

Original Article

Estimation of HIV Prevalence among the Female Population in South India: A Bayesian ApproachElangovan Arumugum^{1,2*}, Vasna Joshua¹¹ICMR-National Institute of Epidemiology, Chennai, Tamil Nadu, India.²Research Scholar, University of Madras, Chennai, Tamil Nadu, India.

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ABSTRACT

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Introduction: The HIV Sentinel Surveillance (HSS) conducted by National AIDS Control Organization (NACO) is the predominant data source for HIV estimations in India. While the HSS targets the key populations at risk of HIV infection, the National Family Health Survey (NFHS) measures the community-based HIV prevalence. Improvised HIV estimates in India were attributed to the HIV prevalence data obtained from the NACO-HSS and NFHS.

Methods: Bayesian analysis was performed to determine the state-level prevalence of HIV among females in seven South Indian States. The analysis involved plotting the prior, likelihood, and posterior distributions, facilitating a visual assessment of the data. The HIV prevalence among females calculated from the NFHS (2015-16) survey data was used for prior distributions. HIV prevalence among pregnant women obtained from the HIV Sentinel Surveillance 2019 was used for likelihood. Bayesian analysis was performed using the R programming (RStudio 2022.02.0). A posterior probability distribution was obtained using the prior distribution and the likelihood by applying the Bayes theorem. Graphical representation was achieved through R's plotting functions. Kerala and Pondicherry were not included in the analysis due to zero or very low prevalence reported in both NFHS and HSS.

Results: The Bayesian estimates of HIV prevalence among females were 0.38 % [95% CI:0.29 - 0.47] in Andhra Pradesh, 0.28 [95% CI:0.23 - 0.35] in Karnataka, 0.27 [95% CI:0.20 - 0.34] Odisha, 0.27 % [95% CI:0.19 - 0.36] in Telangana and 0.19 [95% CI:0.15 - 0.24] in Tamil Nadu.

Conclusion: Bayesian techniques present a versatile and robust strategy for modelling and analysing HIV-related data, offering a flexible and powerful approach to data analysis.

Introduction

The HIV epidemic in India is heterogeneous and predominantly confined to specific high-risk population groups and geographic

locations pertaining to behavioural and social characteristics.¹ Various reports have shown that heterosexual transmission is the major route of HIV transmission in India, accounting for 85% of the total infections. As per the

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2021 HIV estimation report, the adult HIV prevalence in India was 0.21% (0.17-0.25) and 0.22 % (0.18-0.28) among males and 0.19 % (0.15-0.23) among females. Despite low prevalence, India has the third highest burden of HIV in the world, with an estimated 24.01 (19.92-29.07) lakh people living with HIV (PLHIV) in 2021, of which 44% are among females.²

HIV Surveillance and Estimation is an integral part of the National AIDS Control Organization (NACO) in India. HIV estimations in India are predominantly based on the HIV Sentinel Surveillance (HSS) data and the HIV data collected from the National Family Health Survey (NFHS).³ HSS is periodically implemented by the National AIDS Control Organisation (NACO) to monitor the levels and trends of HIV in India. HIV surveillance involves collecting primary data and blood samples from different population groups, and HIV burden estimation is done after each round of surveillance using aggregated de-identified data. The HIV prevalence among different population groups is estimated using Spectrum Software (Avenir Health, Glastonbury, Connecticut, USA). HIV estimations and program-generated data are used for policymaking and program improvement under the National AIDS Control Programme of NACO.¹ HSS was initially implemented in select districts in India and has now expanded to cover most districts across the country. HSS is implemented as a cross-sectional survey among eight population groups, including high-risk groups (Female Sex Workers, Men having sex with men, injecting drug users and transgender people), bridge population (long distant truckers and single male migrants), pregnant women attending antenatal clinic (ANC

attendees) and prisoners. Pregnant women attending the antenatal clinics are considered as a proxy for the general population. Pregnant women attending ANC (Antenatal Care) services represent a broad cross-section of the population, including various age groups, socioeconomic backgrounds, and geographical locations. This diversity makes ANC mothers a representative sample of women in the general population. NFHS, on the other hand, is a large-scale, community-based survey and is conducted periodically among a representative sample of households throughout India. Measuring the HIV prevalence among males and females in the general population is one of the several components of the NFHS survey, and the same was included during NFHS-3 (2005-2006) and NFHS-4 (2015-2016).

NACO has conducted several rounds of HSS since 2003 as a part of the National AIDS Control Programme. The 16th round of HSS was conducted in 2019 among ANC attendees at 833 sites across 642 districts in 35 States/ Union Territories (UTs). HSS is facility-based surveillance and follows consecutive sampling to measure the HIV prevalence among population groups.⁴ The fourth round of NFHS was implemented in 2016 in India, which is a community-based survey that includes participants from randomly selected households to measure various health indicators, including HIV.⁵ Both surveillances provide evidence-based information, which in turn is used to generate HIV estimates that reflect the national and sub-national levels of HIV prevalence. While national-level population-based surveillances are the key source for HIV estimation, they also suffer from limitations such as facility-based study design, selection bias and non-response or

non-participation rates. Hence, accurate HIV estimates that are closer to reality are essential for monitoring levels of HIV, tracking the disease progression, devising, executing, and evaluating prevention and treatment initiatives, and predicting the need for resources.⁶

Our study employed a Bayesian approach to estimate the state-level HIV prevalence among females using the NFHS-2016 and HSS-2019 data. This paper describes the Bayesian approach used to estimate the HIV prevalence among females in the 7 states of South India (Andhra Pradesh, Karnataka, Kerala, Odisha, Pondicherry, Tamil Nadu, and Telangana). The Bayesian approach was used to determine the shape parameters for the prior estimate and likelihood, resulting in the parameter estimation of the state-level HIV prevalence among the female population.

Methods

The HIV sentinel Surveillance data collected among ANC attendees in 2019 and the NFHS data collected in 2015-16 were used to determine the state-level HIV prevalence among females in the 7 southern states of India.^{5,7-13} NFHS is a community-based survey and includes the general female population of all age groups, and the participants are surveyed to provide estimates at district, state, and national levels. However, the HIV testing and the questions related to HIV knowledge and behaviours are administered among a subsample of women aged between 15-49. The sample size for the HIV module in NFHS is calculated to provide only the state and national level estimates. Further details on the study design, sampling methods and sample size for NFHS are described elsewhere.⁵ HSS is facility-based

surveillance and includes only those pregnant women aged 15-49 years attending the sentinel sites during the surveillance period. Detailed methodology of the HSS has been reported in various literatures.¹⁴⁻¹⁸ Both surveillances are conducted at regular intervals across the country, yet vary in their primary objectives, methodology and study population.¹⁹ In this study, the HIV prevalence data from both surveillances were used to estimate the posterior distribution of state-level HIV prevalence among females.

Data on the number of HIV-positive females and the total number of females tested were collected and subjected to Bayesian analysis. Bayesian analysis was performed using the R programming (RStudio 2022.02.0). The analysis involved plotting the prior, likelihood, and posterior distributions, facilitating a visual assessment of the HIV prevalence data.

The HIV prevalence (weighted) among females in each of these states, along with the 95% Confidence Interval, was determined by the NFHS survey data. As NFHS follows a non-proportional allocation of the sample to the different survey units and to their urban and rural areas, weights are required for any the NFHS-4 data to ensure the actual representativeness of the survey results at the national level and as well as at the unit level. In the case of the sampling weights for HIV testing, the weights are normalised at the state level for women.⁵ This data was used as the prior estimate for which the beta distribution was calculated. The beta distribution was estimated such that the mean of the beta distribution corresponded to the original estimate, and the minimum probability density was within the upper and lower limits of the original estimate. This ensures that the determined beta distribution

closely resembles the estimated prevalence. Beta distributions are nothing but probability distributions often used to outline any previous uncertainty about disease prevalence.²⁰ HIV prevalence and shape parameters (α and β) for the corresponding beta distributions for each of the states were calculated based on the methods reported by Wesson et al.²¹ and reported in Table 1.

Assuming a normal distribution, the variance for each HIV estimate was calculated using the equation,

$$\text{Variance} = \left(\frac{\text{Upper Bound} - \mu}{1.96} \right)^2$$

Where μ = mean of the original HIV prevalence.

The shape parameters alpha (α) and beta (β) were then calculated using the mean (μ) and the calculated variance of the estimated HIV prevalence.

$$\alpha = - \frac{\mu(\sigma^2 + \mu^2 - \mu)}{\sigma^2}$$

$$\beta = \frac{(\sigma^2 + \mu^2 - \mu)(\mu - 1)}{\sigma^2}$$

The HSS 2019 data was used to obtain the likelihood distribution. The number of pregnant women who tested positive for HIV was obtained and HIV prevalence was calculated using the total tested population in each state as the denominator. The upper and lower bounds of the original estimate were also obtained as proportions (Table 2).

The estimates from the likelihood and prior distributions were converted into probability distributions and merged based on the Bayes Theorem to synthesise a posterior probability distribution.

$$\text{posterior} \propto \text{likelihood} * \text{prior}$$

$$P(\theta|x) \propto P(x|\theta).P(\theta)$$

Summary statistics, including mode, mean, and standard deviation (sd), were calculated for each distribution, offering insights into parameter estimation. The 95% credible interval also provides a range of plausible HIV prevalence values. Graphical representation was achieved through R's plotting functions, and we discussed the absence of explicit confounder adjustment, as Bayesian analysis indirectly accounts for confounding variables by modelling the joint distribution of parameters. No HIV positivity was reported among the female population in Kerala during the NFHS, and similarly, no HIV positivity was reported among the ANC attendees in Pondicherry during the HSS. Hence, the Bayesian estimates were not generated for these states.

Results

Table 1 presents a comparative overview of reported HIV estimates and their respective 95% confidence intervals (CI) for South Indian states as derived from the NFHS data. Additionally, it provides the estimated shape parameters (α and β) of beta distributions, representing the prior information utilised in the Bayesian analysis. The data reveals regional variations in HIV prevalence, ranging from 0.00% in Kerala to 1.13% in Andhra Pradesh. The shape parameters reflect the prior beliefs about the distribution of HIV prevalence within each state, informing the Bayesian modelling approach.

Table 2 presents likelihood estimates derived from the HIV Sentinel Surveillance (HSS) data

Table 1. The reported HIV estimates (weighted) from the NFHS data and the estimated shape parameters of beta distributions (prior)

State	HIV (%)	95% CI	α	β
Andhra Pradesh	1.13	(0.62 - 1.63)	18.84316	1656.04951
Karnataka	0.71	(0.45 - 0.97)	28.16831	3944.25667
Kerala	0.00	-	-	-
Odisha	0.08	(0.00 - 0.15)	4.229019	5500.94541
Puducherry	0.03	(0.00 - 0.14)	0.196286	759.777768
Tamil Nadu	0.27	(0.13 - 0.41)	14.38796	5305.55462
Telangana	0.58	(0.17 - 1.00)	7.521499	1280.38541

Table 2. Likelihood estimates obtained for the HSS data

State	Tested	Positive	HIV %	95% CI
Andhra Pradesh	15600	47	0.30	(0.22 - 0.39)
Karnataka	24800	54	0.22	(0.16 - 0.28)
Kerala	5600	2	0.04	(0 - 0.09)
Odisha	13200	46	0.35	(0.25 - 0.45)
Puducherry	800	0	0.00	-
Tamil Nadu	28400	50	0.18	(0.13 - 0.22)
Telangana	11600	27	0.23	(0.15 - 0.32)

for South Indian states. It includes information on the number of individuals tested, the number of positive HIV cases, HIV prevalence percentages, and their corresponding 95% confidence intervals (CI). Notably, the data indicates variations in HIV prevalence across states, with Andhra Pradesh having the highest estimated prevalence at 0.30% [95% CI:0.22-0.39] and Puducherry reporting no positive cases in the sample. These likelihood estimates serve as crucial inputs for Bayesian analysis, helping to refine our understanding of regional HIV trends.

In the Bayesian analysis of HIV prevalence among females in South Indian states, we observed significant differences. In Andhra Pradesh, the estimated mean HIV prevalence is 0.381%, with a 95% credible interval (CI) ranging from 0.29% to 0.47%. Similarly, Karnataka reports a mean prevalence of

0.285% and a CI from 0.23% to 0.35%. Odisha exhibits a mean prevalence of 0.268% and a CI spanning from 0.20% to 0.34%, and Telangana has a mean prevalence of 0.267% and a CI from 0.19% to 0.36% (Table 3). Tamil Nadu shows a lower estimated mean prevalence of 0.190%, within a CI of 0.15% to 0.24%.

The figures (1-5) generated based on the provided R code illustrate the Bayesian analysis of proportions, offering a graphical representation of critical statistical insights. The "triplot" includes three distinct curves representing the prior, likelihood, and posterior distributions. The green curve represents the prior distribution, capturing our initial beliefs about the parameter of interest: the state-level HIV prevalence among females. The blue curve represents the likelihood, incorporating the observed data and updating our beliefs based on the evidence. Finally, the red curve

Table 3. Estimated HIV prevalence (%) among women using Bayesian estimation

Bayesian Estimates	Parameters	State				
		Andhra Pradesh	Karnataka	Odisha	Tamil Nadu	Telangana
Posterior values	Mean	0.381	0.285	0.268	0.190	0.267
	[95% CI [^]]	[0.29 - 0.47]	[0.23 - 0.35]	[0.20-0.34]	[0.15-0.24]	[0.19-0.36]
	Mode	0.375	0.282	0.263	0.188	0.260
	SD	0.469	0.315	0.378	0.238	0.455

CI, Credible Interval

represents the posterior distribution, the synthesis of prior knowledge and observed data, providing a refined estimate of the parameter's true value. Graphical representation of the prior (NFHS), likelihood (HSS) and posterior distribution of the HIV prevalence in Andhra Pradesh, Karnataka, Odisha, Tamil Nadu, and Telangana are shown in Figure 1-5.

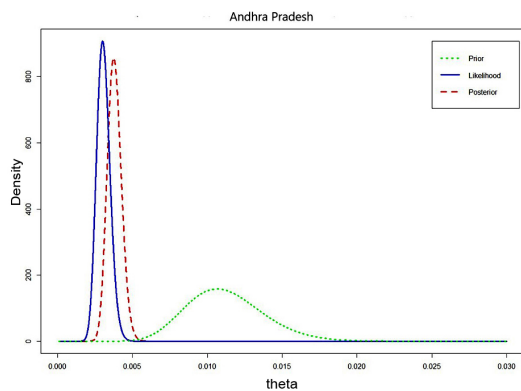


Figure 1. Bayesian (Triplot Analysis) of HIV Prevalence among Women in Andhra Pradesh: Prior, Likelihood, and Posterior Distributions

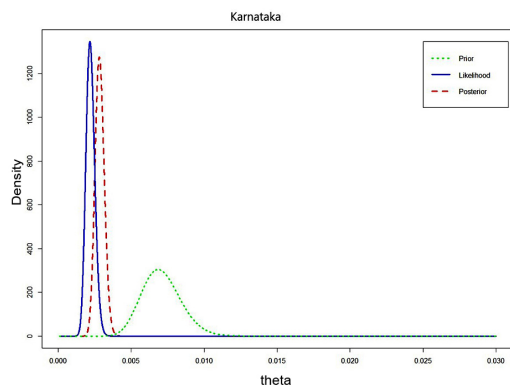


Figure 2. Bayesian (Triplot Analysis) of HIV Prevalence among Women in Karnataka: Prior, Likelihood, and Posterior Distributions

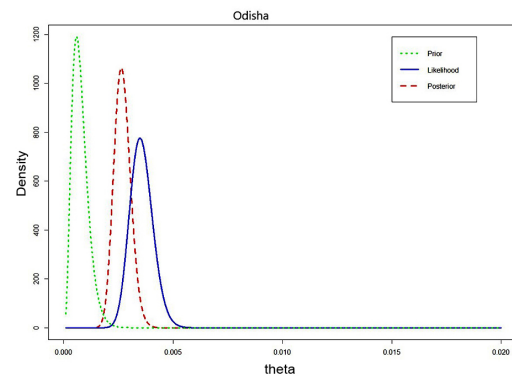


Figure 3. Bayesian (Triplot Analysis) of HIV Prevalence among Women in Odisha: Prior, Likelihood, and Posterior Distributions

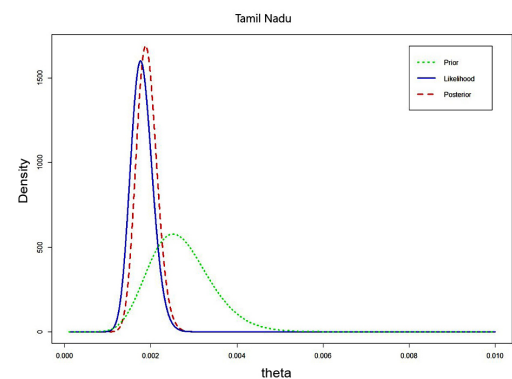


Figure 4. Bayesian (Triplot Analysis) of HIV Prevalence among Women in Tamil Nadu: Prior, Likelihood, and Posterior Distributions

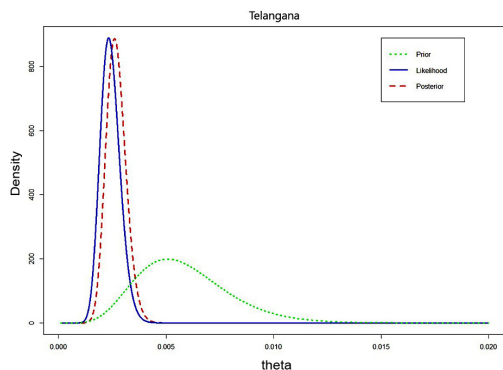


Figure 5. Bayesian (Triplot Analysis) of HIV Prevalence among Women in Telangana: Prior, Likelihood, and Posterior Distributions

Discussion

This work employed a Bayesian approach to determine the state-level HIV prevalence among the female general population in India. For this, the HIV prevalence for each southern state was estimated from two surveys. Based on the NFHS data, the HIV prevalence among females ranged from 0% in Kerala to 1.13% (0.62 - 1.63) in Andhra Pradesh. Likewise, based on the HSS data, the HIV prevalence among females ranged from 0% in Puducherry to 0.35% (0.25 - 0.45) in Odisha. In HSS, over 90% of the study population accounts for the 15-34 age group, of which predominantly 50-73% are in the 15-24 age group.⁷⁻¹³ The female population covered at HSS are young, likely to be sexually more active and have had recent unprotected sex; hence, the HIV prevalence is generally higher among the young women in HSS. Earlier, it was noted that the HIV estimates of HSS were higher than that of the NFHS data, which was attributed to the non-representative nature of the HSS estimates among all adult women.¹⁹ However, in our study, it could be observed

that the HSS estimates were much lower than the NFHS estimates. This could be attributed to the significantly declining trend in the HIV prevalence among young females, especially in the southern region, due to early, large-scale interventions.^{22,23} Another factor could be the matured nature of the HIV epidemic in South India owing to the sustained and prolonged ART coverage leading to the increasing life span of HIV-positive females.^{24,25} While the chances of capturing older HIV-positive women are low in the ANC setup, they can be covered in a community setting. This could explain a higher HIV prevalence among females in the NFHS data. The HIV estimates vary to a significant extent between the NFHS data and the HSS data (Tables 1 and 2), although both data are comparable in terms of the population. The variations could be attributed to several factors, such as the survey methodology, participant profile and behaviours. Hence, the estimates cannot be generalised for all women, limiting their use in estimations closer to the true prevalence. In order to arrive at a more reliable value, several approaches are used for HIV estimations, including Bayesian analysis. The Bayesian methodology incorporates prior knowledge and while updating it with observed data, provides a robust framework for estimating HIV prevalence. This accounts for any uncertainties and dependencies in the data, resulting in more accurate prevalence estimates. Thus, Bayesian estimates generated are based on some previously reported data, which reduces the bias or random errors in the HIV estimates. Therefore, we attempt a Bayesian model to estimate a closer state-level prevalence of HIV among females in the seven South Indian states. Beta Distributions are prior probability distributions frequently

used to describe prior uncertainty about disease prevalence. Before observing any data, Bayesian analysis starts with the beta distributions, representing the initial beliefs or knowledge about the parameters of interest, state-level HIV prevalence among females. This prior distribution incorporates any relevant information or previous data on HIV prevalence, and the NFHS data on HIV prevalence among females was used to obtain the beta distribution. The likelihood is based on the observed data, the HIV prevalence among ANC attendees obtained from the HSS 2019 surveillance data. The posterior probability distribution is obtained using Bayes' theorem, wherein the prior probability distribution is updated using the likelihood and the observed data. The resultant posterior probability distribution indicates the updated beliefs about the state-level HIV prevalence and its parameters after considering the new evidence. By summarising or extracting information from the posterior distribution, the mean estimated HIV prevalence among females, along with its credible intervals, was obtained. Using the NFHS data as a priori and HIV prevalence among ANC attendees in the HSS data as the likelihood estimate, the posterior estimates for HIV prevalence among females were calculated based on the Bayesian approach. The posterior probability distributions of HIV prevalence generated using the method represent an improved HIV estimate that is potentially reliable and precise.²⁶

Estimating HIV prevalence among females is crucial as it helps understand the gender-specific impact of HIV burden in the country, aids in public health planning on HIV prevention and management strategies, and facilitates

prevention of Mother-to-Child Transmission of HIV. Based on the Bayesian analysis, Andhra Pradesh had the highest HIV prevalence (0.381%; CI: 0.29 - 0.47) among females, followed by Karnataka, Odisha, Telangana, and Tamil Nadu. Except Tamil Nadu, the estimated HIV prevalence among females was higher than the 2021 national HIV prevalence among females, 0.19% [0.15–0.23]. This calls for improved and targeted interventions that are essential for preventing new infections providing HIV care and treatment support to affected females so as to achieve the goal of End of AIDS. Overall, our study highlights the role of Bayesian analysis in informing evidence-based healthcare strategies and underscores the need for continued monitoring and tailored interventions to combat the HIV epidemic effectively among women in diverse regions of India. In the future, Bayesian methods can also be used to model the risk of HIV transmission in different populations, such as men who have sex with men (MSM) or people who inject drugs (PWID). Further, Bayesian methods can be useful for modelling and analysing HIV-related data, including the incidence and prevalence of HIV.

Limitations

NFHS is a community-based survey in which the female respondents were selected randomly from the general population. On the other hand, HSS is a facility-based survey that includes only the pregnant women attending the ANC clinics, who are considered a proxy for the general population. Thus, the study participants and settings differ in both surveys. Thus, the data we have used are comparable regarding study participants only at the state

level. Although NHFS-5 conducted in 2020 was the latest, we have used the NFHS-4 data as the HIV testing module was not included in NFHS-5. The primary objective of the NFHS is to provide high-quality data pertaining to population dynamics, health and family welfare and emerging health and family welfare issues. Hence, the sample size tested for HIV in NFHS is not calculated for estimating HIV/AIDS prevalence at the domain level.

Conclusion

According to the Bayesian estimate, Andhra Pradesh records a high HIV prevalence, with Tamil Nadu as the lowest among the southern states of India. Bayesian methods can provide a flexible and robust approach for modelling and analysing HIV-related data, which helps inform policy decisions and public health interventions to reduce the burden of HIV/AIDS.

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Conflicts of Interests

None

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