

A Bayesian Spatial Hierarchical Analysis of Cervical Cancer Screening Uptake in Ethiopia

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Abstract Cervical cancer is the fourth most common cancer among women globally, with the highest burden in sub-Saharan Africa, where screening coverage remains far below the World Health Organization's 70% elimination target. Evidence on screening uptake in Ethiopia has been limited to small, facility-based studies unable to characterise national geographic patterns. This study aimed to identify individual-level and geographic determinants of cervical cancer screening uptake among Ethiopian women using a spatial Bayesian approach. Data were drawn from the 2024–25 Ethiopia Demographic and Health Survey ($N = 20,864$ women aged 15–49). A Bayesian hierarchical logistic regression model with a Besag–York–Mollié (BYM2) spatial random effect and a cluster random effect was fitted via integrated nested Laplace approximation, with fits compared across four nested specifications using the Watanabe–Akaike Information Criterion. Weighted national screening prevalence was 5.89%. Uptake rose with household wealth, education, and mass media exposure, and was higher among currently ($aOR = 2.66$) and formerly ($aOR = 2.50$) married women than never-married women. Region and cluster jointly explained 11.3% of residual variance, but only 23.2% of the regional component was spatially structured. Most of the more than 50-fold disparity between Addis Ababa (16.4%) and Somali (0.3%) reflected population composition rather than a residual regional effect, though a smaller, genuine geographic disparity persisted after adjustment. Screening uptake in Ethiopia is shaped jointly by individual-level disadvantage and geographic disparities not fully explained by population composition. Closing this gap will likely require expanded individual-level access, direct health-system investment in underserved regions such as Somali, and spatially explicit, subnational monitoring to ensure progress reaches the communities currently furthest behind.

Keywords Bayesian Spatial Analysis, Cervical Cancer Screening, Demographic and Health Survey, Ethiopia.

Introduction

Cervical cancer is the fourth most common cancer in women worldwide, and in 2022, there were about 660,000 new cases and 350,000 deaths recorded [1]. Unlike the case with most other cancers, cervical cancer is almost always the result of a persistent infection with high-risk types of human papillomavirus (HPV), the infection leading to a well-established, step-by-step progression from HPV infection through precancerous cervical intraepithelial lesions to invasive carcinoma [2, 3]. Because of this clear cause and the long latency period between infection and the development of invasive disease, cervical cancer is one of the most preventable forms of cancer by ensuring that precancerous lesions are properly screened for and treated in a timely manner.

Even though cervical cancer can be prevented, the burden of the disease is still very uneven: more than 90% of the deaths take place in low- and middle-income countries, sub-Saharan Africa having the highest rates of both incidence and mortality of the disease worldwide [4, 5]. This inequality mainly reflects unequal access to organised screening and early treatment, not differences in disease biology. In response, the World Health Organization (WHO) launched its Global Strategy to Accelerate the Elimination of Cervical Cancer as a Public Health Problem in 2020, which the World Health Assembly approved. The strategy set out the "90–70–90" targets: 90% of girls should be fully vaccinated against HPV, 70% of women should be screened using a high-performance test by the ages of 35 and 45, and 90% of women who have precancer or invasive cancer should receive treatment, all by 2030 [6, 7]. Modelling studies carried out in low- and lower-middle-income countries show that meeting these targets, especially those relating to screening coverage, could prevent tens of millions of cases and deaths from cervical cancer over the next century [8, 9].

The main and practical part of the elimination strategy is screening. Established methods such as visual inspection with acetic acid, cytology-based testing, and HPV DNA testing reduce both incidence and mortality from cervical cancer, provided adequate follow-up is carried out [10–12]. Yet global screening coverage remains far below the WHO's target of 70% and varies considerably between and within countries [13, 14]. Coverage in Sub-Saharan Africa is especially low and is unevenly distributed. Consistent evidence from the region shows that age, education level, household wealth, place of residence, health insurance status, marital status, exposure to health information through mass media, and women's autonomy in making healthcare decisions are key factors affecting screening uptake [15–18]. A study in Kenya also found sociodemographic and healthcare-access factors central to screening uptake, offering a pertinent methodological comparison for the current study [19].

In the case of Ethiopia, there is very little direct evidence available at the population level regarding uptake of cervical cancer screening and the factors that influence it. Rather, the existing studies from Ethiopia have concentrated on the prevalence of precancerous or abnormal cervical lesions among women who are already visiting particular health facilities, for instance, among women attending clinics in West Wollega in western Ethiopia [20], and in Harar in eastern Ethiopia [21]. Although these facility-based studies offer useful clinical data, by nature they address only the prevalence of lesions among women who previously received screening or clinical care at a single location, not screening uptake and its determinants across the wider population. Consequently, they cannot show how screening behaviour, or the spatial pattern of such behaviour, differs across regions of Ethiopia. To date, no study has used a nationally representative sample to examine the determinants of cervical cancer screening

uptake together with an explicit spatial modelling approach that can distinguish between variations in screening behaviour at the individual, community, and regional levels.

It is not just a methodological gap but a substantial one. Behavioural patterns related to health, such as undergoing cancer screening, are influenced by individual characteristics, the immediate community environment, and wider regional factors, which may not align with administrative boundaries. Spatial hierarchical models offer a sound approach to separating these sources of variation, particularly when some administrative areas have small sample sizes [22-25]. The development of approximate Bayesian inference has made it possible to use such models with large, nationally representative survey data of the type regularly collected by the Demographic and Health Surveys (DHS) programme [26].

This study aims to fill the gap by using data from the 2024–25 Ethiopia Demographic and Health Survey. More precisely, it has three objectives: (1) to find the sociodemographic and behavioural factors at the individual level that are associated with the uptake of cervical cancer screening among reproductive-age women in Ethiopia; (2) to measure the degree to which the rate of uptake of screening differs in a systematic way according to geographic region and survey cluster, beyond what can be accounted for by individual characteristics; and (3) to assess whether the regional differences in screening uptake show a spatially structured pattern involving neighbouring regions or instead reflect unstructured, region-specific variability. The study intends to produce evidence that can help to better direct cervical cancer screening programmes geographically in Ethiopia and thus contribute to national and global efforts towards the elimination of cervical cancer.

Materials and Methods

Study Design and Data Source

This study utilised data from the 2024–25 Ethiopia Demographic and Health Survey (EDHS-8), a nationally representative, cross-sectional household survey conducted by the Ethiopian Statistical Service with technical support from The DHS Program [27]. Fieldwork was conducted between August 2024 and April 2025, employing a stratified, two-stage cluster sampling design. In the first stage, enumeration areas (clusters) were selected with probability proportional to size, stratified by region and urban or rural status. In the second stage, households were randomly selected within each cluster. This sampling strategy produces nationally representative estimates suitable for policy and programme planning. The survey's final report provides a comprehensive description of the sampling methodology. Analyses were performed using the Individual Recode (women's) dataset.

Study Population

The EDHS-8 surveyed 21,395 women aged 15 to 49 years. Women who responded 'do not know' to the question regarding cervical cancer screening ($n = 531$, 2.5%) were excluded through complete-case analysis, as this missing outcome data was minimal and not systematic [28]. The final analytical sample comprised 20,864 women, ensuring alignment with the survey's screening measure and supporting accurate policy interpretation.

Study Variables

The dependent variable was a binary indicator of whether a woman had ever undergone cervical cancer screening. Individual characteristics were selected a priori based on existing literature on cervical cancer screening uptake in sub-Saharan Africa. These included age, highest educational attainment, household wealth quintile, place of residence, health insurance status, current marital status, exposure to mass media, and number of living

children. Geographic region was modelled as a spatial random effect, and the primary sampling unit as an unstructured random effect, rather than as fixed effects (see Bayesian Spatial Hierarchical Model for details). This modelling approach helps identify population-level patterns to inform targeted screening policies.

Region Adjacency Structure

The spatial adjacency matrix at the regional level needed for the spatial random effect was obtained directly from the administrative boundary shapefile in the DHS Spatial Data Repository for the particular survey round, not from general geographic knowledge. The regions that were neighbours were determined computationally by identifying those which shared a common polygon boundary using the *spdep* package [29]. Verification was carried out using both strict polygon adjacency and a 500-metre buffer in order to take into account possible gaps caused by digitisation of the boundary files; in both cases, the results were the same. As a result, 23 adjacencies between regions were found among the 14 regions.

Statistical Analysis

Descriptive and Preliminary Analyses

The survey's sampling weights, stratification, and clustering were taken into account when the weighted descriptive statistics were calculated for the outcome and all the covariates. Preliminary bivariate associations between wealth, education, and urban/rural residence were examined to assess collinearity among the key socioeconomic covariates prior to modelling.

Bayesian Spatial Hierarchical Model

This study used a Bayesian hierarchical logistic regression model with a Besag–York–Mollié (BYM) spatial random effect for region [22], using the BYM2 reparameterisation [23], and an exchangeable (unstructured) random intercept for primary sampling unit (cluster), fitted using integrated nested Laplace

approximation (INLA) [26]. The BYM2 parameterisation decomposes the region-level random effect into a spatially structured component, which allows neighbouring regions to share information (spatial smoothing), and an unstructured component capturing region-specific variation not explained by geographic proximity, with a mixing parameter $\phi \in [0, 1]$ governing the proportion of variance attributable to the spatially structured component. The model is specified as:

$$\text{logit}(\pi_{ijk}) = \beta_0 + X_{ijk}\beta + u_j + v_k$$

In this context, π_{ijk} stands for the probability that woman i in cluster j and region k was ever screened for cervical cancer; X_{ijk} is the vector of the individual-level covariates; $u_j \sim \text{Normal}(0, \sigma_u^2)$ denotes the unstructured random effect at the cluster level; and v_k is the BYM2 spatial random effect for region k . Penalised complexity (PC) priors were used for all the variance components (the probability that σ is greater than 1 is 0.01 for both the regional and cluster precisions, and the probability that ϕ is less than 0.5 is 2/3 for the spatial mixing parameter), in line with the current recommended practice for BYM2 models [23, 30]. The fixed-effect regression coefficients, including the intercept, were given weakly informative Normal (0, 1000) priors. The Bayesian spatial hierarchical model was fitted without the use of survey weights, since design-induced imbalance was dealt with structurally by including the region and cluster random effects as well as the individual-level covariates related to the sampling design (see Weighted Sensitivity Analysis section). This approach allowed regional-level inference while accounting for both clustering and spatial dependence.

Model Comparison

In order to provide empirical support for the hierarchical spatial structure, four nested models were evaluated using the Watanabe–Akaike Information Criterion (WAIC) [31, 32]:

(1) a null model containing only an intercept; (2) a model with only the individual-level covariates; (3) a model that included both the covariates and an unstructured cluster random effect; and (4) the complete Bayesian spatial hierarchical model, which incorporated the covariates, the BYM2 spatial region effect, and the cluster random effect. Any differences in WAIC (Δ WAIC) exceeding 10 were regarded as decisive evidence of an improved model fit, in accordance with the standard interpretation guidelines, and were used to show the additional value of the spatial and clustering structure.

Variance Decomposition

The extent to which the variance in the total outcome could be attributed to grouping at the cluster and region levels was determined by means of the intraclass correlation coefficient (ICC), which was calculated on the latent (logit) scale using the formula $\sigma_u^2 / (\sigma_u^2 + \pi^2/3)$, where $\pi^2/3 \approx 3.29$ is the amount of fixed residual variance associated with the standard logistic distribution [33]. For the region-level BYM2 effect, we decomposed the total ICC into spatially structured and unstructured components using the posterior mean of ϕ .

Weighted Sensitivity Analysis

Because the Bayesian spatial hierarchical model did not include DHS sampling weights, we ran a sensitivity analysis by fitting a weighted Bayesian multilevel logistic regression model in brms [34] (R interface to Stan [35]), applying the DHS sampling weights via a pseudo-likelihood weighting method. This sensitivity model used the same individual-level covariates as the Bayesian spatial hierarchical model, with the region specified as a fixed effect (instead of as a spatial random effect, since design-consistent weighting is not currently well established for spatial random-effects models) and a random intercept for cluster. The agreement between the Bayesian spatial hierarchical model and the sensitivity

model was assessed by calculating the Pearson correlation between the log-odds estimates from the two models for all the individual-level covariates that are common to both models (region was omitted from this comparison since it is parameterised differently in the two models) and by looking at the proportion of covariates that had the same direction of effect.

Additional Robustness Checks

For the Bayesian spatial hierarchical model, we carried out two further robustness checks. The first involved assessing the overall fit of the model using the log pseudo marginal likelihood (LPML), obtained from leave-one-out conditional predictive ordinates (CPO) calculated using INLA's built-in cross-validation method. The second check was a prior sensitivity analysis in which the Bayesian spatial hierarchical model was refitted using two different PC prior specifications for the precision parameters relating to the region and cluster: a more restrictive prior (such that $P(\sigma > 0.3) = 0.01$) which favours a smaller variance, and a more relaxed prior (such that $P(\sigma > 3) = 0.01$) which allows for a larger variance, the prior on ϕ remaining unchanged. This analysis showed that the substantive conclusions had not been affected by the particular prior choice made in the main analysis.

Software

The analyses were carried out with R (version 4.5) [36]. The Bayesian spatial hierarchical model was fitted using the R-INLA package [26], and the weighted sensitivity model was fitted with brms [34]. The survey-weighted descriptive statistics were calculated using the survey package [37]. For spatial data processing, the sf [38] and spdep [29] packages were used, with the regional boundaries and the cluster GPS coordinates being obtained from the DHS Program Spatial Data Repository [39].

Results

Sample Characteristics and Descriptive Patterns

Of the 20,864 women who made up the analytic sample, 1,161 had previously been screened for cervical cancer, which equates to a weighted national prevalence of 5.89% (see Table 1). Table 1 and Figure 1 show the unweighted and weighted sample characteristics, along with the weighted screening prevalence in each covariate category. Screening prevalence rose steadily with age, going from 1.80% among women aged 15 to 19 years to a maximum of 10.66% among those aged 40 to 44 years, before dropping slightly to 10.17% among women aged 45 to 49 years (Figure 1A). There was also a clear gradient according to level of education, ranging from 5.06% among women with no formal education to 13.61% among those who had higher education (Figure 1B), and according to household wealth, from 1.18% among the poorest to 11.93% among the richest (Figure 1C), this being the steepest gradient among all the variables examined. Women living in urban areas were screened at more than

twice the rate of those in rural areas (9.78% compared with 3.83%; Figure 1D). The difference in screening prevalence between women with health insurance and those without was only modest, amounting to 6.40% versus 5.46% (Figure 1E). Women who were currently or formerly married had a considerably higher screening rate than those who had never been in a union (7.19% and 9.09%, respectively, compared with 2.15%; Figure 1F), and screening prevalence increased as mass media exposure increased, from 3.60% among women with no media exposure to 11.24% among those with high exposure (Figure 1G).

The prevalence of screening varied greatly across geographic areas, being more than 50 times higher in Addis Ababa (16.36%) than in the Somali region (0.30%), and the national weighted average of 5.89% is provided for reference (Figure 2a). A choropleth map is used in Figure 2b to show the geographic distribution of this variation, illustrating a general trend of higher screening prevalence in and around Addis Ababa as well as in parts of Amhara, and a much lower prevalence in Somali, in Oromia, and over much of the south and southwest of the country.

Table 1. Sample Characteristics and Weighted Cervical Cancer Screening Prevalence Among Women Aged 15–49

Characteristic	N	Weighted % Screened	SE
Age Group (years)			
15–19	4,688	1.80	0.32
20–24	3,639	2.85	0.44
25–29	3,818	5.28	0.66
30–34	2,739	8.42	1.04
35–39	2,584	9.44	1.06
40–44	1,763	10.66	1.19
45–49	1,633	10.17	1.18
Education			
No education	6,935	5.06	0.55
Primary	7,898	4.74	0.57
Secondary	3,819	5.96	0.58

Higher	2,212	13.61	1.25
Wealth Quintile			
Poorest	5,255	1.18	0.26
Poorer	3,604	3.39	0.48
Middle	3,207	4.12	0.62
Richer	3,153	5.59	0.63
Richest	5,645	11.93	1.08
Residence			
Urban	7,666	9.78	0.96
Rural	13,198	3.83	0.33
Region			
Tigray	1,730	4.72	0.62
Afar	1,352	4.27	0.69
Amhara	1,735	8.73	0.92
Oromia	2,100	3.91	0.79
Somali	1,404	0.30	0.16
Benishangul-Gumuz	1,031	4.72	0.87
Central Ethiopia	1,402	4.94	0.70
Sidama	1,880	3.03	0.48
Southwest Ethiopia	1,437	3.50	1.18
South Ethiopia	1,624	3.32	0.48
Gambella	1,241	5.97	0.73
Harari	1,096	8.31	0.86
Addis Ababa	1,671	16.36	1.17
Dire Dawa	1,161	10.18	1.44
Health Insurance			
No	13,405	5.46	0.46
Yes	7,459	6.40	0.51
Marital Status			
Never in union	6,197	2.15	0.29
Currently in union	12,715	7.19	0.55
Formerly in union	1,952	9.09	1.06
Media Exposure			
No exposure	11,861	3.60	0.38
Low exposure	6,240	7.81	0.61
Moderate exposure	2,336	9.37	1.38
High exposure	427	11.24	2.21

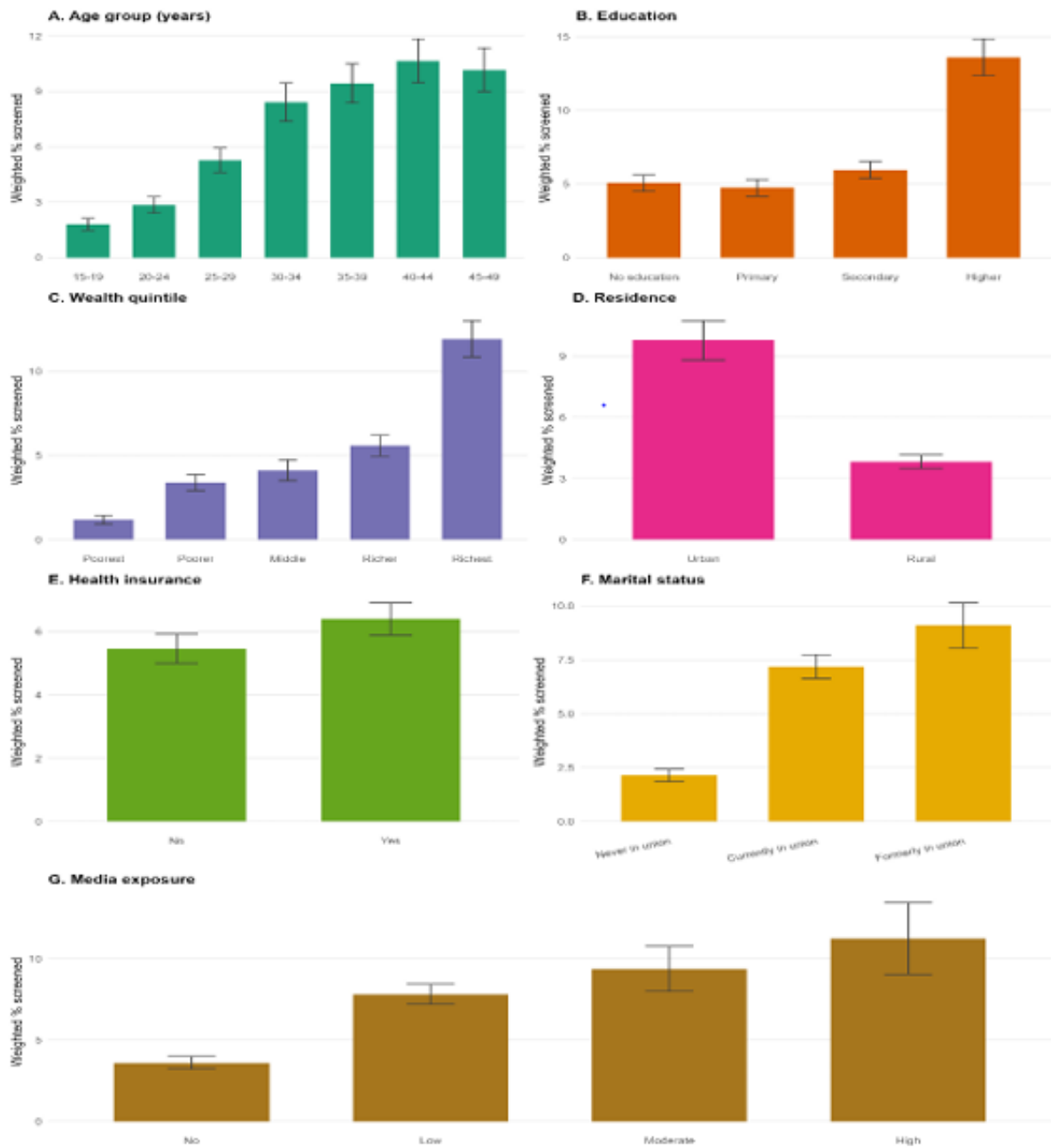


Figure. 1. Weighted Cervical Cancer Screening Prevalence by (A) Age Group, (B) Education, (C) Wealth Quintile, (D) Residence, (E) Health Insurance, and (F) Marital Status. Error Bars Represent 95% Confidence Intervals

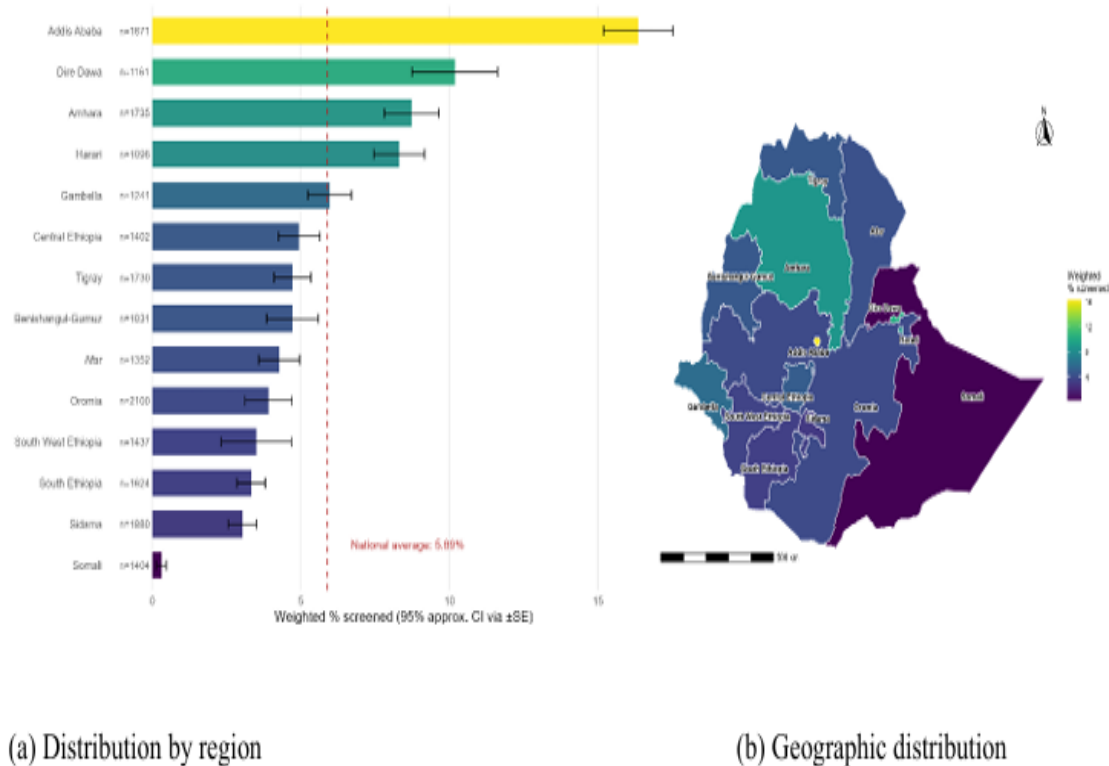


Figure 2. Regional Distribution of Cervical Cancer Screening Prevalence. (a) Regions Sorted by Weighted Percentage Screened; the Dashed Line Indicates the National Weighted Average (5.89%), with Unweighted Sample Sizes (n) shown for Each Region. (b) Choropleth Map of Weighted Prevalence Estimates for Cervical Cancer Screening, with Color Intensity reflecting the Percentage of Women Ever Screened by Region

Model Comparison and Variance Decomposition

To provide empirical support for the Bayesian spatial hierarchical modelling approach, four nested models were compared using the Watanabe–Akaike Information Criterion (WAIC; see Table 2, Panel A). The fit of the models improved considerably and consistently at each stage: incorporating the individual-level covariates into the null model lowered the WAIC by 1283.06 points; then, by adding an unstructured cluster (PSU) random effect, the WAIC was reduced by an additional 122.59 points; and finally, when the BYM2 spatial region effect was included together with the cluster effect, the WAIC decreased by another 52.38 points, thus resulting in the overall best-fitting model. Each of the three successive improvements greatly surpassed the conventional threshold of $\Delta\text{WAIC} > 10$, which is used to signify a decisive improvement in

model fit, and this offers clear empirical evidence in favour of the complete spatial hierarchical specification as compared to simpler alternatives. It is noteworthy that the effective number of parameters fell from 214.2 in the model that had only the unstructured cluster effect to 187.7 in the full model that also included the BYM2 spatial region effect, even though the latter model had a strictly greater random-effect structure. This shows that when region-level spatial dependence was explicitly modelled, the cluster-level random effect did not need to absorb as much of the geographically patterned variation and could therefore achieve a better fit with a more economical use of its parameters.

The variance decomposition presented in the final model (Table 2, Panel B) showed that 6.8% of the residual variance in screening uptake was due to unstructured variation between clusters (PSU-level intraclass

correlation coefficient, ICC = 0.068). At the same time, an additional 5.2% was attributable to differences between regions (region-level ICC = 0.052), giving a total cluster-and-region ICC of 11.3%. When the region-level variance was decomposed using the BYM2 mixing parameter, it was found that only 23.2% of the

regional variation was spatially structured, meaning that it followed a pattern among geographically adjacent regions ($\phi = 0.232$, 95% credible interval: 0.017, 0.696), the rest 76.8% being due to unstructured, region-specific heterogeneity not accounted for by geographic proximity.

Table 2. Model Comparison and Variance Decomposition for Cervical Cancer Screening Uptake, Bayesian Spatial Hierarchical Model

Panel A: Model Comparison (WAIC)

Model	WAIC	Effective Parameters	Δ WAIC (vs. Previous Model)
1. Null (intercept only)	8965.82	1.0	—
2. + Individual-level covariates	7682.76	22.1	1283.06
3. + Covariates + unstructured PSU effect	7560.17	214.2	122.59
4. + Covariates + BYM2 spatial region effect + PSU	7507.79	187.7	52.38

Panel B: Variance Decomposition (Final Model, Model 4)

Component	ICC	% of Total Variance
PSU-level (unstructured)	0.068	6.8%
Region-level (total)	0.052	5.2%
Spatially structured component	0.012	1.2%
Unstructured component	0.040	4.0%
Combined (region + PSU)	0.113	11.3%

Proportion of region-level variance spatially structured (ϕ): 0.232 (95% CrI: 0.017, 0.696)

Individual-Level Determinants of Screening Uptake

Since the Bayesian spatial hierarchical model has been determined to best fit the data, the present study examines the individual-level factors associated with uptake of cervical cancer screening. The adjusted odds ratios (ORs) for each covariate from this model are given in Table 3 and also shown in Figure 3, together with the corresponding estimates from the weighted sensitivity model for comparison. Age still showed a strong, monotonic relationship that plateaued with respect to screening uptake, even after taking into account the other covariates: the odds increased from 1.44 (95% CrI: 1.05, 1.96) for women in the age

groups 25–29 to a peak of 5.40 (95% CrI: 3.82, 7.63) for those in the age groups 40–44 when compared with women in the 15–19 age group, before then decreasing slightly to 4.27 (95% CrI: 2.99, 6.12) for women in the 45–49 age groups. Both education and household wealth exhibited clear, independent dose-response patterns: relative to women with no formal education, those with higher education had 1.79 times the odds of screening (95% CrI: 1.40, 2.29), and compared with women in the lowest wealth quintile, those in the richest quintile had 3.19 times the odds (95% CrI: 2.17, 4.69), which was the steepest monotonic adjusted gradient among all the covariates in the model.

Marital status was closely linked to the likelihood of undergoing screening: compared with women who had never been in a union, the odds for currently married women were 2.66 times greater (95% CrI: 2.11, 3.36) and those for formerly married women were 2.50 times greater (95% CrI: 1.89, 3.29). There was a consistent dose-response relationship with respect to exposure through mass media, the odds being 1.89 times higher (95% CrI: 1.33, 2.68) for women who had high exposure than for those with no exposure. Women with health insurance had odds of screening that were only slightly higher (OR = 1.41; 95% CrI: 1.23, 1.63). Women who resided in rural areas had lower odds of

screening when compared with those who lived in urban areas, although the credible interval included the null value (OR = 0.78; 95% CrI: 0.60, 1.01). For each additional child a woman had, the odds of screening were very slightly reduced (OR = 0.90 per child; 95% CrI: 0.86, 0.94). In general, the direction of the associations was the same across almost all the covariates in both the Bayesian spatial hierarchical model and the weighted sensitivity model (Table 3), with the exception that the point estimates for wealth and marital status were somewhat higher in the weighted model; this comparison is looked at in detail in Sensitivity Analyses section.

Table 3. Adjusted Odds Ratios (95% Credible Interval) for Cervical Cancer Screening Uptake: Bayesian Spatial Hierarchical Model (BYM2, Unweighted) Versus Weighted Multilevel Sensitivity Model

Characteristic	BYM2 Model, OR (95% CrI)	Sensitivity Model, OR (95% CrI)
Age group (ref: 15–19)		
20–24	1.01 (0.75, 1.38)	0.85 (0.62, 1.18)
25–29	1.44 (1.05, 1.96)	1.28 (0.94, 1.77)
30–34	2.53 (1.83, 3.49)	2.16 (1.57, 3.01)
35–39	3.94 (2.84, 5.46)	3.32 (2.38, 4.64)
40–44	5.40 (3.82, 7.63)	4.56 (3.19, 6.53)
45–49	4.27 (2.99, 6.12)	4.13 (2.86, 5.94)
Education (ref: No education)		
Primary	1.28 (1.05, 1.56)	1.11 (0.92, 1.33)
Secondary	1.62 (1.29, 2.04)	1.12 (0.89, 1.40)
Higher	1.79 (1.40, 2.29)	1.62 (1.27, 2.08)
Wealth quintile (ref: Poorest)		
Poorer	1.61 (1.16, 2.21)	2.06 (1.41, 3.06)
Middle	1.69 (1.22, 2.35)	2.41 (1.65, 3.56)
Richer	2.57 (1.86, 3.55)	2.63 (1.78, 3.90)
Richest	3.19 (2.17, 4.69)	5.03 (3.22, 8.03)
Residence (ref: Urban)		
Rural	0.78 (0.60, 1.01)	0.91 (0.66, 1.26)
Health insurance (ref: No)		
Yes	1.41 (1.23, 1.63)	1.34 (1.17, 1.55)
Marital status (ref: Never in union)		
Currently in union	2.66 (2.11, 3.36)	3.53 (2.72, 4.56)

Formerly in union	2.50 (1.89, 3.29)	2.82 (2.09, 3.78)
Media exposure (ref: No exposure)		
Low exposure	1.30 (1.08, 1.57)	1.23 (1.02, 1.48)
Moderate exposure	1.44 (1.15, 1.80)	1.50 (1.19, 1.88)
High exposure	1.89 (1.33, 2.68)	1.59 (1.06, 2.34)
Living children		
for each additional child	0.90 (0.86, 0.94)	0.89 (0.85, 0.93)

BYM2 model: Bayesian spatial hierarchical model. Sensitivity model: weighted Bayesian multilevel logistic regression (brms).

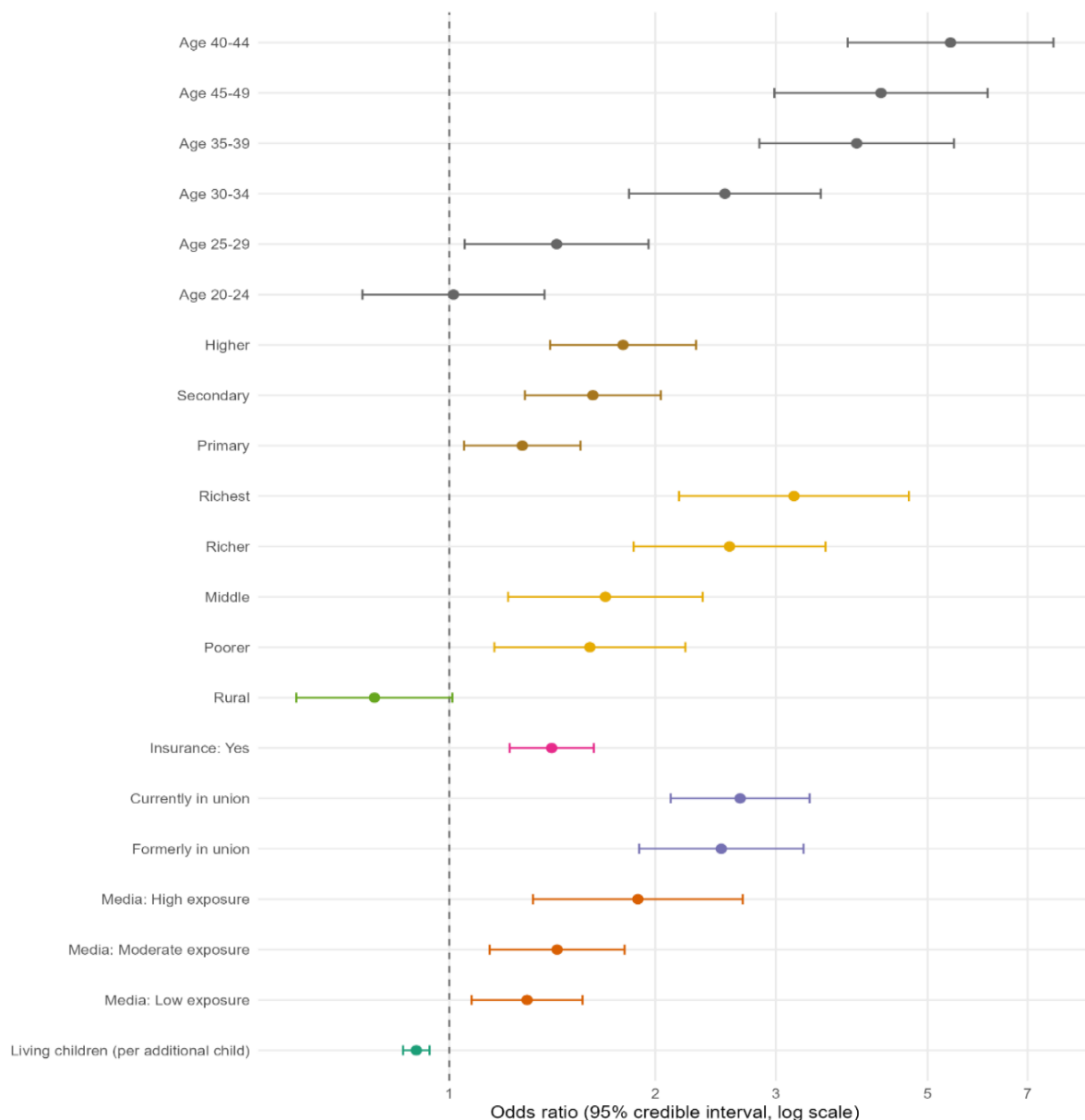


Figure 3. Adjusted Odds Ratios for Cervical Cancer Screening Uptake as Estimated by the Bayesian Spatial Hierarchical Model (BYM2); the Points Represent the Posterior Mean Odds Ratios and the Horizontal Bars Display the 95% Credible Intervals. A Dashed Vertical Line Indicates the Null Value (OR = 1); the x-axis is on a Logarithmic Scale. Different Colours Identify the Various Covariate Domains

Spatial Patterns in Screening Uptake

In addition to the individual-level associations, the Bayesian spatial hierarchical model also provides region-specific estimates that separate the geographic pattern in screening uptake from the individual-level covariates already taken into account. Figure 4a shows the posterior mean adjusted relative risk (RR) for each region, in other words, the region-specific deviation from the national trend that is left after having adjusted for age, education, wealth, residence, insurance, marital status, media exposure, and parity. The adjusted relative risk was highest in Addis Ababa (RR = 1.91) and Amhara (RR = 1.66) and lowest in Somali (RR = 0.32) and Southwest Ethiopia (RR = 0.72), showing that large regional differences in screening uptake continue to exist even after adjusting for the sociodemographic characteristics of each region's population. The posterior exceedance probability for each region is shown in Figure 4b, this being the probability that its adjusted regional effect is positive, which means that, after taking into account the individual-level covariates, the screening uptake in that region is higher than that in the other regions, with proper regard to the posterior uncertainty rather than depending solely on point estimates. Both Amhara and Addis Ababa had exceedance probabilities at or around 1.00, indicating near-certainty that their adjusted screening uptake was higher than that of the other regions. On the other hand, Somali had an exceedance probability of 0.00, indicating near-certainty that its uptake was lower. Some regions, such as Tigray (0.53) and Harari (0.51), had exceedance probabilities close to 0.5, showing a high degree of posterior uncertainty about whether their true adjusted screening patterns differ meaningfully from those of the other regions.

To better describe the geographic pattern, Figure 4c shows the model-smoothed screening prevalence estimates, which have been adjusted to match the distribution of the individual-level covariates in the sample and thus are on the same scale as the unadjusted prevalence estimates in Figure 2b. The smoothed prevalence varied from 0.89% in Somali to 5.08% in Addis Ababa, which represents a considerably narrower range than the unadjusted, raw prevalence estimates (0.30% to 16.36%; Table 1). Figure 5a illustrates this shrinkage on a regional basis by linking each region's raw prevalence to its respective smoothed estimate. The greatest degree of shrinkage was seen in Addis Ababa, where the raw prevalence of 16.36% dropped to a smoothed estimate of 5.08% after taking into account the characteristics at the individual level, showing that a large part of Addis Ababa's apparent screening advantage is because its population is wealthier, more educated, and more urban rather than being the result of a geographic effect specific to the area. On the other hand, Somali exhibited relatively little shrinkage (0.30% raw versus 0.89% smoothed), in agreement with its low screening prevalence being the result of both individual-level disadvantages and an independent regional effect. Finally, the map shown in Figure 4d separates the part of the BYM2 regional effect that is purely spatially structured before combining it with the unstructured part. Since the spatial mixing parameter mentioned in Table 2 is modest and estimated imprecisely ($\phi = 0.232$, 95% CrI: 0.017, 0.696), the pattern displayed here appears visually flatter and more attenuated than that of the combined adjusted effect in Figure 4a, which shows that while the geographic clustering of screening uptake among adjacent regions is real, it is comparatively small when compared with the region-specific, non-spatially-patterned heterogeneity.

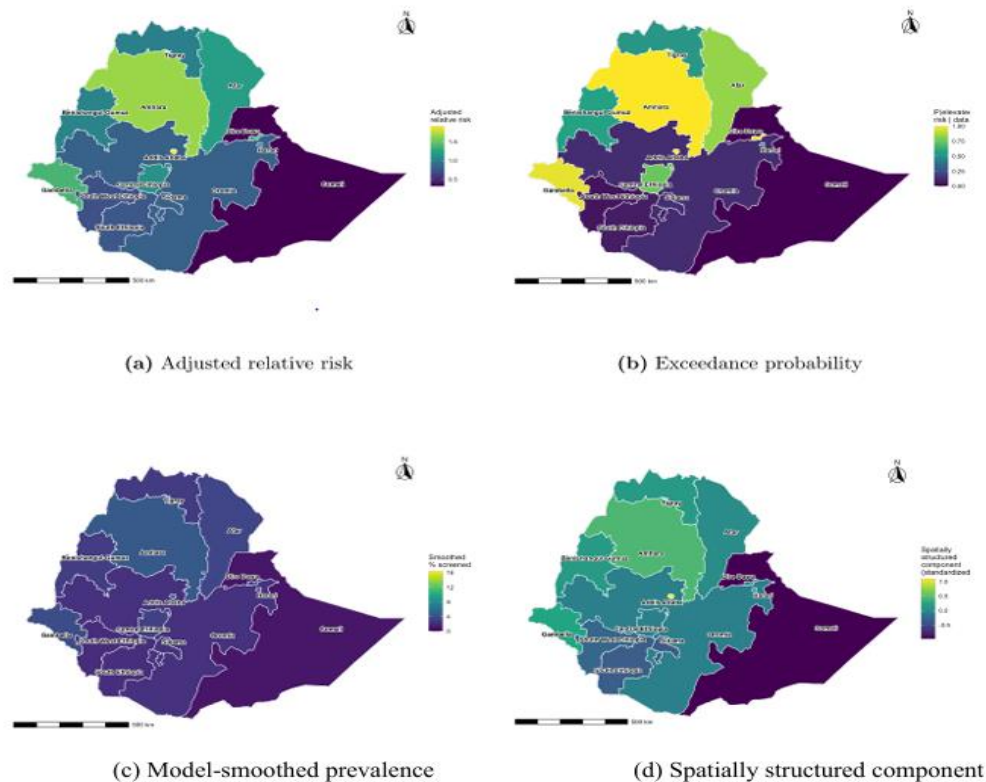


Figure 4. Spatial Patterns of Cervical Cancer Screening Uptake as Determined by the Bayesian Spatial Hierarchical (BYM2) Model. (a) The Posterior Mean of the Adjusted Relative Risk for Each Region. (b) The Posterior Probability that Each Region's Adjusted Effect is Positive, Indicating Higher-than-typical Screening Uptake Relative to Other Regions after Adjustment for Individual-Level Covariates. (c) The Model-Smoothed Screening Prevalence for Each Region, on a Scale Directly Comparable to the Raw Prevalence Map in Figure 2b. (d) The Purely Spatially Structured part of the Regional Effect, on a Standardised Scale, Isolating the Neighbourhood-based Smoothing Pattern from the Unstructured Part of the Overall Effect shown in Panel (a)

Apart from the regional spatial effect already described, the Bayesian spatial hierarchical model also contained an unstructured random intercept for the primary sampling unit (cluster), which captured the remaining cluster-by-cluster differences in screening uptake that could not be accounted for by the individual-level covariates or the regional spatial effect. As shown in Table 2, this variation at the cluster level (PSU) made up 6.8% of the total residual variance ($ICC = 0.068$), similar in size to the regional variance, but structurally different from it since no spatial smoothing was applied between clusters. The odds ratios for the fitted cluster-level effects ranged widely (median $OR = 0.97$; interquartile range: 0.88, 1.15; full range: 0.59, 3.51), which shows that

there is still meaningful heterogeneity in the rate at which screening is taken up among individual clusters even after having taken into account the individual-level characteristics and the region in which each cluster is situated. Figure 5b displays the variation at the cluster level at each cluster's geographical location, together with the region boundaries for reference. Unlike the region-level effect, no spatial smoothing was applied to the cluster-level effects and instead elevated- and reduced-odds clusters were scattered throughout the regions rather than grouping together to form distinct sub-regional clusters of their own, this being in line with the unstructured (as opposed to spatially structured) specification employed for this random effect.

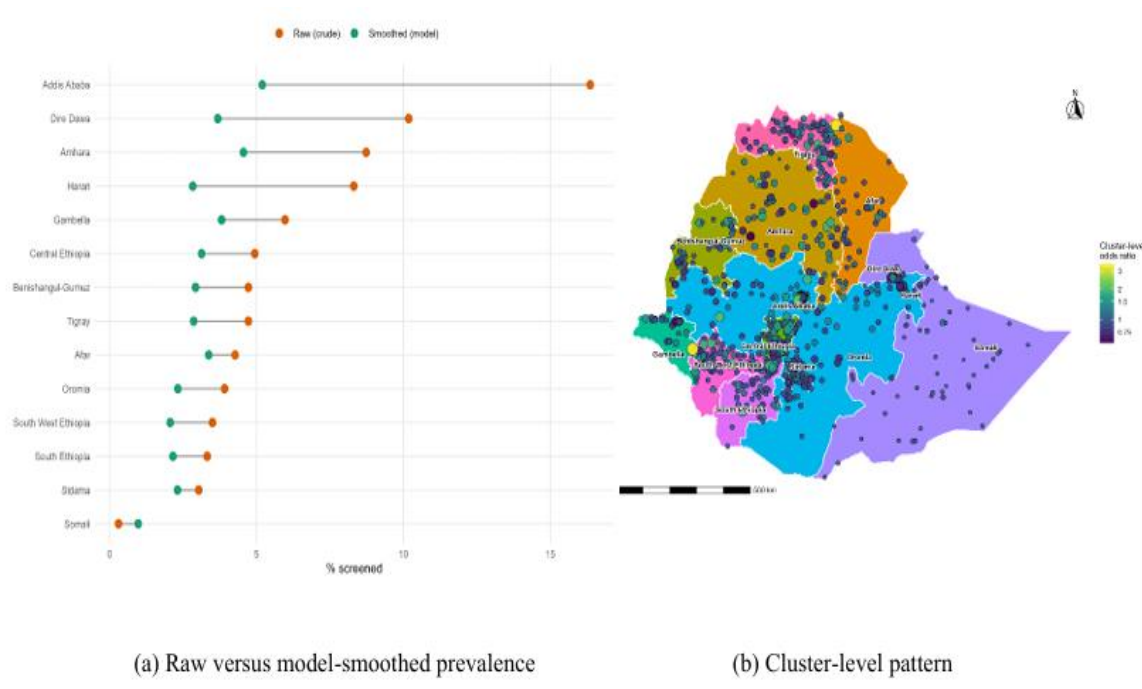


Figure 5. Regional Shrinkage in Cervical Cancer Screening Rates and Variation at the Cluster Level as Described by the Bayesian Spatial Hierarchical (BYM2) Model. (a) A Comparison of the Actual Screening Prevalence by Region with that Which has been Smoothed by the Model, Showing the Phenomenon of Partial Pooling (shrinkage). (b) Pattern at the Cluster Level, with each Cluster's Estimated Odds Ratio Without Structure (Blue Denoting Reduced Odds, Red)

Sensitivity Analyses

In order to determine whether the main conclusions of the Bayesian spatial hierarchical model were affected by the choice not to include the DHS sampling weights, we compared its estimates with those from the weighted multilevel sensitivity model as described in the Methods (see Table 3). For the 21 individual-level covariates that were common to both models, the Pearson correlation between the log-odds estimates from the two models was 0.93, and the two models agreed on the direction of the effect for 20 out of 21 covariates (95.2% agreement on the sign). The one covariate for which the models differed was the age group 20–24, since both models found an effect close to the null (BYM2 model: OR = 1.01, 95% CrI: 0.75, 1.38; sensitivity model: OR = 0.85, 95% CrI: 0.62, 1.18), the credible intervals in both cases overlapping considerably and each containing 1; this indicates consistent evidence of no meaningful effect in either model rather

than a real discrepancy in the substantive conclusions. The point estimates for wealth and marital status were slightly higher in the weighted sensitivity model than in the Bayesian spatial hierarchical model (see Table 3). Nevertheless, the overall pattern and statistical significance of the associations were the same in both specifications, which supports the robustness of the reported associations to survey weighting.

Prior Sensitivity

In order to check that the findings reported were not due to the particular prior distributions employed for the variance components in the Bayesian spatial hierarchical model, the model was refitted using a more restrictive prior ($P(\sigma > 0.3) = 0.01$), a more diffuse prior ($P(\sigma > 3) = 0.01$), as well as the default prior used in the main analysis ($P(\sigma > 1) = 0.01$). The fit of the model was similar in all three cases (WAIC: 7507.79 with the default prior, 7514.45 with the tighter prior, and 7505.99 with

the wider prior), and the estimated proportion of region-level variance that was spatially structured remained stable across the different specifications ($\phi = 0.232, 0.228$, and 0.234 , respectively). The fixed-effect odds ratios also changed only slightly depending on the prior specification; for instance, the odds ratio for the richest wealth quintile compared to the poorest was 3.19 with the default prior, 3.23 with the tighter prior, and 3.17 with the wider prior. Thus, the substantive conclusions from the Bayesian spatial hierarchical model were not a result of the particular prior distributions selected for the main analysis.

Goodness of Fit

The overall fit of the model was evaluated by means of the log pseudo marginal likelihood (LPML), which was obtained from the leave-one-out conditional predictive ordinates (CPO) calculated using INLA's built-in cross-validation method (LPML = -3753.97). During the calculation of the CPO, there were no numerical failures. There was no indication of systematic model misspecification: although a small number of observations ($n = 209$, namely those corresponding by design to the lower approximately 1% of the CPO distribution) had comparatively lower cross-validated predictive densities, these cases were spread out over various regions, age groups, and wealth categories and were not confined to any one particular subgroup.

Discussion

Based on nationally representative data from the 2024–25 Ethiopia Demographic and Health Survey, the present study looked not only at who is screened for cervical cancer but also at where and whether geography has an impact on the likelihood of screening when individual circumstances are taken into account. Three results are particularly noteworthy. First, individual characteristics such as age, education, wealth, marital status and exposure to mass media were strong predictors of

screening uptake, wealth being the one with the steepest monotonic adjusted gradient (age reached a higher peak odds ratio, but its association was non-monotonic, rising then declining slightly at the oldest ages), a finding that is in line with patterns previously observed in other parts of sub-Saharan Africa [15–17]. Second, considerable geographic variation remained even after making the adjustments, with both region and cluster together accounting for 11.3% of the residual variance; yet only a small and imprecisely estimated part of the regional component (23.2%) showed a spatial pattern among adjacent regions, the majority of it being due to unstructured, region-specific heterogeneity, a difference that earlier, geographically limited studies of Ethiopia [20, 21] were unable to identify. Third, when the raw regional estimates were compared with the model-smoothed ones, it became clear that a large part of the striking disparity seen in the unadjusted data, especially the more than 50-fold difference between Addis Ababa and Somali, is due to the different population compositions of the regions rather than to a residual place effect. Nevertheless, a smaller and real geographic disparity still remained. Taken together, these findings suggest that in order to close the geographic gap in screening in Ethiopia it will be necessary to tackle both the individual-level barriers to access [18] and the residual, place-based disparities that continue to exist even among women who are otherwise similar.

The pattern of ages seen here, rising during mid-adulthood before levelling off, more or less matches the age group that the WHO elimination strategy aims at, with the organisation specifically recommending screening at age 35 and 45 [6, 12]. The fact that the adjusted odds reached their peak between ages 40 and 44 rather than continuing to increase indicates that opportunities for coming into contact with screening services are more focused in mid-adulthood than the WHO's upper screening-age benchmark of 45 alone

would suggest. The socioeconomic gradient, which increases with both levels of education and higher wealth, agrees with the wider body of regional evidence [14-17] and with a well-established pattern that when new health interventions are scaled up, they initially benefit wealthier households disproportionately [40]. Notably, the difference between urban and rural areas decreased considerably. It approached no difference when both wealth and education were kept constant, meaning that the urban advantage found in the raw data is mostly mediated by socioeconomic characteristics rather than being due to the fact of living in an urban area, a key point since it means that reaching disadvantaged women in urban areas should be just as important as extending services to rural areas.

Marital status was one of the strongest factors identified, likely because married and previously married women tend to have had more contact with reproductive health services, including family planning, antenatal, and postnatal care, in keeping with the evidence that healthcare decision-making autonomy influences the rate of screening throughout the region [18]. Media exposure also showed a similar dose-response pattern, as it has previously been found in research conducted in sub-Saharan Africa to be related to uptake [15, 16]; since media exposure is easier to change than structural factors such as wealth, it may be one of the more actionable factors identified in this study. Having each additional child was linked to slightly reduced odds of undergoing screening, a small effect which should be interpreted with caution due to the possibility of unmeasured confounding from other demands on women's time.

The main contribution of this study is its spatial analysis. When the two findings are considered together, they tell a more complete story than either one alone: although there remains a real geographical difference in the uptake of screening after adjusting for individual characteristics, most of this

difference is unstructured rather than showing a smooth pattern across neighbouring areas. The fact that an adjusted geographical effect remains, with Addis Ababa and Amhara plausibly being higher and Somali plausibly lower, even among women who are similar in background shows that the place where a woman lives influences her chance of undergoing screening via channels that the individual-level survey data, such as the density of health facilities, the extent of programme coverage, and historical patterns of health investment cannot capture. The fact that this effect remains after adjustment for the factors most frequently cited in the regional literature [15, 16] implies that to close the geographical gap in Ethiopia it will be necessary to implement supply-side, health-system interventions that are specifically directed at the underperforming regions, not just rely on individual-level interventions.

At the same time, the fact that only a modest portion of this regional variation (23.2%) shows a spatial structure is itself significant: if access to screening were mainly determined by smoothly varying factors such as terrain or the movement of people across borders, a more pronounced spatial pattern would have been expected. The fact that the pattern observed is largely unstructured is rather more in keeping with access to screening being influenced by factors that operate within administrative regions, for example, the timing of the rollout of programmes or decisions regarding the investment in facilities, than by continuous geographic gradients, a difference which a conventional non-spatial comparison could not have shown [22-24]. The substantial decrease seen for Addis Ababa (from 16.36% raw to 5.08% smoothed) as compared with the relatively small decrease for Somali reinforces this point: it is plausibly possible to close the gap in places like Addis Ababa through targeted, individual-focused interventions. At the same time, regions such as Somali are likely to need direct investment in the health system.

More generally, these findings indicate that national-level coverage estimates alone can mask disparities of this magnitude, highlighting the importance of subnational, spatially explicit monitoring to track progress towards global elimination targets [6].

These results point to several specific priorities. Firstly, since the degree of unexplained disparity is concentrated in Somali, in south-west Ethiopia and in other poorly served areas, it makes sense to make supply-side investments that are directly aimed at the worst-performing regions rather than to adopt a single nationwide programme, since most of the regional differences are unstructured. It cannot be assumed that successful interventions will spread to adjacent regions just because of their proximity. Secondly, the distinction between compositional and contextual factors indicates two complementary approaches: in cases where the disparities are mainly compositional, efforts should be made to improve individual-level access (for example, by offering fee waivers, carrying out targeted outreach and involving community health workers), and where the disparities are not compositional, direct investment in the health system should be made. Thirdly, the strong socioeconomic gradient, together with the small urban-rural difference, both indicate that it is important to focus on affordability and awareness for women from disadvantaged backgrounds, regardless of whether they live in urban or rural areas, rather than concentrating solely on expanding services geographically [6, 12]. Fourthly, the finding relating to marital status supports integrating screening into the existing family planning, antenatal and postnatal care services, as the World Health Organization already recommends [12], while at the same time making a deliberate effort to reach women who have never been married and who do not fall within these services. Finally, the age pattern shows that outreach should be increased earlier, in a woman's thirties, rather than being

focused on women who are already approaching the World Health Organization's upper age limit of 45.

Strengths and Limitations

The main advantages of this study are its large and nationally representative sample, which is big enough to identify differences at the regional and cluster levels, something that smaller, facility-based studies carried out in Ethiopia [20, 21] were not able to describe; the use of a verified region adjacency structure that was obtained directly from the DHS Program's own shapefile and not merely approximated; the clear separation of spatial variation from unstructured geographic variation and of compositional disparities from contextual regional disparities, a distinction that a standard type of analysis is not capable of making; and the agreement between several robustness checks (WAIC model comparison, weighted sensitivity analysis, prior sensitivity analysis, and cross-validated goodness-of-fit) which supports the reliability of the study's conclusions.

It is also necessary to point out the study's limitations. Since the study is cross-sectional, it can only show associations and not make any causal inferences. The outcome was self-reported and did not specify the type of screening carried out, which does introduce some potential for recall or social desirability bias; however, the good agreement between the unweighted and weighted models is reassuring on this point. The primary model did not include the survey weights directly because, at present, there is no established method for applying design-consistent weighting in spatial random-effects models; this represents a real methodological limitation, although the weighted sensitivity analysis indicates that it did not have a substantial impact on the substantive conclusions. The DHS does not record facility-level or health-system variables, so while it is possible to interpret the unstructured regional variation as being due to

region-specific programme factors, this interpretation remains indirect and has not been directly tested. Finally, a small number of respondents (2.5%) who did not know their screening status were excluded from the analytic sample; although this exclusion was minor and did not seem systematically linked to the variables examined, it cannot be completely ruled out as a source of bias.

Conclusions

This study offers a nationally representative and spatially explicit description of cervical cancer screening uptake in Ethiopia, going beyond information about who is screened to show where access to screening is inadequate and why. Although individual factors, especially income, education, and marital status, continue to be major influences on uptake, a real and mostly unstructured geographic imbalance still remains even when these factors are taken into account, with the worst situation being found in Somali areas and other regions that have historically been poorly served. By distinguishing between the compositional and contextual origins of this imbalance, it becomes clear that narrowing the gap will require two complementary strategies rather than relying on a single national policy. In areas where the regional disparities are mainly due to population composition, such as in Addis Ababa, considerable progress can be achieved by improving individual-level access through fee waivers, by carrying out targeted outreach to women from disadvantaged socioeconomic backgrounds, and by integrating screening into current family planning, antenatal, and postnatal care services. In areas where disparities remain independent of population composition, as is the case in Somali regions, individual-level interventions on their own are not likely to be enough and will probably have to be supplemented by direct investment in regional health-system capacity, such as increasing the number of health facilities, ensuring adequate availability of

health workers, and developing community outreach infrastructure. Since mass media-based health communication is relatively cheap and can be quickly implemented, it might act as an additional complement to these structural investments, especially when it comes to reaching women who do not normally come into contact with the health system, such as those who have never married. More generally, the study shows that national screening coverage figures, no matter how accurate they are, can conceal disparities of the size documented here. As Ethiopia and other countries in the region move towards achieving the WHO's cervical cancer elimination goals [6], these results highlight the need for spatially explicit, subnational monitoring, not just for tracking overall progress but also to make sure that the particular regions and communities that are currently falling behind are not left behind as national indicators improve.

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Conflict of Interest

The authors declare no conflicts of interest.

Ethics Approval and Consent to Participate

Not applicable. This study involved a secondary analysis of de-identified, publicly available survey data from the Ethiopia Demographic and Health Survey (EDHS-8). The Ethiopian Statistical Service and ICF International obtained ethical approval for the original data collection, including clearance from the relevant national ethics review bodies in Ethiopia, before survey implementation. Because this study did not involve collecting primary data or direct contact with human participants, separate institutional review board approval was not required for this secondary analysis, consistent with the DHS Program's data use policies.

Consent for Publication

Not applicable. Informed consent was obtained from all survey respondents by the Ethiopian Statistical Service and ICF International at the time of the original data collection. The authors of this secondary analysis had no direct contact with study participants and used only de-identified data made available through the DHS Program.

Availability of Data and Materials

Data for this study were taken from the Ethiopia Demographic and Health Surveys (EDHS), which is freely available online at <https://dhsprogram.com>.

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Authors' Contributions

Conceptualization, D.B.B. and E.E.; methodology, D.B.B. with input from E.E.; software, D.B.B.; formal analysis, D.B.B.; investigation, D.B.B.; data curation, D.B.B.; writing — original draft preparation, D.B.B.; writing — review and editing, E.E.; supervision, E.E.

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