INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VIII August 2025

Disparities in Fertility Data Reporting: A Regional Perspective from NFHS

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DOI: https://doi.org/10.51244/IJRSI.2025.120800179

Received: 26 Aug 2025; Accepted: 01 Sep 2025; Published: 18 September 2025

ABSTRACT

Background: The National Family Health Survey (NFHS) is a vital source of demographic and health statistics in India, yet concerns remain about the accuracy of self-reported fertility data, particularly the number of living children. Discrepancies in reporting can arise from recall bias, social desirability, and proxy reporting, potentially distorting fertility and health indicators.

Methods: Using NFHS-IV (2015–16) and NFHS-V (2019–21), this study analyzed women who were both household heads and eligible for the women's questionnaire. Data from household and women's files were merged to compare the number of living children reported by household heads and individual women. Matched and unmatched cases were categorized, and discrepancies were examined across age, residence, education, religion, caste, and wealth index. Logistic regression was used to identify predictors of mismatches, while spatial autocorrelation (Moran's I and LISA cluster analysis) was applied to detect geographic patterns of reporting inconsistencies.

Results: In NFHS-IV, 65.3% of reports matched, compared to 63.2% in NFHS-V, with mismatches increasing with women's age. Women aged 40 and above had over 20 times higher odds of mismatch compared to those under 29. Rural women consistently showed higher odds of discrepancies than urban women (OR = 1.27 in NFHS-IV; OR = 1.32 in NFHS-V). Education was a strong protective factor: women with higher education had 63–64% lower odds of mismatch compared to those with no education. Wealthier women reported more accurately, while religion and caste showed only modest differences. Spatial analysis revealed clusters of high mismatches in central and southern states, while districts in the Northeast and Jammu & Kashmir displayed strong consistency.

Conclusion: Reporting discrepancies in NFHS fertility data are strongly associated with age, education, residence, and wealth. Older, less educated, rural, and poorer women are particularly vulnerable to misreporting. These findings underscore the need for targeted survey improvements, enhanced enumerator training, simplified tools, and validation mechanisms to strengthen the reliability of fertility data and ensure more equitable representation across demographic groups.

Keywords: NFHS, fertility data, reporting discrepancies, logistic regression, spatial analysis, data quality, India

BACKGROUND

In India, the National Family Health Survey (NFHS) serves as a critical source of data. Despite its extensive contributions, the NFHS, like many large-scale surveys, faces challenges related to data quality, particularly concerning self-reported variables (IIPS& ICF, 2021). One persistent issue is the discrepancy in reporting of the number of living children or births. The inconsistencies can arise from various factors, including recall bias, social desirability bias, misinterpretation of survey questions, and interviewer effects (Singh, 2021; Pullum, 2018). These discrepancies are especially problematic in secondary data analyses, where researchers rely on the accuracy of pre-collected information without the opportunity for direct verification.

These mismatches are not trivial, as they may distort key reproductive and demographic indicators such as the total fertility rate (TFR), contraceptive prevalence, and unmet need for family planning. Several factors may contribute to such reporting inconsistencies. Proxy reporting by the household head, who may not have accurate knowledge of each woman's childbearing history, can introduce errors. Additionally, eligible women may underreport or overreport their number of living children due to recall errors, social desirability bias, misinterpretation of survey questions, or interviewer effects (Pullum, 2018; Singh, 2021). These errors are especially common among older women, those with limited education, and those living in rural or socioeconomically disadvantaged settings. In such contexts, where formal documentation of births may be lacking and cultural norms influence openness about fertility, misreporting can be more pronounced.

Prior studies have noted these issues in NFHS and similar large-scale surveys. For instance, Singh and Sahu (2021) identified irregularities in fertility reporting across survey rounds and highlighted that inconsistencies in parity distributions may reflect deeper issues with data collection methodologies rather than genuine demographic shifts. Furthermore, Jejeebhoy et al. (2010) found inconsistencies in reported fertility histories within households, suggesting that even intra-household perceptions of reproductive outcomes can differ significantly. While earlier research has often focused on mismatches between husbands and wives, the present study shifts attention to mismatches between household heads and eligible women—a less explored yet equally important dimension of data quality.

These inconsistencies carry serious implications. Inaccurate reporting on the number of living children may result in flawed estimates of fertility levels, misallocation of family planning resources, and misguided evaluations of maternal and child health programs. This, in turn, can undermine the achievement of Sustainable Development Goals (SDGs), particularly those related to reproductive health, gender equity, and child survival. Moreover, discrepancies in fertility data limit the comparability of NFHS estimates across time and regions, hindering longitudinal analyses and policy assessments.

Against this backdrop, the present paper aims to systematically investigate the discrepancies in the number of living children reported by household heads and eligible women in the NFHS IV(2015–16) and NFHS V (2019–21) datasets. Through descriptive statistics and logistic regression analysis, the study identifies the socio-demographic correlates of mismatched cases, such as age, education, residence, caste, religion, and wealth index. By examining patterns of underreporting and overreporting, the analysis contributes to a better understanding of the structural and behavioral factors affecting data accuracy in large-scale demographic surveys. Ultimately, the findings aim to inform improvements in survey design, enumerator training, and data validation protocols, thereby enhancing the overall quality and reliability of national health statistics in India.

Comparisons between NFHS data and other demographic sources, such as the Sample Registration System (SRS), have also revealed discrepancies. Bhat (2002) observed significant differences in TFR estimates between NFHS and SRS data for the same reference years, particularly in certain states, indicating potential issues in sampling, recall, or questionnaire design. Such inconsistencies can lead to distorted projections and misaligned public health programs.

Regional variations in data quality add another layer of complexity. In some states, particularly in rural or low-literacy settings, underreporting of births is more prevalent. This may be due to limited understanding of survey questions, lack of formal birth records, or reluctance to disclose sensitive information. Conversely, overreporting has been observed in regions where respondents feel pressure to conform to perceived family size norms or expectations from field investigators (Singh, 2021). These variations compromise the comparability of data across states and time, limiting the utility of NFHS data for longitudinal or cross-regional studies. The implications of these inconsistencies are far-reaching. Poor data quality affects not only academic research but also the effectiveness of national and international health programs. Inaccurate fertility data may skew the assessment of unmet need for contraception, distort the relationship between fertility and child mortality, or mislead efforts to achieve Sustainable Development Goals (SDGs) related to reproductive health and gender equality. It is therefore imperative to systematically assess the reliability of fertility-related data in the NFHS.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VIII August 2025

This Paper aims to investigate the discrepancies in reporting the number of children or births by couples in NFHS datasets, with a specific focus on mismatches between spouses' responses, patterns of underreporting or overreporting, and differences across survey rounds. Through statistical consistency checks, cross-validation with external sources, and an exploration of demographic correlates, this study seeks to highlight systemic issues in data quality. The broader goal is to contribute to the growing body of research advocating for improved survey instruments, better training of enumerators, and enhanced data validation protocols in large-scale surveys like the NFHS.

DATA AND METHODS

The person's and women's files from NFHS IV and NFHS V were used for this paper. Women who were both heads of their households and eligible for the women's questionnaire were included in the analysis. The outcome variable considered was the number of living children. In NFHS IV, a total of 339,212 women were household heads, while in NFHS V, this number was 401,618. The total number of eligible women was 699,686 in NFHS IV and 724,115 in NFHS V. For the analysis, the person and women's files were merged. The total number of women who were both household heads and eligible for the questionnaire was 37,598 in NFHS IV and 47,324 in NFHS V.

Questions were asked of the household head regarding the number of living children in the household, and the individual file captured the number of living children that women reported as their own. After merging both data sets, discrepancies were found in the total number of living children for some women. Some women reported fewer children than the actual number, while others reported more. The number of living children was categorized into matched (equal to) and unmatched (less than the actual number, 1 difference, 2 differences, or 3 or more differences). These two categories were then analyzed, considering predictor variables that may influence the reporting of the total number of living children. The predictor variables included age, residence, education, religion, caste, and wealth index. Bivariate analysis was performed to find the percentage distribution of discrepancies in the reporting of living children. Additionally, binary logistic regression was used to identify the odds of unmatched reporting based on different socio-demographic characteristics of women.

Logistic Regression Analysis

A binary logistic regression model was applied, as the outcome variable is dichotomous. Predictor variables included age, residence, education, religion, caste, and wealth index. The model estimates adjusted odds ratios with 95% confidence intervals, allowing assessment of how sociodemographic factors influence the likelihood of the outcome in NFHS-IV and NFHS-V (Long & Freese, 2014). The logistic regression equation can be defined as follows:

$$\log(odds) = logit\ (p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k$$

Where p is the expected probability of the outcome variable, and $x_1, x_2, x_3, \ldots, x_k$ is the set of explanatory variables, and $\beta_1, \beta_2, \beta_3, \text{--------} \beta_k$ are the regression coefficients to be estimated in the model (Ryan, 2008).

To analyze the spatial distribution and dependence patterns of matched and unmatched proportions of total living children, a combination of univariate and bivariate Moran's I statistics, significance maps, and Local Indicators of Spatial Association (LISA) were employed. The univariate LISA map was utilized to detect spatial clustering of individual variables across districts, while the bivariate LISA map examined spatial associations between the predicted values and the spatially weighted average of explanatory variables. Moran's I, which ranges from −1 to +1, quantifies the degree of spatial autocorrelation: positive values indicate clustering of similar values (high-high or low-low), negative values reflect clustering of dissimilar values (high-low or low-high), and values close to zero suggest spatial randomness (Anselin, 1995; Getis, 2008).

Descriptive statistics, bivariate, and multilevel regression analyses were conducted using STATA version 16.0. To produce district-level spatial visualizations and generate geographic shapefiles, ArcGIS software (version

10.4) was employed. Additionally, GeoDa software was used to conduct spatial autocorrelation analysis and generate LISA cluster maps, which are essential tools for identifying spatial outliers and local clusters (Anselin et al., 2006; Chainey & Ratcliffe, 2005).

RESULTS

Percentage distribution of matched and unmatched number of living children by background characteristics of the respondent in NFHS IV and NFHS V

Table 1 presents discrepancies between household and individual reports of the number of living children in NFHS-IV. Approximately two-thirds of cases were consistent, while mismatches were disproportionately concentrated among specific subgroups.

Age exhibited the most pronounced gradient: reporting consistency was nearly universal among women under 29 years (95%), but declined to below 50% among women aged 40 and above, with a substantial share showing discrepancies of three or more children. Education demonstrated a similarly strong association, with match rates rising from 58% among illiterate women to over 86% among those with higher education, and large discrepancies virtually absent in the latter group. Residence and wealth also contributed to variation, with higher accuracy observed among urban and wealthier women compared to their rural and poorer counterparts. By contrast, differences across religion and caste were relatively modest.

Overall, reporting accuracy is most strongly conditioned by age, education, and socioeconomic status, underscoring the influence of recall limitations and awareness rather than cultural or group-specific factors.

Table 1 Percentage of Matched and Unmatched Cases for Number of Living Children in NFHS IV

Background Characteristics	**Less than**	**Equal to**	**1 Difference**	**2 Difference**	**3 or more Differences**	**Total**
Age						
Less than 29	1.19	94.91	3.08	0.64	0.18	100
30-39	1.2	78.79	14.39	4.53	1.09	100
40 and above	0.92	46.67	26.63	15.98	9.8	100
Residence						
urban	1.15	69.31	17.58	8.11	3.84	100
rural	1.02	63.62	19.18	10.27	5.91	100
Education						
Illiterate	1.25	57.9	21.25	12.15	7.46	100
primary	0.73	65.33	19.5	9.57	4.87	100
secondary	0.96	76.21	14.75	5.98	2.1	100
higher	0.61	86.03	10.22	2.32	0.83	100
Religion						

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Hindu	1.06	65.1	18.89	9.79	5.18	100
Muslim	1.03	65.31	17.79	9.64	6.22	100
Christian	1.16	68.47	17.6	7.85	4.92	100
others	1.32	68.49	20.03	6.3	3.87	100
Caste						
SC	1.2	63.99	18.77	10.24	5.81	100
ST	1.56	64.07	17.87	10.35	6.14	100
OBC	0.99	66.12	18.71	9.26	4.92	100
OTHERS	0.93	65.45	19.16	9.18	5.27	100
Wealth Index						
poorest	1.04	66.19	17.3	9.05	6.41	100
poorer	1.17	62.02	19.44	11.31	6.07	100
middle	1.1	62.05	20.38	11.27	5.19	100
richer	1.23	66.88	19.19	8.64	4.07	100
richest	0.61	72.43	17.36	6.6	3.01	100
Total	**1.08**	**65.3**	**18.73**	**9.57**	**5.31**	**100**

Table 2 presents reporting consistency between household heads and women's self-reports of the number of living children in NFHS-V. Overall, 63% of cases matched, while over one-third displayed discrepancies, with a notable share involving differences of two or more children. Age again showed the sharpest gradient: nearly 95% of women under 29 reported consistently, whereas accuracy declined to 42% among women aged 40 and above, with more than one in ten reporting discrepancies of three or more children. Education was strongly associated with reporting reliability, ranging from 53% consistency among women with no education to 86% among those with higher education, with large mismatches almost absent in the latter group.

Residence and wealth followed similar patterns, with urban and wealthier women reporting more accurately than their rural and poorer counterparts. Religion and caste displayed relatively modest variation, though Scheduled Tribes and Muslims reported slightly higher rates of large discrepancies. Taken together, NFHS-V results reinforce the patterns observed in NFHS-IV: age, education, residence, and economic status are the most salient predictors of reporting accuracy, underscoring the importance of recall capacity and socioeconomic context over cultural or group-specific factors.

Table 2 Percentage of Matched and Unmatched Cases for Number of Living Children in NFHS V

Background Characteristics	Less than	Equal	1 Difference	2 Difference	3 or More Differences	Total
Age						
Less than 29	0.92	94.92	3.54	0.57	0.05	100

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30-39	0.8	77.58	15.48	4.8	1.34	100
40 and Above	0.71	42.49	28.36	17.31	11.12	100
Residence						
Urban	0.84	67.21	19.47	8.4	4.09	100
Rural	0.75	61.64	20.01	10.96	6.64	100
Education						
No Education	0.79	52.84	23.4	13.57	9.4	100
Primary	0.92	61.63	21.64	10.78	5.03	100
Secondary	0.71	73.93	15.99	6.74	2.63	100
Higher	0.62	85.97	9.61	3.22	0.59	100
Religion						
Hindu	0.74	62.52	20.44	10.53	5.76	100
Muslim	1.05	65.4	17.15	9.5	6.89	100
Christian	0.62	68.61	17.31	8.16	5.3	100
Others	0.53	64.02	20.38	8.23	6.84	100
Caste						
SC	0.82	62.18	20.14	10.58	6.27	100
ST	0.93	62.43	19.73	10.03	6.89	100
OBC	0.66	63.04	20.18	10.45	5.67	100
OTHERS	0.93	64.32	19.73	9.65	5.37	100
Wealth Index						
Poorest	0.77	63.16	18.24	10.32	7.52	100
Poorer	0.77	60.7	19.65	11.69	7.2	100
Middle	0.78	60.95	21.84	10.71	5.73	100
Richer	0.75	63.65	21.74	9.76	4.1	100
Richest	0.83	71.96	17.96	6.94	2.31	100
Total	**0.78**	**63.18**	**20.04**	**10.29**	**5.89**	**100**

Table 3 presents the results of a binary logistic regression analysis examining the predictors of unmatched cases in the number of living children reported by women in NFHS IV and NFHS V. The findings highlight that age is the most significant predictor across both rounds. Compared to women under the age of 29, those aged 30–39 had over four times higher odds of mismatch (Odds Ratio [OR] = 4.45 in NFHS IV and 4.75 in NFHS V), while women aged 40 and above had odds more than 20 times higher (OR = 20.74 in NFHS IV and 21.83 in NFHS V), suggesting that recall errors or data recording inconsistencies increase substantially with

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age. Residence also plays a notable role, with rural women exhibiting higher odds of mismatched reporting than urban women. In NFHS-IV, the odds of mismatch for rural women were 1.27 times higher, which slightly increased to 1.32 in NFHS V. This pattern indicates persistent rural-urban disparities in the quality or accuracy of reporting.

Education level is inversely related to mismatched cases. Women with higher levels of education were significantly less likely to report inconsistencies. Compared to women with no education, those with primary education had around 14–15% lower odds of mismatch, those with secondary education had about 40% lower odds, and those with higher education had the lowest odds, approximately 63–64% lower in both survey rounds. This highlights the role of education in enhancing both awareness and accuracy in reporting. Regarding religion, the NFHS IV data indicated that Muslim women had slightly higher odds of mismatch than Hindus (OR = 1.14), but this difference was not significant in NFHS V, suggesting a possible improvement in data accuracy over time. Christians in NFHS V had significantly lower odds of mismatch (OR = 0.88), indicating relatively better consistency in reporting.

Caste did not emerge as a consistent predictor. Most caste groups, including Scheduled Castes (SC), Scheduled Tribes (ST), and Other Backward Classes (OBC), had odds close to 1, implying no significant deviation from the reference category. The “Other” caste group had slightly higher odds of mismatch in NFHS IV (OR = 1.08), but this was not statistically significant in NFHS V. In terms of wealth index, women from the richest households had significantly lower odds of reporting unmatched cases compared to the poorest women. In NFHS IV and NFHS V, the odds were 0.83 and 0.75, respectively, indicating better reporting among wealthier women. Other wealth categories did not show significant differences.

Overall, the results consistently point toward the influence of age, education, residence, and to some extent, wealth as key factors in predicting mismatched reporting of living children, emphasizing the need to target data quality interventions toward older, less educated, and rural populations in future surveys.

Table 3: Binary logistic regression of unmatched cases of the number of living children

	NFHS IV			NFHS V		
Predictor Variables	**Odds Ratio**	**95% Confidence Interval**		**Odds Ratio**	**95% Confidence Interval**	
Age						
Less than 29						
30-39	4.45***	3.94	5.02	4.75***	4.27	5.30
40 and above	20.74***	18.40	23.36	21.83***	19.63	24.28
Residence						
Urban						
Rural	1.27***	1.19	1.35	1.32***	1.24	1.40
Education						
No Education						
Primary	0.85***	0.79	0.91	0.86***	0.81	0.91
Secondary	0.60***	0.56	0.64	0.58***	0.55	0.62

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Higher	0.37***	0.31	0.43	0.36***	0.32	0.41
Religion						
Hindu						
Muslim	1.14**	1.05	1.23	1.00	0.93	1.08
Christian	0.93	0.84	1.03	0.88***	0.81	0.96
Others	0.88**	0.78	0.99	1.04	0.93	1.16
Caste						
SC						
ST	0.96	0.88	1.05	1.00	0.93	1.08
OBC	0.97	0.91	1.04	1.02	0.96	1.08
OTHERS	1.08*	1.00	1.17	1.04	0.96	1.12
Wealth Index						
Poorest						
Poorer	1.04	0.97	1.12	1.01	0.95	1.07
Middle	1.04	0.97	1.12	0.95	0.89	1.02
Richer	0.96	0.88	1.05	0.93	0.86	1.00
Richest	0.83***	0.75	0.93	0.75***	0.68	0.83
Pseudo R2	**0.17**			**0.18**		

Spatial distribution of matched and unmatched number of living children by background characteristics of the respondent in NFHS IV and NFHS V

Map 1 provides insights into the percentage of unmatched responses regarding the number of living children among women who were both household heads and eligible respondents, highlighting variations in data consistency across districts of India for NFHS IV. At the lower end of the spectrum, districts like East Siang (7.67%) in Arunachal Pradesh, Chennai (8.41%) in Tamil Nadu, and Kupwara (9.06%) in Jammu & Kashmir recorded the smallest discrepancies between household and individual reporting of the number of living children. These low unmatched percentages indicate relatively high levels of consistency and accuracy in data reporting in these areas. Slightly higher unmatched rates were seen in districts such as Mumbai (9.7%), Karnal (10.46%), North Delhi (10.54%), Alappuzha (11.04%) in Kerala, and Dakshina Kannada (11.51%) in Karnataka, which still reflect moderate reliability in data collection. However, a significant number of districts reported unmatched in the range of 13–20%, including Baramulla (13.59%), Faridkot (13.91%), Pashchim Champaran (14.12%), and Badgam (14.93%), suggesting increasing inconsistencies that may arise from discrepancies in survey interpretation or recall errors.

Moving to the higher end of the data, numerous districts fell within the 20–30% of unmatched. Gwalior (23.63%) in Madhya Pradesh, Patiala (23.83%) in Punjab, Lucknow (24.5%) in Uttar Pradesh, Bangalore (24.71%) in Karnataka, Namakkal (24.75%) in Tamil Nadu, and Bahraich (24.7%) in Uttar Pradesh all reported moderate to high levels of unmatched percentages. These figures point toward widespread issues in

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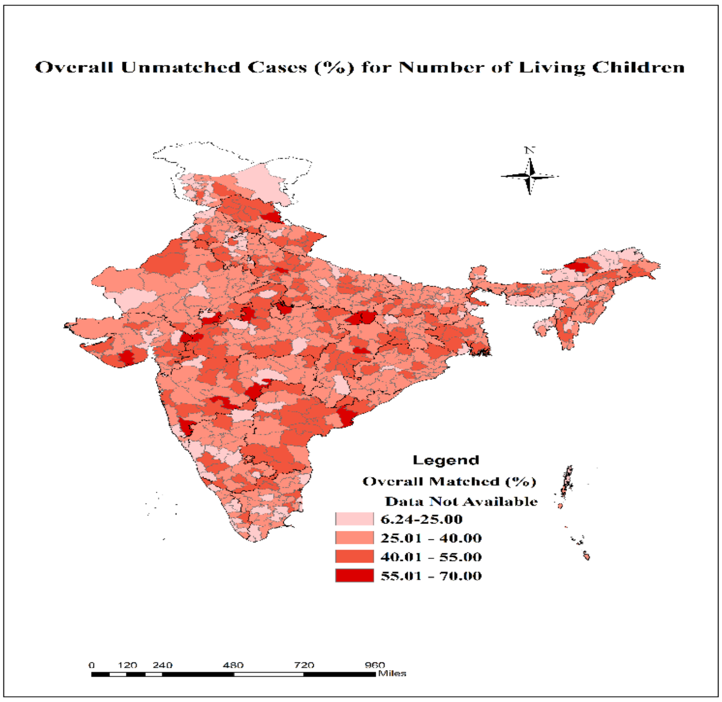
maintaining consistency across different data schedules in the survey process. At the extreme, unmatched percentages crossed 30% in districts such as Allahabad (30.36%) and Deoria (30.15%) in Uttar Pradesh, Porbandar (30.44%) in Gujarat, and Yanam (30.51%) in Puducherry, signaling a need for serious improvements in data recording practices. These high rates of unmatched can reflect challenges such as a lack of synchronization between interview modules, interviewer errors, and misunderstanding among respondents, especially in rural or less literate populations.

Overall, the data from NFHS-IV reveals significant disparities in the accuracy and alignment of reported numbers of living children across districts and states. While some regions demonstrate strong internal consistency, many others show worrying levels of unmatched that could potentially compromise the reliability of demographic and health statistics. These findings underscore the importance of refining survey methodologies, improving training for enumerators, and ensuring clarity in questionnaire design to reduce data inconsistencies in future rounds of health surveys.

Map 1: Unmatched percentage of the number of living children in NFHS IV



Map 2 shows the percentage of unmatched cases in the number of living children reported during the National Family Health Survey V (NFHS-V) across districts in India. A notable observation is the exceptionally low unmatched percentage in districts of Jammu & Kashmir, where eight districts, including Kupwara, Badgam, Leh (Ladakh), Kargil, Punch, Rajouri, Kathua, and Baramula, reported a 0% mismatch, indicating highly accurate data collection and/or excellent survey implementation. Other districts in the region, such as Bandipore (2.11%) and Srinagar (2.12%), also exhibit very low mismatch rates, which further supports the inference of high data quality in this area. Punjab and Haryana show a gradual increase in unmatched percentages, ranging largely between 15% and 24%. For example, districts like Ludhiana (17.02%), Patiala (18.13%), Faridkot (17.43%), and Amritsar (18.33%) illustrate moderate levels of discrepancy. In Haryana, districts such as Hisar (22.65%), Rohtak (22.68%), and Rewari (22.81%) hover near the upper end of the scale, suggesting growing inconsistencies that may require improvements in respondent engagement, questionnaire clarity, or enumerator training.

The trend of increasing mismatch continues into Rajasthan, where the unmatched percentages reach their peak. Districts like Sikar (24.69%), Jaipur (24.4%), Dausa (24.3%), and Karauli (24.19%) demonstrate the highest recorded levels in this dataset, approaching or exceeding 24%. These figures indicate potential challenges in maintaining data quality possibly due to a combination of factors such as larger populations, literacy gaps, or complexities in household reporting.

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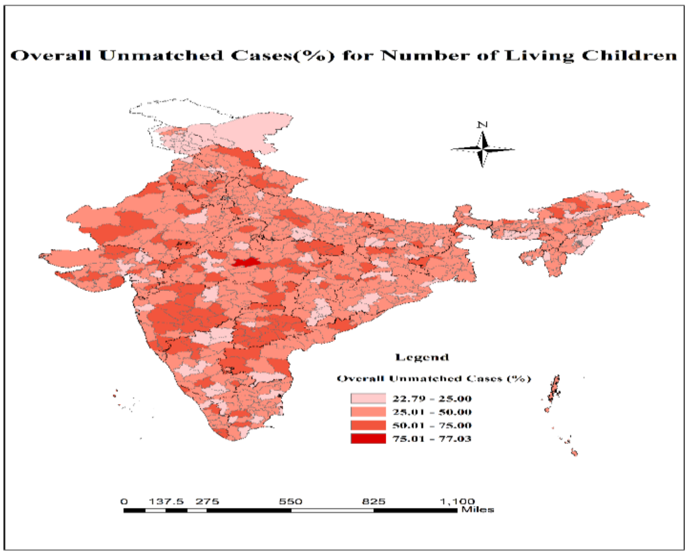
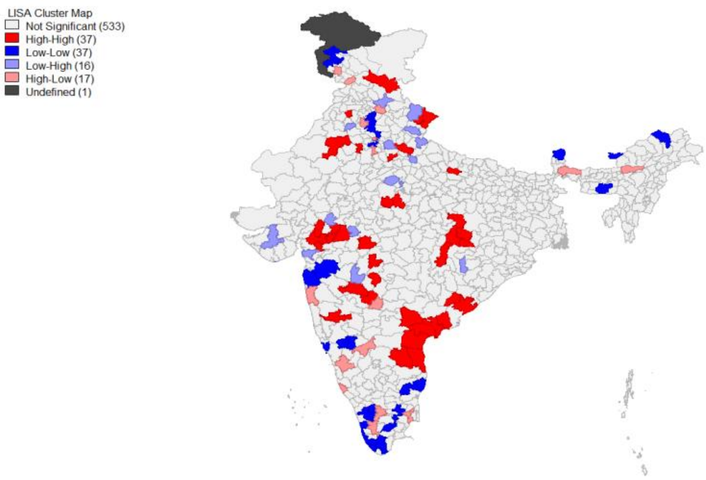
Map 2: Unmatched percentage of the number of living children in NFHS V



The LISA (Local Indicators of Spatial Association) Cluster Map 5.3 for the unmatched percentage in NFHS-IV reveals distinct spatial patterns in the discrepancies between household and individual schedule data across various districts in India. The map identifies five key cluster types based on spatial correlation: High-High, Low-Low, High-Low, Low-High, and Not Significant. High-High clusters, shown in red and comprising 37 districts, indicate regions with high mismatched percentages surrounded by similarly high-mismatch districts, primarily concentrated in the southern states such as Andhra Pradesh, Telangana, Tamil Nadu, and parts of Karnataka. These areas emerge as critical hotspots of data inconsistency, requiring immediate attention. In contrast, the Low-Low clusters, marked in dark blue and also consisting of 37 districts, represent districts with low unmatched percentages that are surrounded by others with similarly low values. These are mostly found in parts of Kerala, Haryana, and the northeastern region, suggesting zones of strong data integrity. Additionally, Low-High clusters (light blue, 16 districts) highlight districts with low mismatches amidst high-mismatch neighbors, pointing to possible localized good practices. Conversely, High-Low clusters (pink, 17 districts) reflect districts with high mismatches surrounded by low-mismatch regions, indicating possible anomalies or localized data quality issues that merit targeted intervention. The vast majority of districts (533) fall under the "Not Significant" category (gray), indicating no notable spatial clustering and possibly reflecting random distribution or inconsistencies not concentrated in specific regions. One district remains undefined, potentially due to data limitations. Overall, the LISA map underscores that while most of India does not show significant spatial clustering, southern and parts of central India require focused efforts to improve data accuracy and survey methodology, whereas certain northern and northeastern areas could serve as benchmarks for better implementation.

Map 3: LISA cluster map for the number of living children in NFHS IV



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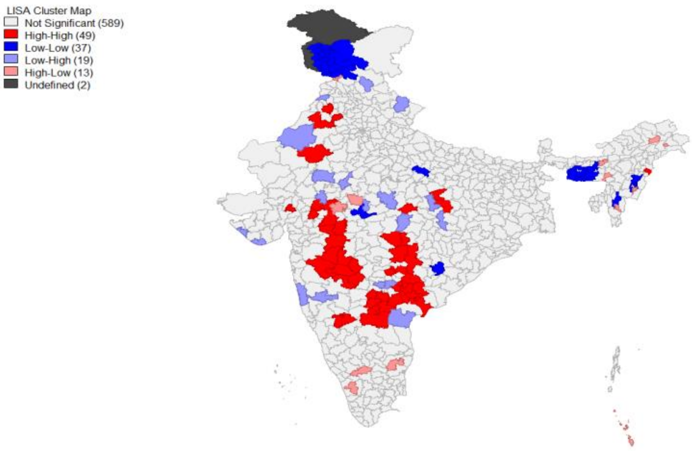
The LISA Cluster Map 4 for the unmatched percentage in NFHS-V presents a spatial analysis of data mismatches across Indian districts, indicating evolving trends in data consistency compared to NFHS-IV. The map categorizes districts into five significant cluster types: High-High, Low-Low, High-Low, Low-High, and Not Significant. High-High clusters (49 districts, in red) represent areas with high unmatched percentages surrounded by similar districts, indicating zones of consistently poor data alignment primarily concentrated in central Indian states like Madhya Pradesh, Chhattisgarh, and parts of Maharashtra and Telangana. These are clear hotspots of concern, reflecting persistent or worsening issues in survey implementation and data recording. Low-Low clusters (37 districts, dark blue) show districts with low mismatches surrounded by similar low-performing neighbors, largely located in northern and northeastern states such as Punjab, Himachal Pradesh, and parts of the Northeast, suggesting relatively strong data consistency in these areas. Low-High clusters (light blue, 19 districts) and High-Low clusters (pink, 13 districts) indicate transitional or outlier districts those that either outperform or underperform their neighbors pointing to local administrative or methodological variations. The majority of the districts (589) fall into the Not Significant category (gray), where no clear spatial clustering exists, potentially due to randomness or lack of spatial autocorrelation. Additionally, two districts remain undefined (black), possibly due to data unavailability. Compared to NFHS-IV, NFHS-V shows a geographic shift and intensification in the High-High clusters, particularly in central India, signaling areas that require targeted quality assurance, while simultaneously reinforcing the role of northeastern and select northern districts as zones of relatively higher data reliability.

Map 4: LISA cluster map for the number of living children in NFHS IV



DISCUSSION

The findings of this study highlight systematic differentials in the accuracy of reporting the number of living children across sociodemographic groups in the NFHS. The results underscore that data quality is not uniform but shaped by structural factors such as age, residence, education, and economic status. These variations are consistent with evidence from previous demographic and health survey research, both in India and globally, which has shown that the reliability of self-reported fertility histories depends on socioeconomic background, literacy, and survey conditions (Pullum, 2006; Becker et al., 1998; Schoumaker, 2014).

A prominent finding was the significantly higher likelihood of mismatches among older women. Women aged 40 years and above had more than 20 times the odds of reporting inconsistencies compared to younger women. Age-related recall bias has long been recognized as a challenge in retrospective fertility surveys, where memory lapses, child mortality, and repeated survey participation may influence reporting (Bairagi & Amin, 1995; Potter, 1977). In the Indian context, where older cohorts often experienced higher child mortality, recall of births and deaths can be particularly complex, explaining the greater inconsistencies observed among them (Retherford & Choe, 2011).

Educational attainment emerged as one of the strongest predictors of reporting accuracy. Women with higher education consistently demonstrated more reliable reporting, with match rates above 85% and substantially reduced odds of mismatch compared to illiterate women. This supports prior studies which argue that education enhances comprehension of survey questions, ability to recall and record life events, and familiarity with written documentation (Bollen et al., 2001; Zulu & Dodoo, 1998). Higher education may also be associated with better interaction with enumerators and increased access to official health records, which further reduces reporting errors.

Economic status was another robust determinant of reporting consistency. Women from the richest households reported more accurately, with the lowest proportions of large mismatches, while women from poorer households exhibited significantly greater discrepancies. This association mirrors findings from earlier NFHS assessments and other large-scale surveys in low- and middle-income countries (LMICs), where poverty often correlates with lower literacy, weaker access to health infrastructure, and greater barriers in communicating with survey fieldworkers (Curtis & Blanc, 1997; Pullum, 2006).

The rural–urban divide also played a notable role. Urban women demonstrated higher reporting accuracy than rural women, with the gap exceeding 5 percentage points in NFHS-V. This pattern may be linked to higher literacy, stronger health system penetration, and wider availability of medical records in urban areas, as reported in other evaluations of survey data quality in India (Chandrasekhar et al., 2017; Guilmoto, 2012). In rural and remote areas, logistical constraints, interviewer workload, and cultural barriers may increase the likelihood of incomplete or inconsistent reporting.

By contrast, religion and caste displayed weaker associations with reporting quality. While some variations were observed, for example, slightly higher mismatches among Muslims and Scheduled Tribes, these effects were relatively modest. The attenuation of religious effects between NFHS-IV and NFHS-V suggests that data collection practices may have become more standardized across groups, reducing disparities. However, the persistently higher mismatch rates among Scheduled Tribes point to challenges linked to geographical isolation, language barriers, and enumeration difficulties, which align with broader discussions on survey undercoverage of marginalized populations in India (Desai & Dubey, 2011; Borooah, 2005).

In addition to these sociodemographic determinants, important spatial patterns were evident. Mismatches were more prevalent in central and southern India, while reporting accuracy was comparatively higher in the Northeast. Several explanations may account for these regional differences. Central and southern states such as Madhya Pradesh, Chhattisgarh, and Andhra Pradesh have larger rural populations, higher proportions of Scheduled Castes and Tribes, and greater socioeconomic inequality, all factors linked to weaker reporting accuracy. These regions also experienced historically higher levels of fertility and child mortality, which may compound recall difficulties, particularly among older women. By contrast, the Northeast is characterized by smaller populations, stronger community-based networks, and comparatively higher literacy rates, particularly among women (Dutta, 2020). Tighter kinship structures and smaller family sizes in many northeastern states may also facilitate more accurate recall of fertility histories. Moreover, survey implementation in smaller states may allow fieldworkers to provide closer supervision and adapt more effectively to local contexts, thereby reducing enumeration errors. These findings align with prior studies showing that regional heterogeneity in survey quality often reflects differences in administrative capacity, demographic histories, and social organization (Casterline & el-Zeini, 2014).

Overall, these results reaffirm that survey data quality is not only a technical issue but also a reflection of broader social inequalities and regional disparities. The groups most vulnerable to inconsistent reporting, older, less educated, rural, and economically disadvantaged women in central and southern states, are also those often-facing structural disadvantages in health and social outcomes. This has important implications for both research and policy. Inaccuracies in reporting fertility histories can bias estimates of demographic indicators such as fertility, mortality, and population projections, which in turn inform program design and resource allocation (United Nations Population Fund [UNFPA], 2019; United Nations, 2017).

To address these challenges, targeted survey strategies are essential. Enhanced interviewer training, culturally adapted tools, and simplified questionnaires have been shown to improve data quality in complex survey contexts (Mensch et al., 2014; Groves et al., 2009). For older and less educated respondents, incorporating visual aids, calendar methods, or community-based verification may help reduce recall error. In addition, leveraging digital health records where available could complement survey data and reduce reliance on memory-based reporting.

The study demonstrates that while NFHS data remain an invaluable resource for demographic research and policymaking in India, attention must be given to both sociodemographic and regional disparities in reporting accuracy. Ensuring equitable data quality across groups and geographies is critical to producing reliable fertility and health statistics and to designing interventions that genuinely address the needs of vulnerable communities.

Declaration

Author Contributions: JG was responsible for the conceptualization, data curation, formal analysis, methodology, visualization, and preparation of the original draft. CS contributed through supervision and provided critical review and editing of the manuscript. Both authors have read and approved the final version of the manuscript.

Originality and Exclusivity: This manuscript is original and has not been published previously. It is not under consideration for publication elsewhere and will not be submitted to another journal.

Conflict of Interest: The authors declare no conflict of interest.

Funding: Not applicable

Ethical Approval: This study is based on publicly available secondary data from the National Family Health Survey (NFHS), which is anonymized and does not require separate ethical approval.

Data Availability Statement: The data used in this study are publicly available and can be accessed through the Demographic and Health Surveys (DHS) Program website upon registration and approval. Specifically, the National Family Health Survey (NFHS) data for Rounds I to V are available at: https://dhsprogram.com/data/available-datasets.cfm.

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