are only two districts – Churachandpur and Senapati – where water supply is adequate in all households having a tap water connection (Figure 7). On the other hand, less than 20 per cent households with tap water connection in Ukhrul and Kangpokpi districts have adequate water supply. The proportion of households having adequate water supply is higher in valley districts than in hill districts. This disparity exists because valley districts draw from perennial rivers across flat, low-cost gravity networks while hill districts rely on rain-fed mountain springs that dry up seasonally, require expensive high-lift pumping, and suffer frequent pipeline damage from monsoonal landslides and siltation. Low VWSC formation in remote hill areas delays essential repairs, reducing water availability.

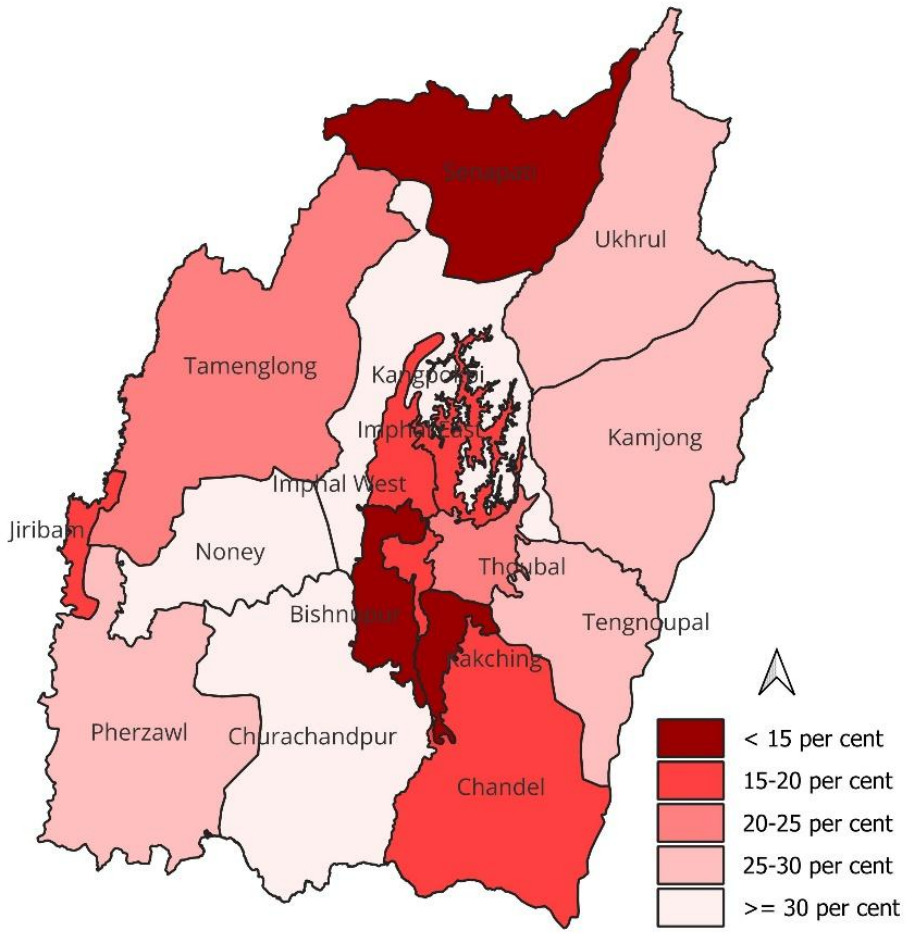

Figure 6: FHTC coverage across districts of Manipur
Source: Government of Manipur (2024).

Improvement in Water Quality

Manipur faces persistent challenges with urban river pollution, driven by untreated municipal runoff, chemical dumping, and plastic accumulation. Efforts to clean up these water ways are currently focused on the Nambul River, a critical tributary running through Imphal that flows into the ecologically vulnerable Loktak Lake. The Imphal Sewerage Project Phase I, which became fully operational in 2021, represents the primary urban waste water treatment investment in the state. The facility processes 27 million litres of sewage daily (MLD), connecting more than 12,000 households and reducing the direct discharge of municipal effluent into the Nambul River. This is supported by the Nambul River Rejuvenation Project, which uses Moving Bed Bioreactor (MBBR) technology alongside eco-friendly sanitation setups along the riverbanks. Phase II of the project aims to expand this infrastructure network to support an estimated 3.11 million users by the end of 2025. However, lack of the availability of publicly accessible post-treatment water quality data makes it difficult to assess the long-term ecological impact of these investments. The infrastructure has expanded, but rapid urban growth continually outpaces treatment connections.

To improve water-use efficiency, the focus is on upgrading urban pumps, repairing leaks, and installing water meters in the urban areas. In the rural areas, water-use efficiency initiatives are tied to solar-powered pumping stations for irrigation in district Chandel and community-led rain water harvesting setups in other districts which are designed to stabilise local agricultural productivity without over-extracting groundwater resources.

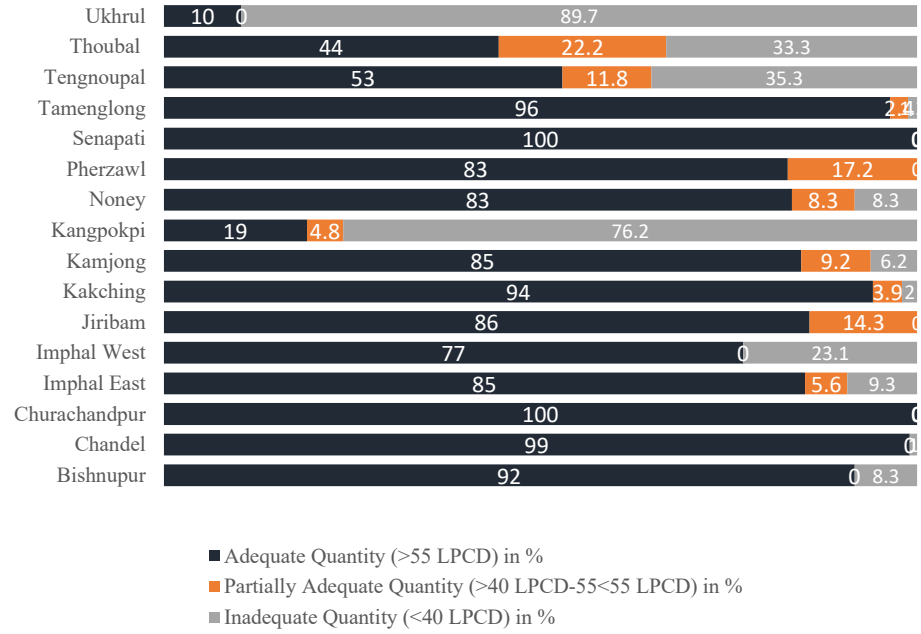

Figure 7: Adequacy of water supply at household level.
Source: Government of Manipur (2024).

The structural disparities between hill and valley districts of the state present a challenging eco-political paradox. Hill districts serve as primary water catchments of the state and host the forested watersheds and natural mountain springs that feed the major river basins of the Imphal valley. However, data demonstrate that these resource-rich upland regions experience the lowest real-world infrastructure functionality, as highlighted by very low FHTC coverage in district Ukhrul. This operational breakdown stems directly from the limitations of the current decentralised governance model in the context of challenging topography of the state. The reliance is on locally managing operations and maintenance through VWSCs, but the absence of active VWSCs creates an institutional vacuum. When a mountain pipeline cracks due to a landslide or an intake well becomes choked with monsoon silt, these remote areas lack the formal local governance and funding required to execute repairs. Consequently, expensive engineering installations break down, forcing rural households to rely on unmonitored private water vendors or traditional streams.

On the sanitation front, while the Swachh Bharat Mission has effectively minimised open defecation, long-term sustainability remains vulnerable. The steep terrain of hill districts limits deployment of standard vacuum trucks for faecal sludge management, raising the risk of localised groundwater contamination. The on-going socio-political instability and ethnic conflict in the state have also disrupted funding channels, slowed maintenance logistics, and halted work on Phase II extension projects, affecting the progress towards SDG 6.

Conclusion

Manipur progress towards SDG 6 presents a dual narrative. At the one hand, large-scale infrastructure investment and targeted programme execution have achieved near-universal baseline toilet access and expanded physical tap water connectivity across rural and urban areas and have earned the state well-deserved recognition at the national level. On the other hand, a substantial gap remains between physical infrastructure installation and daily operational reliability. In the hill districts of the state, challenging terrain, lower community participation, and broader socio-political instability often reduce functional tap connections to critically low levels. To bridge these functional disparities, Manipur water policy must shift its focus from basic asset deployment to long-term hydrogeological and institutional sustainability by empowering VWSCs, securing upstream spring shed catchments, and investing in localised waste water treatment.

Policy Recommendations

1. Prioritise formation and capacity-building of Village Water and Sanitation Committees (VWSCs) as the institutional vacuum directly causes low FHTC functionality despite near 100 per cent tap installation.
2. Earmark dedicated operation and maintenance funds to ensure that pipelines do not sit broken after monsoonal landslides or siltation in rugged terrain.

3. Formalise integrated spring-shed management and community rainwater harvesting across hill districts to reduce reliance on long-distance piped conveyance in fragile hydrogeological zones.
4. Build climate-resilient, decentralised water infrastructure in landslide-prone hill districts, since centralised pipelines are the first casualty of both floods and blocked roads.
5. Introduce terrain-appropriate faecal sludge management tailored to steep topographies to curb ground water and spring contamination risks.
6. Establish publicly accessible water-quality testing protocols to enable continuous monitoring and assess long-term ecological impacts.
7. Formalise and regulate private water vending systems in low-FHTC districts as an interim safety net, tracking vendor reliance as an indicator of public supply reliability.

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Who Pays for Tests that Should Be Free? A Cross-Sectional Household Survey in Upper Assam

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Seema Sharma

Abstract

This study examines the level of awareness of free diagnostic services across tea garden, rural non-tea garden and urban households in Assam and analyses the association between awareness and out-of-pocket diagnostic expenditure and pattern of public versus private diagnostic facility utilisation in different population groups. Based on a purposive sample of households, the study concludes that awareness of free diagnostic services in Assam is critically and equitably low, and The study found critically low awareness of free diagnostic services across all three locality groups. Awareness was positively associated with out-of-pocket diagnostic expenditure, while more aware households showed greater private-facility utilisation. These findings suggest that awareness alone may not translate into financial protection when households perceive limitations in public diagnostic service availability or quality.

Introduction

Accurate and affordable diagnostic services are central to effective healthcare and are widely recognised as a key factor of universal health coverage (UHC). The diagnostic gap in health systems is an increasingly acknowledged concern particularly in resource constrained low- and middle-income regions where poor investment in diagnostic infrastructure has translated directly into high out-of-pocket expenditure for households. Quality diagnostics when integrated into health-care delivery influence disease detection, treatment outcomes and disease surveillance. Henceforth, their absence generates downstream public health consequences including irrational antibiotic use and antimicrobial resistance.

In the year 2018, World Health Organization (WHO) published the first Essential Diagnostics List (EDL) which identifies 113 essential diagnostics that must be done at the primary care level and laboratory-based facilities to place the diagnostics alongside essential medicines as a positioning diagnostic alongside essential drugs as a key component of health system strengthening (WHO, 2018). This global policy signal emphasised the value of country-level framework in assessing and improving diagnostic availability and accessibility.

Under-investment in diagnostics infrastructure has remained a persistent challenge in the public health system in India. Data from the 71st round of the National Sample Survey (NSSO) indicate that diagnostic costs accounted for approximately 10 per cent of all out-of-pocket health expenditure – 11 per cent in outpatient and 9.6 per cent in inpatient settings (Government of India, 2015). In response, India introduced the Free Diagnostics Service Initiative (FDSI) in 2015, the Ayushman Bharat Comprehensive Primary Health Care programme in 2018 and the National Essential Diagnostics List (NEDL) in 2019. While these initiatives mark important progress. Studies consistently report considerable infrastructure gaps, reagent shortages and disparities in implementation across public healthcare settings, particularly in relation to non-communicable diseases and point-of-care diagnostics.

The persistence of diagnostic OOPE may reflect not only the absence of services but a more complex structural failure. Households cannot effectively navigate a fragmented diagnostic ecosystem characterised by multiple providers, referral barriers, administrative complexity and quality concerns. Awareness of free diagnostic entitlements should, therefore, be understood not merely as knowledge of service availability but as the capacity to translate that knowledge into utilisation. The health system failure to communicate and operationalise free diagnostic entitlements meaningfully shifts the financial burden back on households, despite services being officially available and available free of cost.

Despite growing emphasis on strengthening diagnostic infrastructure and broadening policy coverage, relatively little is understood about the ways households perceive, understand and respond to these entitlements which is a question of particular importance in geographically and socioeconomically marginalised regions such as Upper Assam, where tea garden communities face distinct structural barriers to healthcare communication and access.

This study is conceptually situated within Behavioural Model of Health Services Use of Andersen which conceptualises healthcare utilisation as a function of predisposing, enabling, and need factors acting in combination (Andersen, 1995). Within this framework, awareness of free diagnostic entitlements functions as a predisposing factor while financial resources, health insurance coverage and locality-specific infrastructure and referral conditions operate as enabling factors that influence the extent to which such awareness is converted into actual service use. Perceived clinical need for diagnostic testing constitutes the third determinant interacting with predisposing and enabling factors that influence shape eventual facility choice and OOPE. Framing the present inquiry in these terms enables the relationship between awareness and OOPE to be interpreted beyond a simple knowledge deficit but as the outcome of interacting predisposing, enabling and need-based determinants of health-seeking behaviour.

Research Gap

Previous research in this area has focused predominantly on policy design and supply-side infrastructure, leaving the household-level relationship between the

awareness about free diagnostic entitlements and out-of-pocket diagnostic expenditure empirically under examined within the Indian public health landscape. The existing literature has yet to explore this relationship comparatively across tea garden, rural non-tea garden and urban populations in a single sampling frame. This is especially pressing in Upper Assam, where tea garden communities face distinct barriers to healthcare communication and access.

Aims and Objectives

To address the identified gaps, this study focuses on three specific research questions. First, it examines the extent of awareness of free diagnostic services among surveyed households and how does the awareness vary across tea garden, rural non-tea garden and Urban households of Upper Assam. Second, it examines the association of the awareness about diagnostic services with out-of-pocket diagnostic expenditure. Finally, the study explores whether households aware of free diagnostic schemes preferentially use public diagnostic facilities over private ones or not.

Literature Review

India introduced the Free Diagnostics Service Initiative (FDSI) in 2015 to improve access to essential diagnostic services and reduce OOPE. The initiative was further expanded under Ayushman Bharat in 2018. However, despite these policy measures, implementation gaps and infrastructural limitations continue to constrain equitable diagnostic access (Padhan and Padhy, 2025).

Evidence from a pilot facility survey across Karnataka, Uttar Pradesh and Maharashtra documented considerable inter-district variation in availability of diagnostic services with blood count test, glycated haemoglobin test, HIV and syphilis diagnostic and tuberculosis and malaria microscopy unavailable in many primary health centres (Kruk et al, 2018). The study noted that public-private partnership models were linked to relatively better diagnostic availability.

A comprehensive synthesis of Common Review Mission reports under National Health Mission (NHM) from 2007 to 2021 has revealed that despite improved service availability under the NHM, household OOPE on diagnostics remains high. Mean OOPE was estimated at $74.7 for inpatient and $37.9 for outpatient services at private facilities compared to $11.8 and $22.4 respectively at public hospitals (Hannah et al, 2023). This study illustrates the disproportionate cost burden of private diagnostic care.

It has been observed in a study that the share of OOPE attributable to diagnostic tests increased with the socioeconomic status (Ambade et al, 2022). The National Health Accounts data, however, indicate that OOPE as a proportion of overall health expenditure declined from 64.2 per cent in 2013-14 to 39.4 per cent in 2021-22 (Government of India, 2024), but disaggregated expenditure in diagnostics in marginalised communities including tea garden population remains sparse.

There is a broad agreement across different studies that diagnostic OOPE in India has remained substantial despite more than a decade of policy intervention and that availability gaps and quality concerns continue to push households toward costlier private alternatives (Kruk et al, 2018; Hannah et al, 2023; Ambade et al, 2022). A notable concern, nonetheless, emerges between declining national OOPE share reported in aggregate health accounts and persistently high and even regressive, diagnostic-specific burden documented at the facility and household level. This suggests that macro-level improvement may mask micro-level inequities (Government of India, 2024; Ambade et al, 2022). However, none of these studies have disaggregated diagnostic OOPE by population subgroups leaving open whether marginalised communities such as tea garden population experience this burden differently and whether its persistence reflects availability constraints or failure in awareness and entitlement utilisation or both.

Compounding these supply-side constraints, Padhan and Padhy (2025) identify inadequate public awareness as a persistent barrier to the equitable utilisation of free diagnostic services irrespective of the extent to which services are formally provisioned. Similarly, studies related to Rashtriya Swasthya Bima Yojana (RSBY) have consistently documented that high enrolment rates do not translate into utilisation because households, particularly in rural and remote settings, lack actionable knowledge of their entitlements, eligibility criteria and access pathways (Selvaraj and Karan, 2012). The findings additionally suggest that insurance schemes in Tamil Nadu may have paradoxically increased OOPE for the poor given their exclusion of outpatient diagnostic and drug costs.

These two strands of evidence agree on a common mechanism – nominal awareness or scheme enrolment without actionable knowledge of entitlements and access pathways, fails to produce utilisation or financial-protection gains (Padhan and Padhy, 2025; Selvaraj and Karan, 2012). They also highlight that enrolment can paradoxically increase OOPE where coverage is incomplete, challenging any simple equation of scheme presence with protection. What remains unexamined is whether this awareness and utilisation of OOPE disjuncture well documented for health insurance schemes nationally replicates specifically for free diagnostic entitlements and whether it holds within structurally distinct, marginalised settings such as tea garden communities of Assam.

In the context of Assam, an investigative analysis has documented that tea garden workers have to travel to nearby towns for healthcare under compounding barriers of remote location, inadequate roads and poor socioeconomic conditions. Women reported being charged for diagnostic tests that should be free at government hospitals. (IndiaSpend, 2024).

The investigative and institutional evidence from Assam agrees with and plausibly intensifies the national-level pattern established above. Structural isolation, absence of clinical staff and weak government communication compound the supply-side and awareness-related failures while household-level testimony confirms that nominally free entitlements are routinely not honoured at the point of care. This evidence base, however, remains qualitative and institutional rather than systematic and quantitative. To the best of our knowledge, there is no study that has statistically compared awareness of free diagnostic services, diagnostic OOPE and facility-utilisation patterns across tea

garden, rural non-tea Garden and urban households within a single, comparable, sampling frame.

Considering together, the literature establishes that the persistence of diagnostic OOPE in India reflects an interaction between supply-side failures and demand-side information gap which is plausibly intensified within the tea garden ecosystem of Assam by structural isolation.

Methods

Research Methodology

The study is based on a cross-sectional household survey carried out in a purposely selected ample of 400 households from rural tea garden, rural non-tea garden and urban areas in six districts of Upper Assam India – Tinsukia, Dibrugarh, Sivasagar, Charaideo, Jorhat and Golaghat. These districts account for approximately 70 per cent of 879 tea gardens in Assam and represent the core plantation belt of the state. The selection of the districts and households with districts was purposive based on their demographic, economic and institutional significance within the tea sector and high concentration of tea garden healthcare infrastructure in these districts including facilities under the public-private partnership (PPP) model. Only those households were included in the sample which had incurred at least one healthcare expenditure in the preceding three months of the survey. Half of the households covered under the survey were rural tea-garden households while the remaining half of the households were divided equally between rural non-tea garden and urban households. In each household, data were collected preferably from the head of the household head. If the household head was not available data were collected from the most informed adult member of the household who also provided the self-rated awareness assessment described below. Because these variables were captured through one respondent per household rather than aggregated across all household members, the terms “household” and “respondent” are used interchangeably throughout this paper to refer to the same sampled unit. Reported awareness levels and out-of-pocket expenditure accordingly are, therefore, based on the knowledge, recall and reporting by the respondent. This proxy-reporting design is revisited as a limitation below.

A structured, pre-tested questionnaire comprising of two modules was administered to collect the data required for the study. The first module was related to the household sociodemographic profile while the second module was related to healthcare expenditure during three months prior to the survey to minimise recall bias while capturing sufficient variation in healthcare utilisation.

Awareness about free diagnostic services was captured through two components of the questionnaire. A single global item asked respondents to self-rate their awareness about government health schemes in Assam on a four-point categorical scale: “Fully aware,” “Heard but don’t know details,” “Not aware” and “Not sure.” This item generated the primary awareness classification. A supplementary multi-item checklist recorded name-recognition across 14 named state and central schemes, including Chief Minister

Free Diagnostic Services scheme most directly relevant to this study. Eight items from this checklist constituted the "Health Scheme Awareness" scale, which was subjected to internal-consistency testing during instrument development (Cronbach's $\alpha = 0.81$; "Good," per George and Mallery, 2003), as part of a broader psychometric screening of 35-items instrument. "Full awareness" as used in this paper, therefore, denotes global self-rating by the respondents rather than a composite score of verified knowledge. The instrument did not separately probe awareness of eligibility criteria, of which specific tests are free or where free diagnostic services can be accessed.

Primary data were collected through direct interview conducted out by the authors. Pilot testing was undertaken on a small convenience sample to assess questionnaire clarity and estimate interview duration with appropriate modifications implemented before full-scale deployment. Informed verbal and written consent was obtained from each participating household. All completed questionnaires were reviewed daily for completeness and consistency.

All data were compiled, cleaned and analysed using IBM SPSS. Statistical methods used for analysis included Pearson χ^2 tests for categorical association, Kruskal-Wallis H tests for non-normally distributed ordinal and continuous variables, Spearman rank-order correlation for the association between awareness and OOPE and binary logistic regression to identify independent predictors of public versus private facility use. Non-normality of expenditure distributions was confirmed using Shapiro-Wilk and Kolmogorov-Smirnov tests. Descriptive statistics included means, standard deviations, medians and maximum values.

Results

Awareness about Free Diagnostic Services

Sensitization about government-provided free diagnostic services was critically low across all the three subgroups as Only 1.0 per cent reported full awareness of available diagnostic schemes, while 52.3 per cent had heard of such schemes but lacked specific knowledge of entitlements, eligibility criteria or access pathways. Another 25.3 per cent reported no awareness, while 19.5 per cent remained uncertain. These findings reflect a pattern indicating a profound information deficit that undermines scheme effectiveness irrespective of service supply.

Tea garden households exhibited the highest proportion reporting no awareness (33.5%), compared with 19.5% among rural non-tea garden and 13.8% among urban households. Urban households recorded the highest proportion reporting full awareness (3.4%), although this remained small in absolute terms. The 'not sure' category was most prevalent among rural non-tea garden households (25.7%), possibly reflecting partial exposure to information without actionable knowledge. The Pearson χ^2 test confirmed that the categorical distribution of awareness differed significantly across locality subgroups ($\chi^2(8) = 27.295$, $p < 0.001$). However, the Kruskal-Wallis H test of ordinal awareness level was statistically insignificant ($H=0.428$, $df=2$, $p=0.808$) with near-

identical mean ranks across rural tea garden (206.28), rural non-tea garden (207.80) and Urban (198.47) subgroups and a common median score of 2 (Heard but do not know details). The findings show that, while the categorical composition of awareness differs across subgroups, the overall depth of awareness is equally poor everywhere.

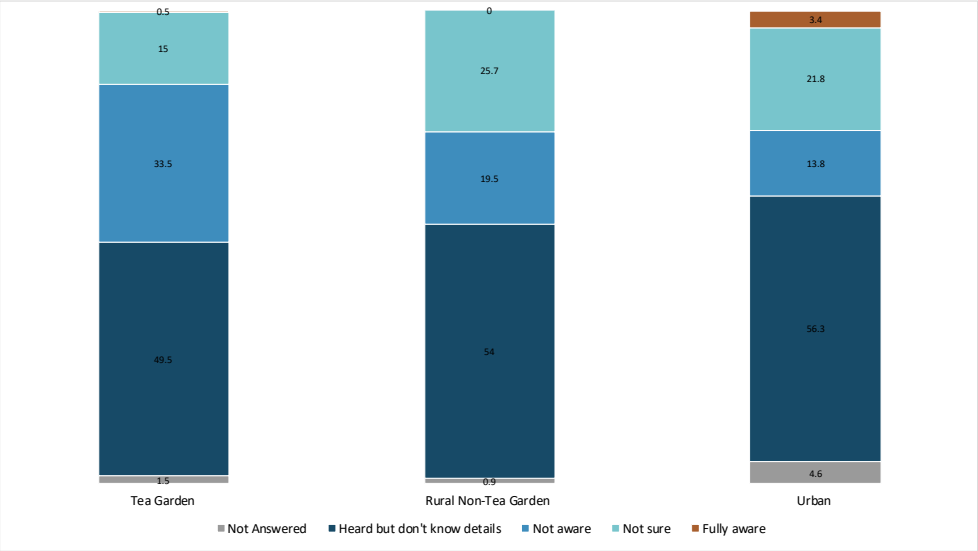

Figure 1: Level of awareness about free diagnostic services across different subgroups of respondents.
Source: Authors

Table 1: Level of awareness about free diagnostic services across different subgroups of respondents.

Awareness Level	Tea Garden	Rural non-Tea Garden	Urban	Total
Not Answered	1.5%	0.9%	4.6%	2.0%
Heard but don't know details	49.5%	54.0%	56.3%	52.3%
Not aware	33.5%	19.5%	13.8%	25.3%
Not sure	15.0%	25.7%	21.8%	19.5%
Fully aware	0.5%	0.0%	3.4%	1.0%
N	200	113	87	400

Source: Authors

Association Between Awareness and OOP Diagnostic Expenditure

Counter to the expectation that awareness about free diagnostic services would reduce out-of-pocket diagnostic expenditure, the average OOP diagnostic expenditure is found to be the highest in the fully aware subgroup, substantially exceeding the 'heard but do not know details' group and 'not aware' group in which the average expenditure was found to be the lowest across all awareness groups.

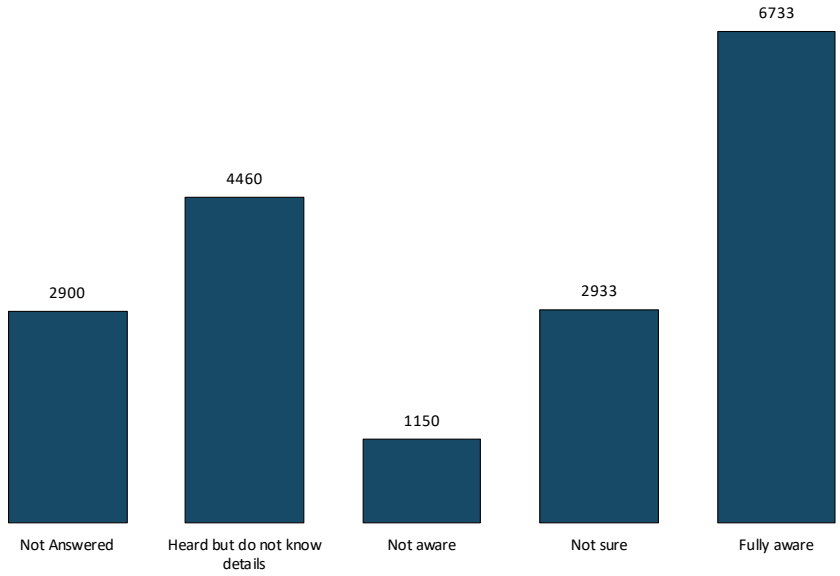

Figure 2: OOP diagnostic expenditure (Rupees) by the level of awareness.
Source: Authors

Table 2: OOP diagnostic expenditure (Rupees) by the level of awareness about free diagnostic schemes.

Awareness level	N	Number used private facility	OOP expenditure (Rupees)		
			Average	Minimum	Maximum
Not Answered	8	2	2900	2900	2900
Heard but do not know details	209	23	4460	1300	12000
Not aware	101	4	1150	300	2700
Not sure	78	17	2933	700	6000
Fully aware	4	3	6733	2300	12000
Total	400	49	3736	300	12000

Source: Authors

Diagnostic expenditure arises only when a paid service is purchased. The comparison across awareness groups was therefore restricted to those 49 respondents who paid for private diagnostic services. The rest either used no diagnostic services or used public facilities without paying and counting them as zero-expenditure cases would have treated non-utilisation as financial protection.

Because the expenditure distribution was non-normal (Shapiro-Wilk and Kolmogorov-Smirnov tests), the Kruskal-Wallis H test was applied to this restricted sample. It found no statistically significant difference in OOP diagnostic expenditure

across awareness groups (H=4.993, df=4, p=0.288). The pattern of mean ranks, however, runs in the same direction as in the full sample: the highest among fully aware respondents (42.17) and the lowest among those who had heard of the schemes without knowing the details (22.78) with the unaware (27.13) and unsure (24.53) groups in between. The three middle categories are closely clustered and the high rank of the fully aware group rests on only three respondents. Among households that used private diagnostic facilities on payment, it is not possible to ascertain whether awareness about free diagnostic schemes resulted in lowering OOP diagnostic expenditure because of the very small sample.

Table 3: Kruskal–Wallis rank of diagnostic expenditure among private-facility users by awareness level.

Awareness level	N	Mean Rank
Not Answered	2	24.50
Heard but don't know details	23	22.78
Not aware	4	27.13
Not sure	17	24.53
Fully aware	3	42.17

Source: Authors

Public and Private Diagnostic Facility Utilisation

The overall distribution of the facility use was heavily weighted toward public facilities (87.8 per cent), with 12.3 per cent of the respondents seeking care in private facilities during their latest healthcare episode. However, this aggregate pattern conceals a striking reversal among fully aware households – 75.0 per cent of these respondents used private facilities compared with 25.0 per cent of those who used public facilities. Private facility utilisation was the least common among respondents who were not sure about the schemes and those who were unaware about the schemes. The Pearson χ^2 test confirmed the association between awareness level with public and private facilities utilisation ($\chi^2 = 29.231$, df=4, $p<0.001$), though very few respondents who were fully aware limit categorical inference.

Table 4: Use of public and private facilities by the level of awareness among responents.

Awareness level	Private facility	Public facility	N
Not Answered	25.00	75.00	8
Heard but do not know details	11.00	89.00	209
Not aware	4.00	96.00	101
Not sure	21.80	78.20	78
Fully aware	75.00	25.00	4
Overall	12.30	87.80	400

Source: Authors

To test the relationship between the awareness about free diagnostic schemes and use of private or public facilities, we initially carried out the conventional binary logistic regression analysis. The dependent variable for the regression analysis was a categorical variable which has value 0 if the respondent used a private facility and value 1 if the respondent used a public facility. Covariates in the analysis included age of the re-

spondent, household size and household asset index while categories included awareness about free diagnostic schemes, level of education of the household head, any member of the household covered by health insurance, gender, whether household had a BPL card and locality. Table 5 shows the codes assigned to different categories of the categorical variables along with the specification of the reference category. The model, however, exhibited complete separation, particularly because there was no private-facility user among household heads who were uneducated. A similar separation problem was observed as there was no private facility use in households with a BPL card. The conventional logistic regression therefore failed to converge and produced unstable estimates. To address this estimation problem appropriately, we have used Firth penalised logistic regression (Firth, 1993). Firth penalised logistic regression is a bias-reduction method that fixes standard maximum likelihood estimation failures when the sample size is small and provides finite bias-reduced estimates in the presence of complete or quasi-complete separation. This approach is specifically recommended for situations in which standard maximum-likelihood logistic regression cannot obtain reliable finite parameter estimates (Suhas et al, 2023).

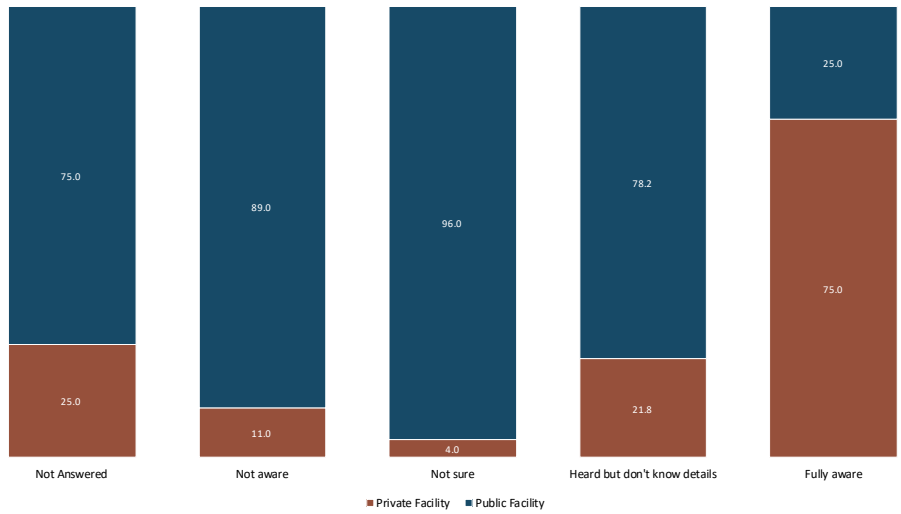

Figure 3: Use of public and private facilities by the level of awareness.
Source: Authors

Results of the regression analysis are presented in table 6. The analysis confirms that awareness about free diagnostic schemes is a statistically significant predictor of the use of public facilities. Households having no awareness about free diagnostic schemes are 66 per cent less likely to use public facilities instead of private facilities when compared with households having any awareness about free diagnostic schemes. The other predictor that has been found to be statistically significant is whether any member of the household had a health insurance. Households in which no member of the household had a health insurance were more than nine times more likely to opt for a public facility instead of a private facility when compared to households in which at least

one member had a health insurance. The household asset index has also been found to be associated with the use of public facilities – the higher the household asset index the lower the probability of using a public facility. Rest of the explanatory variables have not been found to be statistically significantly associated with the use of a public facility relative to the use of a private facility.

Table 5: Specification of categorical explanatory variables used in the analysis.

Variable	Category	Code	
Awareness about free diagnostic schemes	No awareness	1	
	Any awareness	2	Reference category
Education of household head	Uneducated	1	
	Educated up to high school	2	
	Educated above high school	3	Reference category
Gender	Male	1	
	Female	2	Reference category
Household having BPL card	No	1	
	Yes	2	Reference category
Locality	Rural tea garden	1	
	Rural	2	
	Urban	3	

Source: Authors

Discussion

This cross-sectional study has investigated the three interconnected facets of the utilisation of free diagnostic services in 400 households selected purposively from different regions of Upper Assam: 1) level of household awareness about free diagnostic services provided by the government; 2) association between the awareness about free diagnostic services and out of pocket (OOP) expenditure on diagnostic services; and 3) pattern of public versus private diagnostic facility utilisation by the level of awareness about free diagnostic services of the government. The findings of the study, collectively, reveal the existence of a structural paradox. The government scheme of free diagnostic services which is designed to eliminate diagnostic costs are largely unknown to their intended beneficiaries. There is only a small proportion of the households surveyed that are aware about this scheme and these households are incurring disproportionately high expenditure on diagnostic services by preferring private over public diagnostic facilities. This structural paradox has important implications for health equity and the design of demand-side health financing interventions in Assam that needs to be addressed at the policy level. There is little evidence to suggest that availability of free diagnostic services in public institutions has contributed to reducing the cost of diagnostics.

Critically Low and Inequitably Distributed Awareness

The most immediate finding is a near-universal absence of functional awareness about free diagnostic schemes across the households surveyed. Only 1.0 per cent of the respondents reported full awareness of government-sponsored free diagnostic services,

while 52.3 per cent had merely heard about these schemes but had little knowledge of entitlements, eligibility criteria or access pathways. A further 25.3 per cent reported no awareness and 19.5 per cent remained uncertain. This distinction between nominal and actionable awareness is analytically critical (Selvaraj et al, 2019). It aligns with broader evidence suggesting that demand-side information, education, communication (IEC) strategies in India generate nominal awareness so that they fail to transfer the knowledge that is necessary to change behaviour (Baru et al, 2010; Reddy et al, 2021). The proportion reporting no awareness was highest among tea garden households (33.5 per cent), compared with 19.5 per cent among rural non-tea garden and 13.8 per cent among urban households. This awareness gap may be attributed to the structural insularity of the plantation ecosystem, although this study has not directly measured such structural factors, but it limits the fidelity of the government health communication (Gupta et al., 2016; Bhattacharya, 2018). The deficiency in effectively informing and communicating with the people is also reflected from the finding that the common median of all the three localities – tea garden, rural non-tea garden, urban – was 'heard but do not know details'. This convergence indicates a systemic information deficit among the households surveyed rather than a geographically localised one.

Table 6: Determinants of the use of free public diagnostic facilities relative to the private diagnostic facilities.

Predictor	Reference category	Adjusted OR	95 CI	p
Age	Continuous	1.024	0.981–1.069	0.272
Household size	Continuous	1.061	0.676–1.665	0.796
Asset index	Continuous	0.755	0.615–0.927	0.007
Awareness of free diagnostic schemes	No awareness	0.339	0.149–0.772	0.010
	Any awareness®			
Education of household head	Uneducated	0.656	0.033–12.865	0.781
	Up to High school	0.273	0.014–5.449	0.396
	Beyond High school®			
Gender	Male	1.273	0.429–3.781	0.664
	Female®			
BPL Card	No	8.569	0.637–115.241	0.105
	Yes®			
Any member covered by health insurance	No	9.458	2.473–36.177	0.001
	Yes®			
Locality	Rural Non–Tea Garden	1.179	0.208–6.681	0.852
	Tea Garden	0.637	0.267–1.516	0.308
	Urban®			

® Reference category
Source: Authors

The Awareness-Expenditure Paradox

Contrary to the theoretical premise of demand-side health promotion which argues that awareness about free services leads to increased utilisation of these services and thereby reduces OOP expenditure, the present analysis reveals a significant positive association between the level of awareness of diagnostic schemes and the OOP expenditure. The OOP expenditure has been found to be the highest in those households where the awareness about the free diagnostic schemes was the highest. Two intersecting mechanisms may plausibly underlie this paradox, although the cross-sectional design of the study does not allow to directly test this hypothesis. Instead, both observations should be read as possible explanations rather than demonstrated causes. First, a possible endogeneity dynamic, viz awareness about free diagnostic schemes is not randomly distributed across the sample but is concentrated among households with greater health-seeking propensity and more extensive engagement with the formal health system, which would make it a marker of healthcare engagement rather than an independent predictor of lower expenditure (Nandi et al, 2017). Second, a possible quality exit dynamic whereby even households with full knowledge of their entitlements, choose for private diagnostic facilities when public services are perceived as inadequate in test availability, reagent supply and result timeliness (Prinja et al, 2019; Garg et al, 2020). The insignificance of the health insurance as a moderating factor in this relationship reinforces the observation that the insurance architecture as currently designed is insufficient to redirect households aware about free diagnostic services towards free public diagnostics services (Selvaraj and Karan, 2012; Ghosh, 2014).

Facility Utilisation: The Informed Exit

The analysis of the public and private diagnostic facility use by the level of awareness about free diagnostic scheme provides the pattern most consistent with a possible quality exit dynamic though perceived service quality was not directly measured in this study. While 87.8 per cent of households used public diagnostic facilities, 75.0 per cent of the fully aware households (3 out of 4) reported using private diagnostic facilities. This inversion was found to be statistically significant ($\chi^2=29.231$, $df=4$, $p<0.001$), although the very few households fully aware of free diagnostic scheme limits the stability of this categorical comparison. This inversion mirrors the informed exit documented in analogous settings where more health-literate populations preferentially seek private care upon developing a critical appraisal of public service quality (Mohanty & Srivastava, 2013; Rao et al, 2011).

Firth penalised logistic regression analysis has indicated that structural and socioeconomic factors are associated with the utilisation of public and private diagnostic facilities. The higher level of the corrected asset index was found to be associated with lower odds of the use of public diagnostic facilities. Similarly, any type of awareness about free diagnostic scheme was found to be associated with higher odds of the use of public diagnostic facilities compared to households having no awareness about the scheme. Health insurance coverage was strongly associated with the use of private diagnostic facilities. Education, gender, BPL status and locality were not statistically significant after adjustment.

The lower odds of public-facility use among households with awareness are consistent with the descriptive pattern in which more aware households showed greater private-facility use. However, the cross-sectional design does not establish why aware households were more likely to use private facilities, and perceived service quality was not directly measured.

Limitations of the Study

Several limitations qualify the findings of this study. First, the cross-sectional design precludes causal inference. The positive awareness-expenditure association may reflect reverse causation whereby households with greater illness burden simultaneously accumulate scheme awareness through repeated healthcare contact and higher OOP diagnostic expenditure rather than any directional effect of awareness on OOP. Second, the awareness variable measures knowledge of government health schemes broadly rather than free diagnostic programmes specifically risking misclassification of respondents familiar with unrelated entitlements. The study did not assess whether respondents knew their eligibility for free diagnostics, which specific tests are covered or where such services can be accessed. The "full awareness" category should, therefore, be read as an upper-bound rather than a validated measure of functional or actionable awareness. Third, self-reported OOP expenditure over a three-month recall period is susceptible to telescoping and recall bias that may introduce non-differential measurement error that attenuates true associations. Fourth, the fully aware subgroup is very small (n=4), which limits the statistical stability of findings. Finally, the study covers only three locality types, and the findings may not be generalised to tribal belt areas, riverine char communities or states operating under different scheme architectures. The purposive sampling also limits the population-representativeness of the findings. Sixth, because a single adult household member reported on behalf of all members of the household, the reported findings reflect the respondent knowledge and recall rather than a verified household-wide consensus or within-household variation in awareness or in expenditure decision-making.

Policy Implications

The findings carry several implications for health policy in Assam. First, the distinction between nominal and actionable awareness underscores that IEC strategies must move beyond name recognition to provide actionable, step-by-step guidance on eligibility, access pathways and entitlements under the Free Diagnostic Services Initiative (FDSI) of the government of Assam. Second, if the possible quality exit dynamic suggested in the present study holds, it would imply that demand-side awareness interventions cannot succeed without commensurate supply-side investment. NQAS accreditation of public laboratories, reagent supply chain strengthening, expanded the list of test and timely result reporting are prerequisites for retaining even well-informed patients within the public system. Third, tea garden communities require estate-specific, targeted interventions such as mobile diagnostic camps within estates, management-level engagement and trilingual IEC materials that navigate the communication barriers of the

plantation ecosystem. Fourth, the dominant role of health insurance in predicting public facility use reinforces that structural financing mechanisms exert greater influence than information alone in shaping utilisation pathways. The diagnostic benefit packages under AB-PMJAY and state schemes should be reviewed to reduce administrative barriers and extend empanelment to government diagnostic centres. Fifth, sub-district equity monitoring that disaggregates tea garden and rural non-tea garden population should be institutionalised within HMIS and NHM district planning frameworks to enable targeted policy responses.

Conclusion

This study offers important insights into a critical disconnect at the heart of the diagnostic ecosystem of Assam. It reveals that mere existence of free diagnostic schemes is insufficient to reduce out-of-pocket expenditure on diagnosis when awareness remains shallow, supply-side quality is possibly inadequate and access pathways are procedurally complex. Awareness about free diagnostic services was critically low across the surveyed households and differed significantly in categorical composition across locality subgroups. Contrary to the expected protective effect, greater awareness was associated with higher diagnostic out-of-pocket expenditure and lower odds of public-facility utilisation. The findings suggest that awareness alone may be insufficient to generate financial protection when public diagnostic services are perceived as inadequate or difficult to access.

The three findings of the present analysis converge on a single policy conclusion – the demand-side awareness efforts and supply-side quality investment must be advanced in concert. The realisation of universal diagnostic access in Assam requires a coordinated policy response in which financing reform, quality improvement and equity-sensitive communication together enable awareness generation. While this study is limited by its cross-sectional design and purposive sample design, small size of fully aware subgroup and absence of illness severity data, it establishes a clear evidence base for the urgent redesign of both IEC strategies and public diagnostic service delivery in Upper Assam.

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Effect of Four or More Antenatal Care Visits on Basic Childhood Immunisation in India: A Propensity Score Matching Analysis

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Abstract

This paper analyses the relationship between antenatal care visits by women during the pregnancy and child immunisation in India using propensity score matching. Propensity scores were estimated using a logit regression model. Validity of the matching procedure was assessed by examining common support assumption, and sensitivity analysis was conducted to evaluate the robustness of the effect of at least 4 ANC visits on childhood immunisation to potential hidden bias. Based on the data from the fifth round of the National Family Health Survey (2019-2021), the analysis reveals that at least 4 antenatal care (ANC) visits during the pregnancy by women significantly increases the likelihood of complete childhood immunisation of their children which means that at least four ANC visits during pregnancy may serve as a critical platform for achieving universal child immunisation and may contribute to better child health outcomes in India.

Introduction

Childhood immunisation is one of the most effective public health interventions for improving child survival and preventing morbidity and mortality from vaccine-preventable diseases, thereby contributing to increased life expectancy at birth (Andre et al, 2008; Ozawa et al, 2016). In India, under-five mortality rate has declined substantially from around 126 under-five deaths for every 1000 live births in 1990 to approximately 31 under-five deaths for every 1000 live births in 2022, reflecting considerable improvements in maternal and child health services, including vaccination programmes (United Nations Agency Group for Child Mortality Estimation, 2023). Globally, child immunisation is estimated to prevent approximately 3.5–5.0 million child deaths every year by protecting them against vaccine-preventable infectious diseases (World Health Organization, 2024). Although the Universal Immunisation Programme (UIP) of India, launched in 1985, has substantially expanded the vaccine coverage among children of the country, yet the evidence from the latest round of the National Family Health Survey, 2023-2024 suggests that less than 83.6 per cent children aged 12–23 months of the country were fully immunised or received all the basic vaccinations (Government of India, 2026). This indicates that despite the progress, important gaps in universal immunisation of children continue to persist.

A range of individual, household, community, and health system factors influences the uptake of childhood immunisation. Earlier studies have shown that parental knowledge and attitudes, socioeconomic status, access to healthcare services, exposure to health information, and quality of communication between healthcare providers and caregivers influence childhood vaccination uptake (Mathew, 2012). In India, children born to older women, women with higher level of education and from wealthier households in the urban areas are more likely to be fully immunised than their counterparts (Rammohan and Awofeso, 2015; World Health Organization, 2018).

Maternal healthcare utilisation, particularly antenatal care (ANC), represents an important opportunity to improve childhood immunisation. ANC provides repeated contacts between the pregnant woman and the healthcare provider, facilitating health education, counselling, and linkage to essential maternal and child health services. These interactions can improve knowledge of the woman about childhood vaccination, address misconceptions, and strengthen confidence in healthcare services, thereby increasing the likelihood of timely and complete childhood immunisation, particularly in low- and middle-income countries such as India (Kumar et al, 2019).

The World Health Organization (WHO) had earlier recommended a minimum of 4 ANC visits during pregnancy, with the first visit in the first trimester. In 2016, this recommendation was revised to a minimum of eight contacts to improve maternal and perinatal outcomes. However, at least 4 ANC visits remain an important benchmark for evaluating ANC utilisation (UNICEF, 2024). Globally, approximately 70 per cent pregnant women receive at least 4 ANC visits, although substantial regional disparities remain (UNICEF, 2024). In India, NFHS, 2023–24 reported that approximately 65 per cent of women attended at least 4 ANC visits during the most recent pregnancy, while nearly 76 per cent had the first visit during the first trimester (Government of India, 2026; Girotra et al, 2023). However, ANC visits vary considerably across socioeconomic and demographic groups and are influenced by factors such as maternal education, household wealth, caste, religion, residence, parity, and exposure to mass media (Dhawan et al, 2020; Singh et al, 2019).

There are many studies that have reported a positive association between maternal healthcare utilisation and childhood immunisation in India and in other countries (Anichukwu and Asamoah, 2019; Faradita et al, 2022; Gebrehana et al, 2025; Phaway et al, 2022; Usman et al, 2020). These studies have, in general, examined the combined effect of the continuum of maternal healthcare services – antenatal care, institutional delivery, and postnatal care – on childhood immunisation rather than independent contribution of adequate ANC services utilisation on childhood immunisation. For example, Usman et al (2020) have examined the combined effect of the continuum of maternal health care services on childhood immunisation in India using the data available from the fourth round of the National Family Health Survey (NFHS-4) which refers to the period 2015–16. The study, however, tells little about the independent effect of at least 4 ANC visits during pregnancy on the immunisation status of children.

The present paper is directed towards analysing the impact of at least 4 ANC visits by women during pregnancy on the immunisation status of children in India based on the data available from the fifth round of the National Family Health Survey (NFHS-5) which was carried out during 2019-2021 (Government of India, 2022). The sixth round of the National Family Health Survey (NFHS-6) has also been carried out during 2023-2024 (Government of

India, 2026) but microdata from NFHS-6 are not yet available to analyse the relationship between ANC visits and childhood immunisation in the contemporary context. The present study estimates the independent effect of at least 4 ANC visits on immunisation coverage in children in India based on the data from NFHS-5. The propensity score matching (PSM) technique has been used for estimating the effect of at least 4 ANC visits during pregnancy on child immunisation after controlling a host of variables related to the demographic and maternal characteristics of women. PSM provides a more robust estimate of the association between at least 4 ANC visits and child immunisation than estimate based on conventional regression analysis. The analysis provides updated evidence about the contribution of ANC visits to childhood immunisation. NFHS-6 suggests that 65.2 per cent women in India had at least 4 ANC visits during their last pregnancy while 87.1 per cent children aged 12-23 months were fully immunised (Government of India, 2026). The paper suggests that ensuring at least 4 ANC visits during pregnancy may contribute to the realisation of universal child immunisation as ANC visits may be the entry point for improving immunisation coverage and advancing maternal and child health outcomes.

Materials and Methods

The present study utilises data from the fifth round of the National Family Health Survey (NFHS-5) which was carried out during 2019-21. NFHS-5 was spread across the entire country and covered 664972 households, 747176 women aged 15–49 years, and 232920 births during the five years preceding the survey (Government of India, 2021). The sample of households for the survey was selected through a two-stage stratified sampling design with probability proportional to size. The survey provides nationally representative information on selected demographic and health indicators including fertility, maternal and child health, immunisation, nutrition, and reproductive behaviour (Government of India, 2021). The present analysis is based on the Kids Recode files (KR) which is available in the public domain.

The outcome variable for the present study is the immunisation status of children aged 12–23 months. This is a binary variable which has value 1 if the child is fully immunised or the child has received all basic vaccinations and value 0 if the child is not fully immunised. Information on the vaccination status of the child was collected from women who had delivered a live birth during the five years preceding the survey. Women were asked to produce the child vaccination card, if available, from which details regarding the date of vaccination, dose, and type of vaccine administered were extracted. In cases where the vaccination card was either unavailable or incomplete, maternal recall was used to obtain information about the vaccination history of the child.

WHO defines basic vaccination as the administration of one dose of Bacillus Calmette–Guérin (BCG), three doses each of pneumococcal conjugate vaccine (PCV), pentavalent vaccine, and oral polio vaccine (OPV), two doses of rotavirus vaccine, and one dose of measles vaccine. Vaccination information obtained from either maternal recall or from vaccination card was recoded into binary indicators, with 0 denoting children who did not receive the recommended vaccines and doses and were termed as not fully immunised and 1 for those who received the recommended doses and were termed as fully immunised (WHO, 2017; WHO, 2021). The proportion of children fully immunised was estimated

separately for women who had at least 4 ANC visits during the last pregnancy and for women who had less than 4 ANC visits during the last pregnancy to examine the effect of at least 4 ANC visits on childhood immunisation. Since the background characteristics of women having at least 4 ANC visits may be different from those of women having less than 4 ANC visits, this difference may be a contributing factor to the observed difference between the proportion of children fully immunised in women having at least 4 ANC visits and the proportion of fully immunised children in women having less than 4 ANC visits. To exclude this effect, women having 4 ANC visits were matched with women having less than 4 ANC visits based on a set of background characteristics of women using the propensity score matching (PSM) technique (WHO, 2017; 2021). The set of background characteristics of women for propensity score matching was decided based on the evidence from existing literature (Kinfe et al, 2019; Krishnamoorthy and Rehman, 2022; Gebrehana et al, 2025; Caliendo and Kopeinig, 2008; Girotra et al, 2023; Usman et al, 2021; Basha, 2019; Shrivastwa et al, 2015).

The PSM is a statistical method which creates an artificial group of women by pairing women having at least 4 ANC visits with women having less than 4 ANC visits based on a set of background characteristics (Caliendo and Kopeinig, 2008; Li, 2013). The difference between the proportion of children fully immunised among children of matched women having at least 4 ANC visits and matched women having less than 4 ANC visits during the last pregnancy provides a more robust estimate of the effect of at least 4 ANC visits during the last pregnancy on childhood immunisation.

The propensity scores in the present analysis were estimated using a binary logistic regression model. The propensity score represents the conditional probability of a woman having at least 4 ANC visits given the observed covariates relative to a woman having less than 4 ANC visits (Caliendo and Kopeinig, 2008; Li, 2013). It relies on two fundamental assumptions: i) conditional independence (unconfoundedness) and ii) common support (overlap). The conditional independence assumes that, after adjusting for observed covariates, treatment assignment is independent of the potential outcomes, while common support assumption requires sufficient overlap in the propensity score distribution of the treatment and comparison groups to ensure that comparable matches can be identified (Caliendo and Kopeinig, 2008). Multiple iterations of propensity score estimation were performed until satisfactory covariate balance was achieved.

Matching procedure

The one-to-one nearest neighbour without replacement method was used to match women having at least 4 ANC visits and women having less than 4 ANC visits. To reduce the likelihood of poor match, a calliper width of 0.023 (0.2 times the standard deviation of the logit of the propensity score) was applied (Caliendo and Kopeinig, 2008; Li, 2013). The quality of matching was assessed by comparing the distribution of covariates between women having at least 4 ANC visits and women having less than 4 ANC visits before and after matching using standardised bias, two-sample t-test, pseudo-R^2, and likelihood ratio (LR) tests. A standardised bias of less than ± 10 per cent was considered indicative of adequate covariate balance (Austin, 2009; Ali et al, 2015). The two-sample t-test was used to compare the difference in each covariate between the two groups of women. Finally, a pseudo-R^2 value less than 0.05 after matching indicated the absence of systematic differences in observed covariates between the matched women having at least 4 ANC visits

and women having less than 4 ANC visits (Sekine et al, 2021). Moreover, sensitivity analysis was carried out using Mantel–Haenszel (MH) bounds approach to assess the potential influence of hidden bias arising from unmeasured confounding effects (Becker and Caliendo, 2007; Rosenbaum, 2002). The sensitivity parameter, Γ (Gamma), represents the maximum degree to which two matched women with the same observed covariates may differ in terms of the odds of having at least 4 ANC visits relative to women having less than 4 ANC visits because of an unmeasured confounder. $\Gamma=1$ indicates no hidden bias and the higher the Γ the higher the potential hidden bias (Rosenbaum, 2002; Becker and Caliendo, 2007). In this study, Γ was varied from 1.00 to 2.00 in increments of 0.05. For each value of Γ, MH bounds provide two scenarios – Q_{mh+} and Q_{mh-}. Q_{mh+} and its corresponding p-value represent the bound under the assumption that hidden bias may result in overestimation of the effect of at least 4 ANC visits on childhood immunisation, while Q_{mh-} and its corresponding p-value represent the bound under the assumption of underestimation of the effect (Becker and Caliendo, 2007). A p-value<0.05 was considered statistically significant. The sensitivity of the estimated effect of having at least 4 ANC visits was assessed by examining the value of Γ when statistical significance was no longer observed under the adverse bound.

Limitation of PSM

One limitation of PSM procedure is that it cannot account for unmeasured or unobserved confounders (Caliendo and Kopeinig, 2008; Li, 2013). Consequently, validity of the estimated effect of at least 4 ANC visits on childhood immunisation after matching depends on the inclusion of all relevant confounding variables and correct specification of the propensity score model. PSM procedure may also exclude observations outside the region of common support, resulting in a reduced effective sample size and potentially limiting the generalisation of the findings (Caliendo and Kopeinig, 2008). In the present study, this limitation was addressed by including a comprehensive set of socio-demographic and characteristics of the women in the propensity score model, rigorously, assessing the covariate balance after matching using standardised mean differences (standardised bias), and sensitivity analysis. Nevertheless, as is the case with all observational studies, the possibility of residual confounding cannot be completely excluded, and, therefore, findings should be interpreted with appropriate caution. The Mantel–Haenszel sensitivity analysis also indicates that the statistical significance of the estimated association could be affected by a relatively modest degree of unmeasured confounding under the over-estimation bound. The observed association, therefore, should not be interpreted as completely free from residual confounding.

Estimation of effects

We have classified women in terms of a binary variable T which takes value 1 if the woman has at least 4 ANC visits and 0 if the woman has less than 4 ANC visits during the last pregnancy. Children aged 12-23 months have also been classified into two groups in terms of the binary variable Y which takes value 1 if the child is fully immunised and value 0 if the child is not fully immunised. Combining the two classifications, all children aged 12-23 months can then be classified into the following four mutually exclusive and exhaustive groups:

$Y_{11}=\{Y=1 \text{ and } T=1\}$

Y_{10}= {Y=1 and T=0}
Y_{01}= {Y=0 and T=1}
Y_{00}= {Y=0 and T=0}

The effect of at least 4 ANC visits on the probability that the child is fully immunised relative to less than 4 ANC visits (ATT) is estimated as

$$ATT = E(Y_{11} - Y_{10})$$
$$= E(Y_{11}) - E(Y_{10})$$

The ATT may be influenced by the difference in the background characteristics of women who have at least 4 ANC visits and those of women having less than 4 ANC visits. To eliminate this effect, women having at least 4 ANC visits were matched with women having less than 4 ANC visits through propensity scores and the ATT was estimated based on matched women only as follows:

$$ATT^m = E(Y_{11}^m) - E(Y_{10}^m)$$

The propensity score was calculated by regressing the binary variable T on a set of variables reflecting the background characteristics of women using the bivariate logistic regression analysis procedure. The following variables were used to reflect the background characteristics of the women:

1. Age of the woman
2. Level of education of the women
3. Standard of living of the woman as measured through the wealth index
4. Wanted status of the last child
5. Parity of the last child
6. Sex of the last child
7. Residence of the woman
8. Religion of the woman
9. Exposure of the woman to mass media

Results

Background characteristics of women

Table 1 shows that the distribution of women who had at least 4 ANC visits during their last pregnancy by selected background characteristics is statistically significantly different from the distribution of women who had less than 4 ANC visits during their last pregnancy. Table 1 confirms that the probability of at least 4 ANC visits by a woman during her last pregnancy is contingent upon her background characteristics. For example, the probability of at least 4 ANC visits is higher in younger women (<30 years of age) but lower in older women (≥ 30 years of age) compared to women who had less than 4 ANC visits. Similarly, the probability of at least 4 ANC visits is higher in women having at least secondary level education relative to women having less than secondary level education. The standard of living of the women, measured in terms of the wealth index is also found to be directly related to the probability of at least 4 ANC visits. Religion and place of residence also influence the probability of at least 4 ANC visits during the last pregnancy.

Table 1: Distribution of women having at least 4 ANC visits and women having less than 4 ANC visits during their last pregnancy by selected demographic, social and economic characteristics.

Variable		< 4 ANC visits (%)	≥4 ANC visits (%)	χ^2/z	df	P
Age of women (years)						
	Under 21	13.92	13.14	15.99	3	0.000
	22-29	62.77	62.63			
	30-39	21.74	22.93			
	40-49	1.57	1.30			
Mother's education						
	No education	26.35	14.32	1300	3	0.000
	Primary	13.47	10.63			
	Secondary	49.54	56.35			
	Higher	10.64	18.70			
Wealth index						
	Poorest	35.56	19.25	1900	4	0.000
	Poorer	24.92	21.71			
	Middle	17.40	21.26			
	Richer	13.07	20.08			
	Richest	9.05	17.70			
Wanted last child						
	Wanted then	91.38	93.60	92.05	2	0.000
	Wanted later	4.42	3.81			
	Wanted no more	4.20	2.59			
Place of residence						
	Rural	84.36	75.78	439.76	1	0.000
	Urban	15.64	24.22			
Religion						
	Hindu	72.56	75.76	89.23	2	0.000
	Muslim	14.17	13.96			
	Others	13.26	10.28			
Parity						
	One	32.89	41.11	734.09	3	0.000
	Two	32.28	35.28			
	Three	17.74	14.17			
	Four +	17.09	9.43			
Sex of the child						
	Male	51.97	52.64	1.78	1	0.570
	Female	48.03	47.36			
Mass media exposure						
	Yes	61.55	78.44	1400	1	0.000
	No	38.45	21.56			
All		41.94	58.06	36.93		0.000
N		16836	23331			

Source: Authors

The probability of having at least 4 ANC visits has also been found to be higher in women who wanted the child compared to those women who wanted the child later or the pregnancy was unwanted. Parity has also been found to be inversely related to the probability of at least 4 ANC visits. Finally, exposure to mass media has been found to be an important factor that influences the probability of at least 4 ANC visits during the last pregnancy. The gender of the child has not been found to be a factor in influencing the probability of at least 4 ANC visits during the last pregnancy. This is expected as the gender of the child remains unknown before the delivery.

Immunisation Status of the Child

The proportion of fully immunised children in women who had at least 4 ANC visits during the last pregnancy has been found to be statistically significantly higher than the proportion of fully immunised children in women who had less than 4 ANC visits during the last pregnancy. More than 81 per cent children of women who had at least 4 ANC visits were found to be fully immunised compared to around 70 per cent children of women who had less than 4 ANC visits and the difference is found to be statistically significant ($z=26.46$, $p<0.001$). A part of this difference may, however, be attributed to the difference in the background characteristics of the two groups of women which has been found to be statistically significantly different. The proportion of fully immunised children in women having at least 4 ANC visits and the proportion of fully immunised children in women having less than 4 ANC visits during the last pregnancy by background characteristics of women is presented in table 2.

Propensity score matching

To exclude the difference in the proportion of children fully immunised in women having at least 4 ANC visits and the proportion of children fully immunised in women having less than 4 ANC that may be attributed to the difference in the background characteristics of the two groups of women, the propensity score matching was carried out. This matching exercise revealed that 11640 women having at least 4 ANC visits during their last pregnancy matched with 13784 women having less than 4 ANC visits during their last pregnancy. The remaining women differed in terms of their background characteristics and, therefore, excluded from the analysis. The covariate balance diagnostics of the matching exercise is presented in table 3 which shows that standardised bias is markedly reduced after matching and no meaningful differences remained between matched groups of women. The improved covariate balance confirms that the comparison between women who had at least 4 ANC visits and women who had less than 4 ANC visits during their last pregnancy is based on comparable background characteristics.

Table 4 presents results of the matching quality diagnostics. There was a marked reduction in the median standardised bias which decreased from 36.0 per cent to 2.2 per cent and the median bias. The pseudo-R^2 also decreased markedly, while Rubin's B and Rubin's R remained within the recommended limits. These findings confirm that the matching procedure successfully balanced the observed covariates between two groups of women - women who had at least 4 ANC visits and women who had less than 4 ANC visits during their last pregnancy and reduction in the selection bias. These findings strengthened the validity of the estimated effect of at least 4 ANC visits during the last pregnancy on childhood immunisation.

Table 2: Proportion of children aged 12-23 months fully immunised in women having at least 4 ANC visits and women having less than 4 ANC visits during their last pregnancy by selected background characteristics.

Variable	< 4 ANC visits (%)	≥4 ANC visits (%)	z	P	N
Age of women (years)					
Under 21	70.00	81.49	9.88	<0.001	5406
22-29	71.28	81.63	19.34	<0.001	25,168
30-39	68.61	81.86	14.56	<0.001	9,006
40-49	60.00	78.48	4.78	<0.001	567
Mother's education					
No education	63.44	76.18	12.02	<0.001	7,774
Primary	67.62	79.98	9.71	<0.001	4,745
Secondary	73.37	83.10	17.16	<0.001	21,477
Higher	76.79	82.27	4.95	<0.001	6,151
Wealth index					
Poorest	64.21	78.90	16.32	<0.001	10,475
Poorer	70.26	80.44	11.39	<0.001	9,257
Middle	75.04	82.93	8.46	<0.001	7,886
Richer	75.37	84.17	8.73	<0.001	6,881
Richest	78.40	81.58	2.69	<0.007	5,648
Wanted last child					
Wanted then	70.79	81.79	24.92	<0.001	37,205
Wanted later	68.15	80.07	5.51	<0.001	1,632
Wanted no more	62.94	77.94	5.9	<0.001	1,310
Place of residence					
Rural	71.06	79.47	8.44	<0.001	8,279
Urban	70.21	82.31	25.48	<0.001	31,868
Religion					
Hindu	73.32	82.59	19.29	<0.001	29,877
Muslim	62.70	78.16	12.72	<0.001	5,641
Others	61.01	79.08	12.76	<0.001	4,164
Parity					
One	73.64	83.13	13.97	<0.001	15,122
Two	71.65	82.09	14.41	<0.001	13,660
Three	68.72	79.63	9.91	<0.001	6,290
Four +	63.23	76.30	9.97	<0.001	5,075
Sex of the child					
Male	70.91	82.06	19.05	<0.001	21,020
Female	69.73	81.14	18.34	<0.001	19,127
Mass media exposure					
Yes	74.06	82.90	17.88	<0.001	28,648
No	64.39	76.96	14.57	<0.001	11,499
All	70.43	81.62	26.46	<0.001	40,147
N	16836	23331			

Source: Authors

Table 3: The balancing test for the covariates in matched and unmatched women.

Variable	Group	Covariate balance					
		Women having at least 4 ANC visits	Women having less than 4 ANC visits	Bias	Reduction in bias	't'	'P'
Age of woman	Unmatched	2.123	2.195	-10.9	88.7	-5.40	0.000
	Matched	2.123	2.115	1.2		1.41	0.157
Education of woman	Unmatched	1.794	1.209	60.9	94.9	30.48	0.000
	Matched	1.794	1.824	-3.1		-3.60	0.000
Wealth index	Unmatched	2.952	2.016	71.5	94.9	32.86	0.000
	Matched	2.952	2.905	3.6		3.70	0.000
Wanted last child	Unmatched	1.089	1.196	-22.9	90.7	-13.22	0.000
	Matched	1.089	1.079	2.1		3.01	0.003
Place of residence	Unmatched	1.757	1.857	-25.5	89.4	-11.32	0.000
	Matched	1.757	1.768	-2.7		-2.68	0.007
Religion	Unmatched	2.214	4.231	-16.1	90.2	-9.91	0.000
	Matched	2.206	2.404	-1.6		-2.29	0.003
Parity	Unmatched	1.919	2.424	-48.4	94.8	-24.73	0.000
	Matched	1.919	1.892	2.5		2.97	0.003
Sex of child	Unmatched	1.473	1.479	-1.2	-78.7	-0.57	0.570
	Matched	1.473	1.463	2.1		2.29	0.022
Mass media exposure	Unmatched	0.784	0.479	66.7	99.3	34.72	0.000
	Matched	0.784	0.786	-0.4		-0.53	0.596

Source: Authors

Table 5 shows results of the Mantel–Haenszel sensitivity analysis. Under the assumption of no hidden bias ($\Gamma=1$), the association of the proportion of fully immunised children aged 12-23 months in women having at least 4 ANC during their last pregnancy has been found to be statistically significantly different from the proportion of fully immunised children in women having less than 4 ANC visits during their last pregnancy. With the increase in Γ, the significance of the difference under the over-estimation model gradually weakened and turned statistically insignificant after $\Gamma\approx1.15$. This indicates that a relatively small degree of unmeasured confounding effect could influence the effect of at least 4 ANC visits by women during their last pregnancy on childhood immunisation. However, the under-estimation model remains statistically significant across all Γ values, suggesting that the observed association was generally robust to the hidden bias. Overall, the sensitivity

analysis indicates that while the positive effect of at least 4 ANC visits on childhood immunisation is supported by the matched analysis, some caution is warranted because unmeasured factors may still partially influence the estimated effect.

Table 4: Quality of matching tests.

Group	Pseudo R^2	LR X^2	P value of LR	Mean bias	Median bias	Variance ratio (B)	Ratio of variances (R)	Proportion unbalanced (%var)
Unmatched	0.108	1787.48	0	36.0	25.5	91.1	0.82	88
Matched	0.001	76.68	0	2.2	2.1	8.1	1.07	75

Source: Authors

Table 5: Sensitivity analysis.

Gamma	Test Statistics		Significance level	
	(Over-estimation) Q _mh+	(Under-estimation) Q mh-	(Over-estimation) p_mh+	(Under-estimation) p_mh-
1	1.973	1.973	0.024	0.024
1.05	1.850	2.112	0.032	0.017
1.1	1.726	2.237	0.042	0.012
1.15	1.607	2.358	0.053	0.009
1.2	1.494	2.473	0.067	0.006
1.25	1.385	2.584	0.082	0.004
1.3	1.281	2.691	0.099	0.003
1.35	1.181	2.795	0.118	0.002
1.4	1.085	2.894	0.138	0.001
1.45	0.992	2.991	0.160	0.001
1.5	0.902	3.085	0.183	0.001
1.55	0.816	3.176	0.207	0
1.6	0.732	3.264	0.231	0
1.65	0.651	3.350	0.257	0
1.7	0.572	3.433	0.283	0
1.75	0.496	3.515	0.309	0
1.8	0.422	3.594	0.336	0
1.85	0.350	3.672	0.363	0
1.9	0.280	3.747	0.389	0
1.95	0.280	3.747	0.389	0
2	0.145	3.893	0.442	0

Source: Authors

Childhood Immunisation in matched groups

The proportion of fully immunised children aged 12-23 month in matched women who had at least 4 ANC visits during their last pregnancy is estimated to be 81.6 per cent compared to 75.3 per cent in matched women who had less than 4 ANC visits during their last pregnancy. This difference is found to be statistically significant (Table 7). On the other hand, the proportion of fully immunised children in unmatched women having at least 4 ANC visits during their last pregnancy is estimated to be 70.3 per cent compared to 83.4

per cent in unmatched women who had less than 4 ANC visits during their last pregnancy. This means that even after excluding the potential bias associated with the difference in the background characteristics of women who had at least 4 ANC during the last pregnancy and women who had less than 4 ANV visits during their last pregnancy, the proportion of fully immunised children in women who had at least 4 ANC during their last pregnancy was higher than the proportion of fully immunised children in women who had less than 4 ANC visits during their last pregnancy.

Table 7: Impact of ANC visits on childhood immunization using PSM method in India obtained from National Family Health Survey-5, 2019–2021.

Women groups	Women having at least 4 ANC visits	Women having less than 4 ANC visits	Difference	Standard error	t-statistic
All	0.825	0.708	0.116	0.010	10.88
Matched	0.825	0.738	0.087	0.012	7.27
Unmatched	0.708	0.810	0.101		
ATE			0.093		

Source: Author

Table 8 presents the proportion of fully immunised children in matched women having at least 4 ANC visits and matched women having less than 4 ANC visits during the last pregnancy by background characteristics. The proportion of fully immunised children is found to be statistically significantly higher in all categories of different background characteristics in matched women having at least 4 ANC visits during their last pregnancy compared to the proportion of fully immunised children in matched women who had less than 4 ANC visits during their last pregnancy. The only exception is women belonging to the richest wealth index quantiles. The table also shows that the effect of having at least 4 ANC visits relative to less than 4 ANC visits decreases with the increase in the education of the women and with the increase in the standard of living as measured through the wealth index but increases with the increases in parity and with the wanted status of the child. In women belonging to the richest wealth index quantiles, the proportion of fully immunised children in women having at least 4 ANV visits is higher than the proportion of fully immunised children in women having less than 4 ANC visits but the difference is not statistically significant.

The effect of at least 4 ANC visits on the immunisation status of children aged 12-23 months appears to be higher in rural women compared to urban women, in women of Muslim and other religions compared to women of Hindu religion, in female children compared to male children and in women who were not exposed to any type of mass media compared to women who were exposed to any mass media even after controlling the difference in the distribution of women having at least 4 ANC visits and women having less than 4 ANC visits in terms of their background characteristics. The effect of having at least 4 ANC visits by women during their last pregnancy on the immunisation status of their children aged 12-23 months is, however, not uniform across different categories of different background characteristics. This effect is the highest in the poorest, illiterate women and in women who did not want the child.

Table 8: Proportion of fully immunised children (FI) in matched women having at least 4 ANC visits and matched women having less than 4 ANC visits during their last pregnancy.

Background characteristic	Category	Less than 4 ANC visits		At least 4 ANC visits		Difference	'z'	'P'
		n	FI (%)	n	FI (%)			
Age of mother	15–19	1906	70.62	1389	79.06	8.44	5.865	<0.001
	20–29	8889	72.45	5705	79.42	6.97	10.231	<0.001
	30–39	2822	70.27	2535	79.76	9.49	7.987	<0.001
	40–49	167	67.07	165	76.97	9.90	2.009	0.0445
Educational attainment	No education	2386	63.67	2982	75.76	12.09	9.642	<0.001
	Primary	1859	68.42	1785	77.98	9.56	6.506	<0.001
	Secondary	7757	73.77	5869	81.24	7.47	10.264	<0.001
	Higher	1782	76.77	1004	82.07	5.30	3.282	0.0010
Household wealth index	Poorest	3627	64.72	4303	78.58	13.84	13.708	<0.001
	Poorer	3584	70.76	3381	78.64	7.89	7.556	<0.001
	Middle	2858	75.26	2112	80.21	4.95	4.119	<0.001
	Richer	2192	75.36	1278	81.92	6.56	4.484	<0.001
	Richest	1523	78.40	566	81.63	3.23	1.617	0.1058
Wantedness of child	Wanted then	12779	71.96	10641	79.47	7.52	13.303	<0.001
	Wanted later	587	69.68	522	79.50	9.83	3.738	<0.001
	Wanted no more	418	66.27	477	77.78	11.51	3.843	<0.001
Residence	Urban	2534	71.71	1921	76.73	5.03	3.782	<0.001
	Rural	11250	71.68	9719	79.94	8.26	13.863	<0.001
Religion	Hindu	10093	74.29	8443	80.23	5.93	9.559	<0.001
	Muslim	1899	64.24	1848	76.84	12.60	8.449	<0.001
	Other	1792	64.84	1349	77.76	12.92	7.850	<0.001
Parity	1	4960	74.34	3543	80.72	6.39	6.900	<0.001
	2	4801	72.40	3833	80.41	8.01	8.648	<0.001
	3	2303	70.21	2316	78.50	8.28	6.448	<0.001
	4+	1720	64.01	1948	76.13	12.12	8.027	<0.001
Sex of child	Male	6963	72.21	5518	79.46	7.26	9.351	<0.001
	Female	6821	71.16	6122	79.35	8.21	10.767	<0.001
Mass media exposure	No	3708	64.73	4741	76.95	12.22	12.360	<0.001
	Yes	10076	74.24	6899	81.10	6.85	10.426	<0.001

Discussion

The present study was based on 40,147 children aged 12-23 months. Mothers of around 58 per cent of these children had at least 4 ANC visits during their last pregnancy while mothers of remaining 42 per cent children had less than 4 ANC visits including mothers who had no ANC visit during their last pregnancy. The proportion of fully immunised children was higher among women who had at least 4 ANC visits (81.6 per cent) compared to women who had less than 4 ANC visits (70.3 per cent) during their last pregnancy. Propensity-score matching was carried out to improve the comparability between the two groups of women in terms of selected background characteristics of women and the proportion of fully immunised children in matched women having at least

4 ANC visits is found to be 81.6 per cent compared to 75.4 per cent in matched women having less than 4 ANC visits during their last pregnancy. These findings indicate an association between at least four ANC visits during the last pregnancy and childhood immunisation. The proportion of fully immunised children in women having at least 4 ANC visits has also been found to be statistically significantly higher in all categories of different background characteristics except women belonging to the richest wealth index quantiles. These findings should, however, be interpreted as an association rather than evidence of a causal effect, because propensity-score matching can account only for differences in the observed covariates and not for unobserved covariates.

The findings of the present study are consistent with previous studies from India (Krishnamoorthy and Rehman, 2022; Dixit et al, 2013) and Ethiopia (Das et al, 2022). The present study extends the existing evidence by estimating the association between at least 4 ANC visits during the last pregnancy and childhood immunisation using the from NFHS-5 (2019–21) and is comparable to the findings reported by Usman et al (2021) based on NFHS-4 (2015–16). The estimated effect of at least 4 ANC visits by women during their last pregnancy on childhood immunisation may differ from that reported by Usman et al (2021) because of differences in the survey period, population characteristics, analytical approach, covariates included in the propensity-score model, and changes in maternal healthcare utilisation and childhood immunisation coverage between NFHS-4 and NFHS-5. Nevertheless, the consistency of the findings of the present study with earlier studies strengthens the evidence supporting the observed association between at least 4 ANC visits during the last pregnancy and childhood immunisation.

Several mechanisms can explain how at least 4 ANC visits by the woman during pregnancy affects childhood immunisation. Antenatal care provides an important platform for health education and counselling concerning pregnancy, safe delivery, newborn care, and childhood vaccination. Repeated contacts with healthcare providers during these visits enhance the knowledge of women about vaccination schedules, benefits, and potential adverse events, thereby encouraging positive healthcare-seeking behaviour (Sarker et al, 2019). In addition, frequent interactions with healthcare providers strengthen patient–provider trust, which may improve adherence to recommended maternal and child healthcare protocols, including childhood immunisation (WHO, 2018; Darden and Macis, 2024; Hong et al, 2018).

Despite considerable improvements in the proportion of women having at least 4 ANC visits during pregnancy, disparities in the childhood immunisation status in India in terms of the proportion of children aged 12-23 months fully immunised continue to exist in India. Lack of awareness, fear of vaccine side effects, cultural beliefs, misinformation, and inadequate counselling remain important barriers to vaccine uptake (Neupane et al, 2020; Shrivastawa et al, 2015). Regular ANC visits may increase opportunities for healthcare providers to educate women about the importance of timely vaccination of children, address misconceptions, and reinforce confidence in immunisation services (Girotra et al, 2023; Ghosh et al, 2026). Effective counselling by frontline health workers such as Accredited Social Health Activist (ASHA) and Auxiliary Nurse Midwife (ANM), together with the support from family members, particularly husband, can further enhance childhood vaccination uptake (Kumar et al, 2019). Community-based maternal healthcare interventions that improve both antenatal care and immunisation awareness may,

therefore, help reduce persistent inequalities in vaccination coverage in the country (Sharma et al, 2020).

Accessibility of healthcare services is another important determinant of antenatal care. Several studies have demonstrated that longer distance to healthcare facilities is associated with reduced ANC clinic attendance and delay in seeking maternal healthcare (Tanou et al, 2021; Tegegne et al, 2019; Nisingizwe et al, 2020). Women living closer to health facilities are more likely to complete the recommended number of ANC visits because shorter travel distance, reduced transportation costs, travel time, and the physical burden of accessing care. In contrast, women residing in remote and rural areas often face poor transportation infrastructure and geographic barriers that limit timely and regular ANC attendance (Okwaraji et al, 2015; Kyei et al, 2012). Expanding the availability of maternal healthcare services through strengthening primary healthcare facilities, mobile outreach services, and transportation support may, therefore, improve antenatal care and, consequently, improve childhood immunisation coverage.

Conclusion

This study has used the propensity score matching (PSM) to estimate the effect of at least 4 ANC visits during pregnancy on childhood immunisation in India. The findings demonstrate that children born to women who had at least 4 ANC visits during pregnancy were significantly more likely to be fully immunised compared to children born to women who had less than 4 ANC visits. By balancing observed socio-demographic and maternal characteristics of women who had at least 4 ANC visits and women who had less than 4 ANC visits during the last pregnancy through propensity score matching, the study minimised the selection bias and provided more robust evidence of the association between at least 4 ANC visits during pregnancy and full immunisation of children. Findings of the study highlight antenatal care as a key platform for promoting child health through maternal education, counselling, and linkage to immunisation services. Improving antenatal care may, therefore, contribute to improving childhood immunisation coverage and reducing vaccine-preventable morbidity and mortality in India.

Policy Implications

The study highlights the importance of antenatal care in achieving the goal of universal child immunisation. There is a need to improve access to and use of antenatal care services particularly for women from socioeconomically disadvantaged households, rural areas, and other underserved and marginalised population groups. Integrating comprehensive immunisation counselling into routine antenatal care services can enhance the knowledge of women about vaccination schedule, address misconceptions, and encourage timely and full vaccination of children. Strengthening community-based interventions through frontline healthcare workers may be effective in this regard. Targeted health education initiatives and reducing geographic and financial barriers to healthcare access can also contribute to improving both antenatal care and childhood immunisation. Collectively, these measures can contribute to controlling vaccine-preventable diseases and accelerate progress towards universal child immunisation and Sustainable Development Goals (SDGs).

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Age-Specific Migration Schedules for India. Application of a Modified Rogers–Castro Model

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Abstract

The study models age-specific migration in India and selected states by estimating continuous, age-specific migration rates using limited data. A modified 7-parameter multi-exponential model based on the Rogers-Castro framework is used with non-linear optimization techniques to represent childhood and prime adult migration components. The model successfully replicated age-specific migration patterns for total and female population in India and in National Capital Territory (NCT) Delhi, and Uttar Pradesh. However, the model performed poorly for female migration in Maharashtra and failed to capture consistent male migration trends nationally. The present paper offers a refined approach to Rogers–Castro model to estimate age-specific migration. The findings offer a simplified yet insightful framework for migration modelling, suitable for population with limited or irregular data.

Introduction

Population dynamics are primarily driven by three fundamental demographic factors migration, fertility, and mortality. While fertility directly influences the size of younger age groups, the effects of mortality and migration are more complex, as they depend on age-specific patterns of change (Bourgeois-Pichat, 1951; Coale, 1956). Among these, migration plays a crucial role in redistributing the population across regions and is deeply associated with age, as different life stages correspond to varying migration intensities. Studying age patterns not only helps to understand migration behaviour within specific regions but also allows for comparison across countries and time periods. Previous studies have demonstrated that migration rates tend to be highest among young adults, followed by notable movement among children accompanying their parents, before declining during adolescence, peaking again around ages 25 to 30 due to employment and marriage-related moves, and gradually decreasing toward retirement (Rogers and Castro, 1981; Bell et al, 2002).

Despite significant advancements in migration research, challenges persist in estimating internal and international migration flows due to the lack of age- and sex-disaggregated data. Developed countries benefit from comprehensive administrative records and advanced survey methodologies, allowing for more precise migration

estimates. In contrast, developing countries struggle with under-registration and incomplete data coverage, leading to inconsistencies in migration statistics (Abel, 2013; Nowok et al, 2006; Raymer et al, 2013). Addressing these gaps, Rogers (1973) advanced indirect estimation techniques to derive age-specific gross migration rates from incomplete datasets. He developed the multiregional model life table, extending the Coale-Demeny life table to a multiregional population context. Building on this foundation, Rogers (1986) introduced a parameterised approach for estimating migration age profiles using labour-force data, demonstrating how model migration schedules encapsulate universal trends. Similarly, Nair (1985) developed methodologies to estimate period-specific place-to-place migration flows, crucial for understanding demo-economic relationships and forecasting subnational populations. Willekens (1994) further refined migration estimation techniques, bridging the gap between limited data and required migration statistics.

In the context of international migration estimation, Abel (2010) developed a methodology for generating comparable migration flow estimates across countries. Given that migration statistics often differ between sending and receiving nations due to variations in data collection methodologies, Abel's framework standardised these estimates for better international comparability. Wilson (2010) extended the standard migration model schedule to incorporate age-specific student migration, recognising a sharp increase in movement during the late teenage years due to higher education. To systematically analyse age-specific migration patterns, Rogers and Castro (1981) introduced the multi-exponential migration model, which provides a mathematical framework for modelling migration age profiles. They proposed a family of exponential functions with 7-, 11-, and 13-parameter forms, identifying key regularities in internal migration schedules. In recent years, further developments have improved the estimation of age-specific migration schedules. Studies by Bernard and Bell (2020) and Yeung, Alexander, and Riffe (2023) demonstrated that age-specific migration patterns exhibit remarkable regularity across countries and can be effectively estimated using spline-based or Bayesian approaches that quantify uncertainty. These advances underscore the importance of developing flexible models suited for data-scarce contexts such as India, where migration information remains limited to grouped census tables and infrequent surveys.

This study applies the Multi-Exponential Migration Model to 2011 Indian Census data to analyse age-specific migration patterns. Using exponential functions, it captures the underlying demographic behaviour of migration while refining estimation techniques and addressing data gaps. The research further evaluates how India's internal migration aligns with globally observed age-specific migration trends.

Data and Methodology

The present analysis is based on data on migration available from the 2011 population census in India. The decennial population census is the most abundant source of migration data in India. During the2011 population census, information was collected from all individuals about the place of last residence and individuals whose place of last residence was different from the place of enumeration are classified as in-migrants. The present analysis is confined to only those individuals whose duration of residence at the place of enumeration was 0–9. The age and sex-specific migration count is then used to

calculate the proportion of in-migrants for the total population and for males and females separately. The analysis has been carried out for India and for its three states – Uttar Pradesh, NCT Delhi, and Maharashtra.

Age-specific in-migration rate

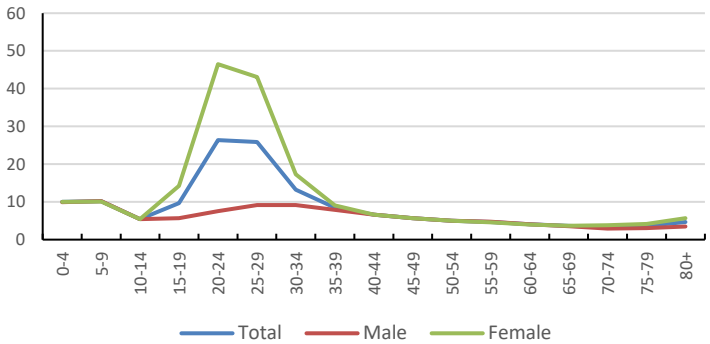
Table 1 gives the in-migration rates for India, Maharashtra, NCT Delhi and Uttar Pradesh by age for total population and separately for males and females. In India, 11 per cent individuals who were residing at the place of enumeration since last 10 years prior to the 2011 population census reported that their place of last residence was different from the place of enumeration. This proportion was more than two times in females compared to males. Among the three states, Maharashtra has recorded the highest female proportion of migration at 23.31 per cent for ages 0–4, while Uttar Pradesh recorded the lowest at 2.77 per cent for ages 10–14. In all the three states, the proportion of individuals whose place of enumeration was different from the place of last residence was higher in females compared to males.

Figure 1 also shows that age-specific in-migration rates differ markedly by sex and destination in the country and in the three states – Maharashtra, NCT Delhi and Uttar Pradesh. In the country and in all the three states, the female in-migration schedule is strongly concentrated in the young-adult ages, while the male in-migration schedule is comparatively flat. In India, the female in-migration rate rises from 5.4 per cent in population aged 10-14 years to 46.5 per cent in population aged 20-24 years and 43.1 per cent in population aged 25-29 years. The male in-migration rate, however, stays between 3-10 per cent in all age groups. The combined in-migration schedule, peaking at 26.4 per cent in population aged 20-24 years, therefore, follows the female pattern which is consistent with the evidence from the 2011 population census that marriage is the leading reason reported by female migrants, while work and employment are the dominating reasons among male migrants. In Maharashtra, the proportion of in-migrants was very high in the child population with little difference between male and female proportions suggesting household migration to major urban centres of the state. The relatively high proportion of male in-migrants in the age group 25-39 years reflect a strong labour component (Bhagat, 2009). Uttar Pradesh has the lowest in-migration rate among children but the highest in-migration rate in females aged 20-24 years which indicates that in-migration to the state is dominated by marriage-related movement of young women. NCT Delhi has the flattest profile, with total in-migration rates between 4.5-9.5 per cent and a modest female bump of around 14 per cent in the age group 25-29 years which suggests that in-migration in the state is spread across the life course for mixed employment, education, and family reasons. These contrasts show that age-specific in-migration rates reflect the importance of economic and social setting of the place of destination. The age-specific male in-migration rates in the country lack the characteristic bimodal structure typically captured by multi-exponential models. It appears that male in-migration in the country is often erratic and driven by diverse motives that are not clearly age-structured, thus making it unsuitable for parametric modelling. In contrast, female age-specific in-migration rates exhibit a well-defined age structure, with in-migration rate peaking prominently in the age group 15-40 years, largely due to marriage migration (Census of India, 2011). As such, modelling the total in-migration rate serves as a reasonable proxy, effectively capturing the dominant migration dynamics in the Indian context.

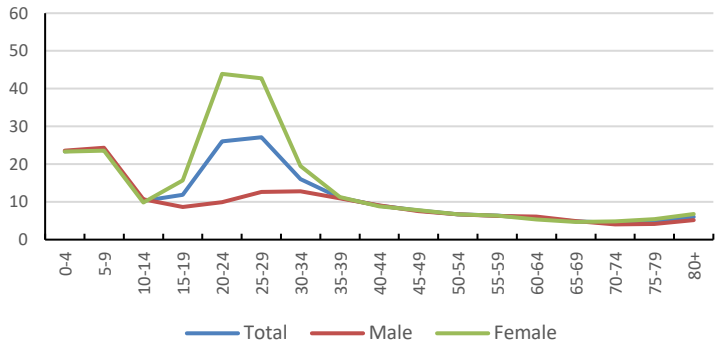
Table 1: Age-specific proportion of population whose place of last residence was different from the place of enumeration in India, Maharashtra, NCT Delhi and Uttar Pradesh, 2011.

Age	Proportion (per cent) of individuals whose place of last residence was different from the place of numeration											
	India			Maharashtra			NCT Delhi			Uttar Pradesh		
	Total	Male	Female	Total	Male	Female	Total	Male	Female	Total	Male	Female
0-4	9.98	9.94	10.00	23.45	23.58	23.31	4.51	4.45	4.58	3.03	2.98	3.15
5-9	10.15	10.21	10.08	23.98	24.34	23.58	6.07	6.02	6.13	3.58	3.62	3.54
10-14	5.44	5.46	5.40	10.25	10.65	9.81	4.75	4.70	4.81	2.76	2.75	2.77
15-19	9.70	5.67	14.26	11.90	8.61	15.73	4.70	4.23	5.28	6.94	4.16	10.12
20-24	26.37	7.54	46.49	26.02	9.96	43.92	7.74	4.53	11.5	27.7	7.58	50.86
25-29	25.89	9.14	43.06	27.13	12.67	42.78	9.48	5.36	14.07	27.47	8.80	47.06
30-34	13.21	9.15	17.33	16.07	12.85	19.50	8.08	6.50	9.86	11.39	7.70	15.03
35-39	8.46	7.86	9.06	11.14	10.98	11.31	6.44	6.32	6.57	6.89	6.24	7.57
40-44	6.62	6.58	6.65	8.95	9.05	8.83	5.33	5.54	5.09	5.35	5.17	5.56
45-49	5.68	5.69	5.67	7.69	7.56	7.82	4.65	4.75	4.54	4.60	4.54	4.67
50-54	5.01	5.02	4.99	6.74	6.73	6.74	4.58	4.48	4.71	3.90	3.87	3.93
55-59	4.65	4.71	4.57	6.33	6.29	6.37	5.02	4.80	5.28	3.43	3.44	3.42
60-64	4.06	4.08	4.03	5.72	6.09	5.38	4.99	5.21	4.78	2.87	2.63	3.14
65-69	3.63	3.57	3.68	4.81	4.96	4.69	5.08	5.70	4.44	2.63	2.35	2.91
70-74	3.35	2.93	3.78	4.47	4.04	4.87	4.23	4.42	4.05	2.43	1.86	3.09
75-79	3.62	3.08	4.13	4.81	4.18	5.40	4.32	4.54	4.09	2.65	1.95	3.38
80+	4.63	3.46	5.66	6.05	5.17	6.81	4.87	4.57	5.15	4.49	2.38	6.74
All ages	9.13	6.19	12.43	13.76	11.51	16.38	30.67	25.47	37.01	6.64	3.12	10.67

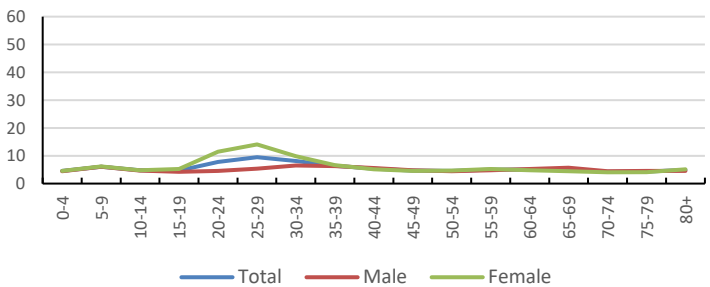
Remarks: All ages do not include those individuals whose age was not known.
Source: Authors.



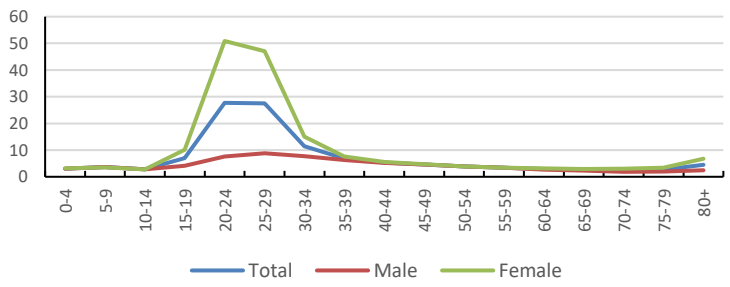
India



Maharashtra



NCT Delhi



Uttar Pradesh

The Model

The standard model migration schedule is the sum of five component curves (Rogers et al, 1990): migration intensity (M_x)= childhood curve + labour force curve + retirement curve +elderly curve + constant.

$$M_x = a_1 \exp(-\alpha_1 x) + a_2 \exp\{-\alpha_2(x-\mu_2) - \exp[-\lambda_2(x-\mu_2)]\} + \exp\{-\alpha_3(x-\mu_3) - \exp[-\lambda_3(x-\mu_3)]\} + a_4 \exp(\lambda_4 x) + c$$

The model includes 13 parameters, out of which 8 (α_1, α_2, μ_2, λ_2, α_3, μ_3, λ_3, and λ_4) define the shape of the migration profile, while the remaining 5 (a_1, a_2, a_3, a_4, and c) control the level or the magnitude. Adjusting the overall area under the curve of the model affects the level-defining parameters but does not alter the parameter defining shape.

The most prevalent form of the model is the 7-parameter reduced model, consisting of the first two components and a constant term. A substantial portion of the migration schedules are also aligned with an 11-parameter model which include a third component to represent a retirement-age peak. Some migration profiles, instead of featuring a retirement peak, display a continuous upward slope during the post-labour force years. These cases were modelled using a 9-parameter version, where the fourth component replaces the third. Additionally, in a study focused on elderly migration, Rogers and Watkins (1987) encountered patterns that exhibited both a retirement peak and a post-retirement upward slope, which required the use of the full 13-parameter model.

In this paper, we have modified the 7-parameter Rogers–Castro multi-exponential migration model for Indian migration pattern in which observed migration data do not exhibit a consistent pattern beyond the typical labour force retirement age. The modified model effectively captures migration dynamics during the pre-labour force and labour force phases while avoiding the added complexity of the full 13-parameter structure. In the traditional Rogers–Castro framework, the second component is labelled as the "labour force" component. However, in the Indian context, particularly for females, this peak, observed between ages 15 and 40 years, is overwhelmingly driven by marriage rather than employment. Therefore, while we retain the structural form and terminology of the "labour force" component for consistency, it should be more appropriately interpreted here as the prime adult migration component, representing the dominant peak of migration shaped by both economic and social (especially marriage) factors. The modified model is

$$M_x = a_1 \exp\{-\alpha_1(x-\mu_1) - \exp(-\lambda_1(x-\mu_1)\} + a_2 \exp\{-\alpha_2(x-\mu_2) - \exp(-\lambda_2(x-\mu_2)\}$$

$M(x)$ = Migration rate at age x.
a_1, a_2 = level of migration
α_1, α_2 = rate of descent of childhood and prime adult migration curve
λ_1, λ_2 = rate of ascent of childhood and prime adult migration curve
μ_1, μ_2 = age shift parameter

In the classical Rogers–Castro model, childhood migration is modelled as a simple exponential decay function $a_1 \exp(-\alpha_1 x)$, implying a monotonically decreasing migration rate with age among children. However, the grouped census data for the 0–4 age interval in India and its major states (e.g., Uttar Pradesh, NCT Delhi, Maharashtra) indicate substantial migration rates, suggesting that early-age movement is non-negligible and

cannot be fully captured by a purely declining curve. To accommodate this, we have adopted a more flexible childhood component $a_1 \exp\{-\alpha_1(x-\mu_1) - \exp(-\lambda_1(x-\mu_1)\}$, which allows for peaking behaviour and asymmetric decline during early life stages. This modification is empirically driven and demographically meaningful, as it reflects child migration often associated with family or household moves. The difference in the original model and the proposed model is shown in the figure 2.

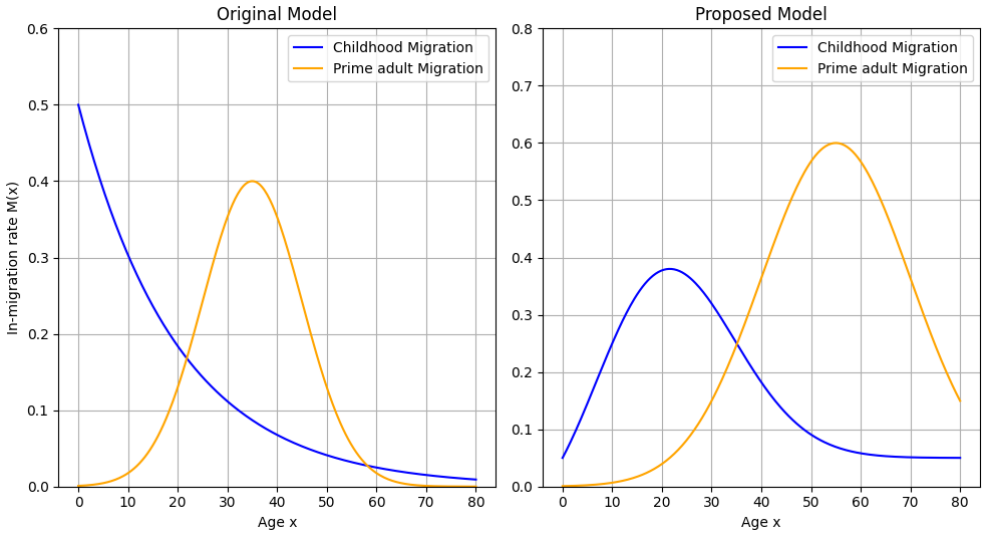


Figure 2: The original and the proposed model.
Source: Authors.

Smoothening of age data using cubic splines

The migration data sourced from the census are available in five-years age groups, whereas fitting a continuous model such as the multi-exponential function requires migration values for each specific age. To overcome this limitation, cubic spline interpolation was applied to convert age-grouped migration data into single-year age estimates. This approach helps to produce a continuous age profile necessary for accurate model fitting. Among various statistical approaches available, non-parametric methods such as cubic splines and kernel regression are used with demonstrated success in fertility (Moguerza et al, 2010), mortality (Peristera and Kostaki, 2005) and migration (Bernard and Bell, 2015). In comparative migration studies, Bernard and Bell (2015) assessed the effectiveness of cubic splines and kernel regression relative to traditional model migration schedules, finding that spline-based smoothing offers superior accuracy in capturing observed age-specific migration patterns.

In the present study, Python's scipy.interpolate module was employed for spline fitting, using CubicSpline function to estimate a smooth curve passing through each data point while ensuring continuity of the first and second derivatives across adjacent age intervals. This technique resulted in a continuous migration profile while preserving the demographic structure of the data. The selection of cubic spline interpolation to smooth grouped data was essential for continuous model fitting. Although splines can introduce

edge effects producing small or even negative estimates for the age group 0-4 years and ensure smooth and differentiable transitions between age groups, preserving the overall demographic pattern of migration. Alternative smoothing methods such as kernel regression, penalised B-splines, or Bayesian hierarchical approaches may alleviate boundary distortions, in which case the inclusion of a constant term could be justified both statistically and demographically. In the current context, however, the cubic spline's boundary behaviour, along with very low and unstable migration activity at extreme ages (specially 0-2 and 65+), warrants the exclusion of the constant term. This ensures a parsimonious and data-consistent model that avoids overfitting while maintaining stability in parameter estimation.

Parameter Estimation

Fitting of the model requires specification of initial parameter estimates which serve as starting values for the nonlinear optimisation algorithm. Choice of these initial values is important as initial values influence both convergence and quality of the model fit. As noted by Plane and Heins (2003), there is no universally optimal method for selecting the starting values for fitting the model. Researchers, therefore, must rely on informed assumptions, exploratory analysis, or prior empirical findings. Rogers and others (2005) have emphasised that the absence of standardised guidelines for selecting starting values often necessitates iterative calibration or trial-and-error approaches, which may not always generalise across different contexts.

In the present study, we have determined initial parameters for fitting the model through exploratory assessment of the spline-smoothed migration profiles and reference to the established literature. The visual inspection of smoothed curves guided the approximate placement and width of migration peaks, particularly during childhood and prime adult age group. Parameters such as modal age, amplitude, and rate of ascent and descent were chosen to reflect the observed trends in the data while accounting for the demographic plausibility.

Actual fitting was carried out using a nonlinear least squares optimisation approach which employs the Levenberg–Marquardt (LM) algorithm. This algorithm is an iterative method that estimates model parameters by minimising the sum of squares of the differences between observed values and values predicted by the model. We estimated a total of eight parameters – four each for the migration component corresponding to the amplitude, shape, location (modal age), and the rate of change. To enhance the convergence stability and minimise the computational time, the starting values were carefully selected to align with the expected patterns revealed by the spline-smoothed profiles.

It is important to emphasise here that the use of the cubic spline interpolation method may also introduce boundary effects, especially at the youngest and the oldest ages. It is, therefore, important that the parameter estimates of the model near the extremes are interpreted with caution so that the fitted model reflects the genuine migration patterns rather than spline-induced artefacts. An alternative to cubic spline interpolation is the Bayesian estimation which potentially improves parameter stability in boundary-sensitive cases. We have, however retained the nonlinear least squares framework for its computational efficiency, interpretability, and consistency with previous migration modelling research.

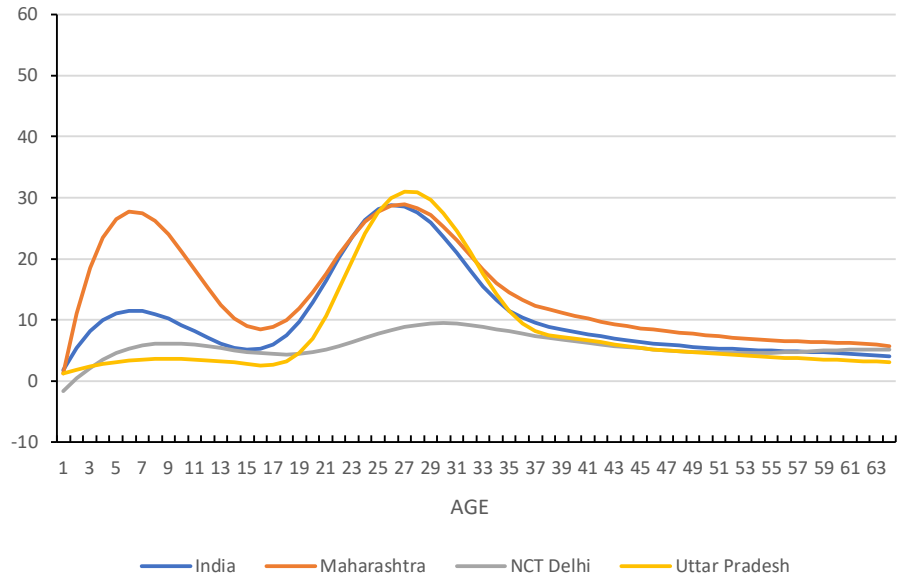


Figure 3: Smoothed age-specific In-migration rates in total population, 2011 – India, Maharashtra, NCT Delhi, Uttar Pradesh.
Source: Authors

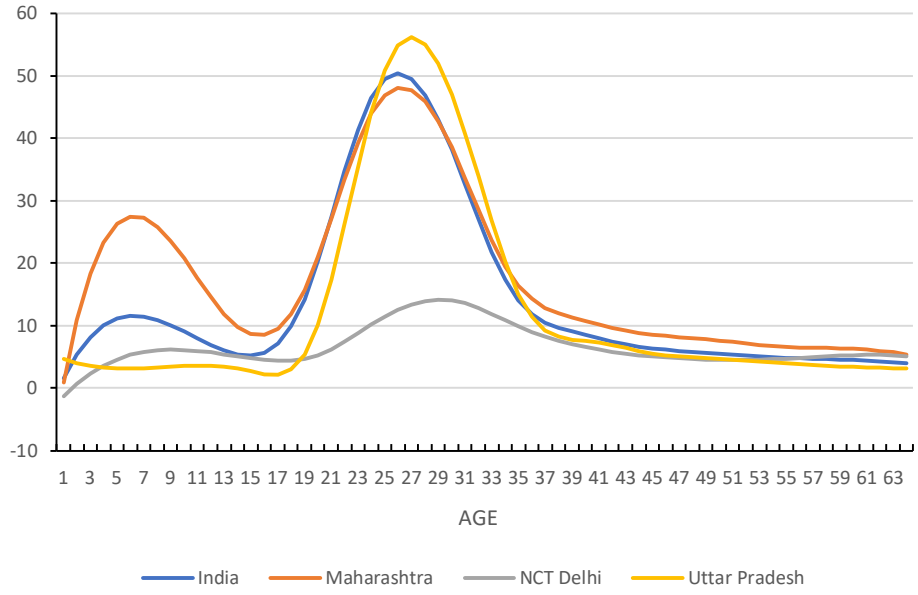
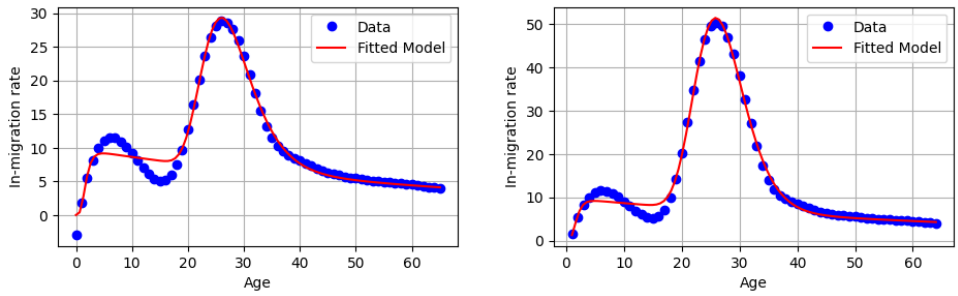


Figure 4: Smoothed age-specific In-migration rates in female population, 2011 – India, Maharashtra, NCT Delhi, Uttar Pradesh.
Source: Authors.

Results

The multi-exponential model was fitted to the age-specific in-migration rates of females and the total population. This approach ensures that the fitted curves capture the dominant and more regular age-specific trends, particularly the strong marriage-related peak in female migration which also shapes the total migration profile. The multi-exponential model is found to be fit for the observed In-migration rate data using the estimated parameters obtained through the nonlinear optimization procedure are substituted into the model equation to generate the fitted migration schedule. For each age X, the estimated migration rate is calculated by evaluating the model using the estimated parameters values of $a_1, a_2, \alpha_1, \alpha_2, \lambda_1, \lambda_2, \mu_1,$ and μ_2 for childhood and prime adult migration component for India and selected states in the proposed model. The fitted values represent the expected age-specific migration rates generated by the model and can therefore be compared with the observed migration rates. This comparison enables the assessment of the model's ability to reproduce the principal features of the age-specific migration pattern, including the childhood and prime adult migration peaks. Model performance is evaluated using goodness-of-fit measures, particularly the mean absolute percentage error (MAPE), which quantifies the difference between observed and fitted migration rates. Aim is to estimate parameters that describe the underlying components of migration behaviour, particularly the childhood and prime adult migration peaks. Figures 5 through 8 show fitted migration curves overlaid on smoothed in-migration rates. The visual alignment between modelled and observed values across supports the adequacy of the two-component exponential model in most cases.

For India, the fitted model reproduce the characteristic bimodal migration pattern, a minor childhood migration peak followed by a significant prime adult migration peak occurring between ages 20 and 30. This pattern is consistent across both the total and female populations, with excellent visual alignment and low MAPE values, reinforcing the robustness of the model. (Figure 5).

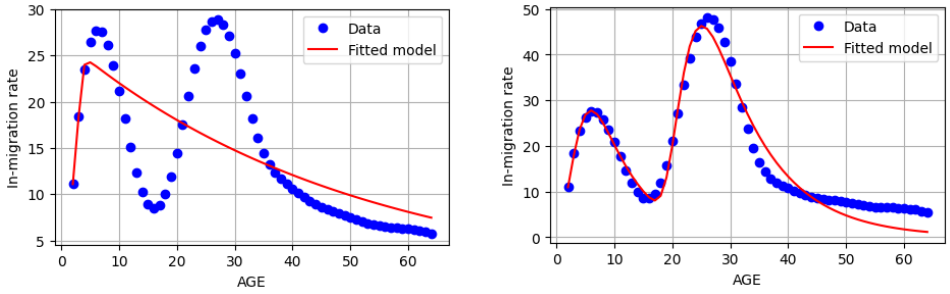


Total population Female population

Figure 5: Observed and fitted in-migration rates in India, 2011.
Source: Authors.

For Maharashtra, the model presents a more nuanced picture. For females, the fitted curve captures both early-age (childhood) and adult migration peaks. The childhood peak appears earlier and sharper than in other states, followed by a prominent adult migration surge around age 28 years. This trend reflects strong urban pull factors in the state, particularly in cities like Mumbai and Pune. The model shows a moderate MAPE,

indicating fair predictive reliability. However, for the total population, the model shows a noticeably poor fit. The observed in-migration rates feature two pronounced peaks, one in the early childhood and the other during the adulthood. However, the fitted curve fails to capture this dual-peak age-pattern of in-migration in the state. Instead, the model produces a flat and declining at pattern of in-migration that underestimates both peaks. This results in a high value of MAPE although it is still acceptable value (Figure 6).

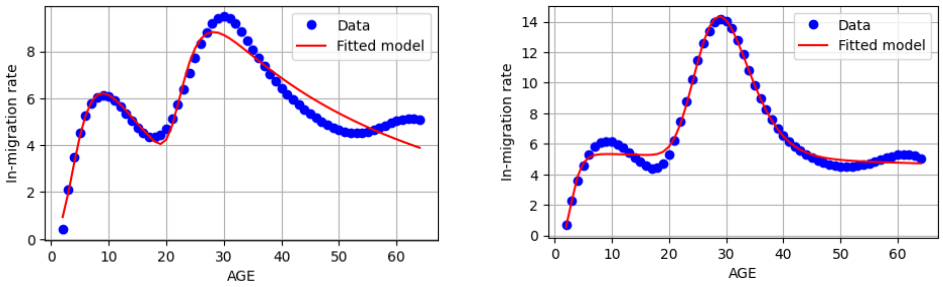


Total population Female population

Figure 6: Observed and fitted in-migration rates in Maharashtra, 2011.
Source: Authors.

The relatively poor fit in Maharashtra indicates that the age-specific in-migration schedule of the state may contain features that are not adequately represented by the two-component model. Maharashtra is a major migrant-receiving state, and migration to large urban centres may involve several overlapping processes, including employment-related movement and associated household relocation producing broader or multiple age-specific peaks rather than the simple structure assumed by the model. The poorer fit of the model, therefore, should be treated as the evidence that a two-component parametric specification may be insufficient to represent the complexity of migration in this setting. This suboptimal fit can be attributed to two main factors: 1) underlying complexity of female migration behaviour in Maharashtra which may not conform to the assumptions of the two-component model; and 2) sensitivity of nonlinear optimisation process to the selection of initial parameter estimates. As emphasised by Rogers et al (2005) and Plane and Heins (2003), inappropriate initial guess can lead the algorithm to converge to local minima, where estimated parameters may not fully capture the observed migration dynamics, particularly when multiple peaks exist in the data.

However, for NCT Delhi and Uttar Pradesh, the model provides a good fit to the observed age pattern of in-migration. In the NCT Delhi, the model slightly underestimates the childhood migration, particularly for females. The female in-migration peak in NCT Delhi occurs earlier than the national average – at around 22 years of age – highlighting the distinct urban migration dynamics in the state, which is driven, the most likely, by the early employment and education-linked in-migration. Model performance, however, remains strong as reflected by the low MAPE (Figure 7). In Uttar Pradesh, on the other hand, the in-migration rate peaks sharply around the age group 30–35 years. There is, however, noticeable disparity between total and female in-migration patterns, especially, in the prime adult age group. However, the model captures both magnitude and age distribution of in-migrants in the state with a high degree of accuracy as is reflected through the low value of MAPE (Figure 8).

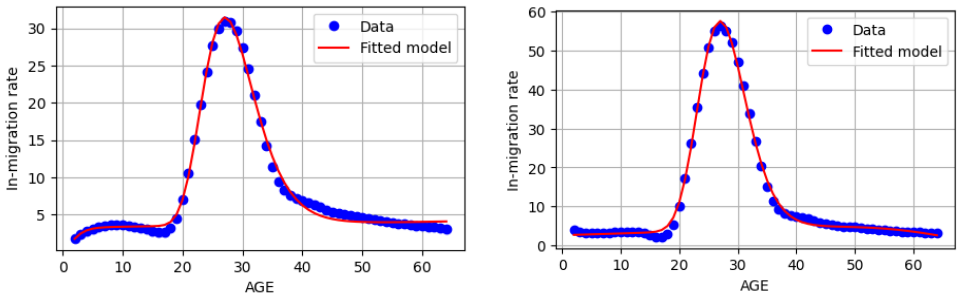


Total population Female population

Figure 7: Observed and fitted in-migration rates in NCT Delhi, 2011.
Source: Authors.

Parameter Estimates

The parameter values presented in Tables 2 and 3 have been reordered based on the value of μ to ensure demographic interpretability. Specifically, the component with μ falling within the expected age range for childhood migration (0–15 years) is labeled as the childhood component, and the one with μ in the range of prime adult migration (15–40years) is labeled as the prime adult migration component. This reassignment is necessary because the curve-fitting algorithm may assign components in arbitrary order during optimization.



Total population Female population

Figure 8: Observed and fitted in-migration rates in Uttar Pradesh, 2011.
Source: Authors.

The parameter estimates derived from the fitted multi-exponential models provide detailed insights into age-specific migration behaviour across India and selected states. These parameters like amplitude (a), decay (α), modal age (μ), and accentuation (λ) capture the intensity, shape, and timing of the two primary migration components for childhood and prime adult migration. Component assignments are based on the value of μ, which reflects the modal age of migration. Components with $\mu < 15$ are considered childhood migration peaks; those with $\mu \geq 20$ are considered labor force peaks. This reassignment ensures demographic interpretability when the optimization algorithm assigns parameter estimates inconsistently. Amplitude parameters (a) determine the height of each component and represent the intensity of migration. Higher values indicate a greater concentration of

migration at the respective peak age. Uttar Pradesh (total) shows a high prime adult migration amplitude (a_1=58.2), suggesting significant movement among working-age individuals. In Maharashtra, the amplitude for female childhood migration is particularly high (a_2 = 84.3), which may reflect concentrated early-age moves associated with family relocation or marriage-related migration. This elevated value supports the visual observation of a complex and overlapping pattern for females in Maharashtra.

Table 2: Parameter estimates for total population.

Region	Component	a	α	μ	λ	MAPE
India	Prime Adult component	38.58	0.39	33.44	0.139	9.48
	Childhood	9.68	0.01	1.51	1.39	
NCT Delhi	Prime Adult component	9.64	0.06	22.45	0.400	9.29
	Childhood	8.13	0.01	4.26	0.41	
Uttar Pradesh	Prime Adult component	58.21	0.31	30.53	0.171	10.29
	Childhood	3.24	-0.00	1.40	0.76	
Maharashtra	Prime Adult component	18.85	0.02	1.91	7.20	33.91
	Childhood	6.80	0.02	3.99	143.24	

Source: Authors.

Decay parameters (α) indicate how quickly migration declines after reaching its peak. Sharp post-peak declines are seen in some female labour components, such as α = 0.526 for Uttar Pradesh, suggesting migration in a narrow, concentrated age band. Broader, more gradual decline such as α = 0.013 for childhood migration in India suggest that children often move across a wider age range, likely accompanying family relocations, or school transitions.

Table 3: Parameter estimates for female population.

Region	Component	a	α	μ	λ	MAPE
India	Prime Adult component	37.96	0.39	33.50	0.13	9.19
	Childhood	9.62	0.01	1.71	1.84	
NCT Delhi	Prime Adult component	15.16	0.03	22.47	0.44	15.93
	Childhood	13.91	0.09	6.24	0.22	
Uttar Pradesh	Prime Adult component	5.15	0.52	40.07	0.11	11.75
	Childhood	7.26	-0.01	63.82	-0.11	
Maharashtra	Prime Adult component	57.86	0.15	21.79	0.41	24.14
	Childhood	84.27	0.10	3.55	0.36	

Source: Authors.

Accentuation parameters (λ) influence the steepness and symmetry of the migration curve near the peak. Steep increases followed by sharp declines are observed in the childhood migration of India (λ = 1.39) and NCT Delhi (λ = 0.41), indicating more abrupt transitions in younger age migration. In Maharashtra, an extremely high λ value of 143.2 for the childhood component (total population) likely reflects rapid early-age changes, possibly amplified by urban dynamics or model overfitting.

In the case of Uttar Pradesh (female), the model yields negative values for the decay (α_2) and accentuation (λ_2) parameters in the childhood component. While such negative estimates may appear counterintuitive. Since both parameters typically govern the decline and sharpness of migration rates this outcome is common in non-linear curve fitting. As

model convergence can sometimes lead to parameter estimates that are mathematically valid but demographically implausible, particularly when the initial guesses are far from optimal or when the migration curve lacks a well-defined second peak. Despite these values, the overall model still offers an acceptable visual and statistical fit, suggesting that the negative signs may reflect algorithmic compensation effects rather than meaningful demographic behaviour. Future modelling may benefit from imposing parameter constraints or refining the initial values.

In summary, these parameter estimates confirm consistent bimodal migration trends across India, UP, and NCT Delhi, while also exposing state-level variations particularly in Maharashtra suggesting the need for region-specific model adaptations. The relative alignment of modal ages and amplitudes across states reinforces the utility of multi-exponential models in capturing complex migration behaviour, though further refinement may be needed in contexts where overlapping motives and irregular migration timing distort classical age profiles

Discussion

We found that female migration in India is disproportionately driven by marriage migration, which is associated with a socially normed age at marriage and therefore produces a sharp, well-defined peak in the age schedule. Male migration, by contrast, reflects a mixture of education-related, employment-related, and circular or seasonal labour migration occurring across a wider and less consistently timed range of ages, without a single dominant life-course transition. This compositional difference is offered as the substantive explanation for the flatter, less clearly structured male age pattern relative to the female pattern and to exclude the male In-migration rate from modelling. The estimation procedure uses nonlinear least-squares optimization with the Levenberg–Marquardt algorithm. Since the modified Rogers–Castro model is nonlinear and involves several interdependent parameters, the estimation can be sensitive to the initial parameter values and convergence behaviour. Previous studies have also documented the need for suitable initial estimates and the possibility of nonconvergence or sensitivity to starting values when fitting Rogers–Castro migration schedules. In the present analysis, alternative initial parameter values were considered for the male schedule. However, the resulting fitted curves did not adequately reproduce the observed age-specific male in-migration pattern in a stable and substantively meaningful manner.

In contrast, the total and female In-migration rate patterns displayed stable bimodal shapes suitable for modelling, with the second major peak (prime adult migration) in this context largely representing marriage-related movements among females, while also incorporating employment-related mobility in the total population. This emphasizes on the need to interpret model components in line with socio-cultural realities rather than relying solely on their conventional demographic labels.

The fitted results confirm that a two-component multi-exponential model can effectively replicate age-specific migration trends in most Indian states, especially for the total population and female migration in India, NCT Delhi, and Uttar Pradesh. The model captures both the timing and intensity of early-life and prime adult migration, providing a

useful comparative framework. The proposed model is able to explain the age-migration relationship for Indian population in totality and well as its states and therefore can be used for other populations with similar migration patterns.

However, the poor fit observed for female migration in Maharashtra and the absence of a clear second peak in male migration highlight important methodological challenges. In such cases, model convergence can produce parameter estimates that are mathematically valid but demographically implausible, particularly when initial parameter guesses are suboptimal or when the true migration curve lacks the expected structure. This can further be explored using Bayesian estimation. A further limitation of the study lies in the dependence on decadal census data, especially in the case of India, which may mask short-term migration fluctuations, and the assumption that the two-component structure can adequately represent complex, overlapping migration motives such as simultaneous marriage and employment moves. These results point to the limitations of a one-size-fits-all approach and the importance of adapting models to region-specific migration dynamics and gendered migration motivations.

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Appendix Table 1: Smoothened in-migration rates for India and selected states using Cubic Splines:

Age	Uttar Pradesh		NCT Delhi		Maharashtra		India	
	Total	Female	Total	Female	Total	Female	Total	Female
1	1.18	4.69	-1.69	-1.31	1.17	0.91	1.77	1.65
2	1.80	4.03	0.41	0.67	11.10	10.92	5.44	5.40
3	2.31	3.57	2.12	2.30	18.43	18.29	8.13	8.15
4	2.73	3.29	3.48	3.59	23.45	23.31	9.97	10.01
5	3.06	3.15	4.51	4.58	26.44	26.27	11.06	11.10
6	3.31	3.13	5.26	5.31	27.70	27.48	11.51	11.54
7	3.48	3.19	5.76	5.79	27.52	27.24	11.44	11.44
8	3.58	3.30	6.03	6.07	26.18	25.84	10.95	10.92
9	3.61	3.42	6.13	6.18	23.98	23.58	10.15	10.09
10	3.58	3.54	6.07	6.13	21.21	20.75	9.16	9.07
11	3.50	3.60	5.90	5.97	18.17	17.67	8.08	7.98
12	3.37	3.59	5.65	5.73	15.13	14.61	7.02	6.92
13	3.20	3.47	5.35	5.44	12.39	11.90	6.10	6.03
14	3.00	3.21	5.04	5.12	10.25	9.81	5.43	5.40
15	2.76	2.77	4.75	4.81	8.94	8.62	5.11	5.19
16	2.55	2.24	4.52	4.55	8.48	8.49	5.27	5.68
17	2.58	2.10	4.37	4.39	8.84	9.55	6.00	7.15
18	3.14	2.97	4.33	4.42	9.99	11.91	7.44	9.91
19	4.50	5.44	4.43	4.69	11.90	15.73	9.70	14.26
20	6.94	10.12	4.70	5.28	14.49	20.97	12.80	20.31
21	10.58	17.31	5.14	6.23	17.50	27.10	16.42	27.41
22	15.03	26.15	5.72	7.45	20.63	33.43	20.16	34.70
23	19.73	35.46	6.38	8.81	23.57	39.26	23.61	41.34
24	24.13	44.09	7.07	10.20	26.02	43.92	26.36	46.49
25	27.70	50.86	7.74	11.49	27.73	46.86	28.09	49.48
26	29.99	54.85	8.32	12.57	28.67	48.07	28.80	50.38
27	31.00	56.15	8.81	13.41	28.86	47.70	28.61	49.44
28	30.84	55.06	9.18	13.96	28.34	45.89	27.61	46.92
29	29.63	51.93	9.41	14.19	27.13	42.78	25.89	43.06
30	27.47	47.06	9.48	14.07	25.29	38.56	23.59	38.16
31	24.52	40.85	9.39	13.58	23.03	33.66	20.92	32.65
32	21.08	33.88	9.17	12.81	20.58	28.53	18.13	27.03
33	17.52	26.82	8.85	11.87	18.18	23.66	15.47	21.76
34	14.17	20.32	8.48	10.85	16.07	19.50	13.20	17.33
35	11.39	15.03	8.08	9.86	14.43	16.42	11.49	14.09
36	9.44	11.43	7.71	8.99	13.23	14.29	10.29	11.91
37	8.21	9.29	7.36	8.23	12.34	12.88	9.47	10.52
38	7.51	8.21	7.03	7.59	11.68	11.97	8.90	9.66
39	7.14	7.77	6.72	7.04	11.14	11.31	8.46	9.06
40	6.89	7.57	6.44	6.57	10.64	10.71	8.05	8.51
41	6.61	7.27	6.18	6.17	10.16	10.15	7.65	7.98
42	6.29	6.87	5.94	5.82	9.71	9.64	7.28	7.48
43	5.95	6.41	5.72	5.54	9.31	9.20	6.93	7.04

Age	Uttar Pradesh		NCT Delhi		Maharashtra		India	
	Total	Female	Total	Female	Total	Female	Total	Female
44	5.63	5.96	5.52	5.29	8.95	8.83	6.62	6.66
45	5.35	5.56	5.33	5.09	8.63	8.55	6.35	6.37
46	5.13	5.26	5.16	4.92	8.36	8.34	6.12	6.14
47	4.97	5.05	5.00	4.78	8.12	8.16	5.91	5.96
48	4.84	4.90	4.86	4.67	7.90	8.00	5.74	5.81
49	4.72	4.78	4.75	4.59	7.69	7.82	5.58	5.67
50	4.60	4.67	4.65	4.54	7.47	7.61	5.44	5.53
51	4.47	4.54	4.58	4.52	7.26	7.38	5.31	5.38
52	4.32	4.39	4.54	4.52	7.07	7.14	5.20	5.24
53	4.17	4.23	4.53	4.56	6.89	6.93	5.10	5.11
54	4.03	4.08	4.54	4.62	6.74	6.75	5.01	4.99
55	3.90	3.93	4.58	4.71	6.62	6.62	4.94	4.89
56	3.78	3.80	4.65	4.82	6.53	6.54	4.87	4.81
57	3.68	3.68	4.74	4.95	6.46	6.48	4.80	4.74
58	3.59	3.58	4.84	5.08	6.39	6.43	4.73	4.66
59	3.51	3.50	4.93	5.19	6.33	6.37	4.64	4.58
60	3.43	3.42	5.02	5.28	6.26	6.29	4.54	4.48
61	3.34	3.35	5.10	5.32	6.17	6.16	4.42	4.37
62	3.25	3.29	5.14	5.31	6.05	5.98	4.30	4.26
63	3.14	3.23	5.14	5.22	5.91	5.73	4.17	4.14
64	3.02	3.18	5.10	5.05	5.72	5.38	4.06	4.03

Source: Authors

Appendix Table 2: Observed and expected in-migration rate using parameter estimates of the model for India and NCT Delhi.

Age	India				NCT Delhi			
	Total		Female		Total		Female	
	Observed	Expected	Observed	Expected	Observed	Expected	Observed	Expected
1	1.77	1.36	1.65	1.29	0.38	0.85	0.47	0.41
2	5.44	5.86	5.40	5.81	0.41	0.94	0.67	0.56
3	8.13	8.37	8.15	8.37	2.12	1.99	2.30	2.24
4	9.97	9.07	10.01	9.07	3.48	3.23	3.59	3.84
5	11.06	9.16	11.10	9.17	4.51	4.39	4.58	4.73
6	11.51	9.09	11.54	9.10	5.26	5.27	5.31	5.12
7	11.44	8.98	11.44	9.00	5.76	5.84	5.79	5.27
8	10.95	8.87	10.92	8.89	6.03	6.13	6.07	5.32
9	10.15	8.75	10.09	8.77	6.13	6.21	6.18	5.33
10	9.16	8.63	9.07	8.66	6.07	6.13	6.13	5.33
11	8.08	8.52	7.98	8.55	5.90	5.96	5.97	5.32
12	7.02	8.40	6.92	8.44	5.65	5.73	5.73	5.31
13	6.10	8.29	6.03	8.33	5.35	5.47	5.44	5.30
14	5.43	8.18	5.40	8.25	5.04	5.20	5.12	5.29
15	5.11	8.08	5.19	8.24	4.75	4.92	4.81	5.28
16	5.27	8.02	5.68	8.47	4.52	4.65	4.55	5.27
17	6.00	8.12	7.15	9.25	4.37	4.39	4.39	5.28
18	7.44	8.64	9.91	11.08	4.33	4.16	4.42	5.34
19	9.70	9.95	14.26	14.46	4.43	4.05	4.69	5.49
20	12.80	12.32	20.31	19.63	4.70	4.24	5.28	5.81
21	16.42	15.72	27.41	26.36	5.14	4.83	6.23	6.40
22	20.16	19.70	34.70	33.89	5.72	5.72	7.45	7.29
23	23.61	23.60	41.34	41.10	6.38	6.67	8.81	8.48
24	26.36	26.74	46.49	46.88	7.07	7.51	10.20	9.88
25	28.09	28.69	49.48	50.42	7.74	8.13	11.49	11.31
26	28.80	29.33	50.38	51.40	8.32	8.53	12.57	12.61
27	28.61	28.76	49.44	49.97	8.81	8.75	13.41	13.61
28	27.61	27.27	46.92	46.64	9.18	8.82	13.96	14.20
29	25.89	25.18	43.06	42.05	9.41	8.79	14.19	14.35
30	23.59	22.79	38.16	36.86	9.48	8.69	14.07	14.10
31	20.92	20.35	32.65	31.60	9.39	8.55	13.58	13.52
32	18.13	18.02	27.03	26.67	9.17	8.38	12.81	12.71
33	15.47	15.89	21.76	22.30	8.85	8.19	11.87	11.77
34	13.20	14.02	17.33	18.58	8.48	8.00	10.85	10.79
35	11.49	12.42	14.09	15.53	8.08	7.80	9.86	9.84
36	10.29	11.07	11.91	13.09	7.71	7.61	8.99	8.96
37	9.47	9.95	10.52	11.18	7.36	7.41	8.23	8.18
38	8.90	9.02	9.66	9.71	7.03	7.23	7.59	7.52
39	8.46	8.27	9.06	8.60	6.72	7.04	7.04	6.96
40	8.05	7.66	8.51	7.76	6.44	6.86	6.57	6.50
41	7.65	7.16	7.98	7.13	6.18	6.69	6.17	6.13
42	7.28	6.75	7.48	6.65	5.94	6.52	5.82	5.84

Age	India				NCT Delhi			
	Total		Female		Total		Female	
	Observed	Expected	Observed	Expected	Observed	Expected	Observed	Expected
43	6.93	6.42	7.04	6.30	5.72	6.36	5.54	5.61
44	6.62	6.14	6.66	6.02	5.52	6.20	5.29	5.43
45	6.35	5.91	6.37	5.81	5.33	6.05	5.09	5.30
46	6.12	5.72	6.14	5.64	5.16	5.90	4.92	5.19
47	5.91	5.56	5.96	5.50	5.00	5.76	4.78	5.11
48	5.74	5.41	5.81	5.39	4.86	5.62	4.67	5.04
49	5.58	5.29	5.67	5.29	4.75	5.49	4.59	4.99
50	5.44	5.18	5.53	5.20	4.65	5.36	4.54	4.95
51	5.31	5.08	5.38	5.12	4.58	5.23	4.52	4.92
52	5.20	4.99	5.24	5.04	4.54	5.11	4.52	4.89
53	5.10	4.90	5.11	4.97	4.53	4.99	4.56	4.87
54	5.01	4.82	4.99	4.90	4.54	4.87	4.62	4.85
55	4.94	4.75	4.89	4.83	4.58	4.76	4.71	4.83
56	4.87	4.68	4.81	4.77	4.65	4.65	4.82	4.82
57	4.80	4.61	4.74	4.70	4.74	4.55	4.95	4.80
58	4.73	4.54	4.66	4.64	4.84	4.45	5.08	4.79
59	4.64	4.48	4.58	4.58	4.93	4.35	5.19	4.78
60	4.54	4.41	4.48	4.52	5.02	4.25	5.28	4.77
61	4.42	4.35	4.37	4.46	5.10	4.16	5.32	4.76
62	4.30	4.29	4.26	4.41	5.14	4.06	5.31	4.74
63	4.17	4.24	4.14	4.35	5.14	3.98	5.22	4.73
64	4.06	4.18	4.03	4.29	5.10	3.89	5.05	4.72

Source: Authors

Appendix table 3: Observed and expected in-migration rate using parameter estimates of the model for Uttar Pradesh and Maharashtra.

Age	Uttar Pradesh				Maharashtra			
	Total		Female		Total		Female	
	Observed	Expected	Observed	Expected	Observed	Expected	Observed	Expected
1	1.45	1.32	3.80	2.35	8.25	7.65	8.52	8.43
2	1.80	1.72	4.03	2.74	11.10	11.10	10.92	10.93
3	2.31	2.42	3.57	2.78	18.43	18.43	18.29	17.90
4	2.73	2.84	3.29	2.82	23.45	23.45	23.31	23.55
5	3.06	3.07	3.15	2.87	26.44	24.38	26.27	26.81
6	3.31	3.19	3.13	2.91	27.70	23.90	27.48	27.74
7	3.48	3.26	3.19	2.96	27.52	23.42	27.24	26.94
8	3.58	3.29	3.30	3.01	26.18	22.96	25.84	25.09
9	3.61	3.32	3.42	3.05	23.98	22.50	23.58	22.74
10	3.58	3.34	3.54	3.10	21.21	22.06	20.75	20.23
11	3.50	3.35	3.60	3.15	18.17	21.62	17.67	17.78
12	3.37	3.36	3.59	3.20	15.13	21.19	14.62	15.51
13	3.20	3.38	3.47	3.25	12.39	20.77	11.90	13.46
14	3.00	3.39	3.21	3.30	10.25	20.35	9.81	11.63
15	2.76	3.40	2.77	3.38	8.94	19.95	8.62	10.04
16	2.55	3.44	2.24	3.55	8.48	19.55	8.49	8.70
17	2.58	3.57	2.10	3.98	8.84	19.17	9.55	8.01
18	3.14	3.98	2.97	5.01	9.99	18.78	11.91	9.05
19	4.50	4.98	5.44	7.16	11.90	18.41	15.73	13.06
20	6.94	6.96	10.12	11.05	14.49	18.05	20.97	20.00
21	10.58	10.17	17.31	17.05	17.50	17.69	27.10	28.33
22	15.03	14.49	26.15	25.04	20.63	17.34	33.43	36.05
23	19.73	19.43	35.47	34.25	23.57	16.99	39.26	41.80
24	24.14	24.22	44.09	43.38	26.02	16.65	43.92	45.14
25	27.70	28.12	50.86	50.99	27.73	16.32	46.86	46.26
26	29.99	30.60	54.85	55.90	28.67	16.00	48.07	45.65
27	31.00	31.48	56.15	57.54	28.87	15.68	47.70	43.87
28	30.84	30.88	55.06	55.97	28.34	15.37	45.89	41.37
29	29.63	29.09	51.93	51.79	27.13	15.06	42.78	38.49
30	27.47	26.53	47.06	45.90	25.29	14.76	38.56	35.48
31	24.52	23.57	40.85	39.22	23.03	14.47	33.66	32.49
32	21.08	20.53	33.88	32.52	20.58	14.18	28.53	29.61
33	17.52	17.64	26.82	26.36	18.18	13.90	23.66	26.91
34	14.17	15.02	20.32	21.05	16.07	13.63	19.50	24.39
35	11.39	12.74	15.03	16.71	14.44	13.36	16.42	22.08
36	9.44	10.83	11.43	13.30	13.23	13.09	14.29	19.96
37	8.22	9.26	9.29	10.73	12.34	12.83	12.88	18.03
38	7.51	8.00	8.21	8.85	11.68	12.58	11.97	16.28
39	7.14	7.00	7.77	7.52	11.14	12.33	11.31	14.70
40	6.89	6.22	7.57	6.59	10.64	12.08	10.71	13.27
41	6.61	5.62	7.28	5.96	10.16	11.84	10.15	11.97
42	6.29	5.17	6.87	5.55	9.71	11.61	9.64	10.80

Age	Uttar Pradesh				Maharashtra			
	Total		Female		Total		Female	
	Observed	Expected	Observed	Expected	Observed	Expected	Observed	Expected
43	5.95	4.82	6.41	5.27	9.31	11.37	9.20	9.74
44	5.63	4.56	5.96	5.10	8.95	11.15	8.83	8.79
45	5.35	4.37	5.56	4.98	8.64	10.93	8.55	7.93
46	5.13	4.24	5.26	4.91	8.36	10.71	8.34	7.15
47	4.97	4.13	5.05	4.86	8.12	10.50	8.16	6.45
48	4.84	4.06	4.90	4.81	7.90	10.29	8.00	5.82
49	4.72	4.01	4.78	4.77	7.69	10.08	7.82	5.25
50	4.60	3.98	4.67	4.72	7.47	9.88	7.61	4.74
51	4.47	3.96	4.54	4.67	7.26	9.69	7.38	4.28
52	4.32	3.95	4.39	4.61	7.07	9.50	7.14	3.86
53	4.17	3.94	4.23	4.53	6.89	9.31	6.93	3.48
54	4.03	3.94	4.08	4.44	6.74	9.12	6.75	3.14
55	3.90	3.95	3.93	4.34	6.62	8.94	6.62	2.83
56	3.78	3.95	3.80	4.22	6.53	8.76	6.54	2.56
57	3.68	3.96	3.68	4.08	6.46	8.59	6.48	2.31
58	3.60	3.97	3.58	3.92	6.39	8.42	6.43	2.08
59	3.51	3.98	3.50	3.74	6.33	8.25	6.37	1.88
60	3.43	3.99	3.42	3.55	6.26	8.09	6.29	1.70
61	3.34	4.01	3.35	3.34	6.17	7.93	6.16	1.53
62	3.25	4.02	3.29	3.11	6.05	7.77	5.98	1.38
63	3.14	4.03	3.24	2.88	5.91	7.61	5.73	1.25
64	3.02	4.05	3.18	2.62	5.72	7.46	5.38	1.12

Source: Authors

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Social Protection in Districts of India: Evidence from NFHS-6

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Abstract

This paper constructs a social protection index (SPI) to assess the progress towards universal social protection in the districts of India based on the data available from the latest round of the National Family Health Survey, 2023-2024. The index combines six indicators into the three dimensions of social protection – social security, inclusion and enabling capacity, and life-cycle vulnerability. The SPI is found to be the lowest in Sukuma district of Chhattisgarh but the highest in Hamirpur district of Himachal Pradesh. In 248 districts of the country, the SPI is found to be very low. These districts may be termed as hotspot districts as far as universal social protection is concerned. The proposed SPI may be used as a basis for planning for universal social protection activities and interventions at the district level.

Introduction

Social protection is increasingly understood as a multidimensional policy system that combines income security, access to essential services and protection against life cycle and socio-economic risks. The International Labour Organization (ILO) emphasises that social-protection measurement involves several dimensions of coverage, including the population and contingencies covered and the adequacy of benefits (ILO, 2024). The ASPIRE framework of the World Bank similarly combines household-survey and administrative information to examine the performance of social protection and labour programmes (World Bank, nd).

At the district level, social protection activities are undertaken by different government departments and agencies. Therefore, information on the coverage of different social protection interventions and activities and adequacy of these interventions and activities in meeting the social protection needs of the people is often fragmented across different departments and various schemes. District level administrative information related to social protection activities is, therefore, not suitable for monitoring the progress towards universal social protection. An alternative is the information available through household-surveys which provides a useful complementary perspective to the administrative data. This study uses the district-level information available through the latest, 2023-2024 round of the National Family Health Survey (Government of India, 2026).

The proposed social protection index (SPI) is designed to answer a focused question: how do districts compare on a selected set of observable conditions associated with social-protection coverage, women economic and digital empowerment, and demographic advantage? It is different from indexes which focus on expenditure, primarily government expenditure, on social protection programmes and activities (Asian Development Bank, 2011; Chaurasia, 2021). Instead, the SPI focusses on the access to selected social protection programmes and activities in the district.

Conceptual Framework

The conceptual framework of the SPI follows the multidimensional measurement approach. Social protection is broader than cash transfer alone and includes income security and access to essential services across the life cycle. International monitoring frameworks also distinguish the coverage of social protection in terms of legal coverage, effective coverage, and adequacy. The index constructed in the present paper captures only the selected enabling-environment component of the broader social protection system.

The SPI proposed in this paper is conceptually aligned with the ILO approach to social protection (ILO, 2012), especially the life-cycle approach. The ILO framework emphasises universal access to essential health care and basic income security across the life course, with particular attention to children, persons of working ages and older persons. The SPI is based on these broad principles and is intended to serve as an analytical framework to monitor the progress towards universal social protection. This framework recognises that social protection is contingent upon not only the direct access to different social protection programmes and interventions but also the extent to which households and individuals are financially, socially, and digitally included and the demographic situation as social protection requirements of different population groups are essentially different.

Accordingly, the present paper conceptualises social protection as a three-dimensional construct comprising of three complementary dimensions**:** 1) Social Security, 2) Inclusion and Enabling Capacity, and 3) Life-cycle Vulnerability. The Social Security dimension captures the extent to which households have mechanisms that can reduce exposure to major economic and social risks. The Inclusion and Enabling Capacity dimension focuses particularly on the ability of women to independently access financial, digital, and human-capital resources. The Life-Cycle Vulnerability dimension, on the other hand, reflects the demographic groups that may have relatively greater or specific social protection requirements.

Since social protection is a multidimensional construct, any measure or index designed to monitor progress towards in social protection must be a composite measure or index that reflects the progress in different dimensions of social protection framework as proposed by ILO. It may also be recognised that each of the three dimensions that have been assumed to constitute the social protection framework is also multi-dimensional in their own context. The construction of any measure or index to

monitor the progress towards social protection, therefore, involves two steps. The first step is to select indicators reflecting the progress in different dimensions of social protection while the second step is to combine different indicators into a single measure or index through a statistically sound methodology. The selection of indicators is commonly constrained by the availability of the data related to the indicators and the very fact that no single indicator can reflect the progress in the three dimensions of social protection because of their multi-dimensional nature. In India, the problem of the availability of appropriate indicators to measure the progress in different dimensions of social protection and hence in social protection increases as one goes down the administrative hierarchy.

There are different approaches to combine different indicators into a single composite measure or index. A comprehensive review of these approaches is given elsewhere (OECD, 2008). The construction of the composite measure or index essentially involves mapping a set of normalised indicators of social protection or a vector quantity on a single scalar quantity using some mapping or aggregation function. This approach, however, always results in some loss of information because there is no mapping or aggregation function which can transfer the entire information embedded in a vector quantity into a scalar quantity (Anand and Sen, 1997). The selection of the mapping function, therefore, matters in the construction of the composite index. Another challenging problem in the construction of any composite measure or index is the assignment of weights to different indicators. The simplest approach is to assign equal weights to all indicators. However, this approach may not be appropriate when progress in different dimensions of social protection is not the same.

The latest round (2023-2024) of the National Family Health Survey in India provides estimates of selected indicators for 715 districts of the country. These estimates can be used to construct SPI to monitor the progress towards universal social protection at the district level. The SPI may be perceived as an analytical adaptation of the ILO social protection framework for district-level assessment of the progress in social protection. It translates key principles of the ILO social protection and life-cycle approach into a measurable district-level index based on a set of available indicators. It may be used to diagnostically interpret the social protection situation at the district level – the level at which all social protection activities are implemented, although they are planned at the national level and customised at the state/Union Territory level.

The Social Protection Index

The conceptual framework for constructing the social protection index (SPI) is presented in the figure 1. As discussed earlier, social protection is assumed to be the composite of three dimensions: 1) social security; 2) inclusion and enabling capacity; and 3) life-cycle vulnerability. Each dimension is further conceptualised as a multidimensional construct which is reflected in terms of two indicators relevant to the dimension. Construction of SPI, therefore, involves constructing a composite index for each of the three dimensions and then combining composite indexes of the three dimensions into SPI. The weighted average approach has been adopted to combine the

normalised values of the indicators representing different dimensions into the composite score of each dimension and then obtaining SPI based on the composite scores of the three dimensions. The data driven exploratory factor analysis technique has been adopted to estimate weights for indicators of different dimensions to construct the dimension-specific composite score and then weights for the three composite scores to construct SPI. These weights determine the relative importance of different indictors in deciding the level of SPI. The limitation of this data driven approach, however, is that the weights so obtained are data sensitive or they are specific to the specific dataset only. Any change in the dataset leads to the change in the weights of different indicators and hence different SPI. As such, the SPI constructed by following this approach is not universal but is specific to the dataset.

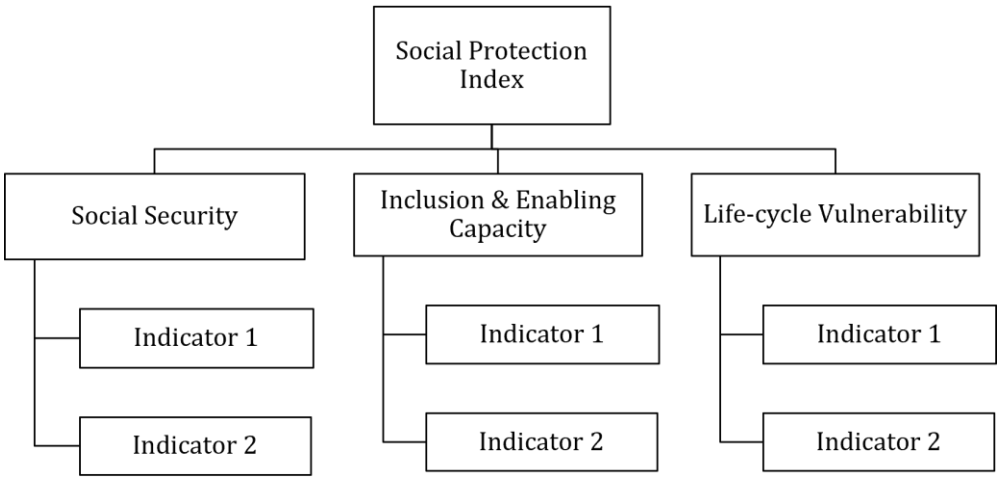

Figure 1: The conceptual framework of the social protection index (SPI).
Source: Author

The following set of six indicators has been selected for the construction of SPI:

1. Proportion of households in which at least one member has health insurance (HI)
2. Proportion of households in which at least one member has a bank/post-office account (BA)
3. Proportion of women having at least 10 years of schooling (WE)
4. Proportion of women having a mobile phone which they exclusively use (WM)
5. Support Ratio defined as the ratio of population aged 15-59 years to population aged <15 years and 60 years and above (SR)
6. Contraceptive prevalence rate (CP)

The proportion of households with at least one member covered by health insurance or a financial health protection scheme reflects the protection against health-related financial risks. The proportion of households having a bank or post-office

account represents basic financial inclusion and facilitates access to Direct Benefit Transfers (DBT), pensions, social assistance, and other government benefits. Together, these indicators provide an indication of the financial and economic protection available to households. In the factor analysis, health insurance was grouped with the contraceptive prevalence rate, which reflects access to and use of family-planning services as a component of reproductive health protection, to form the social security dimension. The bank or post-office account indicator was grouped with the support ratio in the life-cycle vulnerability dimension.

The proportion of women who have a mobile phone that they themselves use reflects digital inclusion and the potential ability to access information, government services, social protection programmes, and digital payment systems. The proportion of women with ten or more years of schooling is treated as a longer-term enabling indicator because education can strengthen access to employment, information, public services, and social protection mechanisms. These indicators therefore capture the broader enabling environment within which social protection can operate effectively.

The support ratio, defined as the ratio of the population aged 15-59 years to the population below 15 years and aged 60 years and above, captures the demographic structure of a district. A lower support ratio indicates a larger share of older persons, who potentially require old-age income security, health care, and social assistance, and of children and adolescents, who require investments in health, nutrition, education, protection, and development, relative to the working-age population. This indicator should be interpreted as a measure of potential social protection need or demographic pressure, rather than as a measure of poor programme performance.

Table 1: Weights for the construction of dimension scores and SPI.

Factor/ Dimension	Indicators	Indicator weight	Dimension weight
Social security	1. Proportion of households in which at least one member has health insurance (HI)	0.450033	0.420819
	2. Contraceptive prevalence rate (CP)	0.549967	
Inclusion and enabling capacity	1. Proportion of women having at least 10 years of schooling (WE)	0.513518	0.277669
	2. Proportion of women having a mobile phone which they exclusively use (WM)	0.486482	
Lifecycle vulnerability	1. Support Ratio defined as the ratio of population aged 15-59 years to population aged <15 years and 60 years and above (SR)	0.340664	0.301512
	2. Proportion of households in which at least one member has a bank/post-office account (BA)	0.659336	

Source: Author

The exploratory factor analysis technique was applied to data related to the six indicators for the 715 districts of the country available from NFHS 2023-2024 to estimate weights for the six indicators for constructing SPI. Application of the

exploratory analysis revealed that the six indicators can be grouped into 3 factors or dimensions, each having high factor loadings in two indicators and the three factors or dimensions, together explained almost 75 per cent of the total variation in the original data set. Based on the results of the exploratory factor analysis, weights of different indicators and different dimensions were estimated and composite scores for the three dimensions of social protection were computed as follows:

SSC = 0.450033*HI+0.549967*CP
IEC = 0.513518*WE+0.486482*WM
LVC = 0.340664*SR+0.659336*BA

Finally, the social protection index (SPI) was calculated from SSC, IEC and LVC as follows:

SPI = 0.420819*SSC+0.277669*IEC+0.301512*LVC

Social Protection in Districts of India

Estimates of SPI for 715 districts along with district rank in SPI and estimates of composite scores of the three dimensions social protection are given in the appendix table. The distribution in SPI across the 715 districts is presented as choropleth map in the figure 2. The SPI varies from a minimum of 0.272 in district Sukma of Chhattisgarh to a maximum of 0.809 in district Hamirpur of Himachal Pradesh with a median of 0.597 and a mean of 0.587. The median SPI is greater than the mean SPI which indicates that the distribution of SPI across the districts is negatively skewed, that is, a long tail of districts with very low SPI pulls the mean below the median, and there are more districts (384) with above-average SPI than districts (331) with below-average SPI.

Based on the distribution of SPI across districts, social protection in a district may be classified as very low if SPI<0.550; low if 0.550≤SPI<0.600; average if 0.600≤SPI<0.650; high if 0.650≤SPI<0.700; very high if SPI≥0.700. The classes are of equal width of 0.05, except for the open-ended lowest and highest classes. This classification suggests that there are 248 (34.7 per cent) districts in which social protection may be classified as very low. These districts may be termed as hotspot districts in the context of universal social protection and are located mainly in Bihar, Chhattisgarh, Gujarat, Jharkhand, Madhya Pradesh, Maharashtra, and Uttar Pradesh, with smaller numbers in Assam, Rajasthan, and Meghalaya. In all the 38 districts of Bihar, social protection may be classified as very low whereas it is very low in 60 of the 75 districts of Uttar Pradesh. Social protection may also be classified as very low in 8 of the 11 districts of Meghalaya. By contrast, there are 14 states and Union Territories in which there was no district where social protection was very low. On the other hand, there are only 72 (10.1 per cent) districts in which social protection may be classified as very high as SPI≥0.700 in these districts. There are 15 states and Union Territories in which there was no district where social protection may be classified as very high. By contrast, in 13 of the 14 districts of Kerala and 8 of the 12 districts of Himachal Pradesh, social protection may be classified as very high.

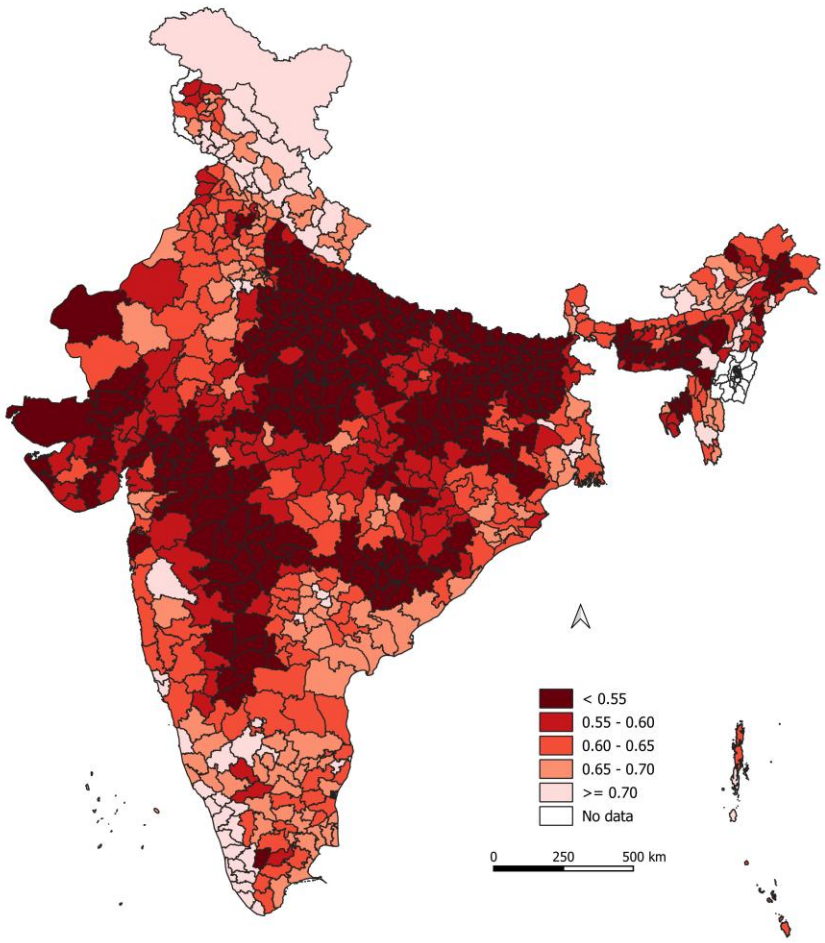

Figure 2: Variation in SPI across 715 districts of India.
Remarks: Estimates of SPI for two districts of Jammu and Kashmir and 16 districts of Manipur are not calculated as the NFHS-6 was not conducted in these districts, and Manipur is therefore not included in the tables.
Source: Author

The progress in the three dimensions of social protection is not the same but markedly different. Progress appears to be particularly poor in dimension 1 (social security) of social protection (Table 3). In almost two-third districts of the country, progress in this dimension of social protection appears to be very poor. In all districts of Bihar, Chhattisgarh and Jharkhand, in 50 of the 51 districts of Madhya Pradesh, 10 of the 11 districts of Meghalaya, 72 of the 75 districts of Uttar Pradesh and in 19 of the 23 districts of West Bengal, progress in this dimension appears to lag compared to the other two dimensions. There are, however, 94 districts including all districts of Kerala,

Chandigarh, Goa, and Lakshadweep, in 9 of the 12 districts of Himachal Pradesh, 8 of the 11 districts of National Capital Territory (NCT) of Delhi and 12 of the 38 districts of Tamil Nadu, progress in this dimension is well-advanced.

Table 2: Distribution of SPI across districts of different states and Union Territories.

State/UT	Social protection index (SPI)					Total
	Very low <0.550	Low 0.550-0.600	Average 0.600-0.650	High 0.650-0.700	Very high ≥0.700	
Andaman and Nicobar Islands	0	0	2	0	1	3
Andhra Pradesh	0	0	5	8	0	13
Arunachal Pradesh	4	3	6	7	5	25
Assam	10	7	9	5	2	33
Bihar	38	0	0	0	0	38
Chandigarh	0	0	0	1	0	1
Chhattisgarh	15	7	3	3	0	28
Dadra & Nagar Haveli and Daman & Diu	0	1	1	1	0	3
Goa	0	0	0	0	2	2
Gujarat	17	10	4	2	0	33
Haryana	2	0	8	10	2	22
Himachal Pradesh	0	0	0	4	8	12
Jammu and Kashmir	0	3	5	5	7	20
Jharkhand	17	2	5	0	0	24
Karnataka	6	6	5	9	4	30
Kerala	0	0	0	1	13	14
Ladakh	0	0	0	0	2	2
Lakshadweep	0	0	0	1	0	1
Madhya Pradesh	26	20	2	3	0	51
Maharashtra	17	4	11	3	1	36
Meghalaya	8	3	0	0	0	11
Mizoram	0	0	3	4	1	8
Nagaland	1	4	1	1	4	11
NCT of Delhi	1	2	3	5	0	11
Odisha	6	8	12	4	0	30
Puducherry	0	0	1	1	2	4
Punjab	1	5	11	4	1	22
Rajasthan	9	9	10	5	0	33
Sikkim	0	0	2	0	2	4
Tamil Nadu	1	1	14	18	4	38
Telangana	4	1	15	10	3	33
Tripura	4	3	0	1	0	8
Uttar Pradesh	60	13	2	0	0	75
Uttarakhand	0	1	1	6	5	13
West Bengal	1	3	10	6	3	23
India	248	116	151	128	72	715

Source: Author

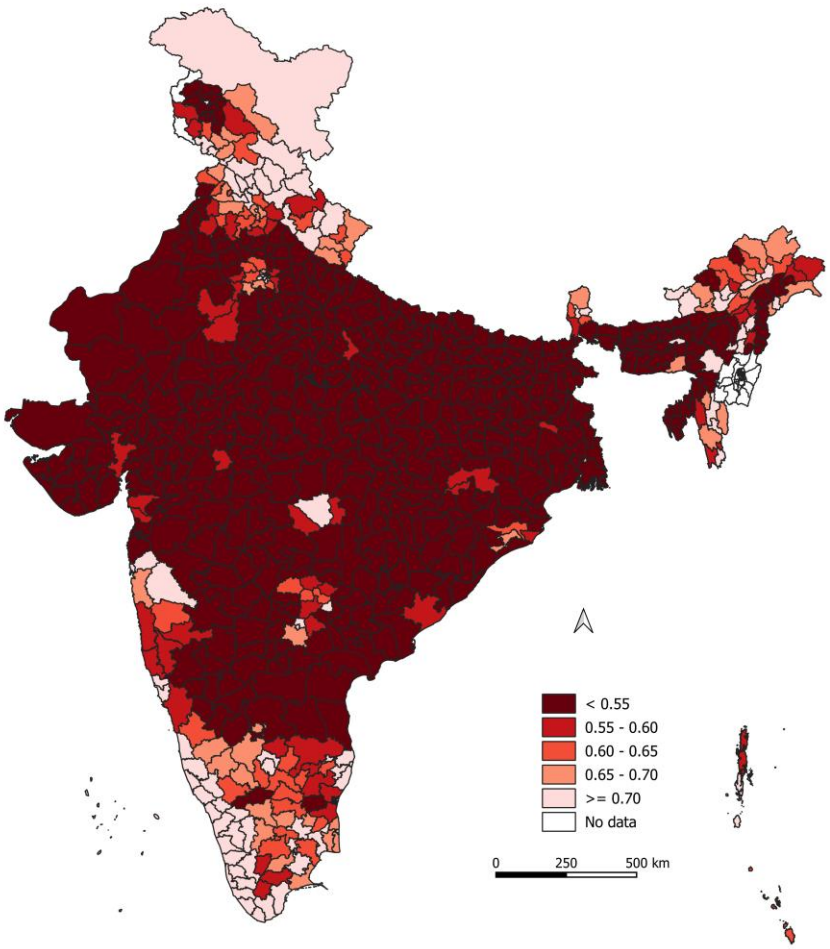

Figure 3: Variation in composite score of the dimension 1 across districts.
Remarks: Estimates of SPI for two districts of Jammu and Kashmir and 16 districts of Manipur are not calculated as the NFHS-6 was not conducted in these districts, and Manipur is therefore not included in the tables.
Source: Author

In contrast to the dimension 1, the progress appears to be fairly advanced in dimension 2 and dimension 3 of social in majority of the districts as may be seen from figures 4 and 5. There are 289 (40.4 per cent) districts in which the progress is well-advanced (composite score of 0.700 or more) in dimension 2 while there are 350 (49.0 per cent) districts in which the progress is well-advanced in dimension 3 of social protection. The primary challenge to universalising social protection in India is universalising social security. There are, however, 196 (27.4 per cent) districts in which progress in dimension 2 is very poor. These include all districts of Bihar and most of the

district of Uttar Pradesh and Jharkhand. By contrast, there are only 30 districts in which progress is very poor in dimension 3. These include 7 districts of Meghalaya, 4 districts each of Arunachal Pradesh and Tamil Nadu and 3 of Assam.

Table 3: Composite score of dimension 1 of social protection across districts.

State/UT	Composite score of dimension 1					Total
	Very low	Low	Average	High	Very high	
	<0.550	0.550-0.600	0.600-0.650	0.650-0.700	≥0.700	
Andaman and Nicobar Islands	0	1	1	0	1	3
Andhra Pradesh	11	2	0	0	0	13
Arunachal Pradesh	3	3	4	8	7	25
Assam	26	3	1	1	2	33
Bihar	38	0	0	0	0	38
Chandigarh	0	0	0	0	1	1
Chhattisgarh	28	0	0	0	0	28
Dadra & Nagar Haveli and Daman & Diu	1	1	1	0	0	3
Goa	0	0	0	0	2	2
Gujarat	30	3	0	0	0	33
Haryana	10	4	5	3	0	22
Himachal Pradesh	0	1	2	0	9	12
Jammu and Kashmir	10	3	1	3	3	20
Jharkhand	24	0	0	0	0	24
Karnataka	15	2	4	4	5	30
Kerala	0	0	0	0	14	14
Ladakh	0	0	0	1	1	2
Lakshadweep	0	0	0	0	1	1
Madhya Pradesh	50	1	0	0	0	51
Maharashtra	23	6	1	1	5	36
Meghalaya	10	0	0	1	0	11
Mizoram	0	2	0	3	3	8
Nagaland	6	1	0	0	4	11
NCT of Delhi	0	0	1	2	8	11
Odisha	25	3	1	1	0	30
Puducherry	0	0	1	0	3	4
Punjab	6	3	5	4	4	22
Rajasthan	30	3	0	0	0	33
Sikkim	0	0	1	1	2	4
Tamil Nadu	1	7	10	8	12	38
Telangana	22	4	3	1	3	33
Tripura	8	0	0	0	0	8
Uttar Pradesh	72	3	0	0	0	75
Uttarakhand	2	1	3	3	4	13
West Bengal	19	2	1	1	0	23
India	470	59	46	46	94	715

Source: Author

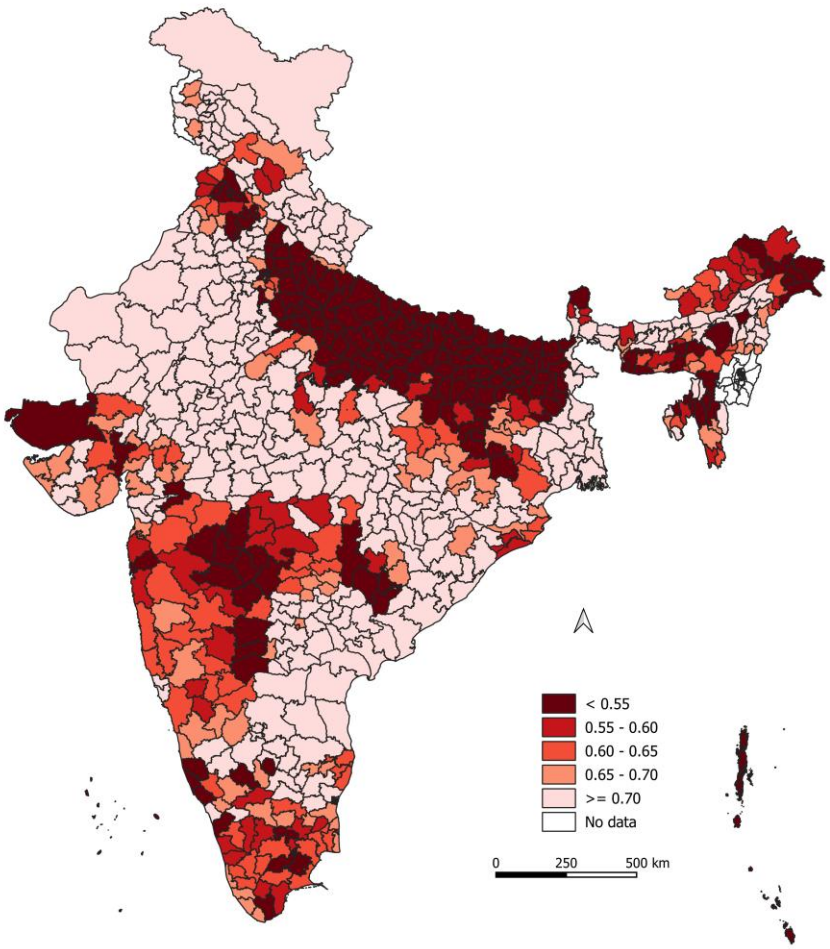

Figure 4: Variation in the composite score of the dimension 2 across districts.
Remarks: Estimates of SPI for two districts of Jammu and Kashmir and 16 districts of Manipur are not calculated as the NFHS-6 was not conducted in these districts, and Manipur is therefore not included in the tables.
Source: Author

In almost half of the districts, progress in dimension 3 is well advanced as the composite score of this dimension in these districts is at least 0.700. In all districts of Andaman & Nicobar Islands, Chandigarh, Dadra & Nagar Haveli and Daman & Diu, Goa and Ladakh, progress in this dimension of social protection is well-advanced. Bihar and Lakshadweep are the only two states and Union Territories in which progress in this dimension of social protection is not well-advanced in any of the district. A notable observation of table 5 is that the progress in this dimension of social protection is well-advanced in only 4 of the 14 districts of Kerala. Kerala is the only state/Union Territory of the country in which SPI is estimated to be at least 0.700 in 13 of the 14 districts. The

districts of the state have a low support ratio because the share of the old persons in the population is very high. The demographic transition is at an advanced stage in most of the districts of Kerala.

Table 4: Composite score of dimension 2 of social protection across districts.

State/UT	Composite score of dimension 2					Total
	Very low <0.550	Low 0.550-0.600	Average 0.600-0.650	High 0.650-0.700	Very high ≥0.700	
Andaman and Nicobar Islands	3	0	0	0	0	3
Andhra Pradesh	0	0	0	0	13	13
Arunachal Pradesh	7	10	4	3	1	25
Assam	3	3	2	3	22	33
Bihar	38	0	0	0	0	38
Chandigarh	0	1	0	0	0	1
Chhattisgarh	3	1	3	6	15	28
Dadra & Nagar Haveli and Daman & Diu	1	0	1	1	0	3
Goa	0	0	0	0	2	2
Gujarat	2	0	6	12	13	33
Haryana	1	0	2	4	15	22
Himachal Pradesh	0	2	1	2	7	12
Jammu and Kashmir	0	0	0	3	17	20
Jharkhand	12	5	3	4	0	24
Karnataka	6	4	7	7	6	30
Kerala	3	2	4	4	1	14
Ladakh	0	0	0	0	2	2
Lakshadweep	1	0	0	0	0	1
Madhya Pradesh	0	0	2	5	44	51
Maharashtra	13	8	12	1	2	36
Meghalaya	6	1	2	2	0	11
Mizoram	2	2	1	2	1	8
Nagaland	0	0	2	3	6	11
NCT of Delhi	9	1	1	0	0	11
Odisha	0	2	3	6	19	30
Puducherry	1	1	2	0	0	4
Punjab	8	3	5	2	4	22
Rajasthan	0	0	0	0	33	33
Sikkim	1	2	0	0	1	4
Tamil Nadu	4	6	13	8	7	38
Telangana	0	0	5	6	22	33
Tripura	3	1	1	1	2	8
Uttar Pradesh	69	4	2	0	0	75
Uttarakhand	0	0	0	1	12	13
West Bengal	0	1	0	0	22	23
India	196	60	84	86	289	715

Source: Author

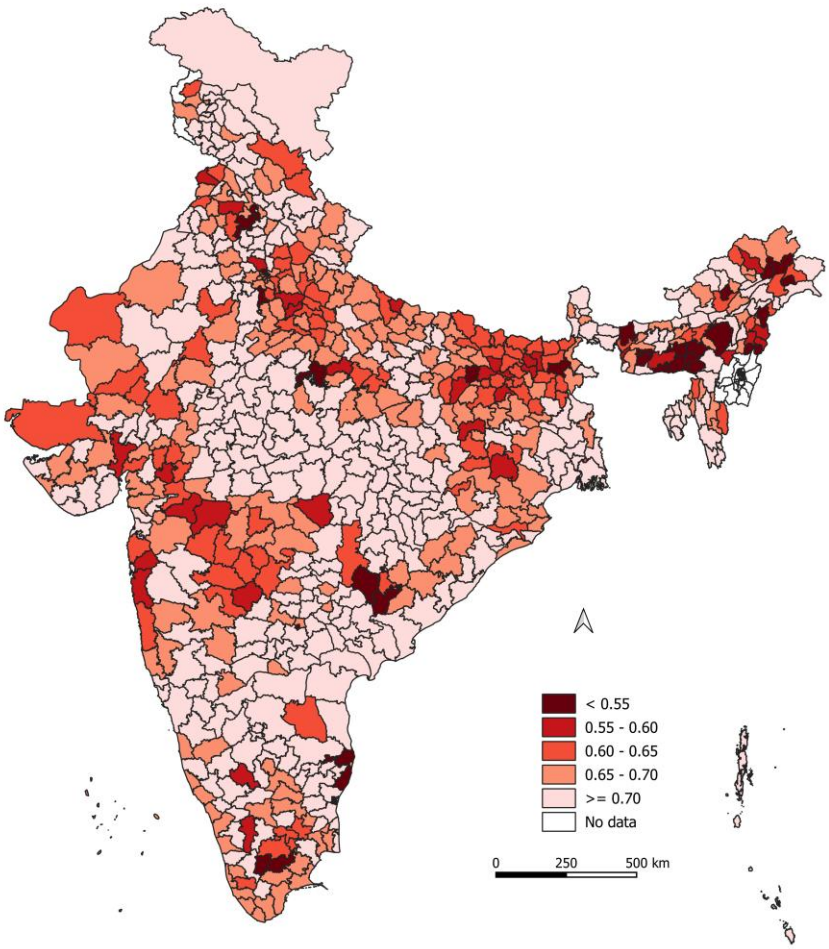

Figure 5: Variation in the composite score of the dimension 3 across districts.
Remarks: Estimates of SPI for two districts of Jammu and Kashmir and 16 districts of Manipur are not calculated as the NFHS-6 was not conducted in these districts, and Manipur is therefore not included in the tables.
Source: Author

Discussion

The results illustrate why a multidimensional approach is useful. Districts can obtain similar composite scores through different combinations of strengths and weaknesses. A district-level planning system should therefore use the composite index together with the indexes of the three dimensions and the score of six underlying indicators.

Table 5: Composite score of the dimension 3 of social protection across districts.

State/UT	Composite score of dimension 3					Total
	Very low <0.550	Low 0.550-0.600	Average 0.600-0.650	High 0.650-0.700	Very high ≥0.700	
Andaman and Nicobar Islands	0	0	0	0	3	3
Andhra Pradesh	0	0	1	0	12	13
Arunachal Pradesh	4	1	4	6	10	25
Assam	3	1	5	9	15	33
Bihar	2	7	23	6	0	38
Chandigarh	0	0	0	0	1	1
Chhattisgarh	2	0	1	2	23	28
Dadra & Nagar Haveli and Daman & Diu	0	0	0	0	3	3
Goa	0	0	0	0	2	2
Gujarat	0	2	4	10	17	33
Haryana	1	1	1	7	12	22
Himachal Pradesh	0	0	2	2	8	12
Jammu and Kashmir	0	0	1	4	15	20
Jharkhand	0	2	8	9	5	24
Karnataka	0	1	0	5	24	30
Kerala	0	0	1	9	4	14
Ladakh	0	0	0	0	2	2
Lakshadweep	0	0	0	1	0	1
Madhya Pradesh	0	0	1	10	40	51
Maharashtra	0	6	12	10	8	36
Meghalaya	7	1	0	1	2	11
Mizoram	0	0	1	2	5	8
Nagaland	1	5	1	2	2	11
NCT of Delhi	2	0	2	5	2	11
Odisha	0	0	2	14	14	30
Puducherry	0	0	0	2	2	4
Punjab	2	2	3	8	7	22
Rajasthan	0	0	6	10	17	33
Sikkim	0	0	0	1	3	4
Tamil Nadu	4	1	3	14	16	38
Telangana	1	0	0	6	26	33
Tripura	0	0	0	1	7	8
Uttar Pradesh	1	4	17	36	17	75
Uttarakhand	0	0	0	4	9	13
West Bengal	0	0	1	5	17	23
India	30	34	100	201	350	715

Source: Author

The inclusion and enabling capacity dimension is relevant to social-protection access because women's education and digital access can affect the ability of women to receive information, use formal financial channels and access public programmes.

However, these variables are enabling conditions and should not be interpreted as direct measures of employment, income, or economic autonomy.

The life-cycle vulnerability dimension combines the support ratio with household bank or post-office account ownership and should likewise be interpreted with care. A lower support ratio, reflecting a higher share of children or older persons, represents a different social-service and income-security need profile; it does not by itself indicate weak or strong programme performance. A low score in this dimension may therefore indicate greater potential need rather than poor progress.

Policy Implications

Use the index as a diagnostic dashboard. Publish the composite index with dimension indexes and indicator-specific scores so that district teams can identify the specific source of variation.

Strengthen convergence. Use social security, inclusion and enabling capacity, and life-cycle vulnerability profiles to support convergence across social protection, health, women and child development, financial inclusion, and local-government interventions.

Prioritise indicator gaps rather than only ranks. A low dimension score should trigger examination of coverage, exclusion, awareness, access, and service delivery before a programme response is selected.

Add administrative measures. A future version should also incorporate pension coverage, maternity benefits, disability support, child benefits, employment protection, benefit adequacy, grievance redress, and actual programme take-up.

Build a time series. Repeating the index across survey rounds or annual administrative datasets would allow analysis of change over time.

Limitations

- The index uses a limited set of six indicators and does not represent the complete social-protection system.
- Min–max normalisation depends on the observed minimum and maximum; adding observations can change normalised scores.
- Demographic indicators describe population composition rather than programme performance.
- Household access indicators do not establish benefit adequacy, utilisation, service quality, or grievance outcomes.
- The cross-sectional design does not establish causal relationships.

Conclusion

This study presents a district-level framework for examining variations in social protection in India through a composite Social Protection Index (SPI) based on NFHS-6 data. The findings reveal substantial inter-district variation in the relative levels of social protection, highlighting geographical disparities in the indicators captured by the index. The three-dimensional structure of the framework provides a more nuanced understanding than a single composite score by identifying whether a district's relative position is primarily associated with social security, inclusion and enabling capacity of women, or life-cycle vulnerability.

The framework offers a basis for identifying district-level gaps, comparing relative performance, and supporting evidence-informed planning and policy prioritisation. However, the SPI should be interpreted as a composite measure of the selected indicators rather than a comprehensive measure of all dimensions of social protection. Its results depend on the indicators included, their conceptual allocation to dimensions, the normalisation procedure, and the factor-analysis and weighting methods employed.

To enhance the transparency, methodological rigour, and reproducibility of the Social Protection Index (SPI), the study describes the indicator definitions, the data source, the normalisation procedure, and the methodology used to derive weights and calculate district-level SPI scores and rankings. This documentation will enable readers to better understand the construction of the index, assess the robustness of the findings, and replicate the analysis, subject to the availability of the underlying data and computational details. Future research may strengthen the framework by incorporating additional administrative and social protection expenditure data and examining the association between district-level SPI scores and relevant social protection outcomes. Overall, the study provides an analytical framework for assessing inter-district disparities in social protection and generating evidence to support more targeted, context-specific policy planning and interventions.

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Appendix Table: SPI, composite score of the three dimensions of social protection and rank of district in SPI in 715 districts of India.

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
Andaman and Nicobar Islands	Nicobar	0.641	0.451	0.754	0.622	296
	North and Middle Andaman	0.569	0.535	0.822	0.636	246
	South Andaman	0.825	0.442	0.807	0.713	55
Andhra Pradesh	Anantapur	0.418	0.777	0.737	0.614	316
	Chittoor	0.592	0.797	0.716	0.686	99
	East Godavari	0.481	0.858	0.742	0.664	159
	Guntur	0.475	0.852	0.742	0.660	172
	Krishna	0.515	0.884	0.744	0.686	98
	Kurnool	0.386	0.803	0.717	0.602	351
	Prakasam	0.502	0.839	0.760	0.673	128
	Sri Potti Sriramulu Nellore	0.451	0.825	0.718	0.636	247
	Srikakulam	0.453	0.911	0.783	0.680	115
	Visakhapatnam	0.559	0.843	0.750	0.696	77
	Vizianagaram	0.428	0.872	0.748	0.648	210
	West Godavari	0.527	0.905	0.727	0.692	84
	Y.S.R.	0.487	0.771	0.639	0.611	324
Arunachal Pradesh	Anjaw	0.593	0.539	0.726	0.618	305
	Changlang	0.698	0.496	0.701	0.643	221
	Dibang Valley	0.662	0.559	0.678	0.638	239
	East Kameng	0.677	0.637	0.685	0.668	145
	East Siang	0.743	0.345	0.542	0.572	422
	Kamle	0.562	0.551	0.656	0.587	385
	Kra Daadi	0.609	0.740	0.792	0.701	70
	Kurung Kumey	0.540	0.641	0.717	0.621	300
	Lepa Rada	0.670	0.694	0.694	0.684	107
	Lohit	0.598	0.391	0.620	0.547	473
	Longding	0.686	0.638	0.613	0.651	197
	Lower Dibang Valley	0.614	0.406	0.442	0.505	557
	Lower Siang	0.720	0.559	0.735	0.680	114
	Lower Subansiri	0.776	0.587	0.545	0.654	187
	Namsai	0.463	0.515	0.487	0.484	605
	Pakke Kessang	0.698	0.653	0.844	0.729	36
	Papum Pare	0.756	0.599	0.624	0.672	129
	Shi Yomi	0.402	0.556	0.650	0.520	535
	Siang	0.632	0.580	0.564	0.597	360
	Tawang	0.757	0.699	0.810	0.757	15
	Tirap	0.733	0.551	0.864	0.722	47
	Upper Siang	0.685	0.489	0.676	0.628	281
	Upper Subansiri	0.646	0.600	0.708	0.652	193
	West Kameng	0.745	0.598	0.909	0.754	19
	West Siang	0.680	0.569	0.667	0.645	217
	Baksa	0.474	0.718	0.680	0.604	344
	Barpeta	0.334	0.785	0.755	0.586	389

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Biswanath	0.488	0.753	0.706	0.627	282
	Bongaigaon	0.343	0.774	0.692	0.568	428
	Cachar	0.400	0.536	0.717	0.534	505
	Charaideo	0.356	0.748	0.735	0.579	407
	Chirang	0.429	0.761	0.757	0.620	302
	Darrang	0.346	0.822	0.689	0.582	401
	Dhemaji	0.684	0.800	0.761	0.739	30
	Dhubri	0.316	0.669	0.607	0.502	566
	Dibrugarh	0.411	0.724	0.740	0.597	357
	Dima Hasao	0.710	0.637	0.772	0.709	59
	Goalpara	0.286	0.742	0.664	0.527	516
	Golaghat	0.427	0.759	0.711	0.605	341
	Hailakandi	0.469	0.725	0.675	0.602	349
	Hojai	0.341	0.789	0.668	0.564	441
	Jorhat	0.564	0.455	0.670	0.566	437
	Kamrup	0.455	0.768	0.766	0.636	245
	Kamrup Metropolitan	0.722	0.569	0.691	0.670	133
	Karbi Anglong	0.498	0.399	0.276	0.404	694
	Karimganj	0.521	0.714	0.637	0.610	328
	Kokrajhar	0.460	0.590	0.542	0.521	529
	Lakhimpur	0.618	0.815	0.689	0.694	80
	Majuli	0.557	0.790	0.745	0.679	116
	Marigaon	0.358	0.678	0.644	0.533	507
	Nagaon	0.368	0.727	0.620	0.544	480
	Nalbari	0.542	0.745	0.772	0.668	149
	Sivasagar	0.571	0.781	0.765	0.688	94
	Sonitpur	0.442	0.751	0.713	0.609	329
	South Salmara Mancachar	0.198	0.662	0.579	0.442	666
	Tinsukia	0.337	0.644	0.646	0.515	541
	Udalguri	0.500	0.739	0.746	0.641	227
	West Karbi Anglong	0.428	0.550	0.447	0.468	627
Bihar	Araria	0.253	0.385	0.634	0.404	692
	Arwal	0.390	0.259	0.652	0.433	676
	Aurangabad	0.435	0.385	0.666	0.491	587
	Banka	0.348	0.315	0.674	0.437	671
	Begusarai	0.391	0.382	0.637	0.463	636
	Bhagalpur	0.421	0.323	0.609	0.450	653
	Bhojpur	0.427	0.378	0.479	0.429	680
	Buxar	0.406	0.301	0.640	0.448	659
	Darbhanga	0.415	0.404	0.629	0.476	616
	Gaya	0.403	0.340	0.617	0.450	654
	Gopalganj	0.441	0.219	0.627	0.436	672
	Jamui	0.388	0.340	0.609	0.441	667
	Jehanabad	0.381	0.280	0.629	0.428	681
	Kaimur (Bhabua)	0.391	0.406	0.638	0.470	626

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Katihar	0.268	0.289	0.539	0.356	711
	Khagaria	0.374	0.340	0.600	0.432	677
	Kishanganj	0.263	0.325	0.620	0.388	701
	Lakhisarai	0.421	0.315	0.642	0.458	643
	Madhepura	0.323	0.444	0.557	0.427	682
	Madhubani	0.354	0.380	0.642	0.448	657
	Munger	0.480	0.379	0.651	0.504	559
	Muzaffarpur	0.368	0.402	0.638	0.459	642
	Nalanda	0.432	0.340	0.627	0.466	631
	Nawada	0.387	0.267	0.583	0.413	689
	Pashchim Champaran	0.320	0.317	0.611	0.407	691
	Patna	0.459	0.349	0.589	0.468	628
	Purbi Champaran	0.330	0.268	0.619	0.400	698
	Purnia	0.248	0.377	0.645	0.404	693
	Rohtas	0.440	0.431	0.581	0.480	613
	Saharsa	0.310	0.426	0.568	0.420	684
	Samastipur	0.403	0.397	0.650	0.476	617
	Saran	0.443	0.389	0.669	0.496	577
	Sheikhpura	0.365	0.229	0.607	0.400	697
	Sheohar	0.362	0.292	0.609	0.417	685
	Sitamarhi	0.328	0.331	0.611	0.414	688
	Siwan	0.472	0.342	0.656	0.491	586
	Supaul	0.321	0.400	0.635	0.437	670
	Vaishali	0.379	0.345	0.586	0.432	678
Chandigarh	Chandigarh	0.762	0.565	0.701	0.689	90
Chhattisgarh	Balod	0.410	0.876	0.826	0.665	158
	Baloda Bazar	0.248	0.747	0.766	0.543	483
	Balrampur	0.219	0.640	0.702	0.482	611
	Bastar	0.246	0.654	0.669	0.487	599
	Bemetara	0.226	0.838	0.744	0.552	465
	Bijapur	0.201	0.377	0.390	0.307	714
	Bilaspur	0.365	0.698	0.754	0.575	415
	Dantewada	0.246	0.439	0.628	0.415	687
	Dhamtari	0.370	0.794	0.766	0.607	334
	Durg	0.503	0.812	0.818	0.684	108
	Gariyaband	0.234	0.823	0.779	0.562	448
	Gaurela-Pendra-Marwahi	0.270	0.714	0.763	0.542	487
	Janjgir-Champa	0.368	0.774	0.750	0.596	361
	Jashpur	0.336	0.672	0.756	0.556	458
	Kabeerdham	0.187	0.822	0.724	0.525	519
	Kondagaon	0.288	0.698	0.762	0.545	479
	Korba	0.397	0.682	0.769	0.588	383
	Korea	0.345	0.626	0.739	0.542	488
	Mahasamund	0.314	0.736	0.702	0.548	471
	Mungeli	0.187	0.786	0.724	0.515	539

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Narayanpur	0.239	0.561	0.745	0.481	612
	Raigarh	0.323	0.736	0.738	0.563	443
	Raipur	0.543	0.802	0.806	0.694	79
	Rajnandgaon	0.379	0.853	0.788	0.634	254
	Sukma	0.078	0.358	0.463	0.272	715
	Surajpur	0.243	0.644	0.737	0.503	561
	Surguja	0.331	0.663	0.689	0.531	509
	Uttar Bastar Kanker	0.387	0.736	0.796	0.607	336
Dadra & Nagar Haveli	Dadra and Nagar Haveli	0.437	0.624	0.804	0.599	353
and Daman & Diu	Daman	0.586	0.524	0.844	0.647	212
	Diu	0.625	0.657	0.718	0.662	166
Goa	North Goa	0.765	0.726	0.769	0.755	18
	South Goa	0.788	0.721	0.742	0.756	16
Gujarat	Ahmedabad	0.579	0.486	0.570	0.551	466
	Amreli	0.314	0.665	0.711	0.531	508
	Anand	0.329	0.674	0.647	0.521	530
	Aravali	0.245	0.727	0.709	0.519	536
	Banas Kantha	0.190	0.603	0.656	0.445	662
	Bharuch	0.461	0.651	0.673	0.578	409
	Bhavnagar	0.353	0.676	0.750	0.562	445
	Botad	0.191	0.622	0.708	0.467	629
	Chhota Udaipur	0.084	0.655	0.552	0.383	703
	Dahod	0.190	0.628	0.633	0.445	663
	Devbhumi Dwarka	0.306	0.694	0.737	0.544	482
	Gandhinagar	0.394	0.677	0.732	0.574	417
	Gir Somnath	0.346	0.757	0.757	0.584	394
	Jamnagar	0.368	0.690	0.689	0.554	461
	Junagadh	0.360	0.780	0.714	0.583	398
	Kachchh	0.295	0.541	0.601	0.455	648
	Kheda	0.179	0.640	0.687	0.460	639
	Mahesana	0.347	0.768	0.741	0.583	399
	Mahisagar	0.211	0.663	0.693	0.482	610
	Morbi	0.417	0.728	0.707	0.591	372
	Narmada	0.206	0.757	0.700	0.508	553
	Navsari	0.566	0.748	0.709	0.659	174
	Panch Mahals	0.203	0.602	0.647	0.448	658
	Patan	0.268	0.693	0.715	0.520	532
	Porbandar	0.310	0.678	0.698	0.529	511
	Rajkot	0.480	0.790	0.684	0.627	283
	Sabar Kantha	0.329	0.734	0.752	0.569	425
	Surat	0.593	0.701	0.684	0.650	198
	Surendranagar	0.247	0.639	0.673	0.484	607
	Tapi	0.347	0.834	0.763	0.607	335
	The Dangs	0.258	0.746	0.684	0.522	526
	Vadodara	0.511	0.720	0.727	0.634	253

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Valsad	0.541	0.694	0.709	0.634	255
Haryana	Ambala	0.617	0.721	0.723	0.678	119
	Bhiwani	0.549	0.794	0.676	0.655	185
	Charkhi Dadri	0.586	0.791	0.732	0.687	96
	Faridabad	0.627	0.646	0.682	0.649	203
	Fatehabad	0.422	0.778	0.736	0.615	312
	Gurugram	0.667	0.686	0.683	0.677	120
	Hisar	0.462	0.761	0.682	0.612	321
	Jhajjar	0.619	0.754	0.659	0.668	144
	Jind	0.512	0.779	0.747	0.657	180
	Kaithal	0.415	0.781	0.738	0.614	315
	Karnal	0.462	0.717	0.738	0.616	311
	Kurukshetra	0.566	0.787	0.710	0.671	131
	Mahendragarh	0.600	0.826	0.752	0.709	58
	Nuh	0.104	0.445	0.548	0.333	712
	Palwal	0.415	0.654	0.630	0.546	475
	Panchkula	0.673	0.635	0.673	0.663	165
	Panipat	0.532	0.748	0.742	0.655	186
	Rewari	0.656	0.815	0.759	0.731	34
	Rohtak	0.634	0.738	0.723	0.689	88
	Sirsa	0.446	0.808	0.736	0.634	256
	Sonipat	0.627	0.699	0.556	0.626	289
	Yamunanagar	0.585	0.685	0.677	0.640	230
Himachal Pradesh	Bilaspur	0.775	0.742	0.715	0.748	23
	Chamba	0.637	0.630	0.751	0.669	135
	Hamirpur	0.885	0.796	0.714	0.809	1
	Kangra	0.816	0.799	0.723	0.783	5
	Kinnaur	0.794	0.754	0.648	0.739	31
	Kullu	0.757	0.595	0.667	0.685	106
	Lahul and Spiti	0.819	0.698	0.645	0.733	32
	Mandi	0.831	0.598	0.687	0.723	46
	Shimla	0.860	0.703	0.731	0.778	8
	Sirmaur	0.590	0.702	0.725	0.662	168
	Solan	0.642	0.669	0.707	0.669	136
	Una	0.793	0.703	0.730	0.749	22
Jammu and Kashmir	Anantnag	0.455	0.770	0.752	0.632	265
	Bandipora	0.377	0.743	0.712	0.580	405
	Baramulla	0.477	0.666	0.679	0.590	375
	Budgam	0.484	0.727	0.726	0.625	291
	Doda	0.653	0.765	0.685	0.694	81
	Ganderbal	0.485	0.847	0.702	0.651	196
	Jammu	0.768	0.713	0.758	0.750	21
	Kathua	0.653	0.813	0.749	0.726	41
	Kishtwar	0.598	0.826	0.754	0.708	60
	Kulgam	0.480	0.756	0.741	0.635	251

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Kupwara	0.442	0.693	0.647	0.573	419
	Poonch	0.575	0.702	0.695	0.646	213
	Pulwama	0.532	0.758	0.767	0.666	155
	Rajouri	0.598	0.682	0.719	0.658	178
	Ramban	0.515	0.703	0.730	0.632	266
	Reasi	0.625	0.825	0.710	0.706	63
	Samba	0.755	0.789	0.731	0.757	14
	Shopian	0.511	0.803	0.762	0.668	147
	Srinagar	0.744	0.705	0.690	0.717	51
	Udhampur	0.670	0.793	0.737	0.725	44
Jharkhand	Bokaro	0.438	0.697	0.742	0.602	350
	Chatra	0.376	0.516	0.665	0.502	564
	Deoghar	0.267	0.587	0.634	0.467	630
	Dhanbad	0.443	0.609	0.697	0.565	439
	Dumka	0.231	0.548	0.707	0.463	635
	Garhwa	0.345	0.515	0.686	0.495	579
	Giridih	0.394	0.588	0.658	0.527	514
	Godda	0.291	0.518	0.643	0.460	641
	Gumla	0.351	0.517	0.641	0.485	604
	Hazaribagh	0.500	0.684	0.696	0.610	327
	Jamtara	0.266	0.498	0.663	0.450	655
	Khunti	0.368	0.527	0.634	0.492	584
	Koderma	0.468	0.618	0.659	0.567	430
	Latehar	0.336	0.527	0.565	0.458	645
	Lohardaga	0.370	0.527	0.665	0.503	562
	Pakur	0.151	0.388	0.637	0.363	710
	Palamu	0.432	0.590	0.651	0.542	485
	Pashchimi Singhbhum	0.338	0.406	0.596	0.435	674
	Purbi Singhbum	0.511	0.640	0.759	0.622	299
	Ramgarh	0.495	0.669	0.744	0.618	306
	Ranchi	0.548	0.666	0.722	0.633	261
	Sahibganj	0.250	0.397	0.622	0.403	696
	Saraikela-Kharsawan	0.343	0.598	0.641	0.504	558
	Simdega	0.398	0.558	0.619	0.509	551
Karnataka	Bagalkote	0.469	0.613	0.726	0.587	387
	Ballari	0.356	0.628	0.702	0.536	501
	Belagavi	0.521	0.667	0.789	0.642	222
	Bengaluru Rural	0.736	0.726	0.773	0.744	25
	Bengaluru Urban	0.813	0.522	0.696	0.697	75
	Bidar	0.479	0.617	0.743	0.597	358
	Chamarajanagar	0.483	0.583	0.704	0.577	412
	Chikkaballapura	0.572	0.749	0.756	0.677	122
	Chikkamagaluru	0.687	0.727	0.662	0.691	86
	Chitradurga	0.534	0.686	0.749	0.641	226
	Dakshina Kannada	0.787	0.481	0.707	0.678	118

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Davanagere	0.490	0.658	0.766	0.620	304
	Dharwad	0.543	0.588	0.770	0.624	293
	Gadag	0.397	0.602	0.743	0.558	451
	Hassan	0.665	0.774	0.767	0.726	43
	Haveri	0.432	0.593	0.735	0.568	429
	Kalaburagi	0.383	0.517	0.720	0.522	527
	Kodagu	0.740	0.609	0.703	0.692	83
	Kolar	0.646	0.710	0.716	0.685	105
	Koppal	0.296	0.637	0.698	0.512	547
	Mandya	0.653	0.507	0.592	0.594	366
	Mysuru	0.635	0.680	0.702	0.668	148
	Raichur	0.258	0.539	0.708	0.472	624
	Ramanagara	0.601	0.671	0.767	0.671	132
	Shivamogga	0.616	0.662	0.749	0.669	140
	Tumakuru	0.684	0.723	0.759	0.718	49
	Udupi	0.778	0.683	0.699	0.728	39
	Uttara Kannada	0.591	0.623	0.752	0.648	205
	Vijayapura	0.421	0.577	0.671	0.540	493
	Yadgir	0.222	0.494	0.718	0.447	660
Kerala	Alappuzha	0.941	0.681	0.654	0.782	6
	Ernakulam	0.963	0.599	0.716	0.787	3
	Idukki	0.858	0.605	0.701	0.741	28
	Kannur	0.919	0.446	0.670	0.713	57
	Kasaragod	0.809	0.396	0.685	0.657	182
	Kollam	0.914	0.683	0.687	0.782	7
	Kottayam	0.946	0.619	0.678	0.774	10
	Kozhikode	0.923	0.701	0.689	0.791	2
	Malappuram	0.875	0.520	0.694	0.722	48
	Palakkad	0.819	0.617	0.716	0.732	33
	Pathanamthitta	0.975	0.610	0.634	0.771	11
	Thiruvananthapuram	0.903	0.673	0.697	0.777	9
	Thrissur	0.937	0.558	0.695	0.759	13
	Wayanad	0.773	0.665	0.717	0.726	42
Ladakh	Kargil	0.668	0.793	0.718	0.718	50
	Leh Ladakh	0.771	0.778	0.706	0.754	20
Lakshadweep	Lakshadweep	0.824	0.420	0.672	0.666	154
Madhya Pradesh	Agar Malwa	0.225	0.740	0.746	0.525	520
	Alirajpur	0.015	0.674	0.622	0.381	705
	Anuppur	0.310	0.771	0.742	0.568	427
	Ashoknagar	0.126	0.783	0.744	0.494	580
	Balaghat	0.311	0.843	0.759	0.594	367
	Barwani	0.116	0.808	0.665	0.474	620
	Betul	0.358	0.820	0.760	0.608	332
	Bhind	0.332	0.651	0.684	0.527	515
	Bhopal	0.535	0.798	0.795	0.686	100

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Burhanpur	0.171	0.764	0.689	0.492	585
	Chhatarpur	0.206	0.701	0.710	0.495	578
	Chhindwara	0.311	0.860	0.755	0.597	356
	Damoh	0.207	0.794	0.775	0.541	489
	Datia	0.247	0.755	0.757	0.542	484
	Dewas	0.254	0.803	0.754	0.557	452
	Dhar	0.257	0.739	0.755	0.541	490
	Dindori	0.226	0.837	0.753	0.554	460
	Guna	0.088	0.740	0.727	0.462	638
	Gwalior	0.382	0.724	0.708	0.575	414
	Harda	0.257	0.736	0.745	0.537	499
	Hoshangabad	0.380	0.744	0.773	0.599	354
	Indore	0.568	0.760	0.753	0.677	121
	Jabalpur	0.458	0.792	0.788	0.650	199
	Jhabua	0.029	0.735	0.651	0.413	690
	Katni	0.386	0.804	0.750	0.612	322
	Khandwa (East Nimar)	0.155	0.819	0.738	0.515	540
	Khargone (West Nimar)	0.158	0.824	0.714	0.511	548
	Mandla	0.258	0.826	0.783	0.574	418
	Mandsaur	0.318	0.782	0.808	0.595	364
	Morena	0.276	0.634	0.681	0.497	575
	Narsimhapur	0.252	0.879	0.784	0.587	386
	Neemuch	0.364	0.763	0.775	0.598	355
	Panna	0.246	0.637	0.696	0.490	589
	Raisen	0.237	0.822	0.773	0.561	449
	Rajgarh	0.231	0.769	0.772	0.544	481
	Ratlam	0.266	0.752	0.718	0.538	498
	Rewa	0.353	0.723	0.658	0.547	472
	Sagar	0.266	0.689	0.740	0.526	517
	Satna	0.317	0.775	0.687	0.556	457
	Sehore	0.272	0.806	0.771	0.570	423
	Seoni	0.322	0.799	0.764	0.588	384
	Shahdol	0.340	0.789	0.750	0.588	381
	Shajapur	0.292	0.827	0.776	0.586	390
	Sheopur	0.085	0.678	0.743	0.448	656
	Shivpuri	0.129	0.756	0.742	0.488	597
	Sidhi	0.307	0.798	0.685	0.557	453
	Singrauli	0.221	0.692	0.665	0.486	601
	Tikamgarh	0.180	0.708	0.720	0.489	593
	Ujjain	0.328	0.769	0.756	0.580	406
	Umaria	0.293	0.831	0.749	0.580	403
	Vidisha	0.240	0.758	0.750	0.538	496
Maharashtra	Ahmednagar	0.493	0.573	0.707	0.580	404
	Akola	0.458	0.584	0.633	0.546	476
	Amravati	0.519	0.594	0.653	0.580	402

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Aurangabad	0.519	0.462	0.632	0.538	497
	Beed	0.407	0.516	0.611	0.499	570
	Bhandara	0.553	0.727	0.768	0.666	153
	Buldhana	0.324	0.506	0.688	0.484	606
	Chandrapur	0.548	0.626	0.716	0.620	303
	Dhule	0.345	0.608	0.582	0.490	592
	Gadchiroli	0.423	0.543	0.639	0.522	528
	Gondia	0.506	0.613	0.739	0.606	338
	Hingoli	0.214	0.498	0.617	0.415	686
	Jalgaon	0.371	0.615	0.554	0.494	582
	Jalna	0.299	0.433	0.612	0.431	679
	Kolhapur	0.581	0.641	0.658	0.621	301
	Latur	0.464	0.458	0.600	0.503	560
	Mumbai	0.765	0.396	0.762	0.662	169
	Mumbai Suburban	0.714	0.456	0.703	0.639	237
	Nagpur	0.703	0.568	0.562	0.623	295
	Nanded	0.330	0.510	0.645	0.475	619
	Nandurbar	0.149	0.494	0.613	0.385	702
	Nashik	0.432	0.607	0.664	0.550	467
	Osmanabad	0.442	0.600	0.604	0.535	504
	Palghar	0.422	0.579	0.631	0.529	512
	Parbhani	0.325	0.483	0.609	0.455	649
	Pune	0.728	0.614	0.742	0.700	72
	Raigad	0.659	0.571	0.571	0.608	330
	Ratnagiri	0.589	0.629	0.625	0.611	326
	Sangli	0.575	0.614	0.732	0.633	260
	Satara	0.633	0.670	0.675	0.656	183
	Sindhudurg	0.595	0.619	0.679	0.627	285
	Solapur	0.439	0.637	0.672	0.564	440
	Thane	0.744	0.546	0.586	0.641	225
	Wardha	0.569	0.715	0.670	0.640	231
	Washim	0.333	0.553	0.681	0.499	571
	Yavatmal	0.331	0.581	0.692	0.510	550
Meghalaya	East Garo Hills	0.390	0.623	0.509	0.491	588
	East Jaintia Hills	0.458	0.682	0.522	0.540	494
	East Khasi Hills	0.678	0.287	0.112	0.399	700
	North Garo Hills	0.475	0.455	0.164	0.376	708
	Ribhoi	0.389	0.532	0.537	0.473	621
	South Garo Hills	0.524	0.424	0.755	0.566	436
	South West Garo Hills	0.518	0.509	0.765	0.590	374
	South West Khasi Hills	0.493	0.698	0.545	0.566	438
	West Garo Hills	0.470	0.445	0.693	0.530	510
	West Jaintia Hills	0.452	0.641	0.478	0.512	546
	West Khasi Hills	0.449	0.568	0.559	0.515	542
Mizoram	Aizawl	0.812	0.499	0.652	0.677	123

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Champhai	0.670	0.707	0.610	0.662	167
	Kolasib	0.659	0.532	0.713	0.640	234
	Lawngtlai	0.559	0.587	0.772	0.631	271
	Lunglei	0.688	0.700	0.759	0.713	56
	Mamit	0.586	0.550	0.718	0.616	310
	Saiha	0.722	0.614	0.737	0.697	76
	Serchhip	0.703	0.665	0.691	0.689	91
Nagaland	Dimapur	0.757	0.638	0.703	0.708	62
	Kiphire	0.440	0.733	0.587	0.566	435
	Kohima	0.746	0.684	0.659	0.703	68
	Longleng	0.542	0.816	0.694	0.664	160
	Mokokchung	0.725	0.776	0.606	0.703	65
	Mon	0.411	0.684	0.532	0.523	524
	Peren	0.510	0.614	0.558	0.553	462
	Phek	0.549	0.689	0.550	0.588	379
	Tuensang	0.457	0.779	0.561	0.578	410
	Wokha	0.729	0.747	0.714	0.729	37
	Zunheboto	0.591	0.775	0.569	0.635	249
NCT of Delhi	Central	0.729	0.448	0.662	0.631	272
	East	0.760	0.365	0.709	0.635	252
	New Delhi	0.717	0.616	0.642	0.666	151
	North	0.661	0.405	0.549	0.556	455
	North East	0.673	0.282	0.460	0.500	569
	North West	0.729	0.513	0.676	0.653	188
	Shahdara	0.646	0.443	0.666	0.596	362
	South	0.782	0.512	0.638	0.664	162
	South East	0.720	0.560	0.702	0.670	134
	South West	0.751	0.533	0.667	0.665	156
	West	0.701	0.516	0.684	0.644	220
Odisha	Anugul	0.511	0.850	0.721	0.669	141
	Balangir	0.361	0.784	0.715	0.585	392
	Baleshwar	0.507	0.724	0.726	0.633	262
	Bargarh	0.375	0.790	0.728	0.597	359
	Bhadrak	0.545	0.669	0.685	0.622	298
	Boudh	0.317	0.785	0.735	0.573	421
	Cuttack	0.638	0.672	0.628	0.645	218
	Deogarh	0.470	0.693	0.723	0.608	331
	Dhenkanal	0.506	0.781	0.698	0.640	229
	Gajapati	0.332	0.796	0.748	0.586	388
	Ganjam	0.452	0.717	0.724	0.608	333
	Jagatsinghapur	0.587	0.643	0.738	0.648	208
	Jajapur	0.548	0.788	0.689	0.657	181
	Jharsuguda	0.559	0.684	0.629	0.615	313
	Kalahandi	0.371	0.822	0.699	0.595	363
	Kandhamal	0.343	0.687	0.679	0.540	491

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Kendrapara	0.529	0.623	0.659	0.594	365
	Kendujhar	0.436	0.776	0.689	0.607	337
	Khordha	0.652	0.564	0.731	0.651	195
	Koraput	0.180	0.737	0.692	0.489	595
	Malkangiri	0.118	0.724	0.675	0.454	650
	Mayurbhanj	0.419	0.630	0.659	0.550	468
	Nabarangpur	0.142	0.711	0.757	0.485	602
	Nayagarh	0.521	0.834	0.707	0.664	161
	Nuapada	0.305	0.791	0.735	0.570	424
	Puri	0.540	0.599	0.696	0.603	347
	Rayagada	0.193	0.722	0.690	0.490	591
	Sambalpur	0.484	0.789	0.692	0.631	270
	Sonepur	0.372	0.770	0.734	0.592	369
	Sundargarh	0.556	0.688	0.670	0.627	286
Puducherry	Karaikal	0.767	0.557	0.696	0.687	95
	Mahe	0.948	0.607	0.728	0.787	4
	Pondicherry	0.789	0.529	0.809	0.723	45
	Yanam	0.613	0.624	0.686	0.638	241
Punjab	Amritsar	0.607	0.572	0.570	0.586	391
	Barnala	0.634	0.662	0.687	0.658	177
	Bathinda	0.573	0.680	0.664	0.630	275
	Faridkhot	0.526	0.700	0.728	0.636	248
	Fatehgarh Sahib	0.640	0.502	0.689	0.617	309
	Fazilka	0.452	0.707	0.749	0.612	318
	Firozpur	0.478	0.615	0.608	0.555	459
	Gurdaspur	0.684	0.622	0.627	0.650	202
	Hoshiarpur	0.754	0.476	0.675	0.653	190
	Jalandhar	0.669	0.547	0.654	0.630	273
	Kapurthala	0.649	0.501	0.702	0.623	294
	Ludhiana	0.675	0.570	0.580	0.617	308
	Mansa	0.487	0.723	0.740	0.629	278
	Moga	0.594	0.639	0.661	0.627	287
	Pathankot	0.745	0.645	0.737	0.715	53
	Patiala	0.607	0.476	0.532	0.548	470
	Rupnagar	0.750	0.628	0.692	0.698	73
	Sahibzada Ajit Singh Nagar	0.692	0.515	0.548	0.600	352
	Sangrur	0.590	0.542	0.630	0.589	377
	Shahid Bhagat Singh Nagar	0.728	0.549	0.712	0.673	127
	Sri Muktsar Sahib	0.514	0.721	0.743	0.641	228
	Tarn Taran	0.482	0.575	0.697	0.573	420
Rajasthan	Ajmer	0.514	0.820	0.640	0.637	242
	Alwar	0.347	0.834	0.707	0.591	373
	Banswara	0.222	0.728	0.682	0.501	567
	Baran	0.235	0.841	0.763	0.563	444
	Barmer	0.442	0.887	0.660	0.632	268

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Bharatpur	0.243	0.743	0.669	0.510	549
	Bhilwara	0.400	0.856	0.661	0.605	340
	Bikaner	0.355	0.818	0.689	0.584	393
	Bundi	0.243	0.875	0.734	0.566	433
	Chittaurgarh	0.373	0.811	0.731	0.603	348
	Churu	0.433	0.785	0.703	0.612	319
	Dausa	0.345	0.864	0.726	0.604	343
	Dholpur	0.201	0.799	0.658	0.505	555
	Dungarpur	0.378	0.761	0.706	0.583	397
	Ganganagar	0.439	0.858	0.785	0.660	173
	Hanumangarh	0.405	0.859	0.730	0.629	277
	Jaipur	0.568	0.811	0.688	0.672	130
	Jaisalmer	0.307	0.775	0.643	0.538	495
	Jalore	0.306	0.783	0.620	0.533	506
	Jhalawar	0.247	0.827	0.737	0.556	456
	Jhunjhunu	0.550	0.847	0.714	0.682	110
	Jodhpur	0.477	0.962	0.721	0.685	103
	Karauli	0.224	0.806	0.682	0.524	523
	Kota	0.469	0.861	0.738	0.659	176
	Nagaur	0.463	0.831	0.725	0.644	219
	Pali	0.432	0.702	0.702	0.588	380
	Pratapgarh	0.245	0.744	0.680	0.515	543
	Rajsamand	0.363	0.757	0.676	0.566	432
	Sawai Madhopur	0.245	0.799	0.712	0.540	492
	Sikar	0.564	0.817	0.606	0.647	211
	Sirohi	0.309	0.741	0.612	0.520	533
	Tonk	0.350	0.870	0.718	0.606	339
	Udaipur	0.400	0.794	0.646	0.584	396
Sikkim	East District	0.775	0.571	0.765	0.715	52
	North District	0.646	0.567	0.688	0.637	244
	South District	0.673	0.475	0.725	0.634	258
	West District	0.729	0.712	0.866	0.766	12
Tamil Nadu	Ariyalur	0.601	0.599	0.726	0.638	238
	Chengalpattu	0.767	0.645	0.437	0.634	257
	Chennai	0.850	0.645	0.700	0.748	24
	Coimbatore	0.746	0.556	0.596	0.648	209
	Cuddalore	0.599	0.663	0.709	0.650	201
	Dharmapuri	0.614	0.744	0.677	0.669	138
	Dindigul	0.609	0.621	0.650	0.625	292
	Erode	0.670	0.657	0.676	0.668	146
	Kallakurichi	0.547	0.702	0.713	0.640	232
	Kanchipuram	0.734	0.633	0.726	0.703	67
	Kanniyakumari	0.842	0.664	0.681	0.744	26
	Karur	0.621	0.546	0.632	0.603	346
	Krishnagiri	0.633	0.701	0.688	0.669	143

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Madurai	0.666	0.529	0.516	0.583	400
	Mayiladuthurai	0.639	0.624	0.744	0.666	152
	Nagapattinam	0.662	0.686	0.722	0.687	97
	Namakkal	0.686	0.688	0.722	0.698	74
	Perambalur	0.667	0.668	0.672	0.669	142
	Pudukkottai	0.639	0.627	0.722	0.660	171
	Ramanathapuram	0.678	0.621	0.682	0.663	164
	Ranipet	0.628	0.699	0.730	0.679	117
	Salem	0.616	0.648	0.663	0.639	235
	Sivaganga	0.701	0.538	0.667	0.646	216
	Tenkasi	0.599	0.594	0.703	0.629	279
	Thanjavur	0.707	0.602	0.697	0.675	125
	The Nilgiris	0.757	0.742	0.715	0.740	29
	Theni	0.580	0.636	0.416	0.546	474
	Thiruvallur	0.726	0.643	0.545	0.648	204
	Thiruvarur	0.674	0.625	0.685	0.664	163
	Tiruchirappalli	0.721	0.594	0.629	0.658	179
	Tirunelveli	0.735	0.512	0.653	0.648	206
	Tirupathur	0.623	0.725	0.705	0.676	124
	Tiruppur	0.676	0.593	0.730	0.669	137
	Tiruvannamalai	0.551	0.711	0.725	0.648	207
	Tuticorin	0.705	0.570	0.682	0.661	170
	Vellore	0.588	0.665	0.722	0.650	200
	Villupuram	0.578	0.733	0.737	0.669	139
	Virudhunagar	0.570	0.632	0.652	0.612	320
Telangana	Adilabad	0.353	0.638	0.741	0.549	469
	Bhadradri Kothagudem	0.471	0.813	0.760	0.653	189
	Hanumakonda	0.708	0.740	0.658	0.702	69
	Hyderabad	0.750	0.620	0.431	0.618	307
	Jagitial	0.588	0.667	0.728	0.652	192
	Jangoan	0.535	0.797	0.726	0.665	157
	Jayashankar Bhupalapally	0.453	0.755	0.837	0.653	191
	Jogulamba Gadwal	0.230	0.788	0.685	0.522	525
	Kamareddy	0.470	0.744	0.754	0.632	267
	Karimnagar	0.634	0.741	0.757	0.701	71
	Khammam	0.437	0.821	0.762	0.642	223
	Kumuram Bheem Asifabad	0.273	0.646	0.767	0.526	518
	Mahabubabad	0.421	0.838	0.758	0.638	240
	Mahabubnagar	0.486	0.792	0.721	0.642	224
	Mancherial	0.500	0.689	0.751	0.628	280
	Medak	0.438	0.772	0.758	0.627	284
	Medchal Malkajgiri	0.750	0.687	0.652	0.703	66
	Mulugu	0.432	0.768	0.767	0.626	288
	Nagarkurnool	0.464	0.784	0.724	0.631	269
	Nalgonda	0.521	0.813	0.781	0.680	113

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Narayanpet	0.296	0.673	0.719	0.528	513
	Nirmal	0.465	0.624	0.737	0.591	371
	Nizamabad	0.603	0.645	0.661	0.632	264
	Peddapalli	0.597	0.664	0.699	0.646	214
	Rajanna Sircilla	0.648	0.694	0.748	0.691	85
	Ranga Reddy	0.651	0.708	0.746	0.696	78
	Sangareddy	0.528	0.724	0.697	0.633	259
	Siddipet	0.597	0.760	0.741	0.686	101
	Suryapet	0.491	0.786	0.734	0.646	215
	Vikarabad	0.440	0.731	0.740	0.611	325
	Wanaparthy	0.464	0.746	0.728	0.622	297
	Warangal Rural	0.472	0.797	0.784	0.656	184
	Yadadri Bhuvanagiri	0.580	0.762	0.760	0.685	104
Tripura	Dhalai	0.321	0.569	0.702	0.505	556
	Gomati	0.404	0.619	0.771	0.575	416
	Khowai	0.326	0.520	0.776	0.516	538
	North Tripura	0.395	0.458	0.665	0.494	581
	Sepahijala	0.382	0.685	0.750	0.577	411
	South Tripura	0.328	0.772	0.793	0.591	370
	Unakoti	0.354	0.536	0.717	0.514	544
	West Tripura	0.517	0.751	0.798	0.667	150
Uttar Pradesh	Agra	0.400	0.454	0.631	0.485	603
	Aligarh	0.376	0.528	0.593	0.484	608
	Ambedkar Nagar	0.525	0.453	0.713	0.562	447
	Amethi	0.378	0.429	0.693	0.487	598
	Amroha	0.350	0.503	0.697	0.497	576
	Auraiya	0.429	0.493	0.651	0.514	545
	Ayodhya	0.447	0.452	0.697	0.524	522
	Azamgarh	0.544	0.458	0.696	0.566	434
	Baghpat	0.450	0.510	0.711	0.546	477
	Bahraich	0.242	0.276	0.635	0.370	709
	Ballia	0.530	0.499	0.659	0.560	450
	Balrampur	0.291	0.200	0.675	0.381	704
	Banda	0.300	0.458	0.634	0.444	664
	Barabanki	0.279	0.429	0.669	0.438	669
	Bareilly	0.263	0.469	0.677	0.445	661
	Basti	0.448	0.469	0.669	0.521	531
	Bhadohi	0.461	0.445	0.727	0.537	500
	Bijnor	0.382	0.445	0.641	0.477	615
	Budaun	0.212	0.466	0.612	0.403	695
	Bulandshahr	0.351	0.498	0.656	0.484	609
	Chandauli	0.473	0.531	0.685	0.553	464
	Chitrakoot	0.316	0.553	0.626	0.475	618
	Deoria	0.496	0.398	0.667	0.520	534
	Etah	0.358	0.476	0.628	0.472	623

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Etawah	0.490	0.506	0.626	0.536	502
	Farrukhabad	0.306	0.423	0.638	0.439	668
	Fatehpur	0.365	0.477	0.672	0.488	596
	Firozabad	0.398	0.515	0.658	0.509	552
	Gautam Buddha Nagar	0.551	0.622	0.613	0.589	376
	Ghaziabad	0.598	0.547	0.694	0.613	317
	Ghazipur	0.512	0.435	0.661	0.536	503
	Gonda	0.387	0.352	0.661	0.460	640
	Gorakhpur	0.545	0.486	0.742	0.588	382
	Hamirpur	0.339	0.524	0.585	0.465	632
	Hapur	0.437	0.505	0.639	0.517	537
	Hardoi	0.225	0.427	0.705	0.426	683
	Hathras	0.322	0.424	0.595	0.433	675
	Jalaun	0.401	0.505	0.659	0.507	554
	Jaunpur	0.527	0.440	0.706	0.557	454
	Jhansi	0.391	0.569	0.449	0.458	646
	Kannauj	0.331	0.371	0.665	0.443	665
	Kanpur Dehat	0.394	0.420	0.698	0.493	583
	Kanpur Nagar	0.588	0.443	0.736	0.592	368
	Kasganj	0.329	0.486	0.629	0.463	634
	Kaushambi	0.342	0.410	0.648	0.453	651
	Kheri	0.159	0.359	0.696	0.376	707
	Kushinagar	0.379	0.490	0.686	0.503	563
	Lalitpur	0.213	0.583	0.698	0.462	637
	Lucknow	0.529	0.497	0.689	0.569	426
	Maharajganj	0.388	0.489	0.661	0.498	573
	Mahoba	0.297	0.541	0.656	0.473	622
	Mainpuri	0.406	0.453	0.631	0.487	600
	Mathura	0.342	0.465	0.655	0.470	625
	Mau	0.516	0.548	0.729	0.589	378
	Meerut	0.498	0.495	0.646	0.542	486
	Mirzapur	0.416	0.572	0.727	0.553	463
	Moradabad	0.331	0.474	0.686	0.478	614
	Muzaffarnagar	0.352	0.456	0.626	0.463	633
	Pilibhit	0.247	0.506	0.688	0.452	652
	Pratapgarh	0.494	0.473	0.743	0.563	442
	Prayagraj	0.526	0.452	0.714	0.562	446
	Rae Bareli	0.399	0.410	0.726	0.500	568
	Rampur	0.300	0.438	0.694	0.457	647
	Saharanpur	0.346	0.492	0.718	0.499	572
	Sambhal	0.181	0.459	0.649	0.399	699
	Sant Kabir Nagar	0.427	0.379	0.706	0.498	574
	Shahjahanpur	0.284	0.476	0.686	0.458	644
	Shamli	0.335	0.477	0.715	0.489	594
	Shrawasti	0.176	0.243	0.590	0.320	713

State/Union Territory	District	SSC	IEC	LVC	SPI	Rank
	Siddharth Nagar	0.328	0.338	0.675	0.435	673
	Sitapur	0.193	0.355	0.654	0.377	706
	Sonbhadra	0.329	0.531	0.717	0.502	565
	Sultanpur	0.444	0.435	0.721	0.525	521
	Unnao	0.402	0.408	0.688	0.490	590
	Varanasi	0.536	0.602	0.699	0.604	345
Uttarakhand	Almora	0.664	0.755	0.678	0.694	82
	Bageshwar	0.638	0.718	0.708	0.681	112
	Chamoli	0.706	0.801	0.691	0.728	38
	Champawat	0.631	0.767	0.700	0.689	89
	Dehradun	0.732	0.772	0.771	0.755	17
	Haridwar	0.397	0.706	0.708	0.577	413
	Nainital	0.670	0.819	0.723	0.728	40
	Pauri Garhwal	0.746	0.796	0.691	0.743	27
	Pithoragarh	0.655	0.723	0.704	0.689	92
	Rudra Prayag	0.722	0.755	0.720	0.731	35
	Tehri Garhwal	0.630	0.723	0.716	0.682	111
	Udham Singh Nagar	0.471	0.694	0.732	0.612	323
	Uttarkashi	0.584	0.806	0.725	0.688	93
West Bengal	Alipurduar	0.447	0.814	0.746	0.639	236
	Bankura	0.240	0.905	0.747	0.578	408
	Birbhum	0.287	0.937	0.742	0.605	342
	Cooch Behar	0.368	0.890	0.738	0.625	290
	Dakshin Dinajpur	0.417	0.828	0.755	0.633	263
	Darjeeling	0.570	0.832	0.712	0.686	102
	Hooghly	0.537	0.943	0.730	0.708	61
	Howrah	0.544	0.923	0.730	0.706	64
	Jalpaiguri	0.492	0.793	0.706	0.640	233
	Jhargram	0.343	0.937	0.749	0.630	276
	Kalimpong	0.643	0.579	0.681	0.637	243
	Kolkata	0.657	0.765	0.647	0.684	109
	Maldah	0.373	0.789	0.689	0.584	395
	Murshidabad	0.399	0.884	0.667	0.614	314
	Nadia	0.449	0.847	0.780	0.659	175
	North 24 Parganas	0.572	0.853	0.782	0.714	54
	Paschim Bardhaman	0.506	0.861	0.736	0.674	126
	Paschim Medinipur	0.376	0.879	0.772	0.635	250
	Purba Bardhaman	0.353	0.968	0.777	0.652	194
	Purba Medinipur	0.456	0.952	0.776	0.690	87
	Purulia	0.293	0.773	0.687	0.545	478
	South 24 Parganas	0.413	0.847	0.735	0.630	274
	Uttar Dinajpur	0.366	0.747	0.683	0.567	431

Source: Author

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Prevalence and Determinants of Non-Communicable Diseases in Urban Slums of Bhubaneswar, Odisha, India

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Abstract

This study estimated the prevalence of self-reported non-communicable diseases (NCDs) and examined its association with demographic, social, cultural and other characteristics of 1269 adults aged 18 years and above residing in selected urban slums of Bhubaneswar city of Odisha, India. The reported prevalence of NCDs was 18.8 per cent. The reported prevalence of cardiovascular diseases was the highest followed by diabetes and arthritis. Among the respondents who reported having an NCD, 22.6 per cent reported having multiple NCDs. The reported prevalence of NCDs was higher in females than in males. Age, low or moderate physical activity, and stage 2 hypertension were independently associated with higher odds of reporting an NCD. High waist-to-hip ratio showed a positive but statistically insignificant association. Women had higher prevalence of NCDs than men. Although based on a purposive sample, these findings call for community-based health promotion, screening, early diagnosis, and treatment of NCDs in the underserved urban populations.

Introduction

India is currently undergoing epidemiological transition, marked by an increasing burden of non-communicable diseases (NCDs). According to the World Health Organization (WHO), NCDs have now emerged as the leading causes of disability and premature mortality among adults in India. It is estimated that approximately one out of every four Indians are, on average, estimated to be at the risk of dying from an NCD before reaching 70 years of age (WHO, 2010). Among different NCDs, hypertension and diabetes alone account for more than 70 per cent of all NCDs morbidity which highlights an urgent need for targeting public health interventions for the management of NCDs in the community. The drivers behind the increasing burden of NCDs include, among others, rapid urbanisation, changes in the life style of individuals and socioeconomic disparities. Urban growth, particularly unplanned urban growth or urban sprawl, characterised by overcrowding, poor sanitation facilities, limited access to clean water, and substandard housing conditions leading to a deteriorated physical environment and adoption of unhealthy behaviours by people living in these areas. These factors disproportionately affect the health status of the population residing in these areas (Brashier et el, 2012; Bhojani et al, 2013).

India has witnessed rapid urbanisation in the recent past because of strong rural to urban migration. However, despite rapid urban expansion, stark health inequalities are common within urban areas. Urban slum residents, specifically, face the dual burden of diseases and social disadvantages, making them highly vulnerable to chronic illnesses. Recent studies have documented high NCDs prevalence among slum populations across different Indian cities, including Bengaluru (Gowda et al, 2015), Puducherry (Naik et al, 2020), Salem (Shanmugam et al, 2018), and Delhi (Singh et al, 2023) underscoring the urgent need for localised health strategies.

Odisha is relatively a less urbanised states compared to some states of India but has marked urban health inequalities. The Annual Health Survey (AHS) 2012–13 covered selected high-focus states, including Odisha, but did not provide a national estimate. According to this survey Odisha had 9417 persons with at least chronic illness per 100,000 population (Government of India, 2013). Studies from Bengaluru, Puducherry, Salem, Delhi, and other Indian cities have described substantial health risks faced by the people living in urban slum. However, comparable evidence of the prevalence of NCDs in Odisha remains limited (Gowda et al, 2015; Naik et al, 2020; Shanmugam et al, 2018; Singh et al, 2023).

Bhubaneswar is the capital and the largest urban settlement of Odisha and is administered by the Bhubaneswar Municipal Corporation. The city of Bhubaneswar is administratively divided into 67 wards (Government of Odisha, 2025). A substantial share of the city population live in recognised, but informal slum settlements, where constrained housing, environmental exposure, and barriers to continuous health care increases the vulnerability to NCDs. The present study is, therefore, aims to estimate the prevalence of NCDs in urban slums of Bhubaneswar and analyse social, cultural and economic factors that may be associated with its prevalence. Collecting reliable community-level data on NCDs is crucial for informing prevention strategies, healthcare resource allocation, and progress toward achieving the United Nations Sustainable Development Goals in general and the goal of reducing premature NCD-related mortality by one-third by 2030.

Materials and Methods

Study Population

The study is based on a purposive sample of 1269 adults aged at least 18 years from 748 households selected from 22 slums, as recognised by the civic administration, in 10 of the 21 Municipal Wards under the North Administrative Zone of the Bhubaneswar Municipal Corporation.

Study Design and Participants

The study is based on the information collected through a community-based survey of a sample of households. All adults aged 18 years and above in the sampled households who were available at the time of the household visit and who provided their informed consent for participation in the survey were surveyed. Direct interview by investigators trained for the purpose was carried out to collect the information related to NCDs. The survey also collected the background demographic, social, economic characteristics of the respondents and the living conditions of the household.

Sampling Method

Although the sample for the study is not statistically representative of the slum population of the Bhubaneswar city, it was selected in three stages. At the first stage one, North Zone, out of the three administrative zones of the Bhubaneswar city was selected. At the second stage, 10 out of the 21 Municipal Wards in the North Zone were selected (Figure 1). At the third stage, 22 slum settlements within the selected wards were selected taking into consideration the operational constraints related to the household survey. In each selected slum, field investigators visited each and every household to identify adults at least 18 years old and sought their consent to participate in the survey. Only those adults aged at least 18 years were covered under the survey who provided their consent for participation in the survey. Since the sample for the survey is purposive, the findings based on the survey cannot be generalised for the entire slum population of the Bhubaneswar city. They, however, provide an idea of the seriousness of the problem of NCDs in urban slums and call for concerted efforts to address the problem.

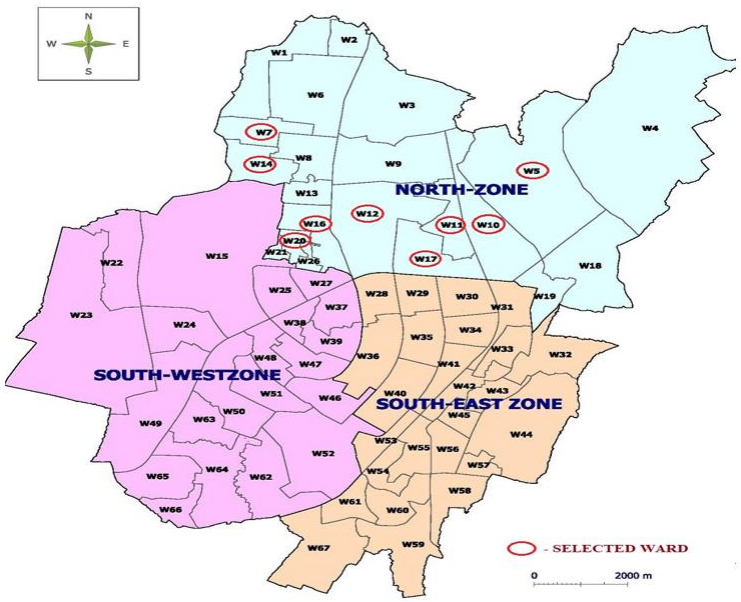

Figure 1: Municipal Wards selected of Bhubaneswar city selected for the survey.
Source: Authors

Technical Details

Data collection was informed by the World Health Organization STEPwise approach to NCD risk-factor surveillance. The step 1 of this approach uses interviewer-administered questions to collect sociodemographic characteristics, behavioural risk factors, and history of previously diagnosed conditions while the step 2 adds standardised physical measurements. In the present study, trained field investigators administered the questionnaire through direct

interview and physically measured height, weight, waist and hip circumferences, and blood pressure of the respondents using standardised procedures. No data about biochemical biomarkers were collected under the study.

Statistical Analysis

The dependent variable was the presence of at least one self-reported NCD (yes=1, no=0). Categorical variables were summarised using frequencies and percentages. Bivariate associations between the binary outcome and categorical explanatory variables were assessed using Pearson's chi-square test while Fisher's exact test was used when expected cell counts were small. Test statistics, degrees of freedom, and p-values are reported. The multivariable binary logistic regression model was then fitted to estimate adjusted associations, expressed as adjusted odds ratios (ORs) with 95 per cent confidence intervals (CIs). Variables were selected from the bivariate analysis and prior evidence. Data were analysed using IBM SPSS Statistics version 25.0, and two-sided $p<0.05$ was considered statistically significant.

Results

Among 1269 respondents residing in 22 selected urban slums of Bhubaneswar, 238 (18.8 per cent) self-reported that they had at least one NCD (Figure 2). The reported conditions were based on the response of the participants and were not independently verified against medical records. Among these 238 participants, cardiovascular diseases were reported by 101 (42.6 per cent), diabetes by 96 (40.3 per cent), and arthritis by 41 (17.2 per cent) respondents. Chronic respiratory disease was reported by 25 (10.5 per cent), while cancer and chronic kidney disease were each reported by 2 (0.8 per cent) respondents. Many respondents reported that they were having more than one chronic condition. The disease-specific reported proportions, therefore, are not mutually exclusive and do not sum to 100 (Table 1).

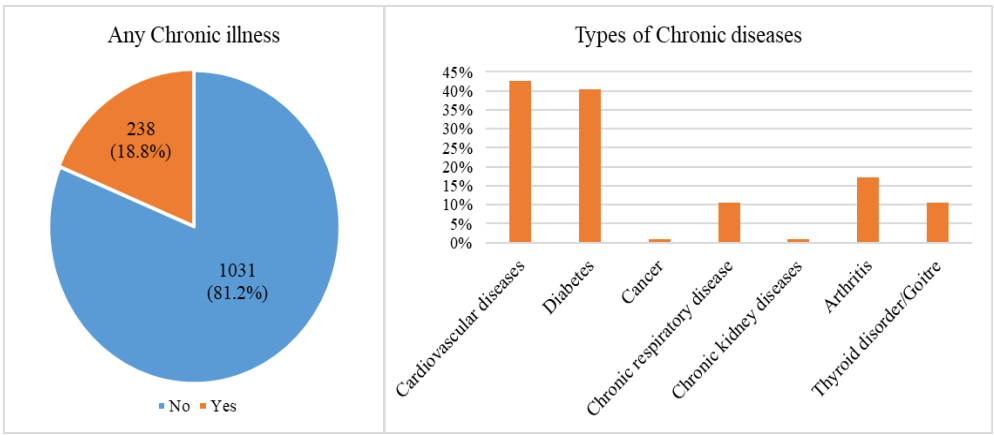

Figure 2: Proportion of respondents reporting at least one chronic disease and proportion of respondents reporting specific diseases.
Source: Authors

Table 1: Reported prevalence of any NCD and of specific NCDs in the total sample and in males and females.

NCD	Total	Male	Female	Female-male difference		
				SE	Z	p
Any NCD	18.8	16.3	20.8	0.022	2.099	<0.05
Cardiovascular diseases	8.0	6.4	9.3	0.015	1.892	≥0.05
Diabetes	7.6	7.4	7.7	0.015	0.156	≥0.05
Cancer	0.2	0.3	0.0	0.002	-1.562	≥0.05
Chronic respiratory diseases	2.0	2.2	1.7	0.008	-0.660	≥0.05
Chronic kidney diseases	0.2	0.3	0.0	0.002	-1.562	≥0.05
Arthritis	3.2	1.2	4.9	0.010	3.756	<0.05
Thyroid disorder/Goitre	2.0	0.3	3.3	0.008	3.843	<0.05
N	1269	578	691			

Source: Authors

Women constituted 54.5 per cent of the total sample. Overall, 144 of 691 women (20.8 per cent) and 94 of 578 men (16.3 per cent) reported at least one NCD. The reported prevalence of NCD in women was statistically significantly higher than that in men (Table 1). The reported prevalence of Cardiovascular diseases, Diabetes, Arthritis and Thyroid disorder/Goitre was higher in women compared to men, but the difference was statistically significant in case of Arthritis and Thyroid disorder/Goitre only. The reported prevalence of Cancer, Chronic respiratory diseases and chronic kidney diseases was higher in men compared to women. The female-male difference in the reported prevalence of these diseases was, however, not statistically significant. (Table 1)

Table 2 compares respondents who did not report any NCD and respondents who reported at least one NCD by their demographic characteristics. Age of the respondent shows a strong gradient. The reported prevalence of NCDs increased from 2.3 per cent in young adults aged 18–25 years to 12.3 per cent in adults aged 26–44 years, 29.1 per cent in middle-aged adults aged 45–59 years, and 42.6 per cent in adults aged 60 years or older and the difference was statistically significant. The reported prevalence of NCDs also differed statistically significantly by caste, marital status, education, and occupation in the bivariate analysis. These differences are, however, unadjusted and should not be interpreted as independent effects.

Table 3 presents bivariate associations between behavioural and measured factors and self-reported NCD status. Alcohol use ($\chi^2=25.455$, df=3, $p<0.001$) and smoking ($\chi^2=10.496$, df=1, $p=0.001$) is found to be statistically significantly associated with the prevalence of NCDs. The inverse pattern should, however, be not interpreted as protective because former users were not distinguished from never-users and reverse causation and reporting bias are possible. Chewing tobacco was not associated with the outcome ($\chi^2=0.123$, df=1, $p=0.726$).

Physical activity levels showed a strong inverse association with chronic illness ($p<0.001$). Individuals with low physical activity had the highest disease burden (40.5 per cent), compared to moderate (19.2 per cent) and high physical activity groups (10 per cent). No statistically significant association was observed between fruit and vegetables intake and chronic illness ($p=0.364$).

Table 2: Bivariate association of demographic, social, cultural and other characteristics of the respondents with self-reporting of at least one NCD.

Characteristic	Category	Reported at least one NCD	Not reported any NCD	Total	Test statistic (df)	p
Religion	Hindu	18.7	81.3	1261	Fisher's exact	0.649
	Muslim	25.0	75.0	8		
Caste	General	21.6	78.4	468	$\chi^2=13.064$ (4)	0.011
	Other Backward Classes	18.8	81.2	313		
	SEBC	21.7	78.3	60		
	Scheduled Castes	18.4	81.6	299		
	Scheduled Tribes	7.8	92.2	129		
Age group (years)	18–25	2.3	97.7	177	$\chi^2=124.813$ (3)	<0.001
	26–44	12.3	87.7	611		
	45–59	29.1	70.9	340		
	≥60)	42.6	57.4	141		
Sex	Male	16.3	83.7	578	$\chi^2=4.326$ (1)	0.038
	Female	20.8	79.2	691		
Marital status	Married	18.9	81.1	996	$\chi^2=54.812$ (2)	<0.001
	Unmarried	4.7	95.3	170		
	Widowed/divorced/separated	40.8	59.2	103		
Education	Illiterate/informal education	27.7	72.3	271	$\chi^2=20.328$ (5)	0.001
	Up to primary	19.8	80.2	167		
	Middle school	15.6	84.4	347		
	High school	17.1	82.9	222		
	Higher secondary	15.7	84.3	134		
	Graduate/postgraduate/professional	13.3	86.7	128		

Characteristic	Category	Reported at least one NCD	Not reported any NCD	Total	Test statistic (df)	p
Occupation	Daily-wage labour	10.3	89.7	155	$\chi^2=16.851$ (4)	0.002
	Private job	18.1	81.9	166		
	Semi-regular/ government job	5.1	94.9	39		
	Self-employed/ own trade or business	18.1	81.9	260		
	Housewife/student	22.1	77.9	647		
N		238	1060	1298		

Source; Authors

Table 3: Bivariate association of behavioural and measured factors with self-reported NCD status

Characteristic	Category	Reported at least one NCD	Not reported any NCD	Total	Test statistic (df)	p-value
Alcohol use	Never	21.7	78.3	954	$\chi^2=25.455$ (3)	<0.001
	Daily	4.3	95.7	92		
	Frequently	7.4	92.6	54		
	Occasionally	13.6	86.4	169		
Smoking	No	20.0	80.0	1130	$\chi^2=10.496$ (1)	0.001
	Yes	8.6	91.4	139		
Chewing tobacco	No	19.1	80.9	739	$\chi^2=0.123$ (1)	0.726
	Yes	18.3	81.7	530		
Physical activity	Low	40.5	59.5	173	$\chi^2=76.892$ (2)	<0.001
	Moderate	19.2	80.8	635		
	High	10.0	90.0	461		
Eating outside	Daily	9.0	91.0	100	$\chi^2=16.674$ (2)	<0.001
	Occasionally	8.3	91.7	108		
	Never	20.7	79.3	1061		
Fruit and vegetable intake	Daily	19.3	80.7	964	$\chi^2=2.023$ (2)	0.364
	Twice weekly	16.2	83.8	272		
	Occasionally	24.2	75.8	33		
Blood pressure	Normal	11.5	88.5	322	$\chi^2=56.768$ (3)	<0.001
	Prehypertension	15.4	84.6	486		
	Stage 1 hypertension	21.6	78.4	306		
	Stage 2 hypertension	38.7	61.3	155		

Characteristic	Category	Reported at least one NCD	Not reported any NCD	Total	Test statistic (df)	p-value
BMI	Underweight	17.0	83.0	100	$\chi^2=12.666$ (3)	0.005
	Normal weight	17.0	83.0	613		
	Overweight	18.3	81.7	431		
	Obese	30.4	69.6	125		
WHR	Low	10.9	89.1	366	$\chi^2=27.321$ (2)	<0.001
	Moderate	17.2	82.8	221		
	High	24.2	75.8	658		
N		238	1060	1298		

Source: Authors

Table 4: Results of binary logistic regression of self-reported NCD on selected explanatory variables.

Variables	Category	β	SE	Wald	p	OR	95 CI for OR
Caste	General	*Ref.*		7.57	0.109		
	OBC	-0.03	0.21	0.02	0.888	0.97	[0.65,1.46]
	SEBC	0.42	0.39	1.15	0.285	1.52	[0.71,3.24]
	SC	0.05	0.22	0.05	0.816	1.05	[0.69,1.61]
	ST	-0.91	0.39	5.37	0.020	0.40	[0.19,0.87]
Age (years)	18-25	*Ref.*		40.29	<0.001		
	26-44	1.54	0.60	6.58	0.010	4.69	[1.44,15.27]
	45-59	2.59	0.62	17.43	<0.001	13.29	[3.95,44.78]
	≥60	2.78	0.66	17.86	<0.001	16.12	[4.44,58.50]
Sex	Male	*Ref.*					
	Female	-0.49	0.31	2.39	0.122	0.62	[0.33,1.14]
Marital status	Married	*Ref.*		3.19	0.203		
	Unmarried	-0.38	0.47	0.68	0.411	0.68	[0.27,1.70]
	Widowed/Divorced/ separated	0.45	0.29	2.46	0.117	1.57	[0.89,2.76]
Education	Illiterate/Informal education	*Ref.*		2.60	0.761		
	Up to primary	-0.12	0.28	0.18	0.668	0.89	[0.51,1.54]
	Middle school	-0.16	0.25	0.39	0.532	0.85	[0.52,1.41]
	High school	0.01	0.29	0.00	0.982	1.01	[0.57,1.76]
	Higher secondary	0.32	0.36	0.82	0.366	1.38	[0.69,2.77]
	Graduate/Post graduate/professional	0.16	0.38	0.17	0.676	1.17	[0.56,2.45]
Occupation	Daily wage labour	*Ref.*		6.03	0.197		
	Private Job	0.52	0.38	1.86	0.172	1.69	[0.80,3.58]
	Semi regular/Govt. job	-1.09	0.81	1.81	0.179	0.34	[0.07,1.65]
	Self-employed/Own trade/business	0.23	0.35	0.44	0.507	1.26	[0.63,2.52]
	Housewife/student	0.42	0.36	1.36	0.244	1.53	[0.75,3.11]

Variables	Category	β	SE	Wald	p	OR	95 CI for OR
Alcohol consumption	Never	*Ref.*		5.31	0.151		
	Daily	-1.34	0.59	5.14	0.023	0.26	[0.08,0.83]
	Frequently	-0.39	0.59	0.45	0.504	0.67	[0.21,2.14]
	Occasionally	-0.09	0.30	0.09	0.770	0.92	[0.51,1.65]
Smoking	No	*Ref.*					
	Yes	-0.97	0.38	6.61	0.010	0.38	[0.18,0.79]
Physical Activity	High	*Ref.*		17.71	<0.001		
	Low	1.15	0.27	17.71	<0.001	3.15	[1.85,5.37]
	Moderate	0.55	0.21	6.47	0.011	1.73	[1.13,2.63]
How often do you eat outside	Never	*Ref.*		0.09	0.957		
	Daily	-0.03	0.44	0.00	0.954	0.97	[0.41,2.32]
	Occasionally	-0.12	0.42	0.09	0.767	0.88	[0.39,2.01]
Blood Pressure	Normal	*Ref.*		9.30	0.026		
	Prehypertension	0.06	0.24	0.07	0.794	1.06	[0.66,1.71]
	Stage 1 Hypertension	0.29	0.26	1.21	0.271	1.33	[0.80,2.22]
	Stage 2 Hypertension	0.74	0.28	6.76	0.009	2.10	[1.20,3.66]
BMI	Under weight	*Ref.*		4.04	0.257		
	Normal weight	-0.06	0.36	0.03	0.871	0.94	[0.47,1.90]
	Over weight	-0.14	0.38	0.13	0.719	0.87	[0.42,1.83]
	Obese	0.38	0.42	0.82	0.366	1.46	[0.64,3.30]
WHR	Low	*Ref.*		4.39	0.111		
	Moderate	0.08	0.28	0.09	0.763	1.09	[0.63,1.89]
	High	0.52	0.28	3.46	0.063	1.68	[0.97,2.91]
Constant		-4.29	0.79	29.32	<0.001	0.01	

Source: Authors

Clinical measurements were significantly associated with the presence of chronic illness (Table 3). Blood pressure showed a clear gradient: individuals with stage 2 hypertension had the highest prevalence (38.7 per cent) compared to those with Stage 1 hypertension (21.6 per cent), prehypertension (15.4 per cent), and normal blood pressure (11.5 per cent) ($p<0.001$). BMI was similarly associated with NCD prevalence ($p=0.005$). Obese individuals had the highest prevalence (30.4 per cent), followed by overweight (18.3 per cent), underweight (17.0 per cent), and normal weight individuals (17.0 per cent). WHR was also significantly linked to chronic illness ($p<0.001$). Participants with high WHR had a chronic illness prevalence of 24.2 per cent, substantially higher than those with moderate (17.2 per cent) or low WHR (10.9 per cent).

In the multivariable binary logistic regression model, the dependent variable was reporting at least one NCD (yes=1; no=0) (Table 4). Compared with young adults aged 18–25 years, adjusted odds were higher among adults aged 26–44 years (OR=4.69, 95 per cent CI: 1.44–15.27; $p=0.010$), middle-aged adults aged 45–59 years (OR=13.29, 95 per cent CI: 3.95–44.78; $p<0.001$), and adults aged 60 years or older (OR=16.12, 95 per cent CI: 4.44–58.50; $p<0.001$). Low physical activity (OR=3.15, 95 per cent CI: 1.85–5.37; $p<0.001$), moderate physical activity (OR=1.73, 95 per cent CI: 1.13–2.63; $p=0.011$), and stage 2 hypertension (OR=2.10, 95 per cent CI: 1.20–3.66; $p=0.009$) were independently associated with higher odds. High WHR showed a positive but non-significant association (OR=1.68, 95 per cent CI: 0.97–2.91; $p=0.063$). Daily alcohol use and current smoking showed inverse associations, but these estimates do not demonstrate protective effects and may reflect reverse causation, former-user misclassification, residual confounding, or reporting bias.

Discussion

This study provides a comprehensive assessment of the prevalence and determinants of NCDs in the urban slums of Bhubaneswar, Odisha. Our findings revealed that nearly one in five individuals (18.8 per cent) reported having at least one chronic condition, with cardiovascular disease (42.6 per cent), diabetes (40.3 per cent), and arthritis (17.2 per cent) being most prevalent. These results are consistent with findings from other studies in India, which report high NCD burdens in slum populations due to adverse living conditions and limited access to healthcare services (Brashier et al, 2012; Bhojani et al, 2013; Shanmugam et al, 2018.

Demographically, older age groups, particularly those aged 60 and above, were significantly more likely to report chronic illnesses, a finding aligned with global and national trends indicating increased NCD risk with advancing age (Naik et al, 2020). Women exhibited a higher burden of disease compared to men, especially in conditions like thyroid disorders, arthritis, and CVDs, indicating a potential gender disparity in disease vulnerability or healthcare access.

Social determinants such as education, marital status, and occupation also influenced NCD prevalence. Illiterate individuals and widowed/divorced/separated persons were disproportionately affected, underscoring the compounding effects of low literacy and social vulnerability on health outcomes. These findings resonate with prior research that

highlights how social-economic deprivation amplifies the health risks in slum environments (Singh et al, 2017).

Low physical activity was independently associated with chronic illness. Participants with low activity had 3.15 times the odds of chronic illness compared with those reporting high activity (OR = 3.15, 95 CI: 1.85-5.37; $p < 0.001$), and those with moderate activity had 1.73 times the odds (OR = 1.73, 95 CI: 1.13-2.63; $p = 0.011$). Similar patterns have been reported in other urban-slum settings, where physical inactivity is an important modifiable risk factor (Naik et al, 2020; Rakesh et al, 2023). Frequency of eating outside the home was not independently associated with chronic illness in the adjusted model.

Among physiological factors, stage 2 hypertension was independently associated with chronic illness: affected participants had 2.10 times the odds compared with those with normal blood pressure (95 CI: 1.20-3.66; $p = 0.009$). High WHR was associated with 1.68 times the odds relative to low WHR, but its confidence interval included the null value, and the association was not statistically significant at the 5 level (95 CI: 0.97-2.91; $p = 0.063$). BMI categories were also not independently associated after adjustment. These findings support regular blood-pressure and anthropometric screening while distinguishing statistically significant from borderline associations (WHO, 2010; Gowda et al, 2015; Mishra et al, 2017; Patel et al, 2011; Gupta et al, 2008).

Counterintuitive inverse associations were observed for current smoking (OR = 0.38, 95 CI: 0.18-0.79; $p = 0.010$) and daily alcohol consumption (OR = 0.26, 95 CI: 0.08-0.83; $p = 0.023$). The direction of coding and reference categories was rechecked against the tabulated analysis: 'No' was the reference for smoking and 'Never' was the reference for alcohol consumption. These estimates should not be interpreted as protective causal effects. Because exposure and disease status were measured at the same time, reverse causation is plausible: participants may have stopped smoking or drinking after diagnosis, moving former users into the non-user reference groups. The alcohol literature describes this as the 'sick-quitter' or former-drinker misclassification problem (Fillmore et al, 2006). Chronic-disease diagnosis has likewise been associated with subsequent smoking cessation (Hu et al, 2021). Residual confounding by age, sex, socioeconomic position, differential reporting, duration and amount of exposure, and survivor selection may also contribute. The survey did not distinguish never-users from former users or capture cumulative exposure; therefore, longitudinal studies with detailed exposure histories are required.

The implications of these findings are substantial for public health policy and urban planning. They emphasize the need for integrated, community-based interventions that address both the medical and socio-environmental determinants of NCDs. Such interventions should include: (i) health promotion and education targeting physical activity and dietary behaviours, (ii) early screening and regular monitoring for hypertension, obesity, and other NCD risk factors, (iii) improved access to healthcare services within slums, (iv) addressing structural inequities like housing, sanitation, and employment opportunities. These strategies are essential to meet the Sustainable Development Goal target of reducing premature mortality from NCDs by one-third by 2030 (WHO, 2010; Singh et al, 2023).

A key strength of this study is the use of a structured NCD-surveillance framework to collect behavioural and physical-measurement data from an underserved urban population. Several limitations should be considered. NCD status and behavioural exposures were self-reported and were not independently verified against medical records, creating potential recall and reporting bias. The questionnaire did not distinguish never-users from former users or quantify cumulative smoking and alcohol exposure. The Northern Zone and participating slums were purposively selected, although wards within the Northern Zone were randomly selected; therefore, the findings may not be generalizable to all slum residents of Bhubaneswar. The cross-sectional design establishes association, not temporal sequence or causation. Residual confounding and survivor selection are possible. Longitudinal studies using probability sampling, verified diagnoses, and detailed exposure histories are recommended.

Conclusion

This study has documented self-reported NCDs among adults in selected urban slums of Bhubaneswar; it did not measure all forms of chronic illness. Cardiovascular diseases and diabetes were the most frequently reported NCD categories. Older age, low or moderate physical activity, and stage 2 hypertension were independently associated with higher odds of reporting an NCD. The inverse associations for current smoking and daily alcohol consumption should not be interpreted as protective. Because disease status was self-reported and the Northern Zone and participating slums were purposively selected, while wards within the zone were randomly selected, the estimates should be interpreted as evidence from the surveyed slums rather than as city-wide prevalence. Prevention should be linked with confirmatory diagnosis, affordable treatment, referral, medication continuity, follow-up, risk-factor reduction, and stronger urban primary-care outreach.

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