Scilight

Journal of Modern Applied Statistical Methods
https://jmasm.com

Article

Check for updates

Suitability of the Chosen Variables for Stratification in Large-Scale Surveys: An Exploration of the Indian Version of DHS

Somnath Jana [1,*], Laxmi Kant Dwivedi [1] and Shiva S. Halli [2]

[1] Department of Survey Research & Data Analytics, International Institute for Population Sciences, Govandi Station Road, Deonar, Mumbai 400088, India
[2] College of Community and Global Health, Rady Faculty of Health Sciences, University of Manitoba, Winnipeg, MB R3E 0T6, Canada
* Correspondence: somnathjana443@gmail.com

How To Cite: Jana, S.; Dwivedi, L.K.; Halli, S.S. Suitability of the Chosen Variables for Stratification in Large-Scale Surveys: An Exploration of the Indian Version of DHS. *Journal of Modern Applied Statistical Methods* **2026**, *25*(1), 7. https://doi.org/10.53941/jmasm.2026.100007

Abstract: Stratification is a foundational technique in survey sampling, designed to enhance the precision of estimates by reducing within-group variability and maximizing differences between subgroups. Choosing the right level of stratification is essential for obtaining accurate and policy-relevant data in a vast and diverse nation like India, where socioeconomic and health status vary significantly even within relatively small administrative units called districts. National surveys use the typical urban-rural division to solve this, although finer segmentation can yield even more precise results, particularly in the more diverse rural settings. This study assesses the relative efficiency of two- versus four-segment stratification frameworks in estimating key health indicators at the district-level in India. Using data from a large-scale health survey, four indicators child stunting, immunization coverage, four plus antenatal care, and sanitation access were analyzed. Results showed that while the two-segment design produced better precision in most districts, particularly in the populous states, the four-segment approach delivered substantial improvements in specific states and for indicators prone to higher sampling variability. These findings emphasize the importance of context-specific stratification strategies, balancing operational feasibility with statistical precision. The study advocates for adaptive survey designs that align stratification choices with local population heterogeneity and indicator-specific characteristics to optimize data quality and policy utility.

Keywords: survey stratification; sampling precision; complex survey design; survey methodology; NFHS; full immunization

1. Introduction

Over the past few decades, stratification has become a core feature in the sampling design of national and subnational surveys, including demographic and health surveys, labor force surveys, and population-based assessments of education and other development indicators [1]. In countries like India, characterized by a vast heterogeneity in population distribution, socioeconomic structure, and public health access, stratification allows survey planners to address the inherent complexity of the sampling frame more effectively [2]. In the design of large-scale surveys, especially those related to public health and sociodemographic research, methodological rigor plays a central role in ensuring that the estimates generated are both reliable and representative [3]. Among the many tools used to enhance the efficiency of survey sampling, stratification stands out as a foundational technique that aims to reduce sampling error by organizing the population into more homogeneous subgroups prior to

Copyright: © 2026 by the authors. This is an open access article under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).
Publisher's Note: Scilight stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

selection [4]. The central premise behind stratification is intuitive: if variability within strata is minimized and variability between strata maximized, then any given sample drawn from within these strata will yield more precise and stable estimates than one drawn without such prior organization [5,6].

Survey sampling in large-scale studies is an indispensable tool for generating reliable and actionable information on key public health and socioeconomic indicators [7]. In India, with its vast and diverse population, the accurate estimation of district-level parameters is critical for designing effective policies and interventions [8]. One of the most powerful techniques to enhance the statistical efficiency of such surveys is stratification process by which the population is divided into relatively homogeneous subgroups (strata) before sampling. This method is designed to reduce the variability of the estimates by ensuring that samples drawn from each subgroup are adequately representative of that subgroup's characteristics [9].

In classical sampling theory, stratification is lauded for its ability to decrease sampling error by reducing the variance within each stratum relative to the overall population variance. In other words, if the population can be divided into groups that are internally similar but distinct from each other, the combination of independent samples drawn from each of these groups tend to produce more precise estimates than a simple random sample of the entire population. The greater the homogeneity within strata, the greater the potential precision gain [10].

Despite its widespread use, stratification employed in large-scale surveys varies considerably in terms of both level and form, often dictated by logistical considerations, cost constraints, or institutional legacy. A common practice at the district level in India, for example, involves dividing each district into two broad segments urban and rural and selecting primary sampling units (PSUs) independently from within each. While this two-segment stratification reflects an elementary urban-rural dichotomy, it does not fully account for intra-rural variability, which can be substantial, especially in geographically and socioeconomically diverse districts. In India, the contrast between sub-regions can sometimes be so sharp that the urban-rural dichotomy fails to capture the true variability [11]. In such cases, a more segmented approach can not only yield better statistical estimates but also provide insights into localized patterns of development or deprivation that may otherwise be masked under a simpler stratification schema. These insights can be vital for district administrators and policymakers who are striving to design localized strategies to address issues unique to specific areas within a district [12]. In districts with more homogeneous rural populations, however, the additional complexity of a multilevel stratification design may not translate into significant gains in precision [13]. This context-dependent variability underscores the need for robust empirical evidence to guide decisions on stratification practices.

Another dimension of this research is the examination of how different indicators may respond to stratification. Public health indicators, for example, can vary widely in their prevalence and distribution [2]. Rare diseases, which have inherently low prevalence, often generate high standard errors in survey estimates [14]. In such cases, even small reductions in variability can lead to statistically significant improvements in precision. On the other hand, stratification adjustments might yield only modest gains for common indicators. By analyzing a range of indicators, the study aims to provide a comprehensive understanding of where the benefits of granular stratification are most pronounced and where they might be marginal [10].

The emerging evidence and the growing discourse among sampling methodologists suggest that a more refined stratification approach in which the rural segment is further divided into sub-segments based on geography, remoteness, development indicators, or other proxies may yield substantial gains in precision. This refined approach, often referred to as four-segment stratification, typically involves dividing districts into three rural strata and one urban stratum. Each rural stratum may represent different levels of development or distance from urban centers, allowing for more nuanced sampling and better representation of rural diversity [15].

Using data from a recent large-scale health survey, we replicated the sampling process of the survey under both the two-segment and four-segment frameworks. By keeping the overall sample size constant, we isolated the effect of the stratification structure on the variability of the estimates. Standard errors were computed for each indicator under both approaches, and the relative gain (or loss) in precision was assessed across districts and states [16]. The comparison helped identify whether gains in precision were more pronounced for certain types of indicators (e.g., rare vs. common events, binary vs. continuous outcomes) and whether the impact of stratification differed between states with high vs. low intra-district variability [10,17].

Our findings have practical implications for survey planners, statistical agencies, and policymakers. In resource-constrained settings, maximizing the precision of the survey estimates without having to proportionally increase the sample size is a key objective. If a shift to a more detailed stratification can deliver substantial gains in precision, particularly for critical health indicators, then investments in refining the stratification process may be well justified. On the other hand, if the gains are marginal or context-dependent, simpler designs may remain preferable for cost and feasibility reasons.

This study seeks to answer a critical question for survey research in India: Does enhancing the stratification of districts from a simple two-segment framework to a more detailed four-segment approach lead to significant reductions in standard error? By addressing this question, the research aims to provide valuable insights that can inform better survey design, and, ultimately, support more effective policymaking at the district level. The findings of this study have the potential to contribute significantly to the literature on survey methodology and offer practical guidance for researchers and decision-makers involved in large-scale surveys throughout India.

In the recent years, a growing body of literature has examined the role of stratification in improving the efficiency of estimates derived from complex survey designs. Methodological studies have consistently emphasized that the effectiveness of stratification depends on how well strata capture the underlying population heterogeneity and how they interact with clustering in multi-stage sampling designs. For instance, K. G. Reddy and colleagues demonstrated in their 2018 study that stratification can substantially reduce variance when strata are constructed using relevant auxiliary information, whereas it may yield negligible or even adverse effects on precision when strata are poorly defined. Similarly, in 2024, G. R. V. Triveni emphasized that increasing the number of strata does not automatically improve efficiency, particularly when sample sizes within strata become too small to support stable estimation [10,18].

Complementing these methodological insights, applied research using large-scale demographic and health surveys suggests that whereas the conventional urban-rural stratification captures broad population differences, it may not adequately reflect intra-rural heterogeneity. Studies, such as the one by K. McBride and C. Moucheraud in 2022, show that finer geographic classifications can reveal important disparities in access to health services that are otherwise masked under a simple dichotomous framework. This is particularly relevant in settings where rural populations are internally diverse in terms of infrastructure, remoteness, and socioeconomic conditions [13,19,20].

Recent empirical and simulation-based studies suggest that the gains from enhanced stratification are context-dependent and vary across indicators. For example, M. Abbas and colleagues demonstrated in 2025 that stratified multi-stage designs improved estimator precision when heterogeneity across subpopulations was substantial, while H. Ali highlighted in 2025 that efficiency gains were sensitive to both the distribution of the outcome and the allocation of sample sizes across strata. The emerging work on small-area estimation underscores that stratification choices can significantly influence the stability of domain-level estimates, particularly in high-variability contexts [21–24].

Despite these advances, the existing studies exhibit two important limitations. First, much of the methodological literature is based on simulation frameworks, which may not fully capture the operational and contextual complexities of large-scale surveys. Second, applied studies often focus on specific indicators or geographic settings, with limited attention to systematic comparisons of alternative stratification strategies across multiple indicators within a single national context. In particular, there is a lack of empirical evidence at the district level for large and heterogeneous countries such as India, where intra-district variability is substantial and policy decisions rely heavily on disaggregated estimates.

This study addresses these gaps by providing a systematic comparison of the conventional two-segment (urban-rural) stratification and a more detailed four-segment framework using real survey data from India. By examining multiple health and service-related indicators with varying distributional characteristics, the study contributes to a more nuanced understanding of when and where finer stratification improves statistical precision in large-scale demographic surveys.

The central objective of the study was to assess the relative gain in standard error that results from implementing stratification at the district level in India, with a specific focus on comparing the conventional two-segment approach (urban vs. rural) with a more detailed four-segment approach (urban plus three rural segments). We focused on indicators commonly measured in health and demographic surveys, such as child stunting, full immunization coverage, antenatal care (ANC) visits, and access to improved sanitation facilities, to evaluate whether finer stratification improves the statistical precision of district-level estimates. Given the critical role that standard error plays in determining the reliability of survey findings, even modest improvements in precision can lead to better-informed policy decisions, particularly in areas such as public health, education, and infrastructure development, where India faces substantial challenges.

2. Methods

2.1. Selection of Key Variables

In order to evaluate the efficacy of stratification techniques in extensive health surveys conducted in India, it was crucial and strategically important for us to choose critical measures of public health and social development that are frequently monitored in national and subnational surveys [25]. Accordingly, we selected four key indicators, namely child stunting, full immunization coverage, antenatal care (ANC) 4+ visits, and access to better sanitation facilities. These indicators reflect different dimensions of health and service access. For example, child stunting serves as a long-term marker of nutritional status and early life deprivation; immunization coverage represents the performance of routine health services; ANC visits capture maternal healthcare utilization; and improved sanitation access sheds light on infrastructure and reveals living condition disparities. These indicators differ in prevalence and distribution patterns, with some like stunting being relatively common, while others such as full immunization or ANC visits varying significantly between and within districts. This makes them ideal for testing whether finer stratification improves the precision of estimates, particularly in heterogeneous settings. By analyzing a mix of rare and common indicators, as well as infrastructure and service-use indicators, the study ensures a comprehensive evaluation of how stratification impacts survey precision across a variety of health outcomes, offering practical insights for optimizing future survey designs in India's diverse population landscape.

2.2. Data and Indicators

The data for this study was derived from the fifth round of the National Family Health Survey (NFHS-5) held between 2019 and 2021. The NFHS is the Indian version of the global Demographic and Health Surveys (DHS) program. The NFHS-5 was a large-scale survey that provided district-level information on health and sanitation indicators. The key indicators selected for the analysis included stunting (proportion of children under five years who are stunted), full immunization (percentage of children aged 12–23 months who have received all recommended vaccinations, 4+ ANC visits (proportion of pregnant women who have had at least four antenatal care visits), and sanitation facilities (percentage of households with access to improved sanitation facilities).

2.3. Sample Design of the Fifth Round of the National Family Health Survey (NFHS-5)

The NFHS-5 used a stratified two-stage sampling approach. Stratification was accomplished by dividing each district into urban and rural areas, with villages in rural areas and Census Enumeration Blocks (CEBs) in urban areas serving as Primary Sampling Units (PSUs) in the initial stage. In rural settings, a second level of stratification was used depending on village size (number of households). Implicit stratification at the PSU level was accomplished by the use of metrics such as the percentage of the Scheduled Caste (SC)/Scheduled Tribe (ST) population and female literacy rates (7+ age group).

Within each rural stratum (three), villages were selected in the first stage using probability proportional to size (PPS) sampling without replacement from the 2011 sampling frame. In the urban areas of each district, implicit stratification was carried out by sorting the sampling frame according to the percentage of the SC/ST population, after which CEBs were selected using PPS without replacement. A household listing operation was conducted in all the selected PSUs prior to the main survey. This operation involved visiting each PSU and listing all residential households within it. The resulting list of households served as the sampling frame for selecting households in the second stage using systematic sampling. All women aged 15–49 years in the selected households were eligible for the interview.

2.4. Variance Estimation Using Multistage Design

In large-scale household surveys like the DHS, data is collected using complex sampling designs involving stratification, clustering, and unequal probability sampling. To produce valid estimates and accurate standard errors that reflect this design, a survey set or survey design declaration is specified before analysis. This involves identifying the primary sampling units (PSUs or clusters), sampling strata, and sampling weights for each observation. The survey set informs the software to adjust variance estimation using appropriate methods, typically Taylor linearization or replication techniques, to account for the design's effects on sampling error. This ensures that point estimates and confidence intervals are unbiased and statistically valid for the population being studied [26–29].

Due to the complex sampling design, standard variance formulas (which assume simple random sampling) are not appropriate for the DHS data. Therefore, specialized methods described below are used instead [30–32].

2.5. Taylor Series Linearization Method

The most common approach for variance estimation in the DHS is the Taylor series linearization, which accounts for clustering, stratification, and unequal selection probabilities.

For a population parameter estimate $\hat{\theta}$, the variance estimate is:

$$Var(\hat{\theta}) = \sum_{h=1}^{H} \frac{1}{n_h(n_h - 1)} \sum_{i=1}^{n_h} (z_{hi} - \bar{z}_h)^2 \quad (1)$$

where:

- H = number of strata
- n_h = number of PSUs in stratum h
- z_{h_i} = linearized value corresponding to the estimator of interest for the i^{th} PSU in stratum h. The linearized variable is derived based on the specific form of the estimator.

In this study, z_{hi} was computed separately for each health indicator, that is, full immunization, stunting, antenatal care, and sanitation facilities, where the estimator represented the proportion of individuals or households with the specified outcome. For example, for full immunization, z_{hi} corresponded to the linearized form of the estimated proportion of children aged 12–23 months who were fully immunized within each PSU.

- $\bar{z}_h$ = mean of the z_{h_i} values in stratum h
- $\hat{\theta}$ = estimated population parameter (mean or proportion)

In practice, survey data involves unequal weights, and, therefore, a weighted version of the Taylor linearization estimator is applied. This adjusted estimator incorporates sampling weights to ensure unbiased population inference.

When we use survey set in any software, it uses a weighted Taylor linearization, the formula for which is as follows:

$$Var_w(\hat{\theta}) = \sum_{h=1}^{H} \frac{1}{W_h^2} \sum_{i=1}^{n_h} w_{hi}^2 (z_{hi} - \bar{z}_h)^2 \quad (2)$$

where:

- w_{hi} = *sampling* weight
- W_h = total weight within stratum h
- PSU h_i = cluster i of stratum h
- N_h= total PSUs in stratum h

For ratio estimators, which are frequently used in survey statistics, the variance expression can be derived as a special case of the Taylor linearization method, where we define ratio as $\hat{R}$, such that:

$$\hat{R} = \frac{Y}{X} = \frac{\bar{y}}{\bar{x}} = \frac{\Sigma \omega_i y_{hi}}{\Sigma \omega_i x_{hi}}$$

Accordingly, the variance of ratio estimator using linearization [31]

$$variance(\hat{R}) = \frac{1}{\bar{x}^2} \left[s_y^2 + \hat{R}^2 \cdot s_x^2 - 2\hat{R} s_{xy} \right] \quad (3)$$

where:

- Y = total of the study variable
- X = total of the auxiliary variable
- y_{hi} = value of the study variable for the i^{th}PSU in stratum h (for example, number of under 5 children who are stunted)
- x_{hi} = value of the auxiliary variable for the i^{th}PSU in stratum h (for example, total number of under 5 children)
- s_y^2 = variance of y
- s_x^2 = variance of x
- s_{xy} = covariance between x and y

Equations (1)–(3), shown above, collectively describe the progression from the general variance estimation framework to its application in weighted and ratio-based survey estimators.

In complex survey designs, the finite population correction (*fpc*) factor is used to adjust variance estimates when sampling is conducted without replacement from a finite population. The *fpc* is defined as:

$$fpc = \frac{N-n}{N-1} \tag{4}$$

where N represents the total population size and n denotes the sample size. It reduces the variance when the sampling fraction $\left(\frac{n}{N}\right)$ is negligible, reflecting the reduced variability due to sampling without replacement.

The use of the fpc is generally recommended when the sampling fraction exceeds 5–10%, as ignoring it in such cases may lead to overestimation of variance. However, in large-scale surveys such as the NFHS, the sampling fraction at the PSU and district levels is typically very small $\left(\frac{\boldsymbol{n}}{\boldsymbol{N}} \approx \mathbf{0}\right)$. Under such conditions, the fpc approaches 1, and its impact on variance estimation becomes negligible. Therefore, consistent with standard practice in large-scale demographic surveys, the fpc was not explicitly applied in the variance estimation as it did not affect the results [16].

We estimated the variance using the Taylor series and then carried out this procedure 100 times. Point estimates were created by averaging the estimations. The standard errors by region were calculated as the square root of the sample variance of the 100 estimations. Bootstrapped confidence intervals were calculated using the 0.025 and 0.975 percentiles across 100 repetitions.

To quantify uncertainty, bootstrap-based confidence intervals were constructed using repeated resampling as follows: Let $\hat{\theta}^{(b)}$ denote the estimate obtained from the b^{th} bootstrap sample, where $b = 1,2,\ldots,B$, and B represents the total number of bootstrap replications (in this study, $B = 100$) [33–35].

2.6. Bootstrap Estimates Set

Let $\{\hat{\theta}^{(1)}, \hat{\theta}^{(2)}, \ldots, \hat{\theta}^{(B)}\}$ denotes the estimates from the bootstrap samples.

The bootstrap estimate of variance is given by:

$$Var_{boot}(\hat{\theta}) = \frac{1}{B-1}\sum_{b=1}^{B}\left(\hat{\theta}^{(b)} - \bar{\theta}\right)^2 \tag{5}$$

where:

- $\bar{\theta} = \frac{1}{B}\sum_{b=1}^{B}\hat{\theta}^{(b)}$ is the mean of bootstrap estimates

The $100(1-\alpha)\%$ bootstrap confidence interval using the percentile method is defined as:

$$CI_{boot} = \left[\hat{\theta}^{\left(\frac{\alpha}{2}\right)}, \hat{\theta}^{\left(1-\frac{\alpha}{2}\right)}\right] \tag{6}$$

where $\hat{\theta}^{\left(\frac{\alpha}{2}\right)}$ and $\hat{\theta}^{\left(1-\frac{\alpha}{2}\right)}$ are the empirical quantiles of the bootstrap distribution. For a 95% confidence interval, this corresponds to the 2.5th and 97.5th percentiles of the bootstrap estimates.

2.7. Stratification Approaches

The study employed three distinct stratification approaches to assess their impact on the precision of survey estimates by comparing the standard errors across each method. First, in the 1× stratification (that is, no stratification), data from each district was treated as a single entity, combining urban and rural populations and serving as the baseline. The 2× stratification divided each district into urban and rural areas, aiming to capture differences in population characteristics and access to services between these two groups, and thus improve representativeness and reduce standard error. Finally, the 4× stratification as used in the NFHS-5, introduced a more detailed division by further segmenting rural areas within each district into three parts while keeping urban areas as one segment. This method sought to account for intra-district variations and assess whether additional segmentation in rural areas leads to a more significant reduction in standard error compared to the 2× stratification.

2.8. Methodological Flowchart of the Study Design

Figure 1 presents the overall methodological framework adopted in the study, including the application of 2× and 4× stratification approaches, estimation of selected health indicators, variance estimation procedures, and comparison of relative standard errors across stratification methods.

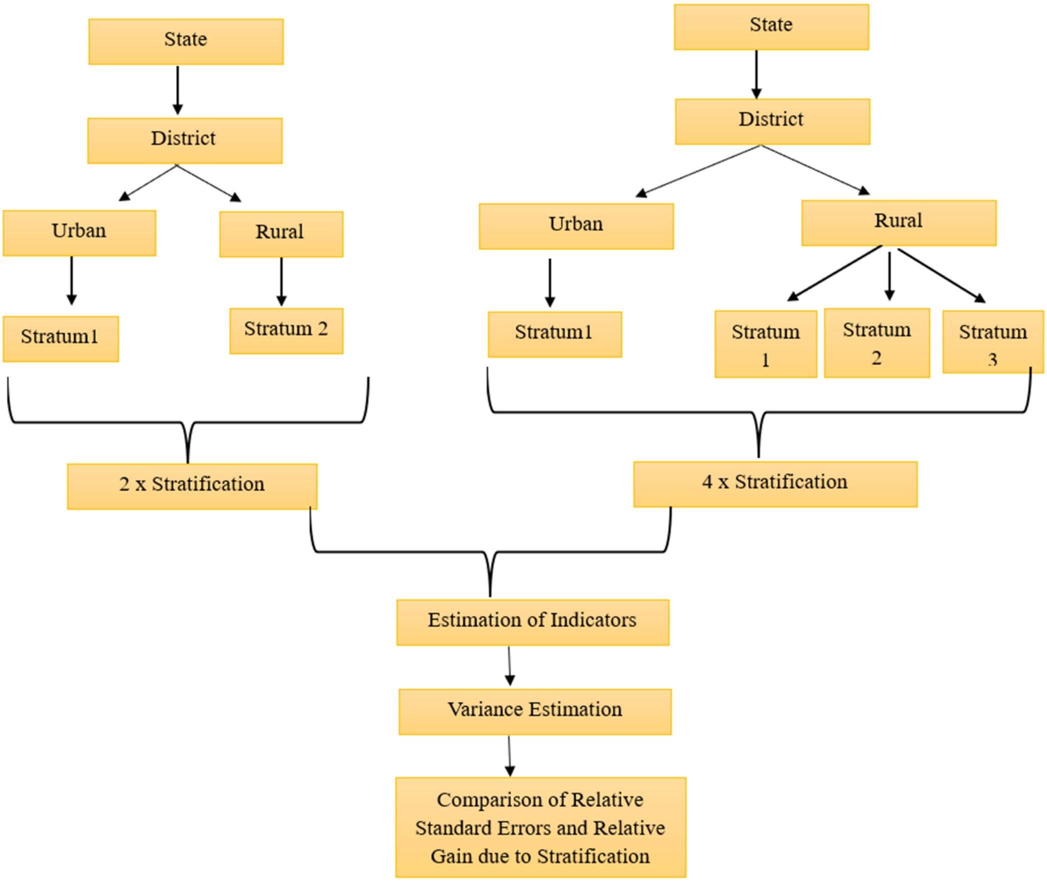


Figure 1. Methodological flowchart of the study design.

2.9. Statistical Analysis

The study examined the standard errors of the selected indicators under each stratification approach to assess the precision of the survey estimates. For each indicator, the average value was calculated at the district level, and the corresponding standard error was computed for each stratification method. We used the "svy" command to capture the true stratification structure and levels of multi-stage design.

The "relative gain in standard error" due to 4× stratification compared to 2× stratification was calculated using the following formula:

$$Relative\ efficiency = \left(\frac{variance\ in\ 4\times\ \text{stratification}}{variance\ in\ 2\times\ \text{stratification}}\right) \tag{7}$$

Therefore,

$$Relative\ gain = \left(1 - \frac{variance\ in\ 4\times\ \text{stratification}}{variance\ in\ 2\times\ \text{stratification}}\right)\times 100 \tag{8}$$

This formula measures the percentage reduction in variance (or standard error) when moving from 2× stratification to 4× stratification. A higher relative gain indicates a greater reduction in standard error, demonstrating the benefits of a more detailed segmentation.

2.10. Comparison of the Stratification Approaches

A two-segment stratification refers to the conventional division of each district into urban and rural strata, consistent with standard practice in large-scale household surveys in India. A four-segment stratification extends this framework by retaining a single urban stratum and subdividing the rural population into three segments according to the NFHS classifications used in the sampling frame.

The present study compared the effectiveness of 2× and 4× stratification in reducing standard error for each indicator. The goal was to determine whether the additional complexity introduced by 4× stratification (dividing rural areas into three parts) results in more precise estimates than the simpler 2× stratification.

3. Results

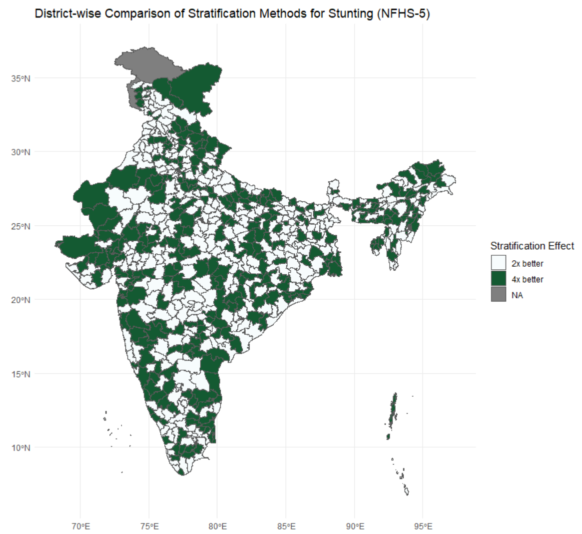
The analysis was based on four key health and household indicators commonly measured in large-scale demographic and health surveys, namely child stunting, full immunization among children aged 12–23 months, four or more antenatal care (ANC) visits, and access to improved sanitation facilities. These indicators represent different dimensions of population health and service access and vary in their prevalence and distribution across districts. Estimates were generated at the district level using a constant sample size under alternative stratification approaches. Across indicators, sample coverage was adequate in all districts, though the distribution of observations varied between urban and rural areas, reflecting underlying population urbanization level. This variation provided an appropriate basis for assessing how different stratification strategies influence the precision of district-level estimates.

Across the four health indicators, a large number of districts in a number of states, including Uttar Pradesh, Madhya Pradesh, Bihar, Haryana, Punjab, Maharashtra, Assam, and West Bengal, showed higher precision (lower standard errors) with the 2× stratification approach than the 4x approach. For example, Uttar Pradesh consistently had more districts favoring 2× stratification across all indicators, with particularly high counts for stunting (41 districts) and vaccination (36 districts). Similarly, Madhya Pradesh and Bihar demonstrated stronger outcomes with 2× stratification for stunting and ANC. These findings indicate that in the more populous and diverse states, the simpler two-segment stratification (urban-rural) performed better in reducing the standard error under a fixed sample size as shown in Table 1.

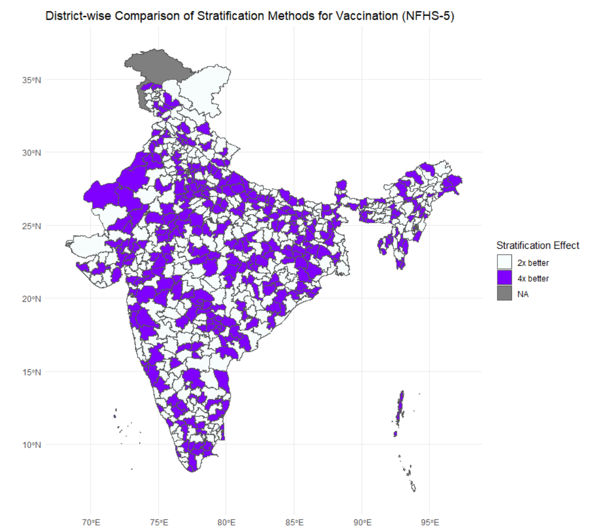
Table 1. Distribution of districts with lower relative standard error (classified as better) across 2× and 4× stratification approaches for various indicators in different states of India, NFHS-5, 2019–21.

States	Stunting			Full Immunization			Sanitation			4+ ANC Visits		
	2× Better	4× Better	Total	2× Better	4× Better	Total	2× Better	4× Better	Total	2× Better	4× Better	Total
Jammu & Kashmir	14	6	20	12	7	19	10	10	20	8	12	20
Himachal Pradesh	6	6	12	5	5	10	5	7	12	7	5	12
Punjab	17	5	22	12	9	21	14	8	22	13	9	22
Chandigarh	1	0	1	1	0	1	0	1	1	1	0	1
Uttarakhand	5	8	13	9	4	13	7	6	13	6	7	13
Haryana	15	7	22	14	8	22	11	11	22	8	14	22
NCT of Delhi	10	1	11	10	1	11	3	8	11	10	1	11
Rajasthan	19	14	33	13	20	33	13	20	33	19	14	33
Uttar Pradesh	41	34	75	36	39	75	42	33	75	35	40	75
Bihar	25	13	38	20	18	38	21	17	38	19	19	38
Sikkim	2	2	4	3	1	4	2	2	4	3	1	4
Arunachal Pradesh	10	10	20	13	7	20	13	7	20	7	13	20
Nagaland	4	7	11	7	4	11	8	3	11	4	7	11
Manipur	6	3	9	7	2	9	2	7	9	7	2	9
Mizoram	6	2	8	4	4	8	5	3	8	5	3	8
Tripura	3	5	8	2	6	8	2	6	8	4	4	8
Meghalaya	4	7	11	6	5	11	6	5	11	6	5	11
Assam	17	16	33	22	11	33	22	11	33	18	15	33
West Bengal	12	8	20	11	9	20	11	9	20	9	11	20
Jharkhand	18	6	24	11	13	24	14	10	24	12	12	24
Odisha	15	15	30	15	14	29	18	12	30	14	16	30
Chhattisgarh	16	11	27	14	13	27	12	15	27	19	8	27
Madhya Pradesh	28	23	51	27	24	51	27	24	51	29	22	51
Gujarat	16	17	33	20	13	33	17	16	33	18	15	33
Dadra & Nagar Haveli and Daman & Diu	2	1	3	2	0	2	2	1	3	2	1	3
Maharashtra	21	15	36	23	13	36	17	19	36	16	20	36
Andhra Pradesh	6	7	13	8	5	13	9	4	13	8	5	13
Karnataka	15	15	30	19	10	29	17	13	30	18	12	30
Goa	1	1	2	0	2	2	2	0	2	1	1	2
Lakshadweep	1	0	1	0	1	1	1	0	1	1	0	1
Kerala	8	6	14	10	4	14	11	1	12	7	7	14
Tamil Nadu	16	16	32	15	16	31	19	13	32	16	16	32
Puducherry	4	0	4	3	1	4	3	0	3	2	2	4
Andaman & Nicobar Islands	1	2	3	1	2	3	1	2	3	2	1	3
Telangana	17	14	31	13	18	31	19	12	31	18	13	31
Ladakh	0	2	2	2	0	2	2	0	2	1	1	2
Overall	402	305	707	390	309	699	388	316	704	373	334	707

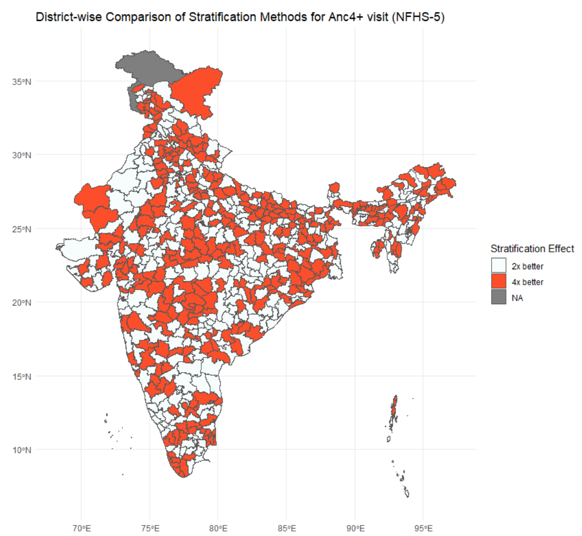
On the other hand, certain states, such as Rajasthan, Gujarat, Tamil Nadu, Telangana, Chhattisgarh, and Kerala, performed better under the 4× stratification approach, particularly for specific indicators. For instance, Rajasthan had more districts favoring 4× stratification for full immunization, sanitation, and ANC, while Gujarat and Telangana showed stronger gains in precision for stunting and vaccination. Even Kerala and Tamil Nadu, states known for their strong health systems and lower intra-district heterogeneity, showed performance gains under 4× stratification, suggesting that finer stratification may capture nuanced rural differences even in more developed regions, as illustrated by the Figure 2a–d. A point to note here that the population size of gram panchayats (PSUs) in Kerala is generally much larger than in other states.



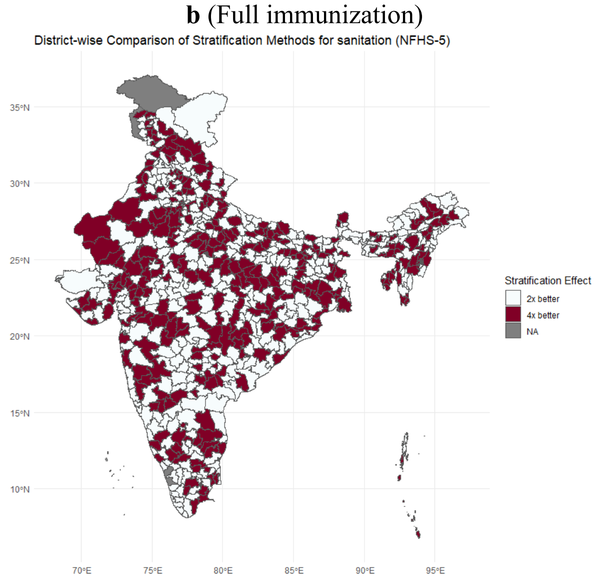
a (Stunting)



b (Full immunization)



c (4+ ANC visits)



d (Access to improved sanitation)

Figure 2. (**a**–**d**): District-wise comparison between 2× and 4× stratification approaches for selected indicators in India.

In general, the comparison between 2× and 4× stratification revealed that while 2× stratification performed better in a larger number of districts overall, the 4× approach offered substantial gains in certain states and for certain indicators. This suggests that the effectiveness of a more granular stratification is context-dependent. While the simpler 2× method may be more efficient in most settings, the 4× stratification has clear advantages in regions where rural heterogeneity is high or where precision in estimating health indicators requires finer segmentation. Hence, the decision to adopt a more detailed stratification approach should be informed by the local context and the specific indicator of interest.

Estimated Gain in Relative Standard Error (RSE) by Different Levels of Stratifications across Different Indicators

The comparison of the relative standard errors (RSE) under two different stratification strategies (2× vs. 4×) provided important insights into the efficiency of sample design across different indicators. When examining child health indicators such as stunting and full immunization, a clear pattern emerged. Districts with relatively high levels of sampling variability (RSE greater than 15%) showed consistent improvements under the 4× stratification. This indicates that increasing stratification helps reduce clustering effects in situations where estimates are otherwise unstable, thereby enhancing precision in the higher error range, as seen in Figures 3 and 4. Conversely, for districts where the RSE was already low (below 10%), the 2× stratification performed better. In such cases, further splitting of strata does not yield additional gains and may even marginally increase variability due to smaller sample sizes within each stratum, as illustrated by Figures 3 and 4.

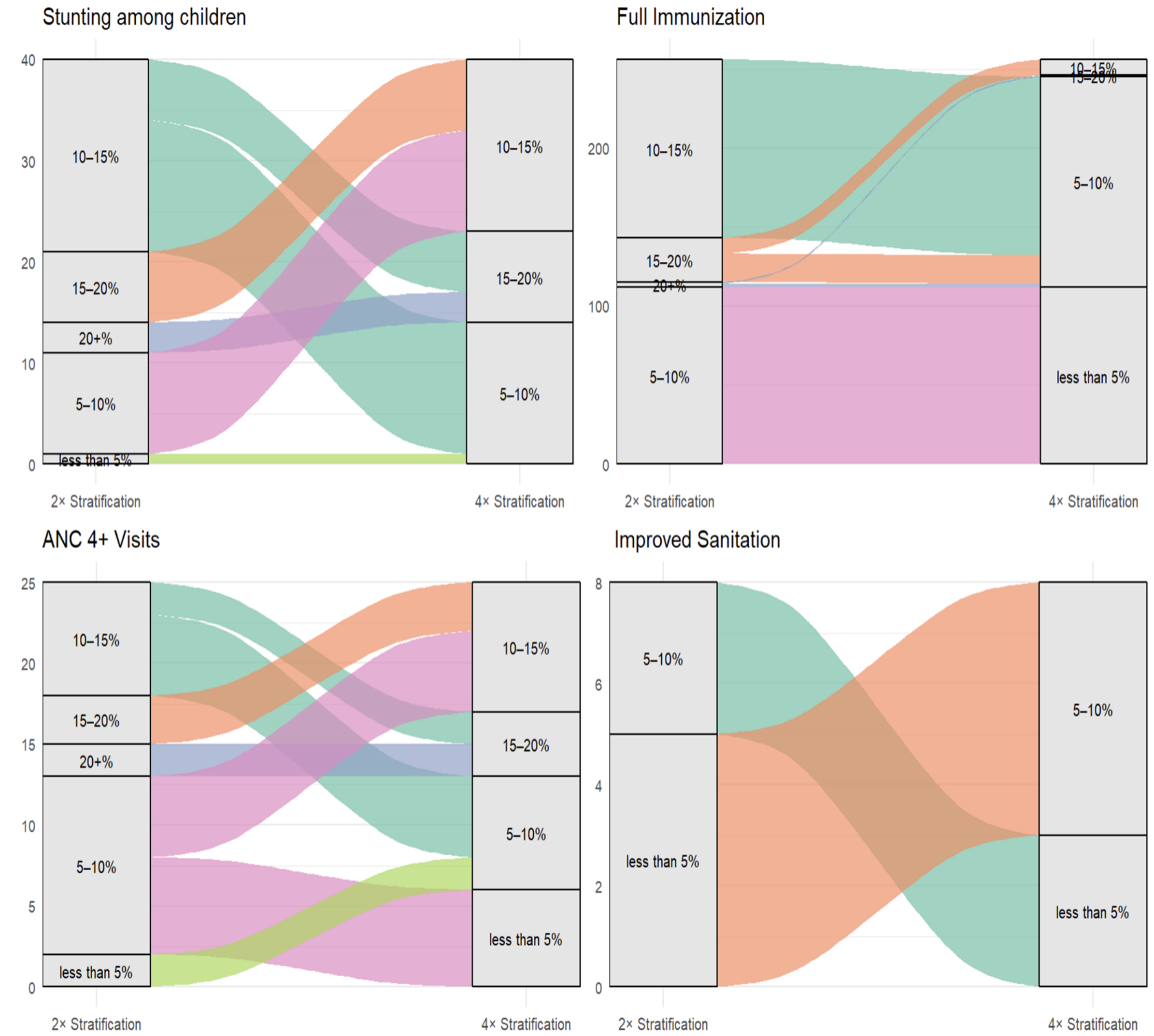


Figure 3. Transition between 2× and 4× stratification approaches in gain in relative standard error across various indicators.

The findings suggest that 4× stratification is particularly effective for addressing high-RSE contexts precisely where gains in precision are most needed. This is especially relevant for indicators like stunting and immunization, where inter-district variability and heterogeneity in outcomes often lead to greater design effects. In contrast, when the RSE is already low, the simpler 2× approach is more efficient, and additional segmentation does not translate into improvements.

For indicators such as ANC coverage and sanitation facilities, the results did not show a consistent or strong pattern in favor of either approach. The differences between 2× and 4× stratification were minimal, and, in some cases, the two strategies performed almost identically. This lack of a systematic trend reflects the nature of these indicators, which are typically less sensitive to stratification refinements because they are more evenly distributed across households.

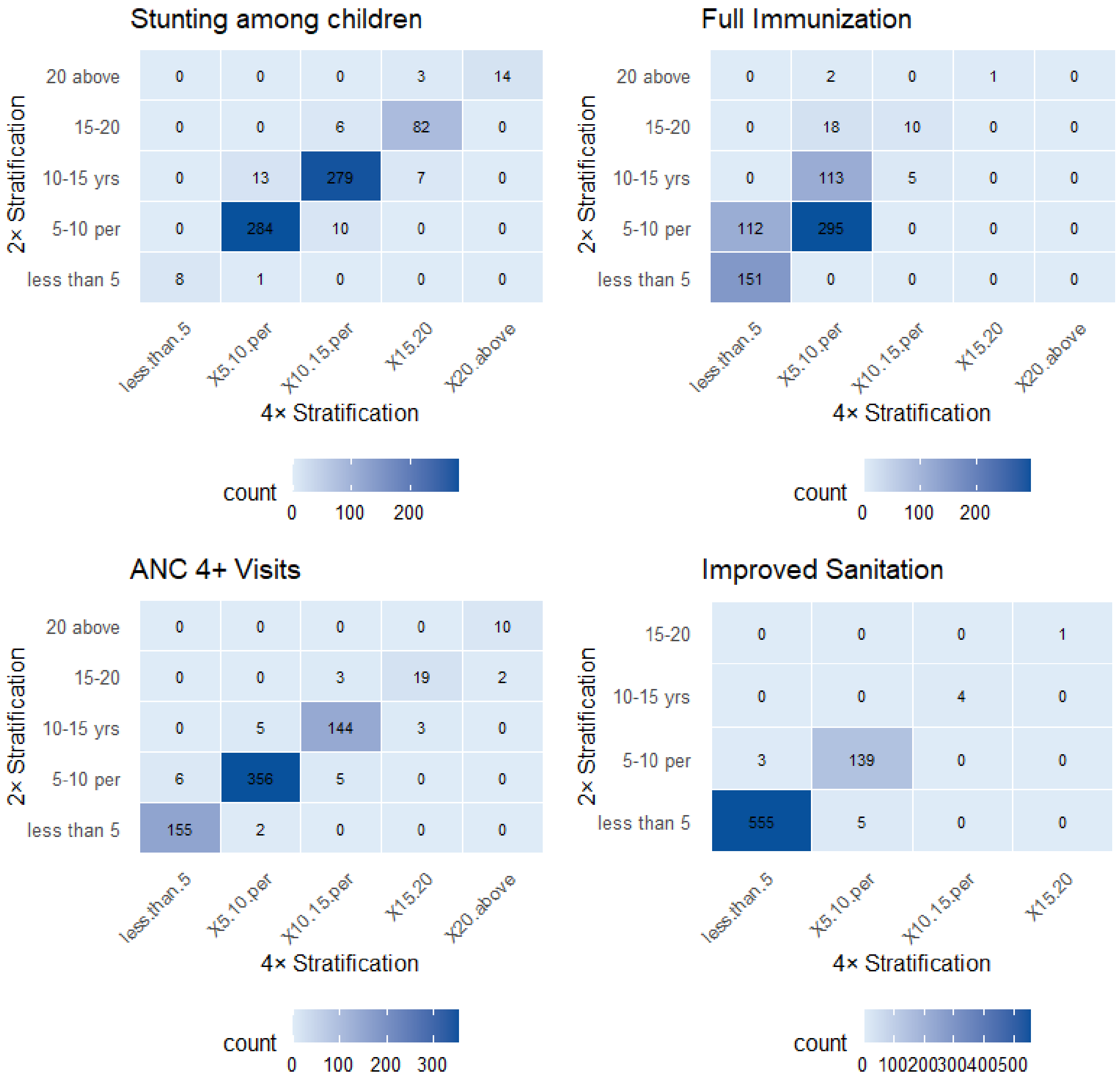


Figure 4. Heatmaps of stunting, full immunization coverage, 4+ ANC visits, and improved sanitation facilities by 2× and 4× stratification approaches according to different categories of relative standard error.

The key factors underlying these differences were the village size and the degree of clustering. In larger villages or areas with higher clustering of outcomes, the 4× stratification proved more effective as it reduced intra-cluster homogeneity by creating smaller, more internally consistent strata. This is why health outcomes that vary significantly across communities, such as stunting or immunization, benefited more from finer stratification. By contrast, household indicators tend to be less affected by village-level clustering, and thus the gains from increasing the number of strata were negligible.

Overall, the results highlight that while 4× stratification is a valuable strategy for improving precision in high-RSE contexts, particularly for child health outcomes, it does not universally outperform the 2× approach. A nuanced application of stratification guided by the indicator type, village size, and expected clustering offers the most efficient path to improving survey precision.

4. Discussion

This study set out to rigorously evaluate the impact of stratification depth on the precision of district-level health estimates in India by comparing the conventional two-segment stratification approach (urban vs. rural) with a more detailed four-segment model (urban plus three rural segments). Using key health indicators, that is, child stunting, full immunization coverage, improved sanitation facilities, and 4+ ANC visits, the analysis systematically explored how different stratification designs affect the standard errors of survey estimates across diverse states and districts.

The findings revealed a nuanced picture. Overall, the two-segment stratification outperformed the four-segment approach in a greater number of districts and states, particularly in the large and populous states of Uttar Pradesh, Madhya Pradesh, Bihar, and Maharashtra. In these states, a basic urban-rural division appeared sufficient to capture meaningful population differences, resulting in lower standard errors and higher statistical efficiency for most indicators. This reinforces the long-held notion in survey research that simpler stratification can be both operationally efficient and statistically effective in contexts where urban-rural contrasts are already pronounced.

However, a critical insight from the study was the state- and indicator-specific advantage observed with the four-segment approach. States such as Rajasthan, Gujarat, Tamil Nadu, Telangana, Chhattisgarh, and Kerala had a greater number of districts benefiting from finer stratification, especially for indicators like full immunization, sanitation, and 4+ ANC visits. These findings suggest that in regions characterized by greater intra-rural heterogeneity driven by factors such as geography, socioeconomic disparities, development levels, and access to services, a more detailed stratification framework can meaningfully improve the precision of survey estimates.

The varied performance of different levels of stratification across different indicators underscores the importance of considering indicator-specific distribution patterns in survey design. Rare events or services with low coverage rates, such as full immunization or 4+ ANC visits, are inherently more prone to sampling variability. Therefore, the potential precision gains from enhanced stratification are higher for these indicators. Conversely, more prevalent outcomes like stunting may show smaller marginal benefits from increased stratification. This differential response highlights that no single stratification strategy is universally optimal and that decisions should be guided by both local context and the specific health indicators prioritized in a survey.

The choice between 2× and 4× stratification at the district level is closely tied to the sociodemographic profile, health service distribution, and heterogeneity of rural populations. In districts where the urban-rural divide already captures the major contrasts in living conditions and health outcomes, the simpler 2× stratification tends to be more effective. For example, in populous states such as Uttar Pradesh and Bihar, rural areas often share similar patterns of deprivation, have similarly limited access to health services, and show homogeneity in practicing agriculture-based livelihoods. In such contexts, further subdividing the rural population into three strata under the 4× design does not substantially reduce intra-stratum variability, and may even inflate standard errors due to unnecessary fragmentation (division) of the sample. Indicators such as child stunting and antenatal care, which reflect structural determinants like long-term nutritional environment or maternal health-seeking behavior, are strongly influenced by this broad rural-urban divide. As a result, the efficiency gains for such indicators are higher under the 2× framework because it captures the essential variation without overcomplicating the sampling design.

In contrast, districts that exhibit pronounced intra-rural heterogeneity benefit more from 4× stratification. This is often the case in geographically diverse states such as Rajasthan, Gujarat, and Kerala, where rural populations are not uniform but segmented by terrain, remoteness, and differential development levels. For instance, tribal hamlets in remote forested areas may have very different health service utilization and sanitation conditions compared to rural households located near district headquarters or semi-urban belts. In such contexts, indicators like immunization and sanitation coverage are especially sensitive to fine-grained differences within rural populations, as service delivery varies widely across sub-regions. The 4× stratification, by dividing rural areas into three segments, captures this internal diversity more effectively, leading to lower standard errors and more reliable district-level estimates. Even in relatively advanced states such as Kerala and Tamil Nadu, where health indicators are generally better, the 4× framework offers advantages because it accounts for subtle rural contrasts; for example, differences in sanitation access between coastal villages, plantation areas, and more urbanized rural belts.

Thus, the empirical evidence shows that the superiority of 2× or 4× stratification is highly context-specific. The 2× approach is better suited to districts with relatively homogeneous rural populations and strong urban-rural contrasts, while the 4× approach provides clear advantages in districts characterized by intra-rural diversity in geography, service provision, and socioeconomic conditions. The benefits also vary by indicator such that structural and widespread outcomes like stunting often require only 2× stratification, whereas indicators dependent on health service access and infrastructure such as immunization, 4+ ANC visits, and sanitation are more sensitive to localized variations, making 4× stratification more effective. This highlights the need for adaptive stratification strategies, where the choice of design is guided not only by statistical efficiency but also by the social and health realities of the districts under study.

Another important consideration in interpreting the relative efficiency of stratification designs is the effect of clustering. In large-scale surveys, households are selected in clusters (PSUs), which tend to share similar socioeconomic and health characteristics. This intra-cluster correlation often inflates standard errors, particularly for indicators that are geographically concentrated. For example, in Uttar Pradesh and Bihar, stunting is highly correlated within villages due to shared nutrition environments, meaning that even with 4× stratification, the clustering effect dominates, and the 2× stratification remains sufficient. In contrast, in states like Kerala and Tamil Nadu, where immunization and ANC services vary between rural pockets, clustering amplifies localized differences; here, 4× stratification helps counterbalance the design effect by ensuring that clusters are drawn from more homogeneous rural subgroups. Similarly, in Rajasthan and Chhattisgarh, sanitation coverage often differs sharply between remote tribal clusters and the more developed rural settlements. In such cases, finer stratification, coupled with clustering, leads to better precision by capturing these distinct pockets of health outcomes. Thus, the interaction of stratification with clustering reinforces the finding that the optimal design is state- and indicator-specific. In other words, in states with strong within-cluster homogeneity and a pronounced urban-rural divide, 2× stratification suffices, but in states where intra-rural clustering introduces large variations in service access, 4× stratification becomes more beneficial.

These results carry valuable operational implications. In resource-limited environments, where increasing sample size is often impractical, maximizing precision through smarter design adjustments like refined stratification becomes essential. However, such adjustments must be balanced against increased complexity in sampling logistics, field implementation, and cost. The evidence from this study advocates for a context-sensitive, adaptive approach to stratification design—one that weighs the potential statistical benefits against operational feasibility on a state-by-state and indicator-by-indicator basis.

Recent studies emphasize that the effectiveness of stratification depends on how well strata capture population heterogeneity and interact with clustering in multi-stage designs [11,20]. Our findings are consistent with this evidence, as the two-segment (urban-rural) stratification performs better in many districts, particularly in large and populous states, where rural populations tend to be relatively homogeneous. Similar conclusions have been reported in other recent analyses of national health surveys, which show that simpler stratification designs often provide stable and efficient estimates when major population contrasts are already well represented [10,22].

At the same time, recent methodological and applied studies also report that finer stratification can improve precision in contexts with high sampling variability and pronounced intra-rural heterogeneity [25,27]. This aligns closely with our results, which show that four-segment stratification offers clear advantages in districts with higher relative standard errors and for indicators sensitive to service delivery, such as immunization, sanitation, and ANC visits. However, consistent with recent evidence, our results also indicate that finer stratification does not uniformly reduce standard errors and may offer limited gains when baseline variability is low or when stratum-level sample sizes are small [26].

This study set out to examine whether a more detailed four-segment stratification offers meaningful precision gains over the conventional two-segment approach in large-scale health surveys. The findings demonstrate that the benefits of finer stratification are highly context-specific. Where sampling variability is high, particularly for child health indicators such as stunting and immunization, the 4× stratification design consistently improves precision by mitigating clustering effects and capturing intra-rural heterogeneity. These gains are most pronounced in districts with diverse rural populations or uneven health service distribution.

By contrast, in districts where relative standard errors are already low (under 10%) or where rural populations are relatively homogeneous, the simpler 2× stratification proves more efficient. In such cases, additional segmentation does not reduce variability and may even marginally increase it due to smaller sample sizes within strata. Household-level indicators like sanitation and ANC coverage also show little advantage from 4× segmentation, as their distribution is more uniform across populations.

5. Conclusions

This study examined whether increasing stratification from a conventional two-segment (urban-rural) framework to a more detailed four-segment approach improves the precision of district-level estimates in large-scale health surveys in India. The findings indicate that neither stratification strategy is universally superior. The two-segment approach performs more efficiently in many districts, particularly in large and relatively homogeneous areas, where the urban–rural divide captures the dominant variation. In contrast, the four-segment approach provides clear advantages in contexts characterized by higher sampling variability and greater intra-rural heterogeneity, especially for indicators related to service utilization such as full immunization for children and 4+ antenatal care visits.

These results highlight that the effectiveness of stratification is inherently context-dependent and varies across both geographic settings and types of indicators. Increasing the number of strata does not automatically lead to improved precision and may yield diminishing returns when the underlying variability is already low.

From a practical perspective, the findings support a flexible and adaptive approach to survey design. Rather than adopting a uniform stratification strategy, survey planners should tailor the level of stratification to the expected heterogeneity of the population and the nature of the indicators being measured. This approach can enhance statistical efficiency while maintaining operational feasibility in large-scale surveys such as the NFHS.

Future research may extend this work by exploring alternative stratification schemes, including finer urban segmentation or data-driven approaches, as well as examining the implications of stratification for small-area estimation and subgroup analysis.

Author Contributions

L.K.D. and S.J.: conceptualization, methodology, software; S.J.: data curation, writing original draft preparation; S.J. and L.K.D.: visualization, investigation; L.K.D.: supervision; S.J. and L.K.D.: software, validation; L.K.D. and S.S.H.: writing reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data is available online on the website and can be downloaded. The NFHS data can be download using the link https://dhsprogram.com/data/dataset_admin/login_main.cfm.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

References

1. Surveys, H.; Verma, V.; Lê, T.; et al. An Analysis of Sampling Errors for the Demographic Analysis of Sampling Errors for the Demographic and Health Surveys. *Int. Stat. Rev.* **1996**, *64*, 265–294.
2. Kim, R.; Liou, L.; Xu, Y.; et al. Precision-weighted estimates of neonatal, post-neonatal and child mortality for 640 districts in India, National Family Health Survey 2016. *J. Glob. Health* **2020**, *10*, 020405. https://doi.org/10.7189/JOGH.10.020405.
3. Parsaeian, M.; Mahdavi, M.; Saadati, M.; et al. Introducing an efficient sampling method for national surveys with limited sample sizes: Application to a national study to determine quality and cost of healthcare. *BMC Public Health* **2021**, *21*, 1414. https://doi.org/10.1186/s12889-021-11441-0.
4. Khan, M.G.M.; Reddy, K.G.; Rao, D.K. Designing stratified sampling in economic and business surveys. *J. Appl. Stat.* **2015**, *42*, 2080–2099. https://doi.org/10.1080/02664763.2015.1018674.
5. Ludington, P.W.; U.S. Bureau. Stratification of Primary Sampling Units for the Current Population Survey Using Computer Intensive Methods. 1992. Available online: http://www.asasrms.org/Proceedings/papers/1992_127.pdf (accessed on 27 February 2025).
6. U.S. Census Bureau. Current Population Survey Design and Methodology Technical Paper 77. 2019. Available online: https://www2.census.gov/programs-surveys/cps/methodology/CPS-Tech-Paper-77.pdf (accessed on 27 February 2025).
7. Korn, E.L.; Graubard, B.I. Analysis of Large Health Surveys: Accounting for the Sampling Design. *J. R. Stat. Soc. Ser. A Stat. Soc.* **1995**, *158*, 263–295. https://doi.org/10.2307/2983292.
8. Triveni, G.R.V.; Danish, F.; Albalawi, O. Advancing Survey Sampling Efficiency under Stratified Random Sampling and Post-Stratification: Leveraging Symmetry for Enhanced Estimation Accuracy in the Prediction of Exam Scores. *Symmetry* **2024**, *16*, 604. https://doi.org/10.3390/sym16050604.

9. Dwivedi, L.K.; Mahaptra, B.; Bansal, A.; et al. Intra-cluster correlations in socio-demographic variables and their implications: An analysis based on large-scale surveys in India. *SSM Popul. Health* **2023**, *21*, 101317. https://doi.org/10.1016/j.ssmph.2022.101317.
10. Reddy, K.G.; Khan, M.G.M.; Khan, S. Optimum strata boundaries and sample sizes in health surveys using auxiliary variables. *PLoS ONE* **2018**, *13*, e0194787. https://doi.org/10.1371/journal.pone.0194787.
11. Vallée, J.; Souris, M.; Fournet, F.; et al. Sampling in health geography: Reconciling geographical objectives and probabilistic methods. An example of a health survey in Vientiane (Lao PDR). *Emerg. Themes Epidemiol.* **2007**, *4*, 6. https://doi.org/10.1186/1742-7622-4-6.
12. Mukhopadhyay, A.; Garcés Urzainqui, D. *The Dynamics of Spatial and Local Inequalities in India*; WIDER Working Paper No. 2018; The United Nations University World Institute for Development Economics Research (UNU-WIDER): Helsinki, Finland, 2018. https://doi.org/10.35188/UNU-WIDER/2018/624-1.
13. McBride, K.; Moucheraud, C. Rural–Urban Differences: Using Finer Geographic Classifications to Reevaluate Distance and Choice of Health Services in Malawi. *Health Syst. Reform* **2022**, *8*, e2051229. https://doi.org/10.1080/23288604.2022.2051229.
14. Sha, A.; Madhan, S.; Karthikeya, M.; et al. Data-Driven Clustering and Insights for Rural Development in India. *Procedia Comput. Sci.* **2024**, *233*, 336–342. https://doi.org/10.1016/j.procs.2024.03.223.
15. Gil, M.A. A note on stratification and gain in precision in estimating diversity from large samples. *Commun. Stat. Theory Methods* **1989**, *18*, 1521–1526. https://doi.org/10.1080/03610928908829983.
16. Sheffel, A.; Wilson, E.; Munos, M.; et al. Methods for analysis of complex survey data: An application using the tanzanian 2015 demographic and health survey and service provision assessment. *J. Glob. Health* **2019**, *9*, 020902. https://doi.org/10.7189/jogh.09.020902.
17. Ahmed, S.K. How to choose a sampling technique and determine sample size for research: A simplified guide for researchers. *Oral Oncol. Rep.* **2024**, *12*, 100662. https://doi.org/10.1016/j.oor.2024.100662.
18. Triveni, G.R.V.; Danish, F.; Tawiah, K. Evolving techniques for enhanced estimation: A comprehensive survey of stratified sampling and post-stratification methods. *AIP Adv.* **2024**, *3193*, 050001. https://doi.org/10.1063/5.0193961.
19. Bokelmann, B.; Lessmann, S. Heteroscedasticity-aware stratified sampling to improve uplift modeling. *Eur. J. Oper. Res.* **2025**, *325*, 118–131. https://doi.org/10.1016/j.ejor.2025.02.030.
20. Yanglem, W.; Khongji, P.; Singh, S.O. Stratified Two-Stage Cluster Sampling Design with Ranking. *Adv. Appl. Stat.* **2024**, *91*, 205–215. https://doi.org/10.17654/0972361724013.
21. Jana, S.; Dwivedi, L.K. Mapping the evolution of sampling design in large-scale surveys: A comprehensive systematic analysis of global trends, methodological dynamics, and journal impact in survey research and data science. *Braz. J. Biom.* **2025**, *43*, e884. https://doi.org/10.28951/bjb.v43i4.884.
22. Abbas, M.; Ahmed Shehzad, M.; Rabia, M.; et al. Estimation of finite population mean in a complex survey sampling. *PLoS ONE* **2025**, *20*, e0324559. https://doi.org/10.1371/journal.pone.0324559.
23. Ali, H.; Mahmood, Z.; AlAbdulaal, T.H. On the enhancement of estimator efficiency of population variance through stratification, transformation, and formulation with application to COVID-19 data. *Alex. Eng. J.* **2025**, *113*, 480–497. https://doi.org/10.1016/j.aej.2024.11.044.
24. Falorsi, P.D.; Falorsi, S.; Nardelli, V.; et al. Defining Ad-Hoc Sampling Designs for Small Area Estimation. *J. Off. Stat.* **2026**, *42*, 92–126. https://doi.org/10.1177/0282423x251388201.
25. Rajpal, S.; Kim, J.; Joe, W.; et al. Small area variation in child undernutrition across 640 districts and 543 parliamentary constituencies in India. *Sci. Rep.* **2021**, *11*, 19952. https://doi.org/10.1038/s41598-021-83992-6.
26. Croft, T.N.; Marshall, A.M.J.; Allen, C.K.; et al. Guide to DHS Statistics DHS-7 (Version 2). 2020. Available online: https://www.dhsprogram.com/pubs/pdf/DHSG1/Guide_to_DHS_Statistics_DHS-7_v2.pdf (accessed on 27 February 2025).
27. Allen, C.K.; Fleuret, J.; Ahmed, J. *Data Quality in Demographic and Health Surveys that Used Long and Short Questionnaires*, DHS Methodological Reports 30; ICF: Rockville, Maryland, USA, 2020.
28. Pullum, T.W.; Juan, C.; Khan, N.; et al. The Effect of Interviewer Characteristics on Data Quality in DHS Surveys. 2018. Available online: https://dhsprogram.com/pubs/pdf/MR24/MR24.pdf (accessed on 27 February 2025).
29. Elkasabi, M.; Ren, R.; Pullum, T.W. Multilevel Modeling Using DHS Surveys: A Framework to Approximate Level-Weights. 2020. Available online: https://www.dhsprogram.com/publications/publication-mr27-methodological-reports.cfm (accessed on 15 November 2024).
30. Demnati, A.; Rao, J.N.K. Linearization Variance Estimators for Model Parameters from Complex Survey Data. 2002. Available online: http://www.asasrms.org/Proceedings/y2002/Files/JSM2002-000748.pdf (accessed on 27 February 2025).
31. Rust, K.F.; Rao, J.N.K. Variance estimation for complex surveys using replication techniques. *Stat. Methods Med. Res.* **1996**, *5*, 283–310. https://doi.org/10.1177/096228029600500305.
32. Cochran, W.G. *Sampling Techniques*, 3rd ed.; Wiley: Hoboken, NJ, USA, 1991.
33. Efron, B. Bootstrap Methods: Another Look at the Jackknife. *Ann. Stat.* **1979**, *7*, 1–26.

34. McCarthy, P.J.; Snowden, C.B. *The Bootstrap and Finite Population Sampling*; U.S. Department of Health and Human Services, Public Health Service, National Center for Health Statistics: Hyattsville, MD, USA, 1985.
35. Chen, H.; Shen, Q.R. Variance estimation for survey-weighted data using bootstrap resampling methods: 2013 methods-of-payment survey questionnaire. *Adv. Econom.* **2019**, *39*, 87–106. https://doi.org/10.1108/S0731-905320190000039004.