

Household and Community Heterogeneity in Childhood Stunting in Ghana

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Code and aggregate non-identifying outputs: GitHub repository

Abstract

Objectives: To estimate how much unexplained variation in childhood stunting in Ghana occurs at the household and survey-community levels, and to assess whether that pattern remains after accounting for water, sanitation, maternal education, and core sociodemographic characteristics.

Methods: We analysed 4,928 children aged 0–59 months from the 2022 Ghana Demographic and Health Survey, representing 3,545 households and 616 survey communities. Survey-weighted prevalence was estimated using the DHS design. Bayesian hierarchical logistic models included household and community random intercepts. We assessed the final model using eight chains and a series of checks covering alternative priors, survey weights, missing data, spline-based age modelling, detailed WASH coding, posterior predictive checks, PSIS-LOO, and independent GEE analyses.

Results: Survey-weighted stunting prevalence was 17.4% (95% CI 15.8–18.9). In the final model, the household SD was 1.23 and the community SD 0.39; the corresponding household VPC and community ICC were 0.31 and 0.03. Boys had higher odds of stunting than girls (OR 1.50, 95% posterior interval 1.24–1.82), as did children aged 24–35 versus 0–5 months

(OR 2.91, 2.06–4.21). Unimproved drinking-water source had OR 1.50 (1.15–1.99), whereas higher maternal education had OR 0.37 (0.20–0.65). Sensitivity analyses preserved the main household-versus-community pattern.

Conclusions: Most of the residual clustering in these data occurred at the household rather than the survey-community level. Because the study is observational, the results do not establish causal effects; instead, they point to household conditions that standard DHS covariates may not fully capture.

Keywords: childhood stunting; Bayesian hierarchical modelling; Ghana; household heterogeneity; community heterogeneity; WASH; maternal education

1 Introduction

Ghana’s national stunting prevalence has fallen, but childhood stunting remains unevenly distributed. In the 2022 Ghana Demographic and Health Survey (GDHS), about 17% of children under five were stunted [1]. The national estimate masks clear differences by region, household wealth, and place of residence. It also leaves an important question unanswered: after measured characteristics are taken into account, how much of the remaining variation is shared within households and how much is shared across survey communities?

The distinction matters because children in the same household share many immediate conditions, including food resources, caregivers, sanitation facilities, and economic circumstances. Households in the same survey cluster may also share markets, health services, infrastructure, and environmental exposures. If a model allows for community clustering but not household clustering, some of the similarity among children living together may be assigned to the wrong level.

Previous Ghanaian studies have documented socioeconomic, household, and geographical differences in stunting. Bayesian geostatistical analyses have described spatial variation [2, 3], while multilevel studies have identified household and socioeconomic correlates [4, 5]. More recent work across 35 sub-Saharan African countries again points to differences by age, sex, maternal education, wealth, and contextual conditions [6]. A 2026 systematic review also found that WASH–stunting associations vary across exposure definitions and settings [7], and work using the 2022 GDHS has examined WASH and child nutrition among children born to young mothers [8]. Against that back-

ground, our focus is narrower: we separate household from survey-community heterogeneity in the eligible under-five sample, then examine how that decomposition behaves as WASH and maternal education are added, using harmonized samples where needed.

We also examine whether the main findings depend on modelling choices that could affect interpretation, including prior scale, treatment of survey weights, missing maternal-education information, categorical versus spline-based age modelling, and binary versus more detailed WASH definitions.

2 Methods

2.1 Data source and analytic sample

This was a cross-sectional secondary analysis of the Household Member Recode from the 2022 GDHS, accessed under authorization from The DHS Program. Fieldwork was conducted from October 2022 to January 2023. The GDHS used a stratified two-stage cluster sample [1]. Children were eligible for this analysis if they were aged 0–59 months, had slept in the sampled household on the night before the interview (`hv103 = yes`), and had a valid height-for-age z-score in `hc70`.

We defined stunting as height-for-age below -2 standard deviations from the WHO reference median, corresponding to `hc70 < -200` in the DHS recode. The resulting core sample contained 4,928 children in 3,545 households and 616 survey communities. For the hierarchical models, community was operationalized as the DHS survey cluster (`hv001`), and households were uniquely identified by the combination of cluster and household identifiers (`hv001` and `hv002`).

2.2 Covariates

The core model included child sex, age, household wealth quintile, urban or rural residence, and administrative region. For the primary model, age was grouped as 0–5, 6–11, 12–23, 24–35, 36–47, and 48–59 months.

Drinking-water source (`hv201`) and sanitation facility (`hv205`) were grouped into improved and unimproved/no-facility categories using JMP-consistent facility-type definitions [9]. These groupings refer to source or facility type; they do not represent the full JMP service ladders. Maternal education came from `hc61` and was classified as no education, primary, secondary, or higher. Ma-

ternal education was unavailable for 425 children, leaving 4,503 children for the complete-case maternal-education model.

2.3 Descriptive analysis

We used the DHS household-member weight (`hv005`) for descriptive prevalence estimates. Taylor linearization was used for standard errors and 95% confidence intervals, with `hv021` as the primary sampling unit and `hv022` as the sampling stratum. The sum of the rescaled weights in our analytic sample was 4,292.97, which reproduces the official GDHS weighted height-for-age denominator of 4,293 after rounding.

2.4 Bayesian hierarchical models

For child i in household j and community k , we modelled

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

with

$$\text{logit}(p_{ijk}) = \alpha + \mathbf{x}_{ijk}^\top \boldsymbol{\beta} + u_k + v_{jk},$$

where $u_k \sim N(0, \tau_c^2)$ is the community random intercept and $v_{jk} \sim N(0, \tau_h^2)$ is the household random intercept. Both random effects were fitted with non-centred parameterizations.

We used $N(0, 1.5^2)$ for the intercept, $N(0, 1^2)$ for regression coefficients, and Half-Normal(1) priors for the household and community standard deviations. Model 1 contained the core covariates together with household and community random intercepts. Model 2 added WASH. Model 3 added maternal education. We also refitted Model 2 on the 4,503-child maternal-education sample so that the Model 2–Model 3 comparison was not confounded by a change in sample composition.

For interpretation of the random effects, we used a latent logistic residual variance of $\pi^2/3$. The community ICC and household variance partition coefficient were

$$ICC_c = \frac{\tau_c^2}{\tau_c^2 + \tau_h^2 + \pi^2/3}, \quad VPC_h = \frac{\tau_h^2}{\tau_c^2 + \tau_h^2 + \pi^2/3}.$$

We also calculated median odds ratios (MORs) as

$$MOR = \exp \left[\sqrt{2} \Phi^{-1}(0.75) \tau \right].$$

2.5 Computation, diagnostics, and sensitivity analyses

Models were fitted with NUTS in PyMC. For the strengthened final Model 3 diagnostic run, we combined eight independent chains, each with 500 warmup and 500 retained draws, giving 4,000 retained posterior draws. We examined divergences, $\hat{R}$, effective sample size, BFMI, and tree depth, and used posterior predictive checks to compare replicated and observed prevalence.

We then challenged the main specification in several ways. We refitted Model 3 with tighter and wider priors; fitted a pseudo-posterior using survey weights rescaled to mean one; retained children with missing maternal education as a separate sensitivity category; replaced the age groups with a cubic B-spline; and replaced the binary WASH variables with more detailed water and sanitation categories. Predictive performance of harmonized Models 2 and 3 was compared with PSIS-LOO and Pareto- k diagnostics. As an independent check on residual clustering and fixed-effect robustness, we also fitted logistic generalized estimating equation (GEE) models with exchangeable working correlation. The GEE working correlations were used only as sensitivity diagnostics and were not interpreted as Bayesian ICCs.

2.6 Ethics and data access

The 2022 GDHS protocol received ethical clearance from the Ethical Review Committee of the Ghana Health Service and from the ICF Institutional Review Board [1]. The original survey used informed-consent procedures under its approved protocol. This secondary analysis used de-identified data obtained through authorized DHS access and involved no direct participant contact. We do not redistribute DHS microdata. The public reproducibility repository contains code and aggregate, non-identifying outputs only.

2.7 Use of generative artificial intelligence

OpenAI ChatGPT (GPT-5.6 Sol; accessed September 2026) assisted with language editing, manuscript organization, code drafting and review, and reproducibility documentation. It was not used to gen-

Table 1: Selected characteristics of the analytic sample and survey-weighted stunting prevalence

Characteristic	Unweighted n	Weighted prevalence, % (95% CI)
Overall	4,928	17.4 (15.8–18.9)
Male	2,529	19.4 (17.2–21.6)
Female	2,399	15.3 (13.3–17.3)
Urban	2,024	15.1 (12.6–17.5)
Rural	2,904	19.6 (17.6–21.6)
Poorest wealth quintile	1,601	22.8 (19.7–25.9)
Richest wealth quintile	536	7.5 (4.7–10.3)
Improved water source	3,904	16.4 (14.7–18.1)
Unimproved water source	1,024	23.0 (19.0–27.0)
Improved sanitation facility	2,219	13.8 (11.8–15.7)
Unimproved/no sanitation facility	2,709	22.3 (19.9–24.6)
No maternal education	1,468	24.4 (21.5–27.2)
Higher maternal education	328	5.7 (2.4–8.9)

Note. Prevalence estimates use DHS sampling weights; confidence intervals use Taylor linearization with survey strata and primary sampling units. Maternal-education counts include only the observed education categories; 425 children had missing linked maternal education.

erate or alter the DHS microdata or the locked model outputs. The author reviewed and revised the resulting text and code, checked the reported numerical results against the saved outputs, and remains responsible for the analysis, interpretation, and integrity of the work.

3 Results

3.1 Stunting prevalence and descriptive pattern

Of the 4,928 children in the analytic sample, 927 were stunted. The survey-weighted prevalence was 17.4% (95% CI: 15.8–18.9). Boys had a higher weighted prevalence than girls (19.4% vs 15.3%), and prevalence was highest at ages 24–35 months (24.6%). The wealth gradient was pronounced: 22.8% of children in the poorest quintile were stunted compared with 7.5% in the richest. Northern (29.6%) and North East (29.3%) had the highest regional estimates. Additional survey-weighted prevalence plots by sex, age, residence, wealth, maternal education, drinking-water source, and sanitation are provided in Figures S1–S7 of the Supporting Information.

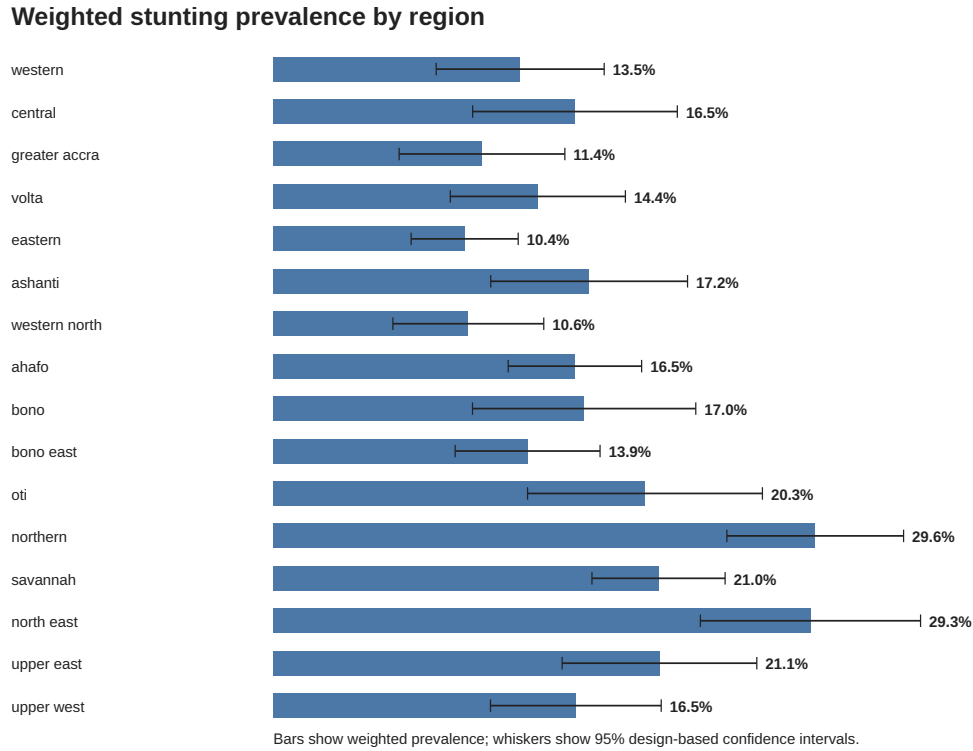


Figure 1: Survey-weighted prevalence of childhood stunting by region.

3.2 Most residual variation was at the household level

Adding a household random intercept changed the interpretation of the clustering structure. In Model 1, the community SD had a posterior median of 0.416 (95% posterior interval 0.159–0.590), while the household SD was 1.066 (0.774–1.346). On the latent scale, the community ICC was 0.038 and the household VPC was 0.246. The corresponding MORs were 1.49 and 2.76.

The difference did not disappear in the fuller model. In the strengthened Model 3 run, the community SD was 0.389 and the household SD 1.234. The community ICC was 0.030, whereas the household VPC was 0.307. The MORs were 1.45 for communities and 3.24 for households. The broad household-versus-community contrast remained clearly apparent after the additional covariates were included. The variance pattern across the model sequence is shown in Figure S8.

3.3 Fixed effects

Several fixed effects were stable across the modelling sequence. In Model 3, boys had higher odds of stunting than girls (OR 1.50, 95% posterior interval 1.24–1.82). Children aged 24–35 months

Table 2: Selected posterior results from the strengthened final model

Parameter or comparison	Posterior median	95% posterior interval
Male vs female OR	1.50	1.24–1.82
Age 24–35 vs 0–5 months OR	2.91	2.06–4.21
Richest vs poorest OR	0.36	0.20–0.64
Rural vs urban OR	0.85	0.64–1.12
Unimproved vs improved water OR	1.50	1.15–1.99
Unimproved/no vs improved sanitation OR	1.12	0.86–1.46
Maternal primary vs no education OR	1.02	0.75–1.41
Maternal secondary vs no education OR	0.89	0.68–1.14
Maternal higher vs no education OR	0.37	0.20–0.65
Community SD	0.39	0.07–0.61
Household SD	1.23	0.94–1.53
Community ICC	0.03	0.001–0.07
Household VPC	0.31	0.20–0.41
Community MOR	1.45	1.07–1.79
Household MOR	3.24	2.45–4.32

Note. OR = odds ratio; SD = random-intercept standard deviation; ICC = intraclass correlation coefficient; VPC = variance partition coefficient; MOR = median odds ratio. Fixed-effect ORs and variance summaries come from the strengthened eight-chain Model 3 run.

had nearly three times the odds of those aged 0–5 months (OR 2.91, 2.06–4.21).

The socioeconomic gradient also remained. For children in the richest households, the posterior OR relative to the poorest group was 0.36 (0.20–0.64).

For WASH, the water result was clearer than the sanitation result. Unimproved drinking-water source had an OR of 1.50 (1.15–1.99). The corresponding sanitation estimate was 1.12 (0.86–1.46), leaving substantial posterior support for both modest harm and little or no independent association.

Maternal education showed a similar contrast across categories. Higher education was associated with lower odds of stunting relative to no education (OR 0.37, 0.20–0.65). The primary and secondary categories were much less distinct from the reference group: OR 1.02 (0.75–1.41) and 0.89 (0.68–1.14), respectively.

3.4 Diagnostics and sensitivity analyses

The strengthened Model 3 run produced no divergences. BFMI ranged from 0.51 to 0.66 across chains, and no chain saturated the tree depth. Fixed-effect convergence was strong: the largest $\hat{R}$ among the reported fixed effects was about 1.003, and bulk effective sample sizes exceeded 2,200. Mixing was slower for the two variance parameters. The community and household SDs

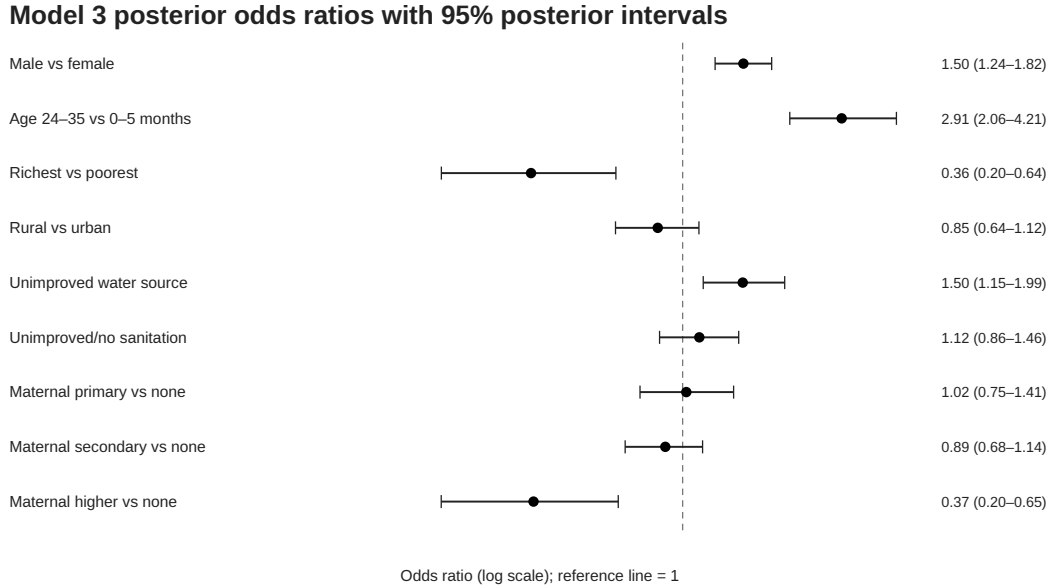


Figure 2: Selected posterior odds ratios from the final maternal-education model.

had $\hat{R}$ values of about 1.021 and 1.018, with bulk ESS of about 544 and 524. Because these $\hat{R}$ values remain above the commonly used 1.01 guideline, exact variance-component interval endpoints are interpreted more cautiously than the fixed-effect intervals; the household-versus-community ordering was nevertheless stable across the model sequence and sensitivity analyses. Full chain-level diagnostics and variance summaries are reported in Tables S1 and S2, respectively.

The posterior predictive distribution reproduced the observed overall prevalence and the prevalence in each of the six age groups (Figure S9). Alternative tighter and wider prior scales produced similar key fixed-effect estimates (Table S3). Changing the functional form of age made little difference to the other main coefficients: in the spline-age model, the OR was 1.49 (1.12–2.00) for unimproved water, 0.37 (0.20–0.67) for higher maternal education, and 0.35 (0.19–0.61) for richest versus poorest (Table S6).

The more detailed WASH analysis helped locate the water signal. Surface-water use had an OR of 1.52 (1.10–2.08) relative to improved sources. The estimate for unprotected groundwater was 1.41 (0.90–2.21). For sanitation, neither open defecation [OR 1.23 (0.92–1.64)] nor other unimproved facilities [OR 0.93 (0.68–1.31)] was clearly separated from the improved-facility group (Table S7).

The survey-weight pseudo-posterior was less precise for water: OR 1.38 (0.90–2.07). This did not reverse the direction of the estimate, but it weakened the strength of the evidence (Table S4).

A full-sample model that retained missing maternal education as a separate category gave similar conclusions (Table S5).

The independent GEE checks pointed in the same direction as the hierarchical model. The exchangeable working correlation was 0.154 when clustering by household and 0.024 when clustering by community. With household clustering, the GEE estimate for unimproved water was OR 1.40 (1.12–1.74); replacing age categories with a spline gave OR 1.39 (1.12–1.74). Under the detailed WASH coding, surface water had OR 1.43 (1.12–1.83), whereas unprotected groundwater remained less precise at OR 1.34 (0.93–1.94). These GEE quantities are sensitivity checks rather than substitutes for the Bayesian variance components (Table S8).

Finally, observation-level PSIS-LOO did not distinguish the harmonized WASH and maternal-education models in a practically meaningful way. Model 3 improved ELPD by 0.92, with an SE of 3.38. No Model 3 observation had Pareto $k > 0.70$; Model 2 had five, and neither model had $k > 1$. Because individual children are left out while household and community effects are estimated from the remaining data, this comparison reflects conditional prediction within the observed hierarchy; it should not be read as performance for entirely new households or communities (Table S9).

4 Discussion

The main result is the size of the household random effect. Once household and community clustering were modelled separately, residual variation between households was much larger than residual variation between survey communities. That ordering remained after WASH and maternal education were added.

This pattern is consistent with earlier Ghanaian work showing meaningful household-level variation in childhood malnutrition [4], and it does not conflict with evidence of geographical heterogeneity from geostatistical studies [2, 3]. A DHS cluster captures a broader shared setting, whereas a household captures a more immediate one. Treating the cluster as the only higher level can blur these two sources of dependence.

The median odds ratios make the contrast easier to see: 3.24 at the household level compared with 1.45 at the community level in the final model. These values summarize the spread of the random effects; they are not causal effects of moving a child from one household to another.

Even so, the size of the household term suggests that measured DHS covariates leave important shared household conditions unaccounted for. Food security, food allocation, maternal nutrition, caregiving, recurrent infection, and short-term economic shocks are plausible contributors.

The age pattern was clear: stunting was most common around the second and third years of life, and adjusted odds were highest at 24–35 months. Replacing the age groups with a spline left the other main coefficients almost unchanged, suggesting that the wealth, water, sex, and education estimates were not artifacts of the chosen age cut-points.

The wealth gradient was one of the most stable findings. Even after WASH and maternal education were in the model, children in the richest households had markedly lower odds of stunting than those in the poorest. Similar socioeconomic inequalities have been reported repeatedly in Ghana [10, 11]. The attenuation of the wealth coefficient after maternal education was added is unsurprising given the relationship between schooling and economic position, but these cross-sectional data cannot establish mediation.

The WASH results were less uniform. A binary unimproved-water indicator was associated with higher odds of stunting in the main model, but the weighted pseudo-posterior was more uncertain. The detailed coding added useful context: surface water showed the clearest signal, while unprotected groundwater was less precisely estimated. Sanitation, despite a large crude difference in prevalence, was weak after multivariable adjustment. The evidence for water source is therefore clearer in these data than the evidence for an independent sanitation association. It does not show that changing water source alone would prevent stunting.

Higher maternal education was associated with substantially lower odds of stunting, whereas primary and secondary education were not clearly different from no education once the other covariates were included. Similar inverse associations between maternal schooling and child under-nutrition have been reported elsewhere in Ghana and sub-Saharan Africa [4, 12, 13]. The pattern here should not be read as evidence of a precise educational threshold. Maternal education is also a marker for differences in health literacy, income opportunities, autonomy, healthcare use, and family circumstances that we cannot fully separate in this dataset.

The model comparison also deserves restraint. Adding maternal education was scientifically useful, but it did not materially improve observation-level predictive performance. The ELPD difference between harmonized Models 2 and 3 was small relative to its uncertainty. Because the

comparison is conditional on the sampled hierarchy, it does not test prediction in entirely new households or communities. Maternal education is therefore retained for substantive reasons, not because Model 3 can be shown to predict better.

4.1 Strengths and limitations

The analysis has several practical strengths. The reconstructed descriptive sample agrees with the published GDHS after rounding for both the weighted denominator and national stunting prevalence. The models separate household from community clustering, use a harmonized sample when Models 2 and 3 are compared, and test the main findings under several alternative specifications rather than relying on a single fit.

The study also has important limitations. The GDHS is cross-sectional, so the odds ratios describe associations rather than causal effects. Several plausible determinants of child growth—including detailed diet, household food insecurity, maternal nutritional status, birth size, and repeated infection—were not available in the analysis. Some of that unmeasured information may be reflected in the household random effect.

Our WASH variables describe source and facility types, not the full JMP service ladders. Maternal education was missing for 8.6% of the core sample, although a sensitivity analysis retaining those children did not materially change the main conclusions. The primary Bayesian likelihood does not fully incorporate the survey design; the weighted pseudo-posterior was therefore treated as a sensitivity analysis.

Finally, household variance is harder to estimate than the fixed effects. Many households contributed only one eligible child, and the two random-effect SDs mixed more slowly than the regression coefficients. The eight-chain run improved the effective sample sizes substantially and left the household-versus-community contrast unchanged, but exact variance-component intervals deserve more caution than the fixed-effect intervals.

4.2 Conclusions

The 2022 GDHS shows that childhood stunting in Ghana remains geographically and socioeconomically uneven, but the variation is not only between places. In these models, much more residual

variation occurred between households within survey communities than between the communities themselves, and that pattern remained after WASH and maternal education were included.

The implication is that standard DHS covariates do not explain a substantial share of the clustering shared by children in the same household. Future work could examine that residual household component more directly using richer information on food security, diet, maternal health, infection, caregiving, and household shocks.

Data Availability Statement

The 2022 Ghana DHS microdata are distributed by The DHS Program and cannot be redistributed by the author. Eligible researchers may request access directly from The DHS Program under its data-use conditions. Reproducibility code, aggregate tables, figures, and non-identifying diagnostic outputs are available at <https://github.com/OG-Kyere/Bayesian-Hierarchical-Modelling-of-Childhood-Stunting-in-Ghana>. Restricted row-level DHS data are not included.

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Conflicts of Interest

The author declares no conflict of interest.

Author Contributions

Gideon Ofori Kyere: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Validation; Visualization; Writing – original draft; Writing – review & editing; Project administration.

Use of Generative Artificial Intelligence

OpenAI ChatGPT (GPT-5.6 Sol; accessed September 2026) assisted with language editing, manuscript organization, code drafting and review, and reproducibility documentation. It was not used to generate or alter the DHS microdata or the locked model outputs. The author reviewed and revised

the resulting text and code, checked the reported numerical results against the saved outputs, and remains responsible for the analysis, interpretation, and integrity of the work.

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Supporting Information

The accompanying Supplementary Material contains additional descriptive figures, sampler and parameter diagnostics, variance summaries, prior and survey-weight sensitivity analyses, missing-data and age-functional-form sensitivity analyses, detailed WASH and GEE robustness checks, posterior predictive checks, and the PSIS-LOO comparison.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryMaterial.pdf](#)