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Healthcare inequity arising from unequal response to need in the older (45+ years) population of India: Analysis of nationally representative data

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ABSTRACT

Given the large and growing number of older (45+ years) people in India, inequitable access to healthcare in this population would slow global progress toward universal health coverage. We used a 2017-18 nationally representative sample of this population (n = 53,687) to estimate healthcare inequality and inequity by economic status. We used an extensive battery of indicators in nine health domains, plus age and sex, to adjust for need. We measured economic status by monthly per capita consumption expenditure and used a concentration index to measure inequalities in probabilities of any doctor visit and any hospitalisation within 12 months. We decomposed inequality with a regression method that allowed for economic and urban/rural heterogeneity in partial associations between healthcare and both need and non-need covariates. We used the associations achieved by the richest fifth of urban dwellers to predict a need-justified distribution of healthcare and compared the actual distribution with that benchmark to identify inequity. We found pro-rich inequalities in doctor visits and hospitalisations, which were driven by use of private healthcare. Adjustment for the greater need of poorer individuals revealed pro-rich inequity that exceeded inequality by about 65% and 39% for doctor visits and hospitalisations, respectively. These adjustments would have been substantially smaller, and inequity underestimated, without allowing for use-need heterogeneity, which accounted for 11% of the inequity in doctor visits and was 373% of inequity in hospitalisations. Targeting service coverage on poorer and rural groups, and increasing their access to private providers, would both reduce inequity and raise average coverage in the older population of India.

1. Introduction

Universal health coverage (UHC) aims to ensure that everyone, irrespective of economic status, gets the healthcare they need (WHO and IBRD/World Bank, 2023). Global progress toward the respective sustainable development goal (SDG) target indicator (3.8.1) has been driven by increasing coverage for infectious diseases with little improvement in health system responses to non-communicable diseases (NCDs) (ibid.). This imbalance is particularly problematic in lower-middle-income countries (LMICs), such as India, with growing elderly populations and service coverage that tends to be low and unequal, to the disadvantage of poorer and rural populations. However, monitoring of service coverage inequality does not establish whether healthcare is delivered equitably.

Forecasts indicate that one fifth of the population of India will be 60 years and older and two fifths will be 45 years and older by 2050, when the country will have the second largest elderly (60+ years) population in the world (IIPS and UNPF, 2023). Ensuring that the older (45+) population of India has equitable access to healthcare is of first order importance to global progression toward UHC goals.

There is international evidence of steep socioeconomic gradients in healthcare utilisation in older populations (McMaughan et al., 2020;

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Yamada et al., 2015) and extensive evidence from India of pro-rich healthcare inequalities among the elderly (Bhan et al., 2016, Channon et al., 2012; Ranjan and Muraleedharan, 2020, Sahoo et al., 2021, IIPS and UNPF, 2023) and non-elderly (Banerjee and Roy Chowdhury, 2020). In addition to evidence of pro-rich healthcare inequity in the all-age Indian population (Ghosh, 2014; Verma and Dash, 2021), two studies used nationally representative data up to 2014 to reveal apparent inequity to the disadvantage of poorer elderly (60+) Indians. However, these studies relied on only a few indicators of reported health, in addition to age and sex, to adjust the distribution of utilisation for inequality in need (Joe et al., 2015; Pandey et al., 2017). Another study documented healthcare inequity by gender, not by economic status, in the elderly Indian population (Roy and Chaudhuri, 2008). Missing from this evidence is a recent (post-2014) assessment of inequity (as opposed to inequality) by economic status in the distribution of healthcare conditional on extensive indicators of need in the older (45+) population of India.

Assessment of horizontal equity – equal treatment for equal need – in the distribution of healthcare has typically assumed that, on average over the population, the health system achieves vertical equity – appropriately unequal treatment for unequal need (Barbosa and Cookson, 2019; Joe et al., 2015; Lu et al., 2007; Pulok et al., 2020; Pulok and Hajizadeh, 2022; van Doorslaer et al., 2004; Wagstaff and van Doorslaer, 2000a,b). This is a particularly strong assumption in LMICs, where health systems are often severely resource-constrained and may lack capacity to respond appropriately to need, even on average. The overall associations between healthcare utilisation and proxy need indicators may understate the responsiveness consistent with vertical equity. Then, they would not provide an appropriate base from which to simulate the distribution of healthcare that would be equitable given the distribution of need. If poorer individuals were in worse health, then applying population-averaged associations between utilisation and need indicators to their indicators would understate their greater need for healthcare. Inequality in healthcare would be insufficiently adjusted for inequality in need, resulting in underestimation of pro-rich inequity.

Van de Poel et al. (2012) showed that these limitations can be avoided by assuming that healthcare responds appropriately to need only in a privileged population that faces the lowest barriers to accessing healthcare. The utilisation-need associations in this population can then be used to predict need-justified utilisation in other, less privileged populations. Comparison of the distribution of actual utilisation with this need-justified distribution gives a more appropriate assessment of whether everyone, irrespective of economic status, gets the healthcare they need (ibid.). This corrected measure of healthcare inequity was found to substantially increase estimated inequity to the disadvantage of poorer adults (18+) in four middle-income Asian countries, including India, in 2002–03 (ibid.). It has also revealed healthcare inequity to the disadvantage of poorer people (of all ages) with cardiovascular diseases in India (Akhtar and Roy Chowdhury, 2023).

By using the Van de Poel et al. (2012) method to capture systematic heterogeneity in the response of healthcare to an extensive battery of need indicators contained in nationally representative data, this study aimed to provide the most robust and enlightening evidence to date on inequity by economic status in healthcare utilisation (doctor visits and hospitalisations) of Indians aged 45 years and older.

2. Methods

2.1. Data

We used data from the first (to date, only) wave of the Longitudinal Ageing Study in India (LASI) conducted from April 2017 to December 2018 in all states and union territories (UTs). Stratified, multistage cluster random sampling produced a sample of 73,396 individuals aged 45+ years that was representative of the older (45+) population nationally and by state/UT (IIPS, 2020). The (individual) response rate was 87.3%.

Ethical approval of LASI was obtained from the Government of India and the institutional review boards of the International Institute for Population Sciences (IIPS) and its collaborating institutions. Written informed consent was given by all respondents. The secondary analysis of the data reported here did not require further ethical approval.

2.2. Measures

We used two indicators of healthcare utilisation in the last 12 months: *any doctor visit* and *any hospitalisation*. Each respondent was asked: *In the last* 12 months*, have you consulted any health care provider?* Those responding positively were asked to specify the type of provider. We coded those who reported that they visited a doctor (surgeon, physician, gynecologist, psychiatrist, ophthalmologist and orthopedist) as 1 for *any doctor visit*, and all other respondents as 0. All respondents were asked two questions about hospital admissions: a) *Number of times admitted to hospital during the last* 12 months*?* b) *Over the last* 12 months*, how many times were you admitted as a patient to a hospital/long-term care facility for at least one night?* Those who reported at least one admission in response to either question were coded 1 for *any hospitalisation*, and all others were coded 0.

In secondary analysis, we distinguished between utilisation of public and private healthcare. The respondent was asked to identify the type of facility (public or private) only for the last outpatient consultation in the last 12 months. For those with *any doctor visit* (=1) and whose last consultation was with a doctor, we categorised the visit as *public* or *private* based on the type of facility at which it occurred (Table 4 notes). For those with *any hospitalisation* (=1), *public* was coded if, in the last 12 months, all hospitalisations were in government hospitals and *private* was coded otherwise (Table 4 notes).

We adjusted for healthcare need in a flexible way using age, sex and an extensive battery of reported and measured indicators over nine domains of health: (a) self-reported health, (b) mobility, (c) adiposity, (d) cognition, (e) pain, (f) vision, (h) symptoms, and (i) miscellaneous (injury, fall, sleep problems and hopelessness) (Supplementary Material (SM) Table S1). We did not aggregate indicators into a composite index or indices (except for cognition scores) because this would have imposed implicit assumptions about relative importance of indicators and resulted in loss of information, while being unnecessary to make the fullest possible control for need with the available data. Each respondent self-reported their general health status twice in response to the same question with two sets of response-category labels. We used both reports in order to extract all relevant information on need while allowing for reporting errors that add noise to each indicator. To obtain indicators that reflected need for healthcare, and not its utilisation, we did not use any measurement or report that could depend on healthcare received, such as diagnosed conditions.

Conditional on the need indicators, we examined variation in the two indicators of healthcare utilisation in relation to economic status, measured by monthly per capita consumption expenditure (MPCE), and covariates that included marital status (married/not), education (0, 1–4, 5–9, ≥10 years), religion (Hindu, Muslim, Christian, Others), living arrangement (alone, with spouse & children, with spouse or others, with children or others), social class (Scheduled Tribe, Scheduled Caste, Other Backward Class, Others), employment (working, not working, never worked), health insurance (yes, no) and region (North, Central, East, North East, West and South). MPCE was constructed from an abridged consumption schedule following the National Sample Survey (NSS) methodology that is used to measure poverty (NSSO, 2014). Household food consumption was reported in ten categories for a reference period of seven days. Non-food expenditure was reported for the last thirty days for frequently purchased items and the last 365 days for rarely purchased durable goods. We used these data to calculate household consumption expenditure, excluding spending on healthcare, for a 30-day period and divided by the household size to get MPCE. We applied sample weights and created urban- and rural-specific MPCE quintile groups, comprising the poorest 20 percent (after weighting) to the richest 20 percent of the full sample in urban locations, $\{Urban\ Q1, \ldots, Urban\ Q5\}$, and the poorest 20 percent to the richest 20 percent in rural locations, $\{Rural\ Q1, \ldots, Rural\ Q5\}$.

Table 1
Sample characteristics, n = 53,687.

	n	(%)
Age, years (mean (SD))	59.9	(10.6)
Age group		
45–54 years	20109	(35.5%)
55–64 years	16723	(30.7%)
65–74 years	11870	(23.6%)
75+ years	4985	(10.2%)
Male	24968	(46.2%)
Female	28719	(53.8%)
Education level, years		
0	25033	(50.6%)
1-4	6285	(11.3%)
5-9	12408	(20.9%)
≥10	9961	(17.1%)
Rural	35245	(71.0%)
Urban	18442	(29.0%)
MPCE quintiles within Rural/Urban		
Rural Q1 (Poorest)	6351	(14.2%)
Rural Q2	6614	(14.5%)
Rural Q3	6370	(14.1%)
Rural Q4	7430	(14.1%)
Rural Q5 (Richest)	8480	(14.1%)
Urban Q1	3456	(6.2%)
Urban Q2	3648	(6.0%)
Urban Q3	3976	(5.6%)
Urban Q4	3721	(5.6%)
Urban Q5	3641	(5.3%)
Religion		
Hindu	39297	(82.3%)
Muslim	6286	(11.1%)
Christian	5555	(3.0%)
Others	2549	(3.6%)
Living arrangement		
Alone	1912	(3.7%)
With spouse only	8274	(16.3%)
With children only	31398	(57.3%)
With children & others	12103	(22.7%)
Marital Status		
Currently Married	40407	(74.6%)
Widowed/Other	13280	(25.4%)
Social class (Caste)		
Scheduled tribes (ST)	9465	(8.7%)
Scheduled castes (SC)	9104	(19.9%)
Other backward classes (OBC)	10188	(44.9%)
Others	14930	(26.4%)
Work status		
Currently working	25389	(48.0%)
Currently not working	13782	(26.6%)
Never worked	14517	(25.4%)
Health insurance		
No	41080	(79.1%)
Yes	12607	(20.9%)
Region		
North	9779	(12.6%)
Central	6912	(19.8%)
East	10096	(25.4%)
North-East	7349	(3.7%)
West	6924	(16.1%)
South	12627	(22.4%)

Note. Table shows frequences (n, unweighted) and percentages (%, weighted) for categorical variables and mean and standard deviation (SD) for continuous variable. Percentages are not equal across MPCE quintiles within Rural/Urban because quintile groups were constructed with the full sample. See SM Table S3 for definitions of regions.

2.3. Statistical analysis

We used a concentration index to measure inequality in each indicator of healthcare utilisation by economic status (O'Donnell et al., 2008). The index (CC_y) is the (scaled) covariance between a utilisation indicator, $y_i \in \{any\ doctor\ visit_i, any\ hospitalisation_i\}$, and fractional ranks, $R_i = {}^{i}/_{n}$, of individuals, $i = 1, 2, \ldots, n$, ordered from lowest to highest MPCE: $CC_y = 8 \times cov(y_i, R_i)$ (Erreygers, 2009). A positive value of this index would indicate that better off individuals, with higher MPCE, were more likely to use healthcare. The index measures absolute inequality, is appropriate for dichotomous indicators and would have the same magnitude if we had measured inequality in non-utilisation (Erreygers, 2009).

To explain inequality in each utilisation indicator, we used the Van de Poel et al. (2012) decomposition of the respective concentration index into: a) inequality in the distribution of need by MPCE rank, b) differences across MPCE groups in the associations between utilisation and need (*discrimination*), c) inequality in the distributions of non-need covariates of utilisation by MPCE rank (*homogeneous non-need*), d) differences across MPCE groups in the associations between utilisation and those covariates (*heterogeneous non-need*), e) differences in utilisation across MPCE groups after adjusting for all need indicators and non-need covariates (*adjusted group differences*), and f) residual unexplained inequality in utilisation (*unexplained*).

Contribution a) was further decomposed into: a1) inequality in utilisation that would be attributed to inequality in need if need-predicted utilisation were obtained from average associations between utilisation and the need indicators (*homogeneous need*), and a2) a correction to the contribution of inequality in need that arises from the average associations reflecting insufficient responsiveness of utilisation to need (*corrected need*). To identify this latter contribution, we selected a reference group – the top MPCE quintile in urban locations – that was likely to face the lowest geographic and economic barriers to accessing healthcare and so would be expected to have utilisation that was most responsive to need.

The decomposition was based on linear probability models capturing partial associations between each utilisation indicator and both the need indicators and covariates in the full population (1) and in each subpopulation distinguished by economic status (2):

$$y_i = \alpha + \sum\nolimits_j \beta_j x_{ji} + \sum\nolimits_k \gamma_k z_{ki} + \varepsilon_i, \tag{1}$$

$$y_i = \alpha^g + \sum\nolimits_j \beta_j^g x_{ji} + \sum\nolimits_k \gamma_k^g z_{ki} + \varepsilon_i^g, \forall i \in g, g \in G, \tag{2}$$

where x_{ji} is need indicator j of individual i, z_{ki} is non-need covariate k, ε_i and ε_i^g represent unobserved determinants of utilisation, and g is one of the MPCE groups, $G = \{Urban\ Q1, \ldots, Urban\ Q5, Rural\ Q1, \ldots, Rural\ Q5\}$. The need indicators were those listed in SM Table S1, plus sex-specific age group indicators. The non-need indicators were those listed in Table 1, excluding age-sex, rural/urban and MPCE groups.

Given these linear models, we decomposed the concentration index for each utilisation indicator as follows (Van de Poel et al., 2012):

$$CC_y = 4\overbrace{\sum\nolimits_j \beta_j \bar{x}_j C_j}^{homogeneous\ need} + \overbrace{\frac{8}{n}\sum_j \left(\beta_j^{g^r} - \beta_j\right)\sum_i x_{ji}(R_i - 0.5)}^{corrected\ need}$$

$$+ \overbrace{\frac{8}{n}\sum_j \sum_i x_{ji}\left(\beta_j^g - \beta_j^{g^r}\right)(R_i - 0.5)}^{discrimination}$$

$$+\overbrace{4\sum_k \gamma_k \bar{z}_k C_k}^{\substack{homogeneous\\non-need}} + \overbrace{\frac{8}{n}\sum_k\sum_i z_{ki}\left(\gamma_k^g - \gamma_k\right)(R_i - 0.5)}^{heterogeneous\ non-need} + \overbrace{8cov(\alpha_g, R_i)}^{\substack{adjusted\ group\\differences}}$$
$$+\overbrace{8cov(\varepsilon_i^g, R_i)}^{unexplained} \quad (3)$$

where C_j and C_k are the standard concentration indices (O'Donnell et al., 2008) of variables x_j and z_k, respectively, $\bar{x}_j$ and $\bar{z}_k$ are the respective means, and $\beta_j^{g^r}$ is the partial association of y with x_j in the reference sub-population, $g^r = Urban\ Q5$.

The *homogeneous need* term gives the inequality in utilisation attributable to inequality in need according to the average responsiveness of utilisation to need in the full population. The *corrected need* term gives additional inequality in utilisation that would be justified by inequality in need if need-predicted utilisation were based on the response of utilisation to need in the most advantaged group (*Urban Q5*). The sum of these two terms gives the inequality in utilisation that may be considered an equitable response to unequal need. We subtracted this justified inequality from the actual inequality measured by the concentration index to get an index of inequitable utilisation (Van de Poel et al., 2012),

$$I_y = CC_y - 4\sum_j \beta_j \bar{x}_j C_j - \frac{8}{n}\sum_j\left(\beta_j^{g^r} - \beta_j\right)\sum_i x_{ji}(R_i - 0.5) = CC_y - 4\sum_j \beta_j^{g^r}\bar{x}_j C_j . \quad (4)$$

A positive value of this index would indicate need-adjusted inequality in utilisation favouring the better off; that is, inequity to their advantage. If $I_y > CC_y > 0,$ then greater need of poorer individuals partially offsets pro-rich bias in utilisation for given need and causes the observed pro-rich inequality in utilisation to understate the degree of inequity to the advantage of the better off.

Whereas the homogeneous and corrected need contributions together capture inequality in utilisation that could be justified given inequality in need, the *discrimination* term in (3) gives the unjustified inequality in utilisation arising from differences in its responsiveness to any given level of need. The *discrimination* label is chosen to signal inequality arising from individuals with the same need but different economic status getting different access to healthcare. This need not arise from purposeful discrimination by healthcare providers. It could result from demand-side differences in seeking healthcare.

The *homogeneous* and *heterogeneous non-need* terms in (3) give the inequality in utilisation generated by inequality in the non-need covariates, which include region, and inequality in the utilisation response to those covariates, respectively. The latter of the two is the non-need equivalent of corrected need and discrimination contributions combined. The *adjusted group differences* term in (3) gives the inequality in utilisation due to different rates of utilisation across the groups that are not due to inequalities in observed need and non-need covariates and the utilisation response to them. The *unexplained* term is the residual inequality in utilisation that is not accounted for by the distributions of the need and non-need covariates, nor by the group differences.

For each utilisation indicator, we used ordinary least squares (OLS) to estimate the partial associations in the linear models (1) and (2). If a nonlinear estimator were used for the dichotomous utilisation indictors, then it would only be possible to obtain an approximate decomposition (van Doorslaer et al., 2004). In addition to introducing an approximation error, results would depend on (arbitrary) values of variables chosen to calculate terms. We used the OLS estimates along with estimated (standard) concentration indices, e.g. $C_j = {}^2/_{\bar{x}_j}\, cov(x_{ji}, R_i)$, and the sample means, $\bar{x}_j$ and $\bar{z}_k,$ to calculate each of the terms in (3). We obtained the unexplained term as the residual difference between the estimated concentration index for utilisation, $\widehat{CC}_y$, and the sum of the estimates of the other terms. We estimated the inequity index by replacing the parameters in (4) with the corresponding sample estimates.

For each of any doctor visit and any hospitalisation, we decomposed inequality in utilisation of public and private providers of the respective healthcare. In supplementary analyses, we stratified by age (45–59 years vs $\geq$ 60) and by sex. We applied sample weights in all analysis and adjusted 95% confidence intervals for sample clustering (and also for stratification for estimates of means and concentration indices). We used a bootstrap (normal approximation, 100 replications) to obtain confidence intervals for contributions to the decomposition. We used Stata version 17.0 for all analysis and a user-written Stata command to estimate concentration indices (O'Donnell et al., 2016).

3. Results

Out of a total sample of 73,396 individuals interviewed, our complete-case analysis sample included 53,687 individuals (73.2%). We excluded those who were younger than 45 years (spouses of main respondents) and who had item non-response, mostly on need indicators (SM Fig. S1). Table 1 shows characteristics of the analysis sample. The mean age was about 60 years. Around 54% was female, 51% did not have any formal education, 71% were in rural locations, 82% were Hindu, 4% were living alone, 74% belonged to lower social classes (Scheduled Castes & Tribes and Other Backward Classes) and almost four fifths did not have health insurance.

Table 2 presents estimated means and concentration indices of inequality for the indicators of healthcare utilisation and need (SM Table S2 for mean utilisation by MPCE groups and Table S3 for means and concentration indices of non-need covariates). We estimated that, over a year, about 53% (95% CI: 51.9, 54.5) of the older population of India visited a doctor (as an outpatient) and about 6.6% (6.1, 7.0) were admitted to hospital. The positive concentration indices of any doctor visit (0.103; 95% CI: 0.070, 0.136) and any hospitalisation (0.015; 0.006, 0.025) indicate that better off individuals, with higher MPCE, were more likely to have visited a doctor and to have been hospitalised in the last 12 months.

The estimated concentration indices of the need indicators generally indicate that poorer individuals had worse health, and so, presumably, greater need. For both versions of self-reported health (SRH), positive indices for the top two categories indicate that individuals with higher MPCE were more likely to report better health. The negative indices for the bottom two SRH categories indicate that poorer individuals were more likely to report worse health. Taking into account a tendency of poorer individuals to assess their health less critically (Bago d'Uva et al., 2008; Sen, 2002), these patterns suggest that they were indeed in worse health. The concentration indices are negative for all but one of the mobility indicators: poorer individuals were more likely to report mobility difficulties, they walked more slowly and they were more likely to be bedridden. While they were less likely to be overweight or obese, they had worse cognitive functioning, which is indicated by positive concentration indices for all dimensions of cognition. Negative concentration indices for pain indicate that poorer individuals were more likely to experience pain rarely, occasionally or frequently compared with having no pain. They were also more likely to be measured with low near vision. For symptoms, most the of the point estimates of the concentration indices are negative, but only for dizziness does the 95% confidence interval not include zero. Poorer individuals were more likely to have an injury, a sleep problem and to report not feeling hopeful. For both males and females, poorer individuals were less likely to be in the youngest age group that, presumably, had less need for healthcare.

Table 3 shows, for each utilisation indicator, equation (3) decomposition of its concentration index into the main contributions to

Table 2
Levels and inequalities of healthcare utilisation and need indicators, older (45+) individuals in India 2017–18 (n = 53,687).

	Mean	(95% CI)	Concentration index	(95% CI)
Healthcare utilisation				
Any doctor visit (0, 1)	0.532	(0.519, 0.545)	0.103	(0.070, 0.136)
Any hospitalisation (0, 1)	0.066	(0.061, 0.070)	0.015	(0.006, 0.025)
Need				
Self-reported health I				
Excellent (0, 1)	0.043	(0.038, 0.047)	0.029	(0.021, 0.038)
Very good (0, 1)	0.175	(0.164, 0.187)	0.058	(0.031, 0.084)
Good (0,1)	0.380	(0.370, 0.390)	0.009	(-0.010, 0.028)
Fair (0,1)	0.299	(0.289, 0.309)	−0.064	(-0.086, −0.040)
Poor (0,1)	0.103	(0.097, 0.109)	−0.032	(-0.045, −0.020)
Self-reported health II				
Very good (0,1)	0.050	(0.046, 0.054)	0.033	(0.024, 0.042)
Good (0,1)	0.332	(0.320, 0.343)	0.042	(0.019, 0.066)
Fair (0,1)	0.443	(0.433, 0.452)	−0.027	(-0.046, −0.008)
Poor (0,1)	0.159	(0.151, 0.166)	−0.038	(-0.054, −0.022)
Very poor (0,1)	0.017	(0.015, 0.019)	−0.011	(-0.015, −0.006)
Mobility				
Time to walk 4-m (seconds)	5.460	(5.419, 5.501)	−0.029	(-0.048, −0.011)
Difficulty getting up after sitting (0,1)	0.313	(0.303, 0.323)	−0.039	(-0.062, −0.015)
Difficulty climbing stairs (0,1)	0.442	(0.430, 0.453)	−0.078	(-0.105, −0.051)
Difficulty stooping (0,1)	0.470	(0.458, 0.481)	−0.044	(-0.074, −0.014)
Difficulty extending arms (0,1)	0.135	(0.128, 0.143)	0.002	(-0.013, 0.018)
Difficulty pulling/ pushing (0,1)	0.391	(0.380, 0.402)	−0.068	(-0.091, −0.045)
Bedridden last 30 days (0, 1)	0.415	(0.378, 0.452)	−0.027	(-0.047, −0.006)
Adiposity				
Overweight (0, 1)	0.202	(0.190, 0.213)	0.159	(0.133, 0.186)
Obese (0, 1)	0.066	(0.059, 0.073)	0.072	(0.053, 0.090)
Cognition (higher better)				
Orientation (0–8)	6.807	(6.766, 6.849)	0.152	(0.131, 0.172)
Arithmetic functioning (0–9)	4.692	(4.598, 4.786)	0.428	(0.377, 0.479)
Executive functioning (0–4)	2.395	(2.364, 2.425)	0.097	(0.080, 0.115)
Object naming (0–2)	1.946	(1.941, 1.951)	0.007	(0.005, 0.010)
Pain (experienced each week)				
Rarely (0, 1)	0.095	(0.089, 0.101)	−0.018	(-0.030, −0.007)
Occasionally (0, 1)	0.149	(0.141, 0.156)	−0.031	(-0.046, −0.016)
Frequently (0, 1)	0.128	(0.120, 0.134)	−0.024	(-0.038, −0.011)
Low near vision (0, 1)	0.289	(0.276, 0.300)	−0.084	(-0.107, −0.061)
Symptoms				
Joint problem (0, 1)	0.462	(0.452, 0.473)	−0.012	(-0.037, 0.014)
Swelling (0, 1)	0.187	(0.179, 0.195)	0.004	(-0.013, 0.022)
Breathing problem (0, 1)	0.070	(0.066, 0.075)	−0.004	(-0.014, 0.006)
Dizziness (0, 1)	0.137	(0.129, 0.144)	−0.034	(-0.050, −0.018)
Back problem (0, 1)	0.314	(0.303, 0.325)	−0.015	(-0.045, 0.016)
Headache (0, 1)	0.120	(0.114, 0.126)	−0.008	(-0.022, 0.006)
Angina (0, 1)	0.087	(0.082, 0.092)	−0.007	(-0.018, 0.004)
Miscellaneous				
Injury (0, 1)	0.134	(0.127, 0.141)	−0.015	(-0.029, −0.001)
Fall (0, 1)	0.105	(0.099, 0.110)	−0.009	(-0.021, 0.003)
Sleep problem (0, 1)	0.369	(0.360, 0.379)	−0.045	(-0.067, −0.022)
Not hopeful (0, 1)	0.663	(0.652, 0.675)	−0.059	(-0.082, −0.036)
Sex × Age group (years)				
Female & 45–54 (0, 1)	0.195	(0.189, 0.201)	0.041	(0.024, 0.059)
Female & 55–64 (0, 1)	0.170	(0.165, 0.176)	−0.013	(-0.029, 0.002)
Female & 65–74 (0, 1)	0.121	(0.116, 0.127)	−0.026	(-0.039, −0.013)
Female & ≥ 75 (0, 1)	0.051	(0.048, 0.055)	−0.008	(-0.016, 0.002)
Male & 45–54 (0, 1)	0.160	(0.155, 0.165)	0.023	(0.008, 0.038)
Male &55–64 (0, 1)	0.136	(0.132, 0.141)	0.002	(-0.006, 0.011)
Male, & 65–74 (0, 1)	0.115	(0.110, 0.120)	−0.013	(-0.024, −0.001)
Male & ≥ 75 (0, 1)	0.051	(0.047, 0.055)	−0.006	(-0.014, 0.002)

Note. Estimates of population means and concentration indices. Sample weights applied. 95% CI adjusted for sample stratification and clustering. Those (spouses) younger than 45 years excluded from the analysis sample. See SM Table S1 for definitions of need indicators, Table S2 for means of utilisation indicators by urban/rural-specific MPCE quintile groups, and Table S3 for means and concentration indices of non-need covariates.

inequality (SM Table S4 & S5 for detailed decompositions and Table S6 & **S7**a-j for coefficients of regression models (1) and (2), respectively). For any doctor visit, the small, positive homogeneous need contribution implies that inequality in need would have appeared to contribute to pro-rich inequality in utilisation, although modestly (2% ≈ 0.0022/ 0.1031 × 100), if the average associations between utilisation and the need indicators were used to estimate need-predicted utilisation. However, the corrected need contribution, which is negative and much larger in magnitude, indicates that the homogeneous need term fails to capture the pro-poor inequality in utilisation that would be warranted given the greater need of poorer individuals. This is because predicting utilisation on the basis of its responsiveness to need in the most advantaged group (Urban Q5) that faced the lowest access barriers generated much higher need-justified utilisation of poorer individuals than was obtained using the average utilisation-need associations. Summing the homogeneous need and corrected need contributions gave a negative overall need contribution (−0.0668), which indicates that poorer individuals would be more likely (than the better off) to visit a doctor if their greater need were responded to in the same way that utilisation responded to need in the most advantaged group.

For any hospitalisation, the homogeneous need and corrected need contributions are both negative. That is, even if the average utilisation-need associations were used to predict need-justified utilisation, poorer individuals, who are in greater need, would be expected to have a higher likelihood of being admitted to hospital. But using the average

Table 3

Decomposition of inequality in healthcare utilisation, older (45+) individuals in India 2017–18 (n = 53,687).

	Any doctor visit	Any hospitalisation
Inequality (concentration index)	**0.1031 (0.0700, 0.1361)**	**0.0154 (0.0060, 0.0250)**
Contributions		
Need		
a1. Homogeneous	0.0022 (−0.0079, 0.0122)	−0.0039 (−0.0086, 0.0008)
a2. Corrected	−0.0690 (−0.1094, −0.0285)	−0.0021 (−0.0202, 0.0159)
b. Discrimination	0.0181 (−0.1683, 0.2045)	0.0798 (−0.0134, 0.1730)
Non-need		
c. Homogeneous	0.0491 (0.0343, 0.0638)	0.0056 (0.0011, 0.0102)
d. Heterogeneous	0.1389 (0.0279, 0.2498)	−0.0413 (−0.1014, 0.0188)
e. Adjusted group differences	−0.0394 (−0.2667, 0.1879)	−0.0236 (−0.1354, 0.0883)
f. Unexplained	0.0033 (0.0006, 0.0059)	0.0010 (−0.0004, 0.0023)
Inequity (= Inequality – (a1 + a2))	**0.1699**	**0.0214**

Note. Equation (3) decomposition of inequality into contributions. See SM Tables S4 and S5 for detailed decompositions into the contributions of need indicators and non-need covariates. See SM Tables S6 & S7a-j for coefficients of pooled and MPCE-group-specific regression models (1) and (2), respectively. 95% confidence intervals in parentheses adjusted for sample clustering and for contributions were obtained by a bootstrap (normal approximation, 100 replications).

associations would underestimate need-justified pro-poor inequality by about one third compared with using the associations estimated for the most advantaged group.

The bottom row of the table shows the inequity indices (equation (4)) that measure inequality (correctly) adjusted for the unequal distribution of need. For any doctor visit, this index is about 65% larger than the concentration index, indicating that need-unadjusted inequality in utilisation substantially understates inequity to the disadvantage of poorer individuals because it does not take account of their greater need. For any hospitalisation, the inequity index is 39% larger than the inequality index.

The discrimination contributions, which measure inequality in utilisation due to differences in its response to need by economic status, are positive and, for hospitalisations, relatively large. This indicates that, for a given distribution of need, the greater responsiveness of utilisation to need in the urban and higher MPCE quintile groups contributed to pro-rich inequality in doctor visits and, even more substantially, in hospitalisations. This unequal response of utilisation to need accounted for 18% of the pro-rich inequality in the likelihood of visiting a doctor. For hospitalisations, inequality resulting from the greater responsiveness to the need of richer individuals is more than five times larger than overall inequality. In fact, this source of inequality is almost solely responsible for pro-rich inequality in hospitalisation. All of the other contributions, with the exceptions of those of homogeneous non-need and a very small residual, push inequality in the opposite direction. Better off individuals were more likely to be admitted to hospital not because they were in greater need but almost entirely because their need was more readily met with hospitalisation.

Positive homogeneous non-need contributions indicate that inequalities in non-need covariates accounted for around one half and one third of the pro-rich inequality in any doctor visit and any hospitalisation, respectively. Better off individuals had characteristics (other than need) associated with higher likelihoods of using healthcare. For both types of care, the largest homogeneous non-need contributions to pro-rich inequality were from higher social class (*Other*) and the Central and East regions (Tables S4 and S5). Better off individuals were more likely to belong to a higher class (Table S3), which was associated with a higher likelihood of using healthcare (Table S6). Poorer individuals were more likely to be located in the Central and Eastern regions (Table S3), where there was a lower average likelihood of using

Table 4

Decomposition of inequalities in public & private healthcare utilisation, older (45+) individuals in India 2017–18 (n = 53,687).

	Doctor visit				Hospitalisation			
	Public		**Private**		**Public**		**Private**	
Mean	**0.1199**	**(0.1129, 0.1269)**	**0.2582**	**(0.2473, 0.2691)**	**0.0233**	**(0.0208, 0.0258)**	**0.0423**	**(0.0391, 0.0455)**
Inequality (concentration index)	**−0.0209**	**(-0.0348, -0.0071)**	**0.1244**	**(0.1037, 0.1452)**	**−0.0020**	**(-0.0067, 0.0028)**	**0.0174**	**(0.0100, 0.0248**
Contributions								
Need								
a1 Homogeneous	−0.0089	(-0.0142, −0.0036)	0.0085	(0.0022, 0.0148)	−0.0035	(-0.0060, −0.0011)	−0.0004	(-0.0044, 0.0035)
a2 Corrected	−0.0033	(-0.0189, 0.0124)	−0.0448	(-0.0894, −0.0001)	−0.0034	(-0.0114, 0.0046)	0.0013	(-0.0139, 0.0164)
B Discrimination	0.0047	(-0.0894, 0.0987)	0.0817	(-0.0610, 0.2244)	0.0406	(-0.0340, 0.1152)	0.0392	(-0.0208, 0.0991)
Non-need								
c Homogeneous	0.0076	(-0.0002, 0.0153)	0.0555	(0.0446, 0.0665)	−0.0022	(-0.0052, 0.0007)	0.0079	(0.0047, 0.0111)
d Heterogeneous	0.0820	(0.0007, 0.1633)	0.1283	(0.0360, 0.2207)	0.0144	(-0.0194, 0.0481)	−0.0557	(-0.1033, −0.0080)
e Adjusted group differences	−0.1022	(-0.2267, 0.0223)	−0.1072	(-0.3005, 0.0861)	−0.0478	(-0.1200, 0.0243)	0.0242	(-0.0561, 0.1046)
f Unexplained	−0.0007	(-0.0025, 0.0010)	0.0023	(-0.0002, 0.0049)	0.0001	(-0.0008, 0.0009)	0.0009	(-0.0001, 0.0019)
Inequity (= Inequality – (a1 + a2))	**−0.0087**		**0.1608**		**0.0049**		**0.0165**	

***Note*.** For each of doctor visit and hospitalisation, public and private are mutually exclusive. For doctor visit, *public/private* refers to the location of the last outpatient consultation with a doctor in the last 12 months. *Public doctor visit* includes health post, primary health (sub-)center, community health center, (sub-)district hospital, government/tertiary hospital, government AYUSH hospital, health camp, and mobile healthcare unit. *Private doctor visit* includes private hospital/nursing home, private (outpatient) clinic, NGO/Charity/Trust/Church-run hospital, private AYUSH hospital, pharmacy/drugstore, home visit, and others. *Public hospitalisation* refers to an overnight stay in a government hospital with no overnight stay in a private hospital. *Private hospitalisation* refers to any overnight stay in a private hospital/nursing home, NGO/Charity/Trust/Church-run hospital, partial Private/Government/NGO hospital. Contributions from equation (3) decomposition of inequality. 95% confidence intervals in parentheses adjusted for sample clustering (and stratification for means and concentration indices). Confidence intervals of contributions by bootstrap (normal approximation, 100 replications).

healthcare (Table S6).

For doctor visits, there were marked differences in the associations between utilisation and non-need covariates by economic status that contributed substantially to the pro-rich inequality in utilisation. This heterogeneous non-need contribution exceeds total inequality. Its disaggregation revealed that better off individuals were more likely to visit a doctor because for them co-residence, higher education and higher class were all more closely associated with the propensity to visit a doctor (Table S4 & Tables S7a–j). Further, for the better off, location in the Central and Eastern regions was less strongly associated with a lower probability of visiting a doctor.

The contributions of adjusted group differences are negative for both types of utilisation, which would indicate that after adjusting for all differences in need and non-need covariates, as well as differential response of utilisation to the covariates, utilisation was actually higher in economically disadvantaged groups. However, the respective 95% confidence intervals include zero. For both types of utilisation, unexplained inequality is pro-rich, although the confidence interval does not contain zero only for doctor visits. The negative (pro-poor) point-estimates of the contributions of adjusted group differences and the small positive (pro-rich) point-estimates of contributions of unexplained inequality imply that most of pro-rich inequality in healthcare utilisation is explained by the distributions of need and non-need covariates and, in particular, unequal responses to these covariates.

Table 4 shows results disaggregated by whether the respective healthcare was public or private. The top row shows that around 12% and 26% visited a doctor in a public and a private facility, respectively (Table S8 for means by MPCE groups). These percentages do not sum to the percentage with *any doctor visit* because the location of a visit could only be identified if it was the last consultation in the last 12 months. Around 2.3% were hospitalised in a public hospital and 4.2% were hospitalised in a private hospital (Table S9 for means by MPCE groups). We found that inequality in the likelihood of visiting a public doctor was pro-poor ($CC = -0.0209$; -0.0348, -0.0071) and inequality was pro-rich for private doctor visits ($CC = 0.1244$; 0.1037, 0.1452). In both cases, decomposition again revealed a negative corrected need contribution, indicating that the greater need of poorer individuals would be underestimated if heterogeneity in the response of use to need were not taken into account. After correcting for need, there was slight pro-poor inequity in public doctor visits and marked pro-rich inequity in private doctor visits. For hospitalisations, there was no significant inequality and slight pro-rich inequity in use of public hospitals, while there was pro-rich inequality and inequity in use of private hospitals.

Point estimates of pro-rich inequalities in any doctor visit and hospitalisation were greater among individuals aged 60+ than among those aged 45–59, although neither difference was statistically significant at conventional levels (SM Table S10). For any doctor visit, the difference in the sample was mainly due to a larger heterogeneous non-need contribution in the older group, while for hospitalisation it was due to greater discrimination in the response to need in this group. For each type of healthcare, the estimate of inequity was substantially greater than that of inequality only in the older group, and this was primarily driven by correction of the need adjustment for heterogeneity in the response to need. Point estimates of pro-rich inequalities were greater among females than males, although neither difference was close to significance (SM Table S11). The estimate of pro-rich inequity in any hospitalisation was greater for males due to a larger adjustment for need.

4. Discussion

We found substantial inequality in the healthcare utilisation of older Indians to the disadvantage of those who were poorer and even greater inequity after adjusting appropriately for the poor's greater need. Poorer older Indians were less likely to have visited a doctor and to have been admitted to hospital in the last year despite being in greater need according to most of a large battery of health indicators. Adjustment for inequality in need was estimated to increase pro-rich inequality in doctor visits and in hospital admissions by about 65% and 39%, respectively. These adjustments would have been substantially smaller if need-justified utilisation were predicted from the average responsiveness of utilisation to the need indicators rather than the responsiveness among the richest fifth of the urban population that faced the lowest economic and geographic barriers to accessing healthcare. If the average responsiveness were used, the pro-poor inequality in hospitalisations that would be justified by the greater need among poorer individuals would have been underestimated by around one third. For doctor visits, using the average responsiveness would have resulted in the wrong direction of adjustment for need. These findings add to evidence from severely resource-constrained health systems that inequity to the disadvantage of poorer individuals is grossly underestimated when need-adjustment is based on the inadequate average response to need (Van de Poel et al., 2012).

Disaggregated analysis revealed that utilisation of private healthcare was responsible for pro-rich inequality and inequity overall. There was actually pro-poor inequality in public doctor visits and no inequality in public hospitalisations. The distribution of private healthcare had the stronger influence on overall inequality because of greater use of the private sector. If an effort to reduce healthcare inequity were to operate only through the public health system, then it may have a muted impact unless it were to increase utilisation of public providers. Otherwise, an effective pro-equity policy would need to change the distribution of private healthcare.

The extended decomposition revealed that inequality in the responsiveness of utilisation to need accounted for 11% of the pro-rich inequity in doctor visits and it was around 373% of the inequity in hospitalisations. In large part, poorer and rural individuals were disadvantaged because variation in their health was less likely to be met with appropriate variation in healthcare. Among better off urban individuals, those in worse health were substantially more likely than their healthier counterparts to visit a doctor or be admitted to hospital. Among poorer rural dwellers, ill-health was less strongly associated with increased use of healthcare. Possible explanations for the more muted response of utilisation to need indicators among poorer groups include forgone unaffordable healthcare. Distance to doctors and hospitals, and related transport costs, are likely additional access barriers that discouraged the rural poor from seeking treatment when sick. Lower awareness of ill-health and the potential for effective treatment may also have contributed. Quantification of the relative importance of these explanations would be a key input to the design of policy interventions to reduce healthcare inequity.

The largest contribution to pro-rich inequality in doctor visits was from heterogeneity in the partial associations with non-need covariates – education, living arrangement, social class and region, in particular. This may have been due to economic and geographic barriers neutering positive effects of other characteristics. Education can increase the effective demand for healthcare only if the educated have the ability to pay and access to health facilities. Similarly, living with others can potentially increase demand through within household diffusion of information on health problems and available treatments. But the scope to act on this information is restricted under tight resource constraints. Low income can also prevent realisation of opportunities for healthcare access that may come from not belonging to the lowest social classes. At the same time, barriers to healthcare may be surmountable for those with sufficiently high incomes. For example, we found that regional differences in healthcare utilisation were weaker among the better off. Lower average utilisation in the Central and Eastern regions contributed to pro-rich inequality not only because the populations of these regions were poorer, on average, but also because richer individuals in these regions were less constrained by whatever it was that reduced access to healthcare compared with other parts of the country.

The standard methods of decomposing the concentration index measure of inequality in healthcare utilisation (Wagstaff et al., 2003) and of measuring horizontal inequity (Wagstaff and van Doorslaer, 2000a,b) would miss these sources of inequality and inequity. They would allow for inequality that arose from education, living arrangement, social class and region each being both associated with utilisation and unequally distributed by MPCE. But they would not allow for the possibility that the associations of the determinants with utilisation differed by MPCE and that this contributed to inequality in healthcare.

After adjusting for all differences in need and non-need covariates, and for differences in the partial associations of these covariates with utilisation across economic groups, we found weak evidence that remaining differences across groups contributed to inequality in favour of poorer individuals. While the 95% confidence intervals include zero, and so there is uncertainty about the reliability of this result, one explanation would be inequality in unmeasured need. We used a very large battery of need indicators, but there will be health variation that was not captured by the measured and reported indicators. We deliberately did not use information on reported diagnosed conditions because they will have resulted from healthcare use, as well as indicating need for healthcare. For both types of utilisation, the residual term, which captures unexplained inequality within groups rather than between them, was extremely small, indicating that the decomposition accounted for almost all of the inequalities in utilisation.

We estimated a concentration index for any doctor visit that is substantially larger than the respective index for any hospitalisation. This does not mean that there was greater inequality in doctor visits than in hospitalisations. Given both types of healthcare are binary, we used a concentration index that ensures that the magnitude of inequality in each would be same irrespective of whether we measured utilisation or non-utilisation (Erreygers, 2009). This index measures absolute inequality. Its value depends on the mean of the outcome. The larger value obtained for any doctor visit reflects the fact that the mean of this outcome is about eight times larger than the mean of any hospitalisation. If we had used the standard concentration index that measures relative inequality, and so has the disadvantage that measures of inequality in utilisation and in non-utilisation differ in magnitude (Erreygers and Van Ourti, 2011), then the index for hospitalisation (0.1136) would have been larger than that for any doctor visit (0.0968). While the magnitudes of the two types of concentration indices differ, essentially reflecting different ways of taking account of the means of the outcomes, the relative contributions of the different sources of inequality would be the same irrespective of the index used (Van de Poel et al., 2012). Our main results are robust to the choice of index.

A strength of survey used is the measurement of consumption expenditure, allowing economic status to be measured by MPCE rather than an assets index, which was initially intended as a feasible proxy when consumption data are not available (Filmer and Pritchett, 2001). A previous study using the same data source showed low association between the two measures (Spearman rank correlation = 0.29, Cohen's κ = 0.09) and found substantially less pro-rich inequality in each of hospitalisations and outpatient visits when an assets index was used to proxy economic status (Mohanty et al., 2022). While this suggests that our results would not be robust to use of an assets index, lack of robustness would merely signal limitations of using that proxy in place of the detailed MPCE measure that is used to obtain the official poverty estimates for India.

The decomposition method we used does have limitations. First, it requires the choice of a reference group in which utilisation is assumed to respond more appropriately to need. We used the richest fifth of older Indians living in urban areas since they plausibly face the lowest economic and geographic barriers to healthcare. Results may be sensitive to this choice. An alternative would be those with health insurance cover, which we did not use because insurance is endogenous to the demand for healthcare and the insured may overuse healthcare due to moral hazard. While moral hazard could remain an issue if the group selected as the reference were to have extensive insurance cover while others did not, in this study it is not a concern since only 22% of even the richest firth of urban dwellers had health insurance. It is possible – though not necessarily probable – that perverse supply-side incentives caused providers to induce demand from those with ability to pay. If this were to push the reference group's use of healthcare to the point where the (true) value of the marginal health benefit were below the marginal private cost, then the utilisation-need relationship of this group would not provide an appropriate benchmark for the measurement of inequity. However, this is an unlikely scenario. There may have been instances in which the reference group made excessive, wasteful use of healthcare resources, but it is unlikely that it did so on average. To identify inequity, we only assumed that the use-need relationship was, *on average,* more appropriate – vertically equitable – in the reference group.

A second limitation is that the method does not respect a budget constraint on the health system. Utilisation could only respond to need as it does among the richest fifth of urban dwellers if substantially more were spent on the healthcare of older Indians. Otherwise, it would be infeasible to eliminate the healthcare inequity we identified. It could not be achieved by redistributing existing health resources toward poorer older persons. However, this might be considered a strength rather than a weakness. Inequities arise from the underfunding of healthcare.

Like all decompositions, our analysis was descriptive. It identified the distributions and associations that accounted for inequality in the utilisation of healthcare. It did not identify causal effects that could be used to predict how inequality would change if policy interventions were to change the distributions of determinants of healthcare utilisation. This limits the implications that can be drawn for policy design. The relevance of the study lies in its implications for the policy agenda. It revealed substantial inequity in the distribution of healthcare to the disadvantage of poorer, older Indians that was mainly due to their utilisation being less responsive to both need and non-need determinants. Documentation of the problem may provoke policy concern and further research to identify how the inequities could be lessened.

A data limitation is that respondents were asked to report any doctor visit in the last 12 months, which precluded analysis of the number of visits and relied on an unusually long recall period. The latter may have biased the estimated utilisation rate downward. Any such bias would transfer to the estimation of inequality only if the likelihood to forget a doctor visit were to differ systematically with MPCE. Even then, it would be unlikely to invalidate our central finding that allowing for heterogeneity in the relationships of utilisation with its determinants revealed greater inequity in the probability of seeing a doctor.

Another measurement limitation is that we could distinguish public and private doctor consultations only for the last visit. This could cause bias. For example, if treatment were initially sought in the public sector and switched to the private sector only if needs were not met, then we would underestimate the likelihood of seeing a public doctor. If this pattern were more prevalent among the poorer population, then we would underestimate pro-poor inequality in utilisation of public doctors. Such bias would not explain the finding of greater pro-rich inequality in private doctor visits.

Our analysis confirmed that when healthcare utilisation is more responsive to need among the better off and need is concentrated among the poor, then imposing homogeneity on the utilisation-need relationship, as done in almost all other studies of healthcare inequity, results in underestimation of pro-rich inequity. We found considerable inequity in the distribution of healthcare in the older population of India to the disadvantage of poorer individuals. Poorer older Indians get less healthcare than would be equitable given their greater need, the health system is less responsive to variation in their needs and they are also disadvantaged because non-need characteristics, such as education, living arrangement, social class and location, are less effective in gaining access to a doctor. Addressing the inequity would require targeted interventions to change distributions of need and non-need characteristics as well as their associations with healthcare.

CRediT authorship contribution statement

Sanjay K. Mohanty: Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Junaid Khan:** Writing – original draft, Visualization, Validation, Software, Formal analysis. **Suraj Maiti:** Visualization, Validation, Software, Formal analysis, Data curation. **Fabrice Kämpfen:** Validation, Formal analysis. **Jürgen Maurer:** Supervision, Project administration, Conceptualization. **Owen O'Donnell:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Formal analysis, Data curation, Conceptualization.

Ethical approval

The research reported in the paper was secondary analysis of data that are publicly available. No ethical approval was required for this analysis. For collection of the data, ethical approval was obtained from the Government of India and the institutional review boards of the International Institute for Population Sciences (IIPS) and its collaborating institutions. Written informed consent was given by all respondents.

Declaration of competing interest

After checking with all of the authors, I can confirm that no author has any conflict of interest regarding the submitted paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2024.117535.

Data availability

The data are publicly available and can be accessed at, https://www.iipsdata.ac.in/datacatalog_detail/5.

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