Namasivayam et al. International Journal for Equity in Health (2025) 24:55
https://doi.org/10.1186/s12939-025-02411-8

International Journal for Equity in Health

RESEARCH

Open Access

An analytical approach towards attaining leave no one behind using patterns and distributions of inequalities in antenatal and facility delivery coverage in Uttar Pradesh, India

Vasanthakumar Namasivayam[1*†], Ravi Prakash[2†], Bidyadhar Dehury[3], Shajy Isac[2,3], Fernando C. Wehrmeister[2], Marissa Becker[2], James Blanchard[2] and Ties Boerma[2]

Abstract

Background Leave No One Behind (LNOB) is a central, transformative promise of the 2030 Agenda for Sustainable Development Goals. To attain LNOB, systematic analysis of patterns and distributions of inequalities in coverage of health outcomes on a continuous basis at different program delivery layers is required to design tailored health interventions. We analysed the patterns of change and geographic distribution of inequalities in coverage of antenatal care and facility-based delivery in Uttar Pradesh (UP), India and developed a framework to guide health programmers to understand inequalities better, to accelerate progress by reaching those left behind.

Methods Data from five-rounds of National Family Health Survey (1992–2021) and two-rounds of Community Behaviour Tracking Survey (2014–2018) is used. Education and wealth have been used as stratifiers. Three measures of inequality- mean difference from mean, slope index of inequality, and inequality pattern index are used to depict the state, district and sub-district level inequalities.

Results UP observed a substantial reduction in the education-related inequality in ANC and facility-delivery during 1992–2021. The slope index of inequality declined from 65.3 [95%CI:60.0-70.6] to 9.3 [95%CI:7.8–10.8] for ANC and from 44.7 [95%CI:38.5–50.9] to 29.9 [95%CI:27.8–32.0] for facility-delivery during 1992–2021. The inequality pattern index showed that, with improved reach of interventions, many districts moved towards bottom inequality from top inequality for any ANC while fewer districts for facility-delivery. Even in districts with high coverage and low inequality, sub-district level(blocks) inequality persisted. Similarly, in blocks with high coverage and low inequality, Accredited Social Health Activist (ASHA) level inequality persisted. Interestingly, for the same ASHA area, the patterns of inequality differed for any ANC and facility delivery; in some districts, inequality direction changed based on the stratifier chosen.

†Vasanthakumar Namasivayam, Ravi Prakash joint first authors.

*Correspondence:
Vasanthakumar Namasivayam
drvasanthias@gmail.com

Full list of author information is available at the end of the article

Conclusions The proposed health equity framework suggests that to achieve LNOB status, understanding inequality with the coverage status is important. If coverage is high and inequality persists, identify the program layer at which maximum inequality persists to identify the left behinds. Whereas, if coverage is poor, programs are required to improve coverage first. Findings also call for a systematic way of collecting and organizing granular data to understand inequality and identify the left-behinds.

Keywords Leave no one behind, Health Equity Framework for Programs (HEFP), Bottom inequality, Inequality Pattern Index, Uttar Pradesh

Background

On 1st January 2016, the world officially began implementing the 2030 Agenda for Sustainable Development, the transformative plan of action based on 17 Sustainable Development Goals (SDGs), to address urgent global challenges over the next 15 years [1]. Universal health coverage and access to quality health care are at the core of goal 3, which deals with ensuring healthy lives and promoting well-being for all at all ages. Leave No One Behind (LNOB) is a central, transformative promise of the 2030 Agenda for Sustainable Development Goals [2], including that for health goals. LNOB means moving beyond assessing average and aggregate progress towards ensuring progress for all population groups at a disaggregated level [3]. To ensure LNOB, expansion of health services to the unreached population is required. However, previous global experience has shown that as health systems introduce and subsequently expand the availability of health services and interventions, there is a general pattern in the evolution of coverage inequalities. For instance, Victora et al. developed and illustrated the concept of the "inverse equity hypothesis", which postulates that when new interventions are introduced they are initially adopted by the wealthy and thus increase inequalities– as population coverage increases, only the poorest will lag behind compared to all other groups [4]. As a result, inequalities by socioeconomic position initially increase, and only decrease later when those in lower socioeconomic strata gain greater access to the programs and services. Even as overall inequalities decrease later when the proportion of the population covered by the programs is high, it is common for a relatively small proportion of the population in the very lowest socioeconomic positions to remain without coverage, leading to "bottom inequalities". Health programmers seeking to accelerate the reduction in inequalities, and to address bottom inequalities i.e. to "Leave No One Behind (LNOB)", need to better understand the specific patterns and distributions of coverage inequalities to tailor the interventions.

Multiple frameworks and measures have been used previously to understand inequalities. The Social Determinants of Health (SDOH) framework, one of the frameworks used to understand drivers of inequality, illustrates how the structure of society through social interactions, norms, and institutions affect population health and how public policies can address those drivers [5]. The existing frameworks emphasize the intermediary determinants (material, behavioural and psychosocial) to address inequalities, for which either data is not readily available on a regular basis (as population-level data are mostly available through surveys) or many of these determinants cannot be addressed through health department interventions.

Similarly, multiple simple and complex health inequality measures have been developed to understand inequalities [6, 7]. While these measures and frameworks help understand the drivers of health inequalities and trends over time, a different framework is needed for programs to identify the program service delivery layers (State/ District/ Blocks/ Villages/ Families) where the equity drop is largest, on a continuous basis to take corrective action. In addition, identifying the unreached population at a state or even district-level will not help achieve the LNOB status, rather the program needs to act based on the understanding of patterns and distributions at lower layers.

Programs intending to achieve LNOB status must identify the gaps in coverage up to the lowest program layer. This requires systematic organization of data and its use through an approach that is based on coverage levels. If the intervention coverage is low at a higher service delivery layer (state or district level), the reasons for low intervention coverage at this layer needs to be identified [8]. Low intervention coverage at the state/district level is generally a result of health systems issues like low human resource availability, drugs, and logistics etc, and requires systemic solutions. However, if the intervention coverage is higher at the same service delivery layers (state/ district), identifying the gaps at the lower service delivery layers (sub-district (blocks) / village / ASHA (Accredited Social Health Activist– in charge of a population of about 1000–1200) areas will be required to progress towards LNOB. The reasons at these layers may be more context-specific, or because of individual-level socio-economic reasons. Health programmers require an analytical approach that can help them identify the heterogeneity in the progress of health intervention coverage to take immediate corrective steps to reduce inequalities in the program layer contributing to maximum inequality.

Shawky made a relevant effort for programmers to identify the health inequality measures relevant for assessing geographic and wealth-related inequalities to demonstrate what can happen in practice to recognize the geographic or wealth-related priority health inequalities in any setting [9]. It used the index of dissimilarity as a measure to understand the under-privileged population. This index measures the magnitude of inequalities expressed as the amount of redistribution required to make estimated geographic inequality equal to zero. While this measure focuses on gaps and redistribution to achieve equality, our approach is towards universality of coverage for programmers to finetune the interventions.

In this paper, we emphasize on the need for developing a framework, Health Equity Framework for Programs (HEFP), following a systematic analytical approach to continuously identify the program layer (i.e. the *place* or administrative layer at which interventions are delivered) that contributes to the maximum coverage gaps so that the reasons can be identified and improvement measures undertaken. This analytical approach requires granular data across various geographic/program layers to better understand the persisting level of inequalities, which was available in Uttar Pradesh (UP), India. We analysed the patterns of change and geographic distribution of inequalities in coverage of antenatal care and facility delivery in UP and developed a framework to guide health programmes to ensure no one is left behind.

Methods

Setting

UP is the most populous state in India, with an estimated population of 238 million in 2024 [10], accounting for 17% of India's population with a wide heterogeneity in the socioeconomic status of its population as well. The state is divided into 18 administrative divisions constituted by 75 districts with an average population of 3 million per district. There are 897 blocks (sub-district administrative units) and about 100,000 villages comprised of about 0.27 million and 1800 population per block and per village respectively [11]. About 78% of its population lives in rural areas and public health services are delivered through 31,234 public health facilities (85 Medical colleges, 108 District Hospitals, 971 Community Health Centres, 4,316 Primary Health Centres, and 25754 Sub Centres) and numerous private sector health facilities [12]. The health services are also delivered through a vast network of Front Line Workers (FLWs) delivering health and nutrition-related services in the rural areas (about 158,000 Accredited Social Health Activists (ASHAs), about 188,000 Anganwadi workers (AWW) both covering population of about 1000–1500). The population size, the large number of public health facilities with its numerous cadres of health personnel and FLWs, their varying competency, and the spectrum of private sector hospitals of varying size, quality etc., along with prevailing socio-economic differences makes the setting complex, particularly for understanding inequality in health outcomes and its drivers to achieve LNOB.

Data sources: sample size and design

The study utilizes data from two different sources, namely, five rounds of data from the National Family Health Survey (NFHS 1992–2021) and two rounds of the Community Behaviour Tracking Survey (CBTS, 2014-15, 2018) conducted in 20 rural Community Development (CD) blocks of UP for analysis. The NFHS data was used for the national, state and district-level analysis, while the CBTS data was used for the sub-district level (block/ASHA area) analysis which was a unique feature and strength of this study.

NFHS The NFHS is a large-scale multi-stage population survey that provides information on population, health, and nutrition for India and each state and union territory. The Indian NFHS is comparable with those of the Demographic and Health Surveys (DHS) conducted in many other countries. The first three rounds of NFHS between 1992 and 2006 provided estimates at the national and state levels, while the last two rounds (2015–2021) expanded the scope to provide district-level estimates for various key health indicators. A uniform sample design was adopted in each round of the survey to allow comparisons at the national, state and district levels over time. More detailed information regarding the survey design and methods are available elsewhere [13, 14, 15, 16, 17]. The current study used the data from 7909 births in NFHS-1(1992-93), 4324 births in NFHS-2(1998-99), 7051 births in NFHS-3(2005-06), 41751 births in NFHS-4(2015-16), and 35766 births in NFHS-5(2019-21) in Uttar Pradesh.

CBTS The CBTS is a cross-sectional survey implemented by the Uttar Pradesh Technical Support Unit (UPTSU) to track the progress of key Reproductive, Maternal, Newborn, Child Health (RMNCH) program interventions coverage at the block level to monitor indicators on a concurrent basis. UPTSU, operated by the University of Manitoba (UoM) in collaboration with the India Health Action Trust (IHAT), is supporting the Government of Uttar Pradesh (GoUP) in its efforts to attain the SDG 3.0, primarily focusing on RMNCH outcomes, in an embedded manner using program science approach [18]. The support started in 25 High Priority Districts (HPDs– districts with poor health outcomes identified by the state government) from 2014 to 2019, and later expanded to all the 75 districts of the state. Community-based studies, including CBTS, were done to provide block-level estimates for more granular planning as such data are not available from national surveys like NFHS. The CBTS administered a structured questionnaire to women with a pregnancy outcome of live birth, stillbirth or abortion in the 59 days preceding the survey, capturing antenatal care, childbirth, newborn care, postnatal care, and home-based newborn care-related information. This timeframe was chosen to obtain the most recent information and to minimize recall bias. The first round of the CBTS was conducted in the 100 CD blocks in 25 HPDs during 2014-15, while the latest round of the survey in 2018 was conducted in 40 randomly selected CD blocks within the 25 HPDs. Of the 40 CD blocks, 20 CD blocks were selected randomly from the initial 100 CD blocks of first round, with the rest randomly selected from the remaining CD blocks (194) of 25 HPDs. There were 20 common CD blocks included in both rounds and thus, the analysis utilized the data from these 20 common CD blocks only. In both rounds of CBTS, ASHA's catchment area, which is the smallest health-service-delivery unit catering for a population of about 1000, was taken as the Primary Sampling Unit (PSU). The required number of PSUs in each CD block was chosen using a simple random sampling approach. Within the PSU, all households were visited to identify eligible women, i.e. women with any pregnancy outcome 59 days preceding the survey, and all the available eligible women from the selected households were interviewed. A total of 11,008 and 4,647 eligible women were interviewed from 2,250 PSUs in 2014-15 and 1,166 PSUs in 2018, respectively.

Two outcomes, namely, any antenatal care (ANC) and facility delivery (FD), are used in this analysis. These indicators have different coverage levels and observed varying levels of improvement over time. Also, ANC services are delivered predominantly through the community platform and FD through the facility platform which allows us to analyse how the changes in inequality are observed across different platforms. A dichotomous variable for ANC and FD was computed with code '1' assigned if the women responded yes to the question "Did you see anyone for antenatal care for this pregnancy?" and "if she delivered in a health facility", respectively. Also, we primarily used women's education (coded as '< 5 years', '5–9 years' and '10 + years') and household wealth as stratifiers to measure the inequality in maternal health outcomes. A household wealth tertile variable was computed from the available national wealth score in the NFHS data which is a composite measure of household economic status using a set of household assets [19]. Both education and wealth-related inequality were measured at the state and district levels, while only education-related inequality was measured at the block level as the wealth index was not available in the CBTS. Therefore, we used the education related inequality to develop the framework using the analytical approach and wealth related inequality analysis to understand the importance of choosing a stratifier. Finally, the observations of the analysis on patterns of inequality led to development of the Health Equity Framework for Programs (HEFP).

Analysis

We computed the Slope Index of Inequality (SII) for the outcomes with both education and wealth as stratifier using logistic regression. The SII is a regression-based, weighted measure of inequality that calculates the absolute difference between the predicted values of the highest category and the lowest category while taking into consideration all the other subgroups. The SII value varies between − 1 to + 1. We present SII values as percentage points in this paper. The positive SII value indicates the concentration among the less vulnerable (> = 10 years of schooling or highest wealth tertile), while the negative SII value indicates the concentration among the most vulnerable (< 5 years of schooling or lowest wealth tertile). The larger the absolute value of SII, the higher the level of inequality, while the SII value of 0 represents no inequality [20]. Data from different time periods were used to assess changes in coverage and inequalities to develop the analytical framework and identify the layers contributing to maximum equity drop over time.

We also plotted the inequality pattern index over time at the district level for both the outcomes to understand the shift in the inequality pattern [4]. In addition, a disaggregated analysis by place of residence was done. All analyses were conducted using STATA 16.0 and applying sampling weights wherever applicable.

Results

The profile of the women who participated in different rounds of NFHS surveys is presented in additional file 1, showing a substantial improvement in the educational status of women 15–49 years over the last 3 decades. At the national level, the mean years of education increased by 4.7 years (from 3.0 years in 1992-93 to 7.7 years in 2019-21), whereas it was an increase of 5.4 years in UP (1.7 years in 1992-93 to 7.1 years in 2019-21). While the composition of sampled women remained the same by religion (~ 80% Hindu in India and UP), there was a slight increase in the proportion of urban population over the period (22.7–26.7% in India and 17.0–20.5% in UP). A significant shift was also observed in parity wherein the proportion of women with 4 plus parity reduced to 12.0% (2019-21) from 31.1% in (1992-93) in India and to 18.6% from 41.1% in UP, respectively.

Figure 1 depicts the trends in coverage of the two outcomes from 1992 to 93 to 2019-21 for the 36 States and Union Territories of India and shows a varying level of inequality as well as changes over this period of time. For example, any ANC for India was 62.5% (range:

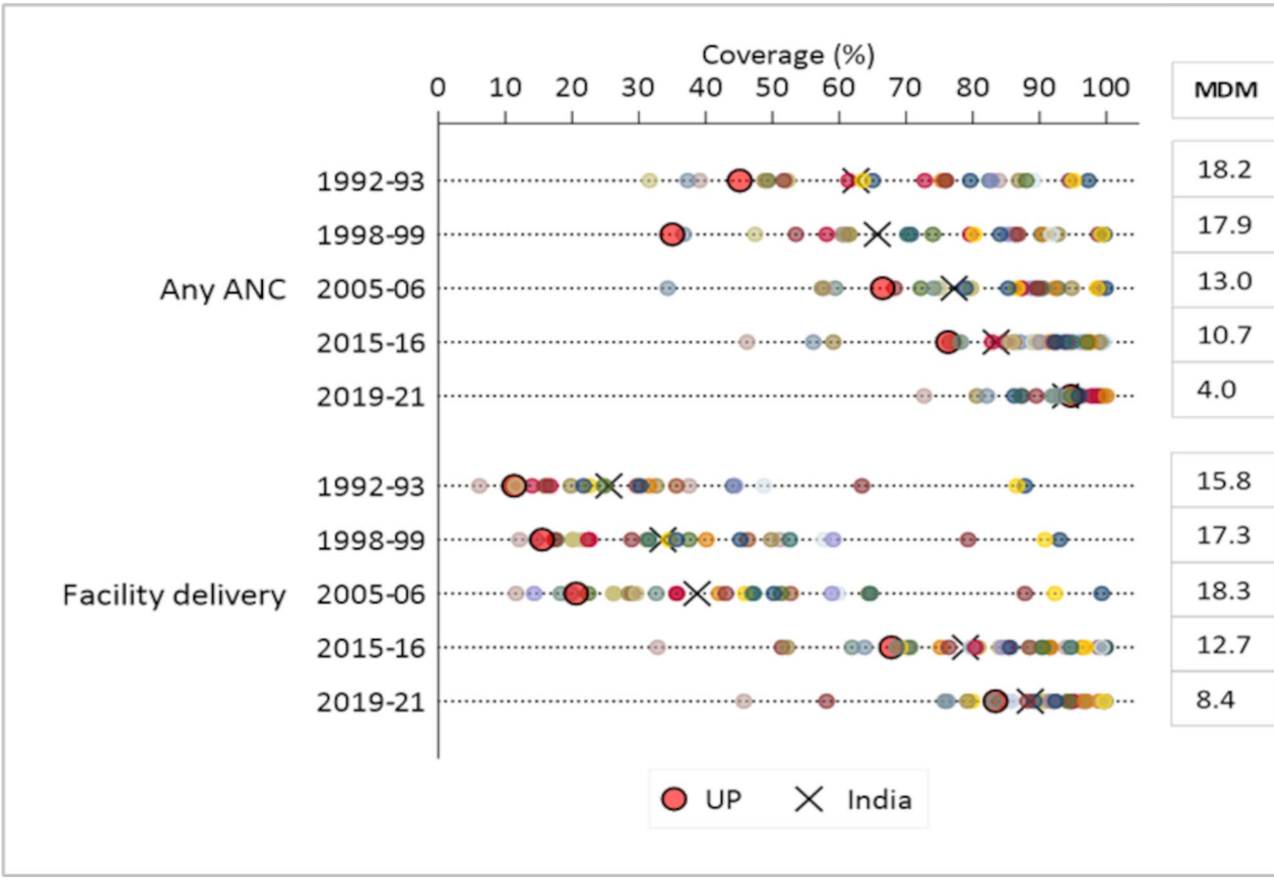

Fig. 1 Trends in state level coverage in outcome indicators (each dot represents state), NFHS (1992–2021)

31.6-97.3%) in 1992-93 which moved to 93.9% (range: 72.7-100.0%) in 2019-21, whereas, FD was 25.5% (range- 6.1– 87.8%) in 1992-93, which has moved up to 88.6% (range– 45.7 –99.8%) in 2019-21. With the improvement in ANC and FD across the states, the coverage inequality showed higher reduction over the period in ANC compared to FD. The inequality measured through Mean Difference from Mean (MDM) reduced from 18.2 to 4.0 in ANC and 15.8 to 8.4 in FD during 1992-93 to 2019-21. The subsequent analysis focused on UP to understand inequality patterns using the UP-specific granular data available up to the lowest level (i.e. ASHA area) so as to guide programs to target and reach those who are left behind.

Figure 2 presents state-level trends in coverage of outcome measures in UP by education (<5 years vs. 10+years) and slope index of inequality (SII). In UP, both ANC and FD coverage followed a general pattern of socio-economic inequalities consistent with the inverse equity hypothesis. In 1992-93, any ANC coverage was only 37.8% among women with low education (<5 years), which improved to 91.2% in almost 3 decades whereas ANC coverage among educated women was 90.9% in 1992-93 (Fig. 2a) and remained at a high level thereafter. Similarly, the FD coverage was much higher among educated women during 1992-93 (63.5%) which was only achieved by the less educated women between 2015-16 to 2019-21, i.e., around 25 years later than the better educated group. The SII for both the indicators by education (any ANC: 9.3 and FD: 29.9 pp) in NFHS-5 indicates that education-related inequalities still persist in 2019-21, although they witnessed a substantial reduction since 1992-93 as SII was 65.3 for any ANC and 44.7 for facility delivery (Fig. 2b).

These findings indicate that there was high coverage with low inequality for any ANC, while despite achieving higher coverage, facility delivery showed persisting moderate inequality between low and better-educated women. Considering that access to ANC and delivery care was almost universal among better-educated women, the persisting inequalities are reflection of the fact that still a proportion of women with less education were not reached. To find them, analysis was done at the district level to identify whether some districts contribute more to persisting inequality than others. Figure 3a and b shows coverage in any ANC among the 75 districts in UP by education between NFHS-4 (2015-16) and NFHS-5 (2019-21). The ANC coverage of >80% improved from 42

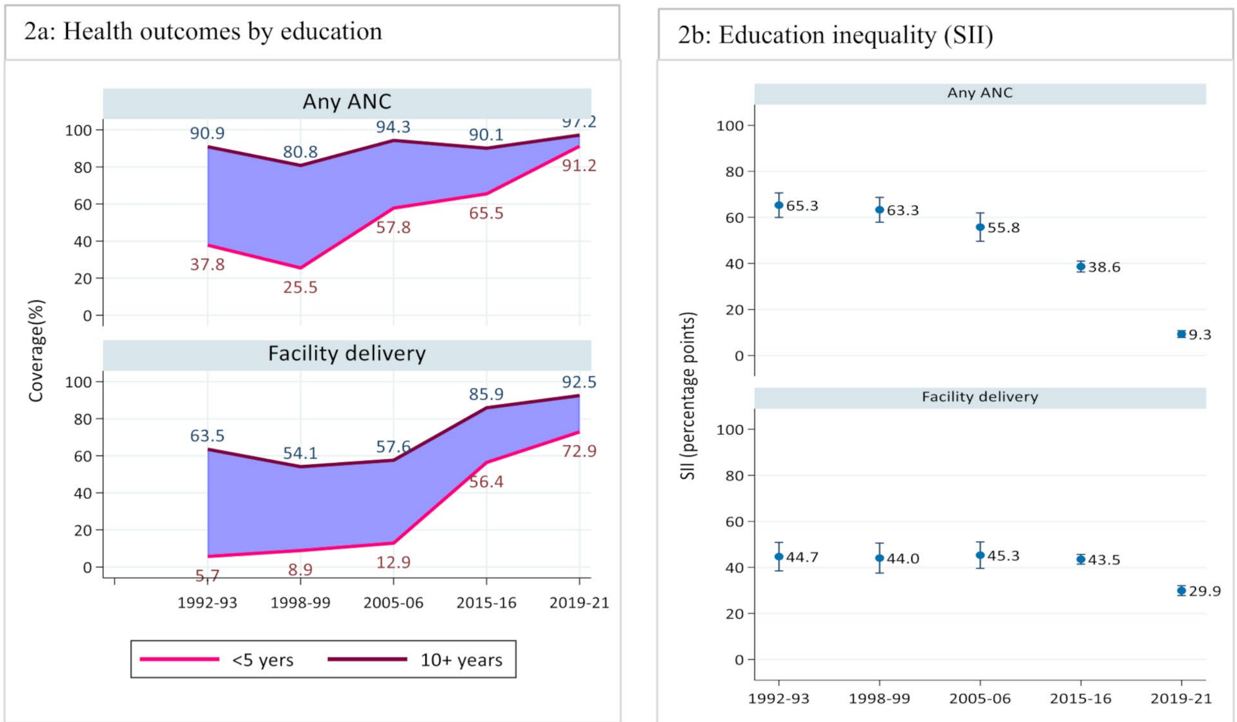

Fig. 2 Trends in health outcomes and SII by education in Uttar Pradesh, NFHS (1992–2021)

districts in 2015-16 to all the districts in 2019-21, whereas the FD coverage of >80% increased from 11 districts to 59 districts between NFHS-4 and 5. Results also show that progress in the levels of inequalities differed at the district level for ANC and facility delivery. For instance, the largest differences in ANC coverage between more and less educated women (10+years vs. <5 years) within a district were 43.0% and 23.2% points (pp) in NFHS-4 and 5, respectively. This was 46.3 pp and 33.2 pp for FD. In the NFHS-4, 56 districts for ANC and 62 districts for FD had more than 10 pp difference between more and less educated women which reduced to just 6 districts for ANC and 47 districts for FD in NFHS-5. The same is also visible in the inequality pattern index (Additional file 4) wherein, between NFHS-4 and NFHS-5, many districts moved towards bottom inequality from top inequality for any ANC while relatively fewer districts for FD.

To achieve the goal of 'LNOB', it is important that the program continue to focus on the districts that continue to show higher inequality and understand the socio-economic and programmatic determinants that cause such inequalities. While for FD, programs may still need to address district-level inequality, the approach needs to be different for ANC. Also, if the coverage is consistently high at the district-level and with low inequality as in the case of ANC, it will be important to identify the inequalities at the next level, blocks in this case, and identify if any population group is missing out or any geography has lower program reach. Figure 4 shows outcomes by education across 20 common blocks of HPDs in the CBTS study in UP and depicts a pattern opposite to that observed for states and districts, i.e., only a few blocks with high coverage and low inequality while others with low/moderate coverage and high inequality in 2018. Even for the high coverage indicator, like any ANC at the district level, the block level any ANC coverage varied from 20% to 90% among less educated women (<5 years of education) and women with 10+years of education in 2014-15, respectively, and from 58% to 98% among the women with same two groups of education, respectively, in 2018. The inequality pattern also showed a substantial reduction in education-related inequality within the block, with some of the blocks moving towards universal ANC coverage. Block-level heterogeneity was higher than for districts to which these blocks belonged to indicating the need for context-specific intervention to reduce inequality at the block-level.

Inequalities in FD showed persistence at the block level. While some blocks showed higher reduction in education-related inequality in FD coverage by education (Milak, Amariya, Nagar, Rudauli), many blocks continued to witness moderate to low reductions in inequality. In this case, the program has to concentrate on these blocks to improve the FDs. The inequality pattern index

Fig. 3 District-level trends in outcomes by education in UP, NFHS (2015-16 and 2019-21)

Fig. 4 Trends in outcomes by education across 20 common blocks in HPDs, CBTS (2014-15 and 2018)

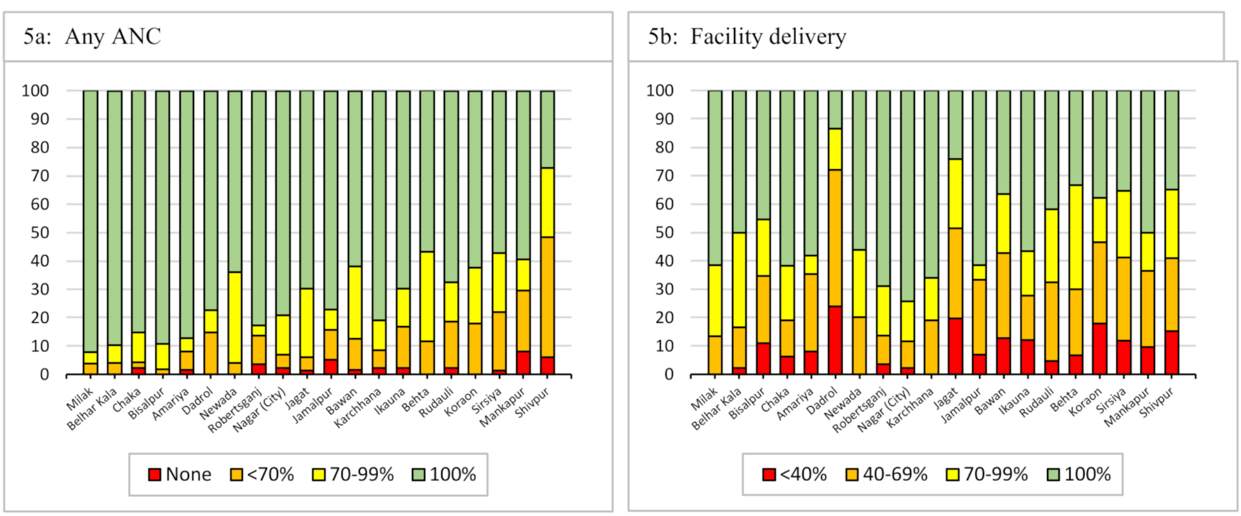

Fig. 5 Distribution of ASHA areas according to coverage in outcomes by blocks in HPDs, CBTS (2018)

(Additional file 5) also shows that blocks have moved from top to bottom inequality for any ANC, whereas in the case of facility delivery, a few blocks continued to show the top inequality while only two blocks moving towards linear inequality over time.

In those blocks that have achieved high coverage, and low inequality status, to further identify who are left behind, analysis was done to understand the ASHA area-level inequality. Since the number of women with less and more education was not evenly distributed within the ASHA areas (due to a small sample size), the analysis focused on assessing the inequality between the ASHA areas within the blocks. Figure 5 denotes the distribution of ASHA areas by coverage outcomes categories (5a-5b). Results show that within the same block, the inequality varied for the indicators by ASHA area, especially with high coverage. For instance, in very high ANC coverage blocks like Milak, Belhar Kala and Bisalpur in 2018, while more than 80% ASHA areas had all the women received ANC, the remaining 20% ASHA areas had women who were left out. However, for the same blocks in 2018, the FD education-related inequality was higher compared to any ANC, and as a result, there were 40–60% of ASHA areas that had left out women who didn't deliver at facility. In contrast, for both ANC and FD, the block which did not attain high coverage, only a few ASHA areas (~30%), had 100% ANC or FD coverage. This means, if the outcome coverage is high in certain blocks, programs need to identify those ASHA areas and individuals within the ASHA area who are not able to access service to ensure no one 'left behind'.

Discussion

Using data from multiple rounds of representative surveys, we analysed the inequality patterns in different health outcomes from the national level to the ASHA areas level with a special emphasis on UP. The analysis found that, in UP, ANC and FD coverage followed a general pattern consistent with the "inverse equity hypothesis" for ANC and FD. Also, the progress in the levels of inequalities differed at the district level for different indicators (higher inequality for facility delivery, whereas lower inequality for ANC) in a high proportion of districts. Finally, despite the fact that ANC and FD coverage improved over time, the level of increase was not found at the same pace across geographies (districts or blocks) and across the indicators within the same geographies, indicating that interventions have been accessed unequally by certain population segments (better educated in the current illustration).

To understand the inequalities, it was important to identify the program implementation layer (state, district, block, ASHA area) that contributes to maximum equity drop so that the reasons can be identified and improvement measures are undertaken despite the underlying social-determinants of health. Alongside, understanding changes in inequality over time becomes crucial so that programs can be modulated to initiate needful measures to reduce inequalities further. Such analyses required unitized data on different health outcomes linked with the program layers. i.e., each individual should be linked to the lowest unit of the geography (village), FLW (ASHA), and facility (Sub Centre) with aggregation up to the top layer. (Division/District/State). Since UP has set up this data generation process, it was the most suitable geography to conduct this analysis. Data from multiple rounds of NFHS surveys was used to show the trends in inequalities in coverage of outcomes across states and also within UP over time. Data showed significant improvements in health outcomes between 1992 and 2021 in UP (any ANC increased from 45.1% to 94.7%, and FD from 11.3% to 83.4%). But at the same time, to identify the remaining 5% who are not getting ANC and 16% who are not delivering at facility, this paper provides an approach to systematically analyse and identify those left out. With the increase in the coverage, the state also witnessed reduced inequality in selected outcomes by educational status of women in both rural and urban areas (Additional file 2).

Encouraging patterns in inequality reduction were also noted at the district-level. The inequality pattern index indicated that most of the districts in UP shifted towards linear (for facility delivery) or bottom inequality (for ANC) from top inequality. The findings also highlighted that within the high coverage districts, there persists a significant block level inequality, and within the high coverage blocks, there are significant ASHA area level inequalities. To attain LNOB, it is important that the program opportunities are identified regularly to optimize the intervention. In this case, if some districts have lower intervention coverage, it would be prudent to identify the drivers for lower coverage at the district level to improve the coverage. Some of the drivers for low coverage might be poor strategies for program implementation, quality, lack of infrastructure, poor health systems (lack of delivery points, poor quality of service at community platform etc) or inappropriate policy planning. On the other hand, if the district has high coverage and low inequality, it would be important to identify those who are left behind by analysing the inequality at the next level. If some ASHA areas are contributing to the ANC coverage gap, context specific interventions for identifying left behind (eg. better microplanning, mobilization, counselling etc) can be undertaken and the marginal cost may not necessarily be very high as the inputs are already in place to provide the services to left out population. Even in FD, if some/most women in the village are already delivering at a facility, the marginal cost of improving access for women left behind to deliver in facility may not be necessarily high. Beyond the differentials in the service provisioning, the differentials in the health inequality may also occur due to the way in which health institutions "process" people differently. It may also be due to the economic and social status divisions, or the differentials in functioning and capabilities due to which the "treatment" received is not "converted" into "equivalent" health outcomes or gains. To ensure that socio-economically disadvantageous populations receive the care that they need, active participation of community or community-level workers with service design and delivery (i.e., community-centred)" may better inform the policies and programs [21, 22].

We packaged this analytical approach in the form of a framework, called "Health Equity Framework for Programs (HEFP)" which could be more relevant for program managers. This framework highlights that to understand the left behind, it is important to first identify the program layer contributing to maximum disparity in health outcome at that time, considering coverage and social determinants. In the case of UP, we categorized the program service delivery layers into geography (division/

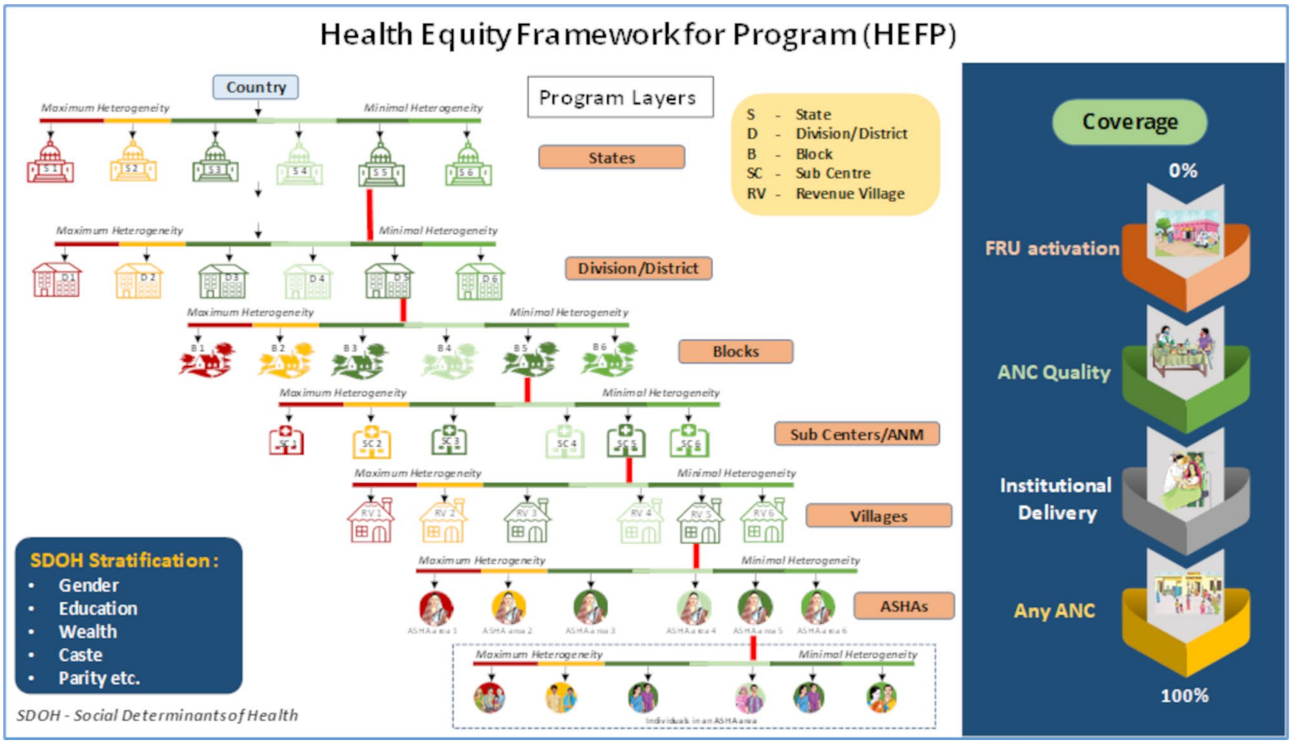

Fig. 6 Health Equity Framework for Programs (HEFP)

districts, blocks, villages,) facilities (public, private), care providers (doctors, nurses, FLWs, etc.), or individuals, not necessarily organized in the same order (Fig. 6). Since the different health outcomes related to RMNCH in UP are at various coverage levels, the framework should be cognizant of that while identifying the layer at which the maximum equity drop occurs. We used social determinants (education/wealth/residence) as a stratifier instead of as factors, as data from UP showed that the disparities of health outcomes based on various SDOH parameters were on already expected patterns, irrespective of the level of health outcomes, thereby not helping the program implementers much. For example, the ANC coverage in UP is 94.7% and showed that women who were less educated were worse off than those who were well educated (91.0% versus 97.2%). The health outcome FD is 83.4% and showed that women who were less educated were worse off than those who were well educated (72.9% versus 92.5%). The pattern observed for many other health outcomes was similar. Hence, the HEFP first considers the layers of programs in a context and the level of health outcomes (coverage), and uses SDOH factors as a stratifier rather than as a predictor to assess inequality. Second, we explored the heterogeneity pattern between units of the program delivery layers starting from the top (example– states in India). In case there is wide heterogeneity in the health outcomes noted, then that layer contributes to the equity drop, whereas, if there is minimal heterogeneity with high coverage, move to the next program layer and explore the heterogeneity pattern. This process is repeated until the layer contributing to the maximum equity drop is identified to enable programmers to explore the reasons for the drop and implement appropriate interventions (Fig. 6). This framework offers a systematic approach for conducting the equity analysis in a program context. Considering the levels and patterns of inequality, this framework suggests taking coverage into account while understanding the inequality. If coverage is moderate or low, program actions are required to improve the coverage first rather than putting a lot of focus on inequality, whereas if coverage is high and inequality persists for some groups (stratifiers) - analyse the program layer to identify the left-behinds and target programs to improve equity. Also, since the effect of the SDOH on inequality often remains known, we suggest using the SDOH indicators (education, wealth, caste, residence, etc.) as a stratifier. The stratifiers are likely to present similar patterns of inequalities for outcomes across geographies (districts, blocks) but with different magnitudes.

While a large body of equity research focusses on wealth related inequalities as a determinant, we used education and wealth as stratifier to analyse the inequality pattern. This is mainly because we used the data of last three decades where not only population-level wealth status has improved significantly, but also there has been a change in the indicators used to measure wealth status in the surveys. This brings the real challenge of assessing whether the intervention coverage among poor/less-educated has improved or the population composition of poor and rich, less-educated and more-educated changed over time. In the present analysis, we can see that the ANC and FD coverage improved across different levels of education. While the proportion of less educated women decreased over time, the proportion of women having any ANC or FD in the less educated group significantly improved implying program focus on the less-educated (Additional file 6). We also analysed the data by wealth as a stratifier and present the findings in additional file 3. Findings on inequality followed almost similar pattern as of education, however, the difference found was in the quantum of inequality. In addition, while the choice of stratifier did not matter for most of the districts, there were some districts where results on inequality patterns were different for wealth and education. Additional file 7 shows that the district-level inequality patterns were different in 9 and 23 districts for any ANC and FD, respectively, if two different stratifiers were considered for the same district. This also implies that the choice of stratifier needs to be context-specific and the program managers may choose the stratifier which shows maximum inequality at multiple levels or the stratifier that can be managed in a shorter time like education in this case compared to wealth.

While we attempted to make this framework very simple, it has some implementation constraints as well. The most important one is the availability of granular data to analyse the inequality at the lowest level. The national sample surveys like NFHS do not provide coverage estimates below district-level. Even the district-level data is not available prior to the NFHS-4, hindering opportunity of measuring long-term shift in district-level inequality. Such challenges have been documented previously as well [23]. Second, it requires thorough knowledge of the program context which may not be always available. Analytically, we could not conduct the sub-district or sub-block analysis at length due to the unavailability of data for all the blocks. Also, we did not use wealth as a stratifier as the wealth index measure was not available for CBTS-1 restricting the block-level comparative analysis for the selected indicators.

Conclusions

To attain the health-related SDGs, the Government of Uttar Pradesh implements multiple health programs covering almost all indicators [24]. Despite this, the data showed that a proportion of the population is either not accessing the services or has unfavourable outcomes. Using the data from multiple rounds of representative surveys, we attempted to analyse from a programmers perspective which led to the HEFP identifying who is being left behind, where they are, so that the programs can be targeted to achieve LNOB status. The findings of this paper showed that, within the same geography, there is a possibility of inequality patterns being different for different outcomes. This pattern could be driven by both supply and demand factors, including those related to social context and community behaviour. Though studies in developed countries context estimates lack of access or poor quality of care (supply) to contribute very less to inequality [25], it may differ in the context of developing countries. This framework emphasizes the importance of conducting inequality analysis separately for each outcome rather than looking into a composite measure considering different levels of inequality for different outcomes within geography. Also, for LNOB, this framework emphasizes going deeper into those program layers with higher coverage and lower inequality to identify the left-behinds. Of course, to effectively conduct this equity analysis following the proposed approach, the data needs to be organized in a systematic way. The state of Uttar Pradesh has systematically worked on key health system building blocks (HR, drugs, infrastructure, and data systems) and built upon a strong digital architecture such as e-HRMS system to track human resource availability, digital drug and logistics management system to strengthen supply-chain, and is also implementing a unitized service delivery recording system compatible with the flagship national Ayushman Bharat Digital Mission (ABDM) framework recently launched in India. These systems when organized well can help understand equity drop on a real-time basis and possibly also the cause for non-provision of services to beneficiaries encountering service delivery platforms. With more and more unitized data coming in UP, steps have been initiated in organizing data in a way that such analysis is possible and enable the programmers in the state to attain SDG goals effectively.

Abbreviations

ABDM	Ayushman Bharat Digital Mission
ANC	Antenatal care
ASHA	Acredited Social Health Activist
AWW	Anganwadi workers
CBTS	Community Behaviour Tracking Survey
CD	Community development
DHS	Demographic and Health Surveys
e-HRMS	Electronic-Human resource management system
FD	Facility delivery
FLWs	Front line workers
HEFP	Health equity framework for programs
HPDs	High priority districts
HR	Human resource
LNOB	Leave no one behind
NFHS	National Family Health Survey
pp	Percentage point
PSU	Primary sampling unit
RMNCH	Reproductive maternal newborn child health
SDG	Sustainable development goals
SDOH	Social determinants of health

SII	Slope index of inequality
UP	Uttar Pradesh
UPTSU	Uttar Pradesh Technical Support Unit

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12939-025-02411-8.

Supplementary Material 1

Supplementary Material 2

Supplementary Material 3

Supplementary Material 4

Supplementary Material 5

Supplementary Material 6

Supplementary Material 7

Supplementary Material 8

Acknowledgements
We thank all the study participants as well as the survey team who conducted the CBTS. We also thank the state government for providing necessary approvals to conduct CBTS study. Thanks to Professor Shiva Halli, Vikas Gothalwal and Dr BM Ramesh, working at the Institute for Global Public Health, University of Manitoba for providing feedback on the earlier version of analysis.

Author contributions
VN, RP, BD, FCW, JB contributed to the conception and methodology of this paper. BD and RP compiled the data and performed the statistical analysis. VN, RP and BD wrote the original draft of the paper. All authors participated in the discussion and revision of the versions of the paper. FCW, MB, JB, SI, and TB provided substantial review and editing of the content. All authors had read and approved the final manuscript.

Funding
The CBTS study was funded by the Bill & Melinda Gates Foundation (Investment ID: INV-003343) to track and monitor the quality and progress of the family planning program in Uttar Pradesh, India. The views expressed herein are those of the authors and do not necessarily reflect the official policy or position of the BMGF.

Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
The NFHS data used in this study is conducted by International Institute for Population Sciences and has received all the necessary approvals. This data is publicly available for secondary analyses, and therefore, does not require a separate ethics approval for this work. The CBTS study received ethics approval from the Institutional Review Board of Sigma Research and Consulting Pvt. Ltd., New Delhi, India (10001/IRB/D/18–19) and the University of Manitoba's Health Research Ethics Board (HS20187 (H2016:385)). Participants were informed about the purpose and procedure of the survey and confidentiality was assured. Participants had the freedom not to answer any question or withdraw at any point in time during the survey. Verbal informed consent was obtained from all participants.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Author details
[1]Secretary Health, Union Territory of Ladakh, Leh, India
[2]Institute for Global Public Health, University of Manitoba, Winnipeg, Canada
[3]India Health Action Trust, Lucknow, India

Received: 10 July 2024 / Accepted: 10 February 2025
Published online: 25 February 2025

References

1. The Sustainable Development Goals. Report 2016 [Internet]. [cited 2024 Feb 21]. Available from: https://unstats.un.org/sdgs/report/2016/The%20Sustainable%20Development%20Goals%20Report%202016.pdf
2. Rava N, Lisa Kurbiel. Leave No One Behind [Internet]. Leave No One Jt. SDG Fund. [cited 2024 Feb 21]. Available from: https://jointsdgfund.org/article/leave-no-one-behind
3. United Nations System. Leaving No One Behind: Equality and Non-Discrimination at the Heart of Sustainable Development [Internet]. UN. 2017. Available from: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://unsceb.org/sites/default/files/imported_files/CEB%20equality%20framework-A4-web-rev3.pdf
4. Victora CG, Joseph G, Silva ICM, Maia FS, Vaughan JP, Barros FC, et al. The inverse equity hypothesis: analyses of institutional deliveries in 286 national surveys. Am J Public Health. 2018;108:464–71.
5. Solar O, Irwin A. A conceptual framework for action on the social determinants of health. 2010 [cited 2024 Feb 21];76. Available from: https://iris.who.int/handle/10665/44489
6. Rosalia Munoz-Arroyo. Matt Sutton. Measuring socio-economic inequality in health: a practical guide 2007; Public Health Information for Scotland.
7. Hosseinpoor AR, Nambiar D, Schlotheuber A, Reidpath D, Ross Z. Health Equity Assessment Toolkit (HEAT): software for exploring and comparing health inequalities in countries. BMC Med Res Methodol [Internet]. 2016 [cited 2024 Feb 21];16:141, s12874-016-0229–9. Available from: http://bmcmedresmethodol.biomedcentral.com/articles/https://doi.org/10.1186/s12874-016-0229-9
8. Vine MM, Mulligan K, Harris R, Dean JL. The Impact of Health Geography on Public Health Research, Policy, and practice in Canada. Int J Environ Res Public Health. 2023;20.
9. Shawky S. Measuring Geographic and Wealth Inequalities in Health Distribution as Tools for Identifying Priority Health Inequalities and the underprivileged populations. Glob Adv Health Med. 2018;7:216495611879195.
10. National Commission on Population Ministry of Health & Family Welfare. Population Projections for India and States 2011–2036. Nirman Bhawan, New Delhi- 110011; 2019.
11. Office of the Registrar General & Census Commissioner, India (ORGI). A-01: Number of villages, towns, households, population and area (India, states/UTs, districts and Sub-districts)– 2011 [Internet]. Ministry of Home Affairs, Government of India., 2011. Report No.: ORGI Census 2011 Tables: PC11_A01. Available from: https://censusindia.gov.in/nada/index.php/catalog/42526
12. Directorate of Medical & Health Services. Uttar Pradesh. List of Uttar Pradesh Health Facilities [Internet]. Accessed on 07.10.2024. Available from:, accessed on 07.10.2024 http://arogyamela.dgmhup.in/en/upfacility
13. National Family Health Survey. (NFHS– 5), 2019–21 [Internet]. [cited 2024 Feb 21]. Available from: https://dhsprogram.com/pubs/pdf/FR375/FR375.pdf
14. National Family Health Survey (NFHS-2). 1998-99 [Internet]. [cited 2024 Feb 21]. Available from: https://dhsprogram.com/pubs/pdf/frind2/frind2.pdf
15. National Family Health Survey (NFHS-3). 2005-06 [Internet]. [cited 2024 Feb 21]. Available from: https://dhsprogram.com/pubs/pdf/frind3/frind3-vol1andvol2.pdf
16. National Family Health Survey (NFHS-4). 2015-16 [Internet]. [cited 2024 Feb 21]. Available from: https://dhsprogram.com/pubs/pdf/fr339/fr339.pdf
17. National Family Health Survey (NFHS). 1992-93 [Internet]. [cited 2024 Feb 21]. Available from: https://dhsprogram.com/pubs/pdf/SR162/SR162.pdf
18. Crockett M, Avery L, Blanchard J. Program science–a framework for improving global maternal, newborn, and child health. JAMA Pediatr. 2015;169:305–6.
19. Rutstein SO, Johnson K, ORC Macro. The DHS wealth index [Internet]. Calverton, Maryland, USA:; 2004. Available from: http://dhsprogram.com/pubs/pdf/CR6/CR6.pdf
20. Schlotheuber A, Hosseinpoor A. Summary Measures of Health Inequality: A Review of Existing Measures and Their Application. Int J Environ Res Public

Health [Internet]. 2022 [cited 2024 Feb 21];19:3697. Available from: https://www.mdpi.com/1660-4601/19/6/3697
21. Gkiouleka A, Wong G, Sowden S, Bambra C, Siersbaek R, Manji S, et al. Reducing health inequalities through general practice. Lancet Public Health. 2023;8:e463–72.
22. Carruthers E, Dobbin J, Fagan L, Humphrey A, Nagasivam A, Stevenson K, et al. Interventions to improve access to primary care for inclusion health groups in England: a scoping review. Lancet Lond Engl. 2023;402(Suppl 1):S32.
23. Victora C, Boerma T, Requejo J, Mesenburg MA, Joseph G, Costa JC, et al. Analyses of inequalities in RMNCH: rising to the challenge of the SDGs. BMJ Glob Health. 2019;4:e001295.
24. Uttar Pradesh National Health Mission [Internet]. [cited 2024 Feb 27]. Available from: https://upnrhm.gov.in/Home/PIP
25. Adler NE, Stewart J. Health disparities across the lifespan: meaning, methods, and mechanisms. Ann N Y Acad Sci. 2010;1186:5–23.

Publisher's note