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BAYESIAN MULTILEVEL LOGISTIC REGRESSION OF CHILDHOOD IMMUNIZATION STATUS AMONG CHILDREN AGED 12–23 MONTHS IN BAUCHI STATE, NIGERIA

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ABSTRACT

Background: Childhood immunisation is a key public health intervention for preventing vaccine-preventable diseases. However, immunisation outcomes may vary across children, households and communities. This study examined factors associated with childhood immunisation status among children aged 12–23 months in Bauchi State, Nigeria, using a Bayesian multilevel modelling approach.

Methods: The study analysed secondary data from the 2024 Nigeria Demographic and Health Survey (NDHS), comprising 208 children from 196 households across 41 communities (Enumeration Areas). Full immunisation was defined as receipt of eight specified vaccine doses: Bacille Calmette–Guérin (BCG), three doses of diphtheria–pertussis–tetanus-containing vaccine, three doses of polio vaccine (excluding the birth dose), and the first dose of measles-containing vaccine. Seven Bayesian multilevel logistic regression models were fitted using Markov Chain Monte Carlo methods to account for the three-level hierarchical data structure. The modelling framework incorporated random intercepts, a random slope for maternal education and cross-level interactions involving selected community characteristics. Model convergence and adequacy were assessed using convergence diagnostics, posterior predictive checks, the Widely Applicable Information Criterion (WAIC) and Pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO).

Results: Of the 208 children analysed, 99 (47.6%) were fully immunised, while 109 (52.4%) were not fully immunised. Latent-scale variance partitioning in the null model attributed 31.4% of the variation to communities and 24.9% to households. In the final inferential

model (Model 7), maternal age was the only fixed-effect predictor with posterior evidence of an association with full immunisation (OR = 1.224; 95% credible interval: 1.027–1.605). The estimated random-slope standard deviation for maternal education was 1.523 (95% credible interval: 0.043–4.860), indicating variation in its association with immunisation across communities, although the estimate was imprecise. The examined cross-level interaction between maternal education and community-level antenatal care utilisation was not supported by posterior evidence. Although Model 2 recorded the lowest WAIC, its difference from Model 7 was small, while elevated Pareto-k values warranted caution in interpreting comparative predictive performance.

Conclusion: Childhood immunisation status in Bauchi State exhibited substantial household- and community-level variation. Maternal age was the only fixed-effect predictor with posterior evidence of an association in the final inferential model, while the association between maternal education and immunisation varied across communities. These findings highlight the importance of accounting for hierarchical data structures and contextual variation when investigating childhood immunisation outcomes.

KEYWORDS: Childhood immunisation; Bayesian multilevel logistic regression; random slopes; cross-level interactions; household clustering; community variation; Bauchi State; Nigeria.

1. INTRODUCTION

Childhood immunisation is one of the most effective public health interventions for preventing vaccine-preventable diseases and reducing childhood morbidity and mortality. Despite sustained global and national efforts, many children, particularly in low- and middle-income countries, remain incompletely vaccinated or receive no routine vaccines. In sub-Saharan Africa, immunisation coverage varies considerably across countries and population groups, reflecting differences in socioeconomic conditions, healthcare access, and other contextual factors (Fenta et al., 2021; Tamir et al., 2026). A pooled analysis of Demographic and Health Surveys from 14 West African countries also reported persistent inequalities in childhood immunisation coverage (Azumah & Saani, 2026).

Nigeria continues to face substantial challenges in achieving equitable childhood immunisation. The 2024 Nigeria Demographic and Health Survey (NDHS) reported that only 39% of children aged 12–23 months had received all basic antigens, with notable differences across maternal education, household socioeconomic status, and place of residence (Federal

Ministry of Health and Social Welfare of Nigeria et al., 2025). Previous analyses of Nigerian survey data have similarly identified socioeconomic, geographic, maternal, child, and healthcare-related inequalities in childhood vaccination (Aheto et al., 2022; Williams et al., 2024). A community-based study in Ebonyi State also reported low coverage of timely and age-appropriate childhood immunisation, highlighting the importance of considering not only vaccine receipt but also the timing of vaccination (Omale et al., 2025). More recent evidence indicates geographical variation in immunisation outcomes across Nigerian settings, including differences between urban and rural health facilities in Kano and Lagos States (Kaduru et al., 2025; Sato et al., 2026). These findings suggest that national coverage estimates alone may not adequately explain variations in immunisation outcomes across communities.

Bauchi State provides an important setting for examining these variations. Although the NDHS provides state-level estimates, such figures do not fully explain how immunisation outcomes differ between households and communities or how individual and household characteristics relate to vaccination status within different community contexts. A facility-based study in Azare, Bauchi State, identified parental knowledge, attitudes, and sociocultural factors as relevant to childhood immunisation uptake (Abah et al., 2026). However, findings from a facility-based sample may not represent the wider population of households and communities in the state. In addition, recent immunisation initiatives in other Nigerian settings have emphasised the need to identify and reach zero-dose children in underserved communities through localised enumeration, geospatial planning and community mobilisation (Jimoh et al., 2026). Population-based analysis is therefore needed to investigate childhood immunisation while accounting for differences across children, households, and communities.

Childhood immunisation may be influenced by factors operating at multiple levels. Child characteristics, such as age, sex, and birth order, may be associated with vaccination status, while household characteristics, including maternal age, education, employment, and wealth, may influence caregivers' access to and utilisation of immunisation services. Community conditions may also shape healthcare access, health information, and the availability or utilisation of maternal and child health services. Previous studies in Nigeria and other sub-Saharan African countries have reported associations between childhood vaccination and socioeconomic, maternal, and healthcare-related factors (Aheto et al., 2022; Fenta et al., 2021; Alabi et al., 2024; Williams et al., 2024). Bayesian and multilevel studies have further demonstrated the importance of geographical and contextual variation in vaccination

outcomes (Ahmed et al., 2024; Lawal et al., 2023; Endalamew et al., 2025; Kaduru et al., 2025).

An important methodological consideration in analysing NDHS data is its hierarchical structure. Children are nested within households, and households are nested within communities, meaning that observations within the same cluster may be more similar than observations from different clusters. Conventional logistic regression assumes independence of observations and may not adequately account for this clustering. Multilevel logistic regression addresses this limitation by incorporating random effects to account for variation across higher-level units (Aheto et al., 2022). Bayesian hierarchical modelling provides an additional framework for estimating complex multilevel relationships and quantifying uncertainty in model parameters (Endalamew et al., 2025; Utazi et al., 2026).

However, models based only on random intercepts assume that the effects of explanatory variables remain constant across communities. This assumption may overlook contextual differences in how household characteristics relate to childhood immunisation. A random-slope model allows selected household-level effects to vary across communities, while cross-level interactions make it possible to examine whether community characteristics modify these relationships. Although previous studies have applied multilevel and Bayesian approaches to childhood vaccination in Nigeria (Aheto et al., 2022; Ahmed et al., 2024; Lawal et al., 2023), further investigation using a three-level Bayesian random-slope framework with cross-level interactions is warranted in Bauchi State.

This study therefore examined childhood immunisation status among children aged 12–23 months in Bauchi State, Nigeria, using data from the 2024 NDHS. Specifically, it investigated child-, household-, and community-level factors associated with immunisation status; applied a Bayesian three-level random-slope multilevel logistic regression model to assess variation in the effect of maternal education across communities and examine selected cross-level interactions; and evaluated the performance of the fitted models. The study seeks to provide a better understanding of childhood immunisation patterns in Bauchi State while accounting for the hierarchical structure of the data and potential contextual variation in predictor effects.

2. METHODS

2.1 Study design

This study employed a quantitative cross-sectional analytical design using secondary data from the 2024 Nigeria Demographic and Health Survey (NDHS). The study examined factors

associated with childhood immunisation status among children aged 12–23 months in Bauchi State, Nigeria. A multilevel analytical approach was adopted to account for the hierarchical structure of the data, in which children were nested within households and households were nested within communities (Enumeration Areas). A Bayesian multilevel logistic regression framework was subsequently used to examine individual-, household-, and community-level factors associated with childhood immunisation status.

2.2 Data source and study population

The study used secondary data from the 2024 Nigeria Demographic and Health Survey (NDHS), which employed a stratified two-stage cluster sampling design involving the selection of Enumeration Areas (EAs), followed by systematic household selection. The study population comprised children aged 12–23 months in Bauchi State, Nigeria. Initially, 209 eligible records were identified. During data preparation in R, one record was reported as missing and excluded from the analysis, resulting in a final analytical sample of 208 children from 196 households across 41 EAs. The data had a three-level hierarchical structure, with children nested within households and households nested within EAs (National Population Commission [NPC] and ICF, 2025).

2.3 Study variables and measurement

The dependent variable was childhood immunisation status, coded as a binary outcome: fully immunised (1) or not fully immunised (0). It was constructed from eight vaccination indicators in the NDHS dataset: Bacille Calmette–Guérin (BCG; h2), first dose of diphtheria–pertussis–tetanus-containing vaccine (DPT/Pentavalent 1; h3), first dose of polio vaccine (h4), second dose of DPT/Pentavalent (h5), second dose of polio vaccine (h6), third dose of DPT/Pentavalent (h7), third dose of polio vaccine (h8), and first dose of measles-containing vaccine (h9). Responses coded 1, 2 or 3 were classified as evidence of vaccine receipt, while code 0 indicated non-receipt. Code 8 (don't know) and other missing responses were treated as unknown. A child was classified as fully immunised if all eight specified doses had been received, and as not fully immunised if at least one dose was confirmed as not received. Records with an unknown vaccination response that prevented a definitive classification were treated as missing and excluded from the analytical sample.

The explanatory variables were grouped according to the study's three-level structure. Child-level variables included age in months, sex, birth order (first, second–third, fourth–fifth, and sixth or higher), and place of delivery (health facility or home). Household-level variables comprised maternal age in years, maternal education (no formal education or primary education and above), household wealth quintile (poorest, poorer, middle, richer, and richest),

and maternal employment status (employed or not employed). Community-level variables included place of residence (urban or rural), community poverty, community literacy, and community antenatal care (ANC) utilisation.

2.4 Statistical Model Specification

2.4.1 Bernoulli Likelihood

Since the response variable, childhood immunization status, is binary (fully immunized or not fully immunized), it is assumed to follow a Bernoulli distribution. Let Y_{ijk} denote the immunization status of the ith child in the jth household and the kth community, where

Y_{ijk} = 1, if the child is fully immunized

Y_{ijk} = 0, if the child is not fully immunized

Thus,

$$Y_{ijk} \sim Bernoulli(p_{ijk})$$

Where

p_{ijk} is the probability that the ith child in the jth household and the kth community is fully immunized. This likelihood specification is appropriate for modelling binary outcomes within a Bayesian framework (Gelman et al., 2013).

The probability mass function of the Bernoulli distribution is

$$P(Y_{ijk} = y_{ijk}|p_{ijk}) = p_{ijk}^{y_{ijk}}(1 - p_{ijk})^{1-y_{ijk}} \quad (1)$$

where

$0 \leq p_{ijk} \leq 1$;

$y_{ijk} \in \{0,1\}$.

Assuming conditional independence of observations given the model parameters, the likelihood function for all observations is

$$L(\theta|Y) = \prod_{k=1}^{K} \prod_{j=1}^{J_k} \prod_{i=1}^{n_{jk}} p_{ijk}^{y_{ijk}} (1 - p_{ijk})^{1-y_{ijk}} \quad (2)$$

where

K is the total number of communities; J_k is the number of households in community k; n_{jk} is the number of children aged 12–23 months in household j of community k; and θ denotes the vector of unknown model parameters.

2.4.2 Level 1 Model (Child-Level Model)

At Level 1, the model relates the probability of complete childhood immunization to child-level characteristics using the logistic link function.

The logit transformation is expressed as

$$\log\left(\frac{p_{ijk}}{1-p_{ijk}}\right) = \eta_{ijk} \quad (3)$$

where ηijk is the linear predictor.

The child-level model is specified as

$$\eta_{ijk} = \beta_{0jk} + \beta_1 X_{1ijk} + \beta_2 X_{2ijk} + \beta_3 X_{3ijk} + \beta_4 X_{4ijk} \quad (4)$$

where

X_{1ijk} is Child's age; X_{2ijk} is Child's sex; X_{3ijk} is Birth order; X_{4ijk} is Place of delivery.

The intercept β_{0jk} is allowed to vary across households and communities.

The predicted probability of complete immunization is therefore

$$p_{ijk} = \frac{e^{\eta_{ijk}}}{1+e^{\eta_{ijk}}} \quad (5)$$

2.4.3 Level 2 Model (Household-Level Model)

At Level 2, the household-specific intercept is modelled as a function of household characteristics.

The household-level model is

$$\beta_{0jk} = \gamma_{00k} + \gamma_{01} Z_{1jk} + \gamma_{02} Z_{2jk} + \gamma_{03} Z_{3jk} + \gamma_{04} Z_{4jk} + u_{0jk} \quad (6)$$

where

Z_{1jk} is Mother's educational level; Z_{2jk} is Mother's age; Z_{3jk} is Household wealth index; Z_{4jk} is Mother's employment status; and $u_{0jk} \sim N(0, \sigma_u^2)$

The random effect u_{0jk} captures unobserved household characteristics that influence childhood immunization after accounting for the measured household covariates. The inclusion of random effects allows the model to account for dependence among observations within the same higher-level units and to estimate variation in outcomes across clusters (Gelman & Hill, 2007).

2.4.4 Level 3 Model (Community-Level Model)

The household intercepts are further modelled as functions of community-level characteristics.

The Level 3 model is

$$\gamma_{00k} = \delta_{000} + \delta_{001} C_{1k} + \delta_{002} C_{2k} + \delta_{003} C_{3k} + \delta_{004} C_{4k} + v_{0k} \quad (7)$$

where

C_{1k} is Place of residence (Urban/Rural); C_{2k} is Community poverty level; C_{3k} is Community literacy level; and C_{4k} is Community antenatal care utilization.

The community-level random effect satisfies

$v_{0k} \sim N(0, \sigma_v^2)$

This random effect accounts for unexplained contextual differences between communities that may influence childhood immunization status.

The three-level specification enables simultaneous estimation of child-, household-, and community-level effects while accounting for the hierarchical structure of the NDHS data.

2.4.5 Random-Slope Specification

To account for possible variation in the effect of maternal educational level across communities, the coefficient associated with mother's educational level is allowed to vary randomly. The random-slope model is specified as

$$\gamma_{01k} = \delta_{010} + v_{1k} \quad (8)$$

where

γ_{01k} is the community-specific effect of mother's educational level; δ_{010} is the overall average effect of mother's educational level across all communities; v_{1k} is the community-specific random slope. Allowing regression coefficients to vary across higher-level units provides a flexible approach to modelling contextual heterogeneity in the relationships between explanatory variables and outcomes (Gelman & Hill, 2007).

It is assumed that $v_{1k} \sim N(0, \sigma_{v1}^2)$

2.4.6 Cross-Level Interaction Model

To investigate whether community characteristics modify the relationship between maternal education and childhood immunization status, cross-level interaction effects between maternal education and selected community-level characteristics are examined. Specifically, alternative theoretically motivated interactions between maternal education and community poverty, community literacy, and community antenatal care utilization are evaluated during model development.

The cross-level interaction terms are specified generally as

$$\gamma_{01k} = \delta_{010} + \delta_{011} C_{3k} + v_{1k} \quad (9)$$

Substituting this expression into the Level 1 model gives

$$\eta_{ijk} = \beta_{0jk} + (\delta_{010} + \delta_{011}C_{3k} + v_{1k})Z_{1jk} + \beta_2 X_{2ijk} + \beta_3 X_{3ijk} + \beta_4 X_{4ijk} \quad (10)$$

where

C_{3k} is Selected community-level characteristic (community poverty, community literacy, or community ANC utilization); Z_{1jk} is Mother's educational level.

The interaction coefficient δ_{011} measures whether the effect of maternal education on childhood immunization varies according to the selected community-level characteristic.

2.4.7 Prior Distributions

Fixed Effects

The regression coefficients are assigned weakly informative Normal priors:

$\beta_r \sim N(0, 1.5), \quad r = 1, 2, 3, 4$

$\gamma_{0s} \sim N(0, 1.5), \quad s = 1, 2, 3, 4$

$\delta_{0t} \sim N(0, 1.5), \quad t = 1, 2, 3, 4$

These priors reflect minimal prior knowledge while allowing the observed data to dominate the posterior inference. The use of weakly informative priors provides regularisation while allowing the observed data to contribute substantially to posterior estimation (Gelman et al., 2013).

Random Effects

The household-level and community-level random effects are assumed to follow Normal distributions:

$u_{0jk} \sim N(0, \sigma_u^2)$

$v_{0k} \sim N(0, \sigma_v^2)$

$v_{1k} \sim N(0, \sigma_{v1}^2)$

Variance Components

The variance parameters are assigned weakly informative Student-t priors:

$\sigma_u \sim \text{Student} - \text{t}(3, 0, 1.5)$

$\sigma_v \sim \text{Student} - \text{t}(3, 0, 1.5)$

$\sigma_{v1} \sim \text{Student} - \text{t}(3, 0, 1.5)$

These priors constrain the variance parameters to be positive while providing adequate flexibility for estimation.

Correlation Structure

For models incorporating correlated community-level random intercepts and random slopes, the correlation matrix was assigned an LKJ prior with shape parameter 2, denoted as LKJ(2).

This prior was used to model the correlation between the community-level random intercept and the random slope for maternal education (Gelman et al., 2013).

2.4.8 Joint Posterior Distribution

Bayesian inference combines the likelihood function with the prior distributions through Bayes' theorem to obtain the joint posterior distribution of the model parameters (Gelman et al., 2013).

The posterior distribution is given by

$$P(\theta|Y) \propto L(Y|\theta)P(\theta)$$

where

$P(\theta|Y)$ *is the joint posterior distribution;*

$L(Y|\theta)$ *is the Bernoulli likelihood function;* and

$P(\theta)$ *denotes the joint prior distribution of all unknown parameters.*

Expanding the posterior distribution gives

$$P(\theta|Y) \propto L(Y|\theta) \times P(\beta) \times P(\gamma) \times P(\delta) \times P(u_0) \times P(v_0) \times P(v_1) \times P(\sigma_u) \times P(\sigma_v) \times P(\sigma_{v1})$$

Where

θ represents the complete vector of fixed effects, random effects, and variance parameters.

2.5 Estimation and Model Assessment

The Bayesian multilevel logistic regression models were fitted in R using the *brms* package with the *cmdstanr* backend. Four Markov Chain Monte Carlo (MCMC) chains were run for each model, with 4,000 iterations per chain, including 2,000 warm-up iterations. A random seed of 1234 was specified to support reproducibility, and the sampler control parameter was set to $\delta_{adapt} = 0.99$.

The fitted models did not incorporate the NDHS sampling weights or explicitly adjust for the survey stratification variables. Although household- and community-level random effects were included to account for the hierarchical structure of the data, these effects do not fully account for the complex survey sampling design.

Weakly informative priors were assigned to the model parameters. Normal distributions with mean 0 and standard deviation 1.5 were specified for the fixed-effect coefficients and intercept. Random-effect standard deviations were assigned Student-t priors with 3 degrees of freedom, location 0 and scale 1.5. For models with correlated community-level random

intercepts and slopes, an LKJ prior with shape parameter 2 was used for the correlation structure.

Posterior estimates were summarised using means, standard deviations and 95% credible intervals. Regression coefficients were exponentiated to obtain posterior odds ratios for interpretation. Model convergence was assessed through visual inspection of MCMC trace plots, the Gelman–Rubin diagnostic (R-hat) and bulk effective sample sizes. R-hat values close to 1 were taken as evidence of satisfactory convergence (Gelman et al., 2013).

Model fit and predictive performance were assessed using the Widely Applicable Information Criterion (WAIC) and Pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO). Lower WAIC values indicated better estimated predictive performance among models fitted to the same data. PSIS-LOO diagnostics were examined using Pareto k values, with values greater than 0.7 treated as indications of potentially influential observations requiring caution in interpreting the estimates. Posterior predictive checks were also conducted by comparing observed outcomes with replicated outcomes generated from the posterior predictive distribution. These diagnostics and model assessment criteria were considered collectively when evaluating the adequacy of the fitted models.

2.6 Ethical considerations

The present study involved secondary analysis of data from the 2024 Nigeria Demographic and Health Survey (NDHS). Permission to access and use the dataset was obtained through the NDHS data-access process. The analysis was conducted using the existing survey data, without direct contact with participants.

3. Result

3.1 Characteristics of study participants

A total of 208 children aged 12–23 months were included in the analysis. The mean age of the children was 16.856 months (SD = 3.582), while the mean maternal age was 28.053 years (SD = 6.955). The mean community poverty, literacy, and antenatal care (ANC) measures were 0.757, 0.238, and 0.433, respectively. Most children were male (51.9%). The majority of mothers had no formal education (78.8%), were not employed (77.4%), and delivered at home (69.2%). Most participants resided in rural areas (88.0%), while 47.1% belonged to the poorest household wealth quintile. The characteristics of the study participants are presented in Table 1.

Table 1. Sociodemographic, household, and community characteristics of study participants. (N = 208)

Characteristic	Mean	SD	Frequency, n (%)
Child age (months)	16.856	3.582	—
Maternal age (years)	28.053	6.955	—
Community poverty	0.757	0.337	—
Community literacy	0.238	0.287	—
Community ANC	0.433	0.287	—
Child sex	—	—	
Male	—	—	108 (51.9)
Female	—	—	100 (48.1)
Birth order	—	—	
First birth	—	—	41 (19.7)
Second–third	—	—	60 (28.8)
Fourth–fifth	—	—	57 (27.4)
Sixth or higher	—	—	50 (24.0)
Maternal education	—	—	
No formal education	—	—	164 (78.8)
Primary education or higher	—	—	44 (21.2)
Place of delivery	—	—	
Health facility	—	—	64 (30.8)
Home	—	—	144 (69.2)
Place of residence	—	—	
Urban	—	—	25 (12.0)
Rural	—	—	183 (88.0)
Household wealth index	—	—	
Poorest	—	—	98 (47.1)
Poorer	—	—	59 (28.4)
Middle	—	—	29 (13.9)
Richer	—	—	16 (7.7)
Richest	—	—	6 (2.9)
Maternal employment	—	—	
Not employed	—	—	161 (77.4)
Employed	—	—	47 (22.6)

Note: SD = standard deviation; ANC = antenatal care. Dashes indicate that the statistic is not applicable.

3.2 Distribution of childhood immunization status

Of the 208 children included in the analysis, 99 (47.6%) were fully immunized, while 109 (52.4%) were not fully immunized. Thus, slightly more than half of the children had not received the complete set of recommended vaccinations. The distribution of childhood immunization status is presented in Table 2.

Table 2. Distribution of childhood immunization status among children aged 12–23 months. (N = 208)

Immunization status	Frequency, n	Percentage (%)
Fully immunized	99	47.6
Not fully immunized	109	52.4
Total	**208**	**100.0**

Note: Immunization status was classified as fully immunized or not fully immunized according to the study's operational definition.

3.3 Bivariate associations between explanatory variables and childhood immunization status

The bivariate analysis examined the unadjusted relationships between the explanatory variables and childhood immunisation status among children aged 12–23 months. Among the categorical variables, statistically significant associations were observed for maternal education ($\chi^2 = 4.970$, $p = 0.026$) and maternal employment ($\chi^2 = 4.141$, $p = 0.042$). However, no statistically significant associations were observed for child sex, birth order, place of delivery, place of residence or household wealth quintile.

For the continuous variables, maternal age was significantly higher among mothers of fully immunised children than among mothers of children who were not fully immunised (29.28 ± 7.11 years compared with 26.94 ± 6.65 years; $p = 0.016$). In contrast, child age was not significantly associated with immunisation status ($p = 0.637$). At the community level, Spearman's rank correlation analysis, based on 41 communities, showed a negative correlation between community poverty and immunisation prevalence ($\rho = -0.315$, $p = 0.045$), whereas community literacy showed a positive correlation ($\rho = 0.341$, $p = 0.029$). Community antenatal care (ANC) utilisation also showed a positive correlation, but this was not statistically significant ($\rho = 0.286$, $p = 0.069$). The results of the bivariate analysis are presented in Table 3.

Table 3. Bivariate associations between explanatory variables and childhood immunization status.

Explanatory variable	Test statistic / Result	df	p-value
Categorical variables			
Child sex	$\chi^2 = 0.093$	1	0.761
Birth order	$\chi^2 = 5.304$	3	0.151
Maternal education	$\chi^2 = 4.970$	1	**0.026**
Place of delivery	$\chi^2 = 2.297$	1	0.130
Place of residence	$\chi^2 \approx 0.000$	1	1.000

Household wealth quintile	Fisher's exact test	—	0.121
Maternal employment	$\chi^2 = 4.141$	1	**0.042**
Continuous variables			
Maternal age (years)	Not fully immunized: 26.94 ± 6.65; Fully immunized: 29.28 ± 7.11	—	**0.016**
Child age (months)	Not fully immunized: 17.02 ± 3.80; Fully immunized: 16.68 ± 3.34	—	0.637
Community-level variables	Spearman's ρ		
Community poverty	−0.315	—	**0.045**
Community literacy	0.341	—	**0.029**
Community antenatal care utilisation	0.286	—	0.069

Note: Values are unadjusted. Maternal age is presented as mean ± standard deviation for fully immunised and not fully immunised children, respectively. Community-level Spearman correlations were calculated using 41 community observations. This indicates statistical significance at the 5% level. ANC = antenatal care. Dashes indicate that the corresponding test statistic is not reproduced here.

3.4 Multilevel variation and variance partitioning

A three-level null model was fitted to examine the extent of variation in childhood immunization status attributable to household- and community-level clustering before the inclusion of explanatory variables. The model revealed substantial variation at both levels. The community-level random effect had an estimated standard deviation of 1.71 (95% credible interval [CrI]: 0.82–3.50), while the household-level random effect had an estimated standard deviation of 1.54 (95% CrI: 0.07–4.61).

The variance partition coefficients (VPCs) indicated that 31.4% of the total latent-scale variation in childhood immunization status was attributable to differences between communities, while 24.9% was attributable to differences between households. Together, these two levels accounted for 56.3% of the total variation. These findings indicate substantial clustering of childhood immunization status within households and communities, supporting the use of a multilevel modelling approach. The null model also showed satisfactory convergence, with R-hat values of 1.00 and 1.01 for the community- and household-level random effects, respectively. The results are presented in Table 4.

Table 4. Variance components and variance partitioning from the three-level null model.

Component	Estimate	95% credible interval	R-hat
Random-effect standard deviations			
Community level	1.71	0.82–3.50	1.00
Household level	1.54	0.07–4.61	1.01
Variance partition coefficients (VPC)			
Community	0.314 (31.4%)	0.128–0.521	—
Household	0.249 (24.9%)	0.001–0.651	—
Combined household and community	0.563 (56.3%)	0.219–0.907	—

Note: CrI = credible interval; VPC = variance partition coefficient. VPCs represent the proportions of total latent-scale variation attributable to the respective levels. R-hat values are reported for the random-effect standard deviations.

3.5 Bayesian multilevel logistic regression results

The final inferential model (Model 7) incorporated child-, household-, and community-level explanatory variables, a community-level random slope for maternal education, and a cross-level interaction between maternal education and community antenatal care (ANC) utilisation. Among the fixed-effect predictors, maternal age was the only variable with posterior evidence of an association with childhood immunization status. Each additional year of maternal age was associated with approximately 22.4% higher posterior odds of full immunization (OR = 1.224; 95% CrI: 1.027–1.605).

The other fixed-effect predictors did not show posterior evidence of an association, as their 95% credible intervals for the odds ratios included 1. The maternal education × community ANC interaction was also not supported (OR = 1.470; 95% CrI: 0.113–20.815), suggesting insufficient posterior evidence that community ANC utilisation modified the association between maternal education and childhood immunization.

The random-effects estimates indicated substantial variation across communities and households. In particular, the maternal education random-slope standard deviation was 1.523 (95% CrI: 0.043–4.860), suggesting that the association between maternal education and childhood immunization varied across communities. The community- and household-level random-intercept standard deviations were 2.451 and 4.109, respectively. The posterior estimates from Model 7 are presented in Table 5.

Table 5. Posterior parameter estimates and odds ratios from the final inferential model. (Model 7)

Parameter	Estimate (β)	95% CrI for β	Posterior OR	95% CrI for OR	Posterior evidence
Intercept	−7.00	−14.47 to −1.10	0.001	0.000001–0.332	Supported
Child age	−0.10	−0.40 to 0.15	0.901	0.668–1.166	Not supported
Female (vs male)	−0.16	−1.63 to 1.43	0.852	0.196–4.161	Not supported
Second–third birth order (vs first)	1.42	−0.41 to 3.29	4.129	0.662–26.844	Not supported
Fourth–fifth birth order (vs first)	0.46	−1.43 to 2.27	1.583	0.238–9.635	Not supported
Sixth or higher birth order (vs first)	−0.35	−2.56 to 1.84	0.706	0.077–6.266	Not supported
Home delivery (vs health facility)	−1.00	−2.84 to 0.63	0.368	0.059–1.883	Not supported
Primary education or higher (vs no formal education)	0.85	−1.33 to 2.97	2.341	0.266–19.487	Not supported
Maternal age	0.20	0.03–0.47	1.224	1.027–1.605	Supported
Poorer wealth (vs poorest)	−1.04	−2.84 to 0.68	0.352	0.059–1.972	Not supported
Middle wealth (vs poorest)	0.25	−1.78 to 2.47	1.278	0.169–11.861	Not supported
Richer wealth (vs poorest)	0.35	−2.00 to 2.70	1.419	0.136–14.906	Not supported
Richest wealth (vs poorest)	−0.07	−2.66 to 2.56	0.928	0.070–12.872	Not supported
Employed (vs not employed)	0.40	−1.45 to 2.22	1.498	0.235–9.248	Not supported
Rural residence (vs urban)	1.08	−1.45 to 3.57	2.939	0.235–35.598	Not supported
Community poverty	−0.35	−2.80 to 2.09	0.701	0.061–8.111	Not supported
Community literacy	0.01	−2.44 to 2.56	1.015	0.087–12.945	Not supported
Community ANC utilisation	1.57	−1.00 to 4.08	4.820	0.367–58.963	Not supported
Maternal education × community ANC	0.39	−2.18 to 3.04	1.470	0.113–20.815	Not supported

Random-effect parameters

Parameter	Estimate	95% CrI
Community-level random-intercept SD	2.451	0.57–5.28
Maternal education random-slope SD	1.523	0.04–4.86
Household-level random-intercept SD	4.109	1.11–9.18
Community intercept–slope correlation	0.072	−0.75 to 0.82

Note: β = posterior regression coefficient; OR = posterior odds ratio; CrI = credible interval; SD = standard deviation; ANC = antenatal care. Posterior evidence was considered supported when the 95% credible interval for the odds ratio excluded 1. Reference categories are shown in parentheses. The intercept–slope correlation is reported on the correlation scale and therefore has no odds ratio.

3.6 Model comparison and predictive performance

The seven Bayesian multilevel logistic regression models were compared using the widely applicable information criterion (WAIC) and Pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO). Model 2 recorded the lowest WAIC (188.864), followed by Model 7 (189.274). However, the difference between their WAIC values was small (0.410) relative to the associated standard errors, suggesting that the WAIC results do not provide strong evidence of a meaningful difference in predictive performance between the two models.

Furthermore, the PSIS-LOO diagnostics identified substantial numbers of observations with Pareto k values greater than 0.7 across the fitted models. This indicates that the PSIS-LOO estimates may be unreliable and that the resulting model rankings should be interpreted cautiously. Consequently, the available model-comparison results do not establish a definitive predictive advantage for any one model.

Model 7 was retained as the final inferential model because it incorporated the community-level random slope for maternal education and the cross-level interaction with community ANC utilisation, which directly addressed the methodological objectives of the study. Its selection was therefore based on its inferential structure and alignment with the research objectives, rather than a claim of superior predictive performance. The findings from this model should be interpreted with appropriate caution, particularly in view of the limited number of communities and the uncertainty associated with some model parameters.

Table 6. Predictive performance comparison of the seven Bayesian multilevel models.

Model	ELPD difference	SE difference	P(worse)	Observations with k > 0.7	WAIC	WAIC SE
Model 1: Individual	−8.4	3.2	1.00	84	232.148	10.103
Model 2: Individual and household	0.0	0.0	—	152	**188.864**	10.343
Model 3: Community	−3.8	1.5	0.99	140	199.292	10.553
Model 4: Random slope	−2.2	1.6	0.92	137	197.053	10.209
Model 5: Education × community poverty	−3.7	1.6	0.99	143	192.712	10.177
Model 6: Education × community literacy	−3.0	1.6	0.97	148	195.504	10.293
Model 7: Education × community ANC	−2.0	1.7	0.89	152	189.274	9.993

Note: ELPD = expected log pointwise predictive density; SE = standard error; WAIC = widely applicable information criterion; ANC = antenatal care. Model 2 was used as the PSIS-LOO reference model. Lower WAIC values indicate better estimated predictive performance. Pareto k values greater than 0.7 indicate potentially influential observations. Bold indicates the lowest WAIC.

The results show that Model 2 recorded the lowest WAIC, while Model 7 performed closely, with only a small difference between their WAIC values. However, the substantial number of observations with Pareto k values greater than 0.7 indicates that the PSIS-LOO comparisons should be interpreted cautiously. Model 7 was therefore retained for final inference based on its alignment with the study objectives and its incorporation of the proposed random-slope and cross-level interaction structure, rather than on a claim of superior predictive performance.

3.7 Model diagnostics and adequacy

The convergence and adequacy of the fitted Bayesian multilevel logistic regression models were assessed using the Gelman–Rubin convergence diagnostic (R-hat), effective sample sizes (ESS), visual inspection of Markov Chain Monte Carlo (MCMC) trace plots, and posterior predictive checks.

For Model 2, most parameters had R-hat values of 1.00, while the household-level standard deviation had an R-hat value of 1.01. The effective sample sizes were also adequate. For the final inferential model (Model 7), all parameters had R-hat values of 1.00, with adequate bulk and tail effective sample sizes, indicating satisfactory convergence.

Visual inspection of the Model 7 trace plots showed that the four MCMC chains generally overlapped and fluctuated around stable regions, with no obvious systematic upward or downward trends. This suggested satisfactory mixing and approximate stationarity of the sampled chains. Although some random-effect standard deviation parameters exhibited greater variability and occasional spikes, there was no persistent pattern indicating non-convergence. The trace plots for selected fixed-effect and random-effect parameters are presented in Figures 1 and 2, respectively.

Posterior predictive checks were also conducted for Models 2 and 7 by comparing the observed immunization outcomes with replicated data generated from their posterior distributions. The posterior predictive density plots showed close agreement between the observed and replicated distributions. For Model 7, the observed numbers of children who were not fully immunized (109) and fully immunized (99) were consistent with the posterior predictive distributions. Overall, the checks indicated adequate agreement between the observed and replicated data, with no major evidence of systematic lack of fit.

Taken together, the R-hat statistics, effective sample sizes, trace plots, and posterior predictive checks provided evidence of satisfactory MCMC convergence and model adequacy. These findings support the reliability of the posterior estimates obtained from Model 7 for subsequent interpretation.

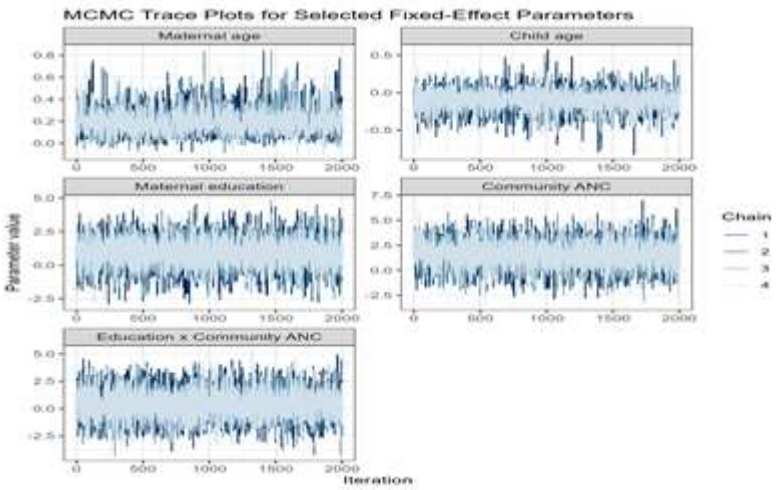

Figure 1. MCMC trace plots for selected fixed-effect parameters of Model 7.

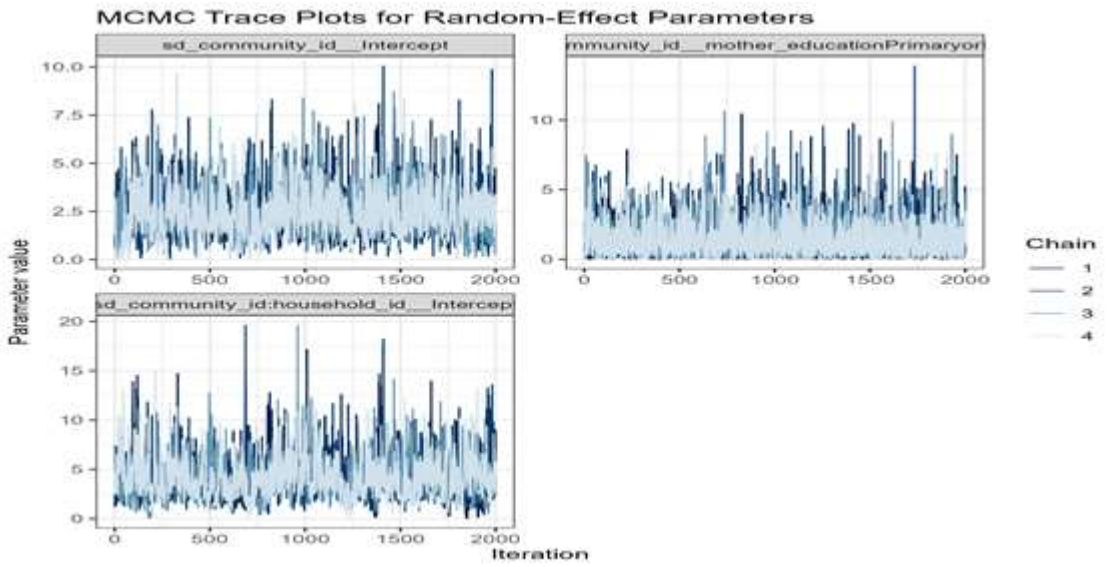

Figure 2. MCMC trace plots for random-effect parameters of Model 7.

4. DISCUSSION AND LIMITATIONS

4.1 Discussion of findings

This study examined childhood immunisation status among children aged 12–23 months in Bauchi State, Nigeria, using a Bayesian three-level multilevel logistic regression framework. By accounting for the clustering of children within households and households within communities, the study assessed individual-, household- and community-level variation in immunisation status and investigated whether the association between maternal education and childhood immunisation varied across communities. The findings showed that fewer than half of the children were fully immunised according to the study's operational definition, substantial variation existed at household and community levels, and maternal age was the only fixed-effect predictor with posterior evidence of an association in the final inferential model.

The proportion of fully immunised children was 47.6%, indicating that more than half of the children had not received all eight vaccines included in the study's definition. This finding points to a considerable immunisation gap in the study population. The 2024 Nigeria Demographic and Health Survey also documented substantial gaps in childhood vaccination, with marked differences across states and regions. However, its indicator of receipt of all basic antigens is not identical to the eight-vaccine definition used in this study; therefore, the estimates should not be interpreted as directly comparable (NPC and ICF, 2025). Earlier evidence from northern Nigeria similarly reported low full-immunisation coverage among children of young mothers, with estimates of 11% in 2013 and 18% in 2018 (Alabi et al.,

2024). More recent national analyses have also highlighted persistent geographical inequalities and changes in state-level vaccination coverage (Ahmed et al., 2024; Sato et al., 2026). Evidence from Bauchi State itself, including the facility-based study conducted in Azare by Abah et al. (2026), further demonstrates the importance of parental knowledge, attitudes and sociocultural circumstances in understanding childhood immunisation. Although differences in populations, settings and outcome definitions limit direct comparisons, these studies collectively demonstrate the continuing need to improve childhood vaccination coverage in northern Nigeria.

An important finding was the substantial variation in childhood immunisation status at household and community levels. The null model attributed 24.9% of the total latent-scale variation to differences between households and 31.4% to differences between communities, giving a combined proportion of 56.3%. This suggests that immunisation status was not explained solely by individual child characteristics; the household and community contexts in which children lived also accounted for considerable variation. Similar contextual differences have been reported in Nigeria. Aheto et al. (2022) identified variation in childhood vaccination indicators across communities, while Lawal et al. (2023) demonstrated spatial and temporal variation in vaccine uptake using a hierarchical Bayesian approach. Studies examining wider geographical patterns have likewise reported substantial immunisation inequalities across West African countries and sub-Saharan Africa (Azumah and Saani, 2026; Tamir et al., 2026). These findings support the relevance of multilevel and spatial approaches to childhood immunisation research. The present study extends this evidence by distinguishing household-level from community-level variation within Bauchi State.

Maternal age was the only fixed-effect predictor with posterior evidence of an association with childhood immunisation in the final inferential model. The estimated odds ratio was 1.224 (95% CrI: 1.027–1.605), indicating that each additional year of maternal age was associated with higher odds of a child being fully immunised, conditional on the other variables in the model. This finding is consistent with the Nigerian study by Ahmed et al. (2024), which reported lower odds of incomplete vaccination among children of older mothers. A recent multilevel analysis in Kenya also identified higher odds of full immunisation among children of older mothers (Lakew et al., 2026). These findings suggest that maternal age may be relevant to childhood vaccination patterns across different settings. Greater experience with child healthcare and familiarity with vaccination services may partly explain this relationship, although these mechanisms were not directly examined in the present study and should therefore be interpreted cautiously.

Maternal education was not supported as an average fixed-effect predictor in the final model; however, its estimated random-slope standard deviation was 1.523 (95% CrI: 0.043–4.860). This indicates variation in the association between maternal education and childhood immunisation across communities. Previous studies have reported positive associations between maternal education and childhood vaccination. Aheto et al. (2022) identified maternal education as an important predictor of several childhood vaccination indicators in Nigeria, while Fenta et al. (2021) reported higher odds of full immunisation among children whose mothers had secondary or higher education in a multilevel analysis of nine sub-Saharan African countries. Ahmed et al. (2024) also found that increasing maternal education was associated with a lower likelihood of incomplete vaccination in Nigeria. More recent evidence from East Africa and Kenya similarly identifies maternal education as relevant to childhood immunisation (Endalamew et al., 2025; Lakew et al., 2026). The absence of a supported average fixed effect in the present study does not necessarily contradict these findings. Rather, the random-slope result suggests that the association may differ across communities, potentially reflecting differences in local socioeconomic conditions, access to health services and other contextual circumstances. This finding highlights the importance of allowing relevant individual-level effects to vary across communities rather than assuming that the same association applies uniformly to all settings.

The cross-level interaction between maternal education and community antenatal care utilisation was not supported by posterior evidence. Thus, the analysis did not establish that community-level antenatal care utilisation modified the association between maternal education and childhood immunisation. This result should be distinguished from evidence that antenatal care is associated with vaccination uptake. For example, Alabi et al. (2024) identified antenatal care attendance as a predictor of full immunisation among children of young mothers in northern Nigeria, while Fenta et al. (2021) reported an association between antenatal care attendance and full childhood immunisation across sub-Saharan African countries. These are associations involving antenatal care, not necessarily evidence that community-level antenatal care modifies the effect of maternal education. Consequently, the unsupported interaction in the present study should not be interpreted as showing that antenatal care is unimportant. It indicates only that the specific modifying effect examined was not clearly established by the available data.

The bivariate analysis identified statistically significant associations between childhood immunisation status and maternal education, maternal employment, and maternal age. At the community level, community poverty showed a significant negative correlation with

immunisation prevalence, while community literacy showed a significant positive correlation. However, these associations were not all supported as independent predictors in the adjusted final model. This difference illustrates the distinction between unadjusted relationships and associations estimated after accounting for other explanatory variables and the hierarchical structure of the data. Previous Nigerian studies have also identified socioeconomic and contextual characteristics as relevant to childhood vaccination (Aheto et al., 2022; Lawal et al., 2023). In addition, the pooled West African analysis by Azumah and Saani (2026) highlighted inequalities in immunisation coverage across socioeconomic groups. The present findings therefore reinforce the importance of considering socioeconomic circumstances while recognising that bivariate associations do not necessarily represent independent effects after multilevel adjustment.

The model comparison results also require consideration. Model 2 recorded the lowest WAIC (188.864), indicating the best numerical predictive performance among the seven models compared. Model 7 had a slightly higher WAIC of 189.274 but was retained for final inference because it incorporated the random-slope and cross-level interaction structure central to the study's methodological objective. Its selection was therefore based on the need to examine variation in the maternal education effect and its potential modification by community context, rather than on superior predictive performance. Furthermore, the presence of numerous observations with Pareto k values greater than 0.7 in the PSIS-LOO assessment warrants caution in interpreting the predictive comparison. The findings from Model 7 should consequently be understood in light of both the model's inferential purpose and the limitations of the predictive diagnostics.

Overall, this study demonstrates that childhood immunisation status in Bauchi State is characterised by substantial household- and community-level variation, an association with maternal age, and community-level variation in the association between maternal education and immunisation. These findings are consistent with broader evidence that childhood vaccination is shaped by individual characteristics and wider social and geographical contexts. Recent studies examining zero-dose vaccination, missed opportunities for vaccination and immunisation service delivery in African settings further emphasise the need to identify underserved populations and address service-related barriers (Isah et al., 2026; Salaudeen et al., 2026; Tamir et al., 2026; Tamuzi et al., 2026). In practical terms, improving childhood immunisation in Bauchi State requires sustained routine and outreach vaccination services, effective communication with caregivers, and monitoring of coverage across

communities. Interventions should also recognise that the relationship between caregiver characteristics and immunisation may differ across local contexts.

4.2 Study Limitations

This study has some limitations that should be considered when interpreting the findings. First, the analysis was based on a relatively small sample of 208 children from 196 households across 41 communities. Although this sample supported the planned multilevel analysis, the relatively small number of communities may have limited the precision of estimates for community-level effects, random slopes and cross-level interactions. Consequently, some parameter estimates, particularly those relating to variation in effects across communities, should be interpreted cautiously.

Second, the Bayesian multilevel models did not incorporate the NDHS sampling weights or explicitly adjust for the survey stratification variables. Although random effects were included to account for household- and community-level clustering, they do not fully reproduce the complex survey design. Therefore, the findings should be interpreted as model-based associations within the analytical sample rather than fully design-adjusted population estimates.

Third, the cross-sectional nature of the NDHS data limits the ability to establish causal relationships between the explanatory variables and childhood immunisation status. In addition, the analysis was restricted to children aged 12–23 months in Bauchi State, which may limit the generalisability of the findings to other age groups or states in Nigeria. Despite these limitations, the study provides useful evidence on individual-, household- and community-level variation in childhood immunisation status.

5. CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

This study examined childhood immunisation status among children aged 12–23 months in Bauchi State, Nigeria, using a Bayesian three-level random-slope multilevel logistic regression framework with cross-level interactions. Among the 208 children analysed, 47.6% were fully immunised, while 52.4% were not fully immunised, indicating that a substantial proportion had not received the complete set of vaccine doses specified in the study.

The findings revealed considerable variation in childhood immunisation status at household and community levels, which together accounted for 56.3% of the total latent-scale variation. Maternal age was the only fixed-effect predictor with posterior evidence of an association

with full immunisation in the final inferential model. The effect of maternal education also varied across communities, as indicated by the estimated random-slope standard deviation. However, the examined cross-level interaction between maternal education and community-level antenatal care utilisation was not supported by posterior evidence.

Although Model 2 recorded the lowest WAIC, Model 7 was retained for final inference because it incorporated the random-slope and cross-level interaction structure central to the methodological objectives of the study. Its selection was therefore based on its suitability for investigating contextual variation rather than superior predictive performance. Overall, the findings demonstrate the importance of accounting for household and community clustering and allowing relevant predictor effects to vary across communities when analysing childhood immunisation outcomes. Given the cross-sectional nature of the data, the observed associations should not be interpreted as causal relationships.

5.2 Recommendations

Based on the findings of this study, the following recommendations are proposed:

1. Strengthen routine and outreach immunisation services: Health authorities should intensify routine and outreach vaccination activities, particularly in rural and underserved communities, to address gaps in childhood immunisation coverage.

2. Promote maternal health education and engagement: Health workers should strengthen communication with mothers and caregivers on recommended childhood vaccination schedules and the importance of completing all required doses. These efforts should use accessible communication approaches that accommodate different educational backgrounds.

3. Integrate immunisation counselling into maternal healthcare services: Immunisation education and counselling should be reinforced during antenatal, delivery and postnatal care to encourage timely vaccination and continuity of follow-up.

4. Strengthen community-level monitoring: Immunisation programme managers should monitor vaccination coverage across communities to identify areas with lower coverage and guide the allocation of outreach, follow-up and other immunisation resources.

5. Improve vaccination tracking and follow-up: Health facilities should strengthen vaccination record-keeping and follow-up systems to identify children who miss scheduled doses and support caregivers in completing the recommended vaccination schedule.

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