Research Article

Vol.9, No 1, 2026
ISSN 2591–6769
eISSN 2953–2663

East African Journal of Applied Health Monitoring and Evaluation

Multilevel Modelling of the Factors Associated with Stunting among Under-five Children in Tanzania: A Bayesian Approach

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Received: March 29, 2025 Accepted: August 27, 2026 Published: September 6, 2026

Abstract

Introduction

In Tanzania, prevalence exceeds 30% and is unevenly distributed across geographical areas. The observed distribution may reflect unobserved contextual factors; however, little literature applies Bayesian multilevel generalised linear mixed (B-MGLM) models, which can account for them. This study aimed to model the determinants of stunting, controlling for contextual factors at both the region and enumeration area levels.

Methods

This was a secondary data analysis using four recent Tanzania Demographic and Health Surveys (TDHS) datasets. We studied 7,492, 6,806, 8,929, and 4,797 under-five children in TDHS 2004/5, 2010, 2015/16, and 2022, respectively. We used B-MGLM models to evaluate the determinants of stunting. We used the deviance information criterion to compare the models.

Results

About 41.4%, 34.1%, and 28.96% of under-five children were stunted in 2010, 2015/16, and 2022, respectively. Controlling for other factors in the model, a unit increase in MPI increased the odds of stunting by 10% [AOR = 1.1; 95% CI: 1.1, 1.2], while a unit increase in WAMI reduced the odds of stunting by 64% [AOR=0.36; 95% CI: 0.3, 0.4] in 2015/16 and 2010, respectively. Other interesting results were that children with multiple births had 17% [AOR=0.83; 95% CI: 0.7, 0.9] lower odds and 68% [AOR=1.68; 95% CI: 1.5, 1.9] higher odds of stunting in 2004/5 and 2010, respectively.

Conclusion

Stunting is associated with individual and contextual factors. Critical efforts should focus on the availability of items that form WAMI and MPI, with greater emphasis on elements that form WAMI because of its consistent negative relationship with stunting across the two surveys. Nutrition education should target working mothers and households with food insecurity.

Keywords: *Stunting, Bayesian Multilevel Generalised Linear Mixed Models, Tanzania*

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ISSN 2591–6769
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INTRODUCTION

Stunting was defined as the failure to reach optimal linear growth potential due to poor nutrition and repeated infections (de Onis & Branca, 2016; iAHO & WHO, 2023; WHO, 2006, 2024). Compared to other indicators of undernutrition, stunting measures the child's well-being and reflects social inequities (de Onis & Branca, 2016; iAHO & WHO, 2023; WHO, 2006, 2024). Stunting hampers national economic development, children's academic performance, and increases morbidity and mortality (Olofin et al., 2013; Soboksa et al., 2021). Being a global and national concern, different efforts, including vitamin A supplementation, deworming, exclusive breastfeeding, as well as local production of nutritious food (FAO et al., 2015; MoHCDGEC, 2019; MoHCDGEC et al., 2016; UNICEF et al., 2021), have been implemented to combat stunting. However, prevalence remains high globally and nationally.

Globally, the prevalence of stunting was estimated at 149.2 million (22%) in 2021 (UNICEF et al., 2021). Stunting prevalence varies by socioeconomic status. In 2017, it was reported that of 155 million stunted children, more than 2% lived in high-income countries (HIC), while over 50% lived in low-income countries (LIC) (Crochemore et al., 2018). Furthermore, of the 155 million stunted children in 2017, about 59 million resided in Africa, while 24 million lived in Eastern Africa (Crochemore et al., 2018). In Tanzania, studies revealed that stunting declined from 34% in 2016 to 31.8% in 2018 (MoHCDGEC, 2019). However, some regions had a higher prevalence above 30%, according to the WHO-UNICEF classification (UNICEF et al., 2021). About 26 and 6 regions had prevalence rates exceeding 30% and 40%, respectively (MoHCDGEC, 2019). If the observed uneven distribution of stunting is not addressed, we should anticipate an increased burden of health spending among the socioeconomically disadvantaged population.

To reduce stunting, researchers have developed different models and frameworks to support intervention design. These models/frameworks pinpointed different factors, including child, maternal, household (Sansón-Rosas et al., 2021), and spatial (Fenta et al., 2021), as important factors for stunting among under-fives. Most of these factors are shaped by unmeasurable socio-cultural norms and beliefs, including eating behaviour, use of family planning methods, and child-feeding practices like exclusive breastfeeding (EBF), which varies across geographical areas. For instance, EBF was influenced by unmeasurable contextual factors due to differences in country (Yalçin et al., 2016) and enumeration area (Jahanpour et al., 2022) levels. EBF is an important component in child growth, this makes it important to take into account contextual factors when evaluating the determinants of stunting. Furthermore, previous studies extended the idea of measuring SES in health studies (Omer & Al-Hadithi, 2017). However, very little is known about the association between different measures of SES and stunting (Psaki et al., 2014).

Additionally, Musheiguza et al. (2023) found that, among all SES measures, MPI best predicted stunting for TDHS 2004/5 and 2015/16, while WAMI best predicted it for TDHS 2010. However, it did not exhaustively discuss the impact of other variables on stunting, controlling for SES indices. The current study extends the previous study (Musheiguza et al., 2023), aiming to fill these gaps. Furthermore, despite the available advanced statistical modelling techniques for child health, like Bayesian multilevel generalised linear models (BM-GLM), they are still not sufficiently utilised. Most studies use maximum likelihood (MLE) multilevel models, which are prone to biased estimates in case enumeration areas have small sample sizes. Multilevel models account for unmeasured factors (Austin & Merlo, 2017). However, the BM-GLM produces unbiased estimates even in areas with smaller sample sizes (Zitzmann, Lüdtke, et al., 2021), as a small sample size (below 50) at level two may lead to biased estimates (Maas & Hox, 2005). The multilevel model uses random effects to control for the correlation between subjects and geographical areas, thereby identifying the presence of clusters (Jahanpour et al., 2022).

Mother-child pairs living in the same geographic areas may share common characteristics related to stunting, and some enumeration areas may have fewer observations, raising concerns about using BM-GLM. If we do not account for this, we should expect underestimated standard errors, increasing the likelihood of a type I error. Therefore, the study aimed to determine the factors contributing to stunting among children under five years old in Tanzania, accounting for correlations across regions and enumeration areas using Bayesian multilevel mixed generalised linear equations.

LITERATURE REVIEW

Theoretical Literature Review

The study was guided by two theories: parent-offspring conflict theory and life history theory. Furthermore, because environmental factors affect human life, the ecological model was considered. The parent-offspring conflict theory discusses the relationship between mother and child growth pertaining to the mother's decisions about feeding their offspring on the basis of maximising their reproductive fitness and carrier (Trivers, 1974). A mother may choose to terminate breastfeeding to pursue a new pregnancy or to gain more energy for specific jobs and employer satisfaction. Consequently, a child employs psychological strategies to compete with his or her mother (Trivers, 1974).

Life history theory examines how phenotypes shaped by genetic patterns influence traits passed down from one generation to the next, linking a mother’s traits to those of her child. For example, consider the relationship between the mother’s size and offspring size, the mother's BMI and child growth patterns, and the number of offspring in relation to the growth and maturity of particular offspring(Stearns, 2000). The ecological model emphasises the relationship between child growth potential and the immediate environment, particularly the family, which may influence nutritional intake (Sims et al., 1972).

Determinants of Stunting

Socioeconomic status (SES) was reported to be the main determinant of child stunting (Schultink, 2015). Children from poor, middle, rich and richest wealth quintile households had lower odds of stunting as compared to children born to the poorest wealth quintile households (Fenta et al., 2021; Lindtjørn, 2021; Musheiguza et al., 2021; Takele et al., 2020). Similarly, children born to mothers with primary, secondary and higher education had lower odds of stunting as compared to children born to uneducated mothers (Fenta et al., 2021; Lindtjørn, 2021; Musheiguza et al., 2021; Takele et al., 2020). The availability of safe water and sanitation, assets and maternal education and income (WAMI) index predicted stunting better than other measures of SES (Psaki et al., 2014).

Apart from SES, other control variables affect child stunting. These factors include: child characteristics, maternal characteristics, household and spatial factors. For the case of child characteristics, studies revealed lower odds of stunting among females as compared to males (Taleke et al., 2022). However, another study revealed higher odds of stunting among females (Abeway et al., 2018), born in the first, second or third order as compared to children born to the fourth and above (Takele et al., 2020), children born at an interval of 24-47 and 48 and above as compared to children born at an interval of less than 24 months (Takele et al., 2020), born with medium or large as compared to smaller sizes (Takele et al., 2020) as well as currently breastfed as compared to not breastfed (Takele et al., 2020; Taleke et al., 2022). The higher odds of stunting were among children having diarrhoea (Paudel et al., 2012; Taleke et al., 2022), home delivery as compared to health facility Taleke et al., 2022), aged 12-23 months, 24-35 months as compared to being aged 0-11 months (Das et al., 2022) as well as being a twin as compared to single births (Taleke et al., 2022).

Based on maternal characteristics, studies revealed that children had lower odds of stunting if they were born to mothers with BMI>18.5 as compared to BMI<18.5 (Haile et al., 2016), to primary, secondary or higher-educated mothers as compared to uneducated mothers (Takele et al., 2020), born to mothers with media exposures (Taleke et al., 2022). Furthermore, as the mother’s age increases, there are lower odds of stunting among under-five children (Lindtjørn, 2021).

Based on household characteristics, studies revealed that stunting was negatively associated with improved drinking water and toilets, and with households headed by a person aged 39 years and above compared to those headed by a person aged 38 years and below (Taleke et al., 2022). Furthermore, lower odds of stunting were among children living in households located in urban areas as compared to rural areas and male-headed households (Lindtjørn, 2021; Takele et al., 2020). Unexpectedly, households with severe and moderate food insecurity had lower odds of stunting as compared to households with secure and mild food insecurity (Lindtjørn, 2021). The spatial covariate varied across studies; some studies used zones, while others used regions, districts or enumeration areas. The odds of stunting varied across geographical areas (Takele et al., 2020; Taleke et al., 2022).

METHODS

Data Source

This was a secondary data analysis using the 2004/5, 2010, 2015/16, and 2022 TDHS datasets. The study used the four surveys to assess the consistency of the constructed indices in predicting stunting. The DHS uses a unified methodological approach across years; it obtains a sampling frame and applies two-stage sampling to select households after stratifying study areas into rural/urban in each region. Two-stage sampling begins by selecting primary sampling units (PSUs) from the most recent census enumeration areas (EAs). After selecting PSUs from each stratum using probability proportional to size, a fixed number of households is selected from each PSU using equal-probability systematic sampling. Because each participant has a different probability of participating in the survey, sampling weights are required during analysis. The detailed methodology for the DHS collection and analysis guide is available elsewhere (MoHCDGEC, 2016).

The DHS collects household-level information on men and women of reproductive age who slept in the household the night before the survey. After parents/guardians of eligible children provided consent, the survey collected birth records and anthropometric measurements for both mothers and under-five children. The unit of analysis is the child-mother pair. The survey recruits women aged 15-49 years; their respective under-five-year-old children are interviewed. We merged the household member, household, individual, and child recode datasets for each survey year using unique identifiers. The study included children aged 0-59 months; we excluded children not living with their mothers and those with missing or out-of-range HAZ measurements.

Measurement of Variables

The outcome of interest was stunting, classified as yes if the child’s HAZ score was below – 2.00; otherwise, it was not stunted (WHO, 2006). We selected independent variables based on previous studies, grouped into three categories: child, maternal, and household covariates. Child covariates include sex, age (coded: 0–11, 12–23, 24–35, 36–47, 48–59 months), size at birth (coded: small, medium and large), birth order (Asmare & Agmas, 2022)and diarrhoea status (coded as yes or no). Maternal characteristics included age (Chirande et al., 2015), age at birth, breastfeeding duration, use of ANC services, maternal BMI (coded: below 18.5 and above) (Asmare & Agmas, 2022; Haile et al., 2016), work status and age at first birth (Asmare & Agmas, 2022). Household characteristics included number of under-five children, household size, area of residence (rural/urban), and wealth index (Taleke et al., 2022).

The independent variables of interest were four socio-economic status constructs derived using principal component analysis, as described in the parent study (Musheiguza et al., 2023): Household Wealth Index (HWI); Water and Sanitation, Assets, Maternal education and Income (WAMI); Wealth, Assets, Education, and Occupation (WEO); and the Multidimensional Poverty Index (MPI). These four indices were compared for their predictive capacity, thereby revealing that the WAMI and MPI had better predictive capacity for stunting than other indices depending on the specific survey year under consideration (Musheiguza et al., 2023).

Statistical Analysis

Descriptive analysis

The study summarised the data using frequency distribution tables. The Chi-square test was used to determine independence between groups, and the association was considered statistically significant at the 5% level.

Inferential analysis

Inferential analysis was undertaken using the Bayesian multilevel generalised linear model. We tested the need for multilevel analysis at the second and third levels without independent variables. The second level included enumeration areas, while the third level included both regions and enumeration areas. We compared the models using the Deviance Information Criterion (DIC). The model with the smaller DIC was considered better. Thereafter, independent variables were included in the model starting with the best indicator of SES as determined from the previous study (Musheiguza et al., 2023). Other control variables were added; a variable was retained if the DIC was smaller than that of the previous best model without the variable. Further details of the Bayesian inference and mathematical model specifications are provided below.

Bayesian inference

The Bayesian model uses prior and posterior information to estimate parameters. Prior information is the knowledge known in advance which can be used to update the posterior distribution using Bayes' theorem. Let Y be a random variable for the presence or absence of stunting with density function $f(Y)$. The prior distribution with density function $f(\theta)$ can be used to compute the posterior density $f(\theta|Y)$ (Held & Bové, 2014). There are two main ways to model the random effects in the multilevel Bayesian analysis: a random-intercept model and a random-coefficient model (Mackfallen et al., 2020). This accounts for baseline differences between higher-level units, such as regions. A random-coefficient model allows the intercept and one or more regression coefficients to vary across clusters, so predictor effects can differ from one group to another. The current study analysis adjusted for clustering in the TDHS data by including random effects at the regional and cluster levels but did not estimate random coefficients because the model was specified with random intercepts only, which accounts for variation between clusters in baseline stunting risk. Mathematically, the posterior distribution is defined defined as; $f(\theta \mid Y) = \frac{f(Y|\theta)f(\theta)}{\int f(Y|\theta)f(\theta)\, d\theta}$, where $f(Y \mid \theta)$is the likelihood function.

Thus, the posterior distribution is the product of the likelihood and the density of the prior distribution; $f(\theta \mid Y) \propto L(\theta)f(\theta)$. Because stunting status follows the binomial distribution, the logit link function was used to estimate the odds of stunting. Based on the prior distribution, one can use either the non-informative or the informative priors (Box & Tiao, 1992). Because informative priors may not be accessible, not carefully chosen, or may even be obtained from sources where they are weakly defined, thus leading to biased estimates (Zitzmann, Helm, et al., 2021), weakly diffuse/non-informative prior were preferred in this study. Compared to informative priors, non-informative priors provide a larger number of parameters to be estimated (Zondervan-Zwijnenburg et al., 2017) and have minimal influence on the posterior distribution (Held & Bové, 2014). The study used flat diffuse normal priors with a distribution of (0, 10000) for fixed-effect estimates and inverse-gamma priors for the higher hierarchical orders (hyperparameters) with a distribution of (0.01, 0.01). To update the posterior distribution, we ran 10,000 simulations for each model with a burn-in of 2500. The Bayesian models normally report estimates using the posterior mean and median. However, the estimates may be presented as Bayesian posterior odds ratios (Hicks et al., 2018). Additionally, because of the capability of using prior distributions to update the posterior information, Bayesian models may work in the absence of sampling weights, even for complex survey datasets (Gelman, 2007). Thus, this study used unweighted samples.

Specification of a mathematical model

The weighted and unweighted frequencies were presented in a frequency distribution table. The study used the Chi-Square Test to determine the significance of differences between covariates and stunting status. We used the B-MGLM to evaluate factors associated with stunting. The hierarchical nature of the data was considered, as children living in the same enumeration area or region may share characteristics that influence the risk of stunting. Thus, children were nested in enumeration areas, and enumeration areas were nested in regions. The standard logistic regression model without hierarchy and the two- and three-level hierarchical models were constructed and compared. The hierarchy reflected that enumeration areas were nested within regions. The three models are:

Standard logistic regression: $h(p_{ji}) = \beta_0 + \beta X$

Random effect model: $h(p_{ji}) = \beta_0 + \beta X + \mu_i$

Nested random effect model: $h(p_{jik}) = \beta_i X_{k|j} + \beta_j X + \mu_{k|j} + \mu_i$

Where:

$h(p_{ji})$ is the logit function describing the log odds of stunting for child j living in region i

$h(p_{jik})$ is the logit function describing the log odds of stunting for child j in region i and enumeration area k.

$X's$ are the covariates

$\beta's$ are the regression coefficients

$\beta_j X$ shows the extent to which region affects the slope of X

$\beta_i X_{k|j}$ shows the extent to which enumeration area affects the slope of X in a given similar region

μ_i is the region-specific random effects

$\mu_{k|j}$ is the random effect capturing the variation due to different enumeration areas k within a common region i

The Bayes prefix was used when conducting the B-MGLM; estimates, including coefficients and 95% confidence intervals, were summarised using adjusted odds ratio and the association was deemed statistically significant if the 95% confidence interval did not include 1, being a rule of thumb when estimates are summarized using odds ratio compared to zero when mean estimates are used. All analyses were conducted using STATA version 15.

Ethical considerations

This study used secondary data from the Tanzania Demographic and Health Survey based on four recent surveys (2004/5, 2010, 2015/16 and 2022). The dataset was accessed after an online request and approval for use through the DHS Program website. The data were analysed strictly for academic purposes, in line with the conditions for using DHS data. The study used an anonymised dataset, and the researchers had no direct contact with respondents. Confidentiality and privacy were maintained throughout the analysis, and no new data were collected.

RESULTS

Participants' Demographic Characteristics

Table 1 presents the study participants' demographic characteristics. We revealed that out of 6806 children in TDHS 2010, about 2697 (41.39%) were stunted, 5219 (79.11%) living in rural areas, 1492 (22.31%) aged 0 – 11 months, 3422 (50.3%) females, 4761 (70.11%) had average size at birth, 2587 (56.3%) born to mothers who attended less than 4 ANC visits, 3516 (50.6%) born at home and 4290 (68.2%) born to mothers with primary education. For the case of TDHS 2015/16, the study revealed that out of 8929 children, 2991 (34.1%) were stunted, 6911 (74.13%) lived in rural areas, 2073 (23.4%) aged 12 – 23 months, 4476 (50.8%) were males, 6279 (71.2%) had average size at birth, 3150 (51.6%) born to mothers who attended at least 4 ANC visits, 4976 (61.3) born at health facility and 5368 (64.5%) born to mothers with primary education.

Table 1 Background characteristics of study participant

Variable	TDHS 2004/5 (N = 7492)		TDHS 2010 (N = 6806)		TDHS 2015/16 (N = 8929)		TDHS 2022 (N = 4797)	
	Unweighted n (%)	Weighted %	Unweighted n (%)	Weighted %	Unweighted n (%)	Weighted %	Unweighted n (%)	Weighted %
Stunting								
No	4322 (57.7)	56.2	4109 (60.37)	58.61	5938 (66.5)	65.94	3408 (71.04)	70.35
Yes	3170 (42.3)	43.8	2697 (39.63)	41.39	2991 (33.5)	34.06	1389 (28.96)	29.65
Area of residence								
Urban	2401 (32)	40.5	1587 (23.32)	20.89	2018 (22.6)	25.87	1289 (26.87)	26.84
Rural	5091 (68)	59.5	5219 (76.68)	79.11	6911 (77.4)	74.13	3508 (73.13)	73.16
Child age in months								
0 - 11	1584 (23.3)	23.3	1492 (21.92)	22.31	1980 (22.2)	22.19	1074 (22.39)	21.96
12 - 23	1464 (21.5)	21.9	1467 (21.55)	21.56	2073 (23.2)	23.42	1045 (21.78)	22.09
24 - 35	1377 (20.3)	19.9	1278 (18.78)	18.87	1734 (19.4)	19.19	930 (19.39)	19.02
36 - 47	1201 (17.7)	18.2	1361 (20)	19.67	1579 (17.7)	17.98	881 (18.37)	18.54
48 - 59	1174 (17.3)	16.7	1208 (17.75)	17.6	1563 (17.5)	17.22	867 (18.07)	18.39
Child sex								
Male	3738 (49.9)	49.8	3384 (49.72)	49.7	4476 (50.1)	50.75	2421 (50.47)	50.95
Female	3754 (50.1)	50.2	3422 (50.28)	50.3	4453 (49.9)	49.25	2376 (49.53)	49.05
Child size at birth								
Small	929 (12.4)	11.1	530 (8.05)	8.12	941 (10.61)	9.71	199 (6.90)	7.04
Average	4992 (66.8)	66.5	4761 (72.33)	70.11	6279 (70.8)	71.24	1780 (61.76)	60.61
Large	1548 (20.7)	22.4	1291	21.77	1645 (18.6)	19.06	903 (31.33)	32.36

			(19.61)					
Childbirth order								
First – second order	2958 (39.5)	40.7	2484 (36.5)	38.25	3619 (40.5)	42.27	2013 (41.96)	42.97
Third - fourth order	2037 (27.2)	28	1949 (28.64)	29.14	2400 (26.9)	27.28	1471 (30.66)	31.19
Fifth or more order	2497 (33.3)	31.3	2373 (34.87)	32.61	2910 (32.6)	30.45	1313 (27.37)	25.84
Diarrhea status								
No	5865 (86.3)	86.6	5840 (85.86)	84.84	7838 (87.9)	87.56	4398 (91.76)	91.29
Yes	934 (13.7)	13.4	962 (14.14)	15.16	1084 (12.2)	12.44	395 (8.24)	8.71
Duration of breastfeeding								
< 6 months	1037 (14.4)	14.4	792 (11.84)	12.07	945 (27.2)	27.32	522 (30.62)	30.08
6 – 12 months	1501 (20.8)	20.9	1357 (20.28)	20.21	1134 (32.6)	32.3	552 (32.38)	31.57
13 – 24 months	6079 (56.6)	56.1	3982 (59.52)	59.63	1285 (37)	37.18	589 (34.55)	35.51
25+ months	584 (8.1)	8.6	463 (6.92)	8.09	110 (3.17)	3.19	42 (2.46)	2.84
Sex of household head								
Male	6281 (83.8)	83	5711 (83.91)	83.25	7519 (84.2)	83.33	3710 (77.34)	77.30
Female	1211 (16.2)	17	1095 (16.09)	16.75	1410 (15.8)	16.67	1087 (22.66)	22.70
Age of household head								
<24 years	361 (4.8)	5.1	221 (3.25)	3.51	366 (4.11)	4.38	210 (4.40)	4.63
25 – 30 years	1595 (21.3)	21.9	1219 (17.92)	18.57	1465 (16.4)	16.57	860 (18.01)	19.28
31 – 40 years	2586 (34.6)	33.4	2465 (36.24)	36.78	3066 (34.4)	34.92	1621 (33.94)	35.39
41 – 50 years	1406 (18.8)	18.1	1496 (21.99)	20.94	1983 (22.2)	21.77	1013 (21.21)	20.16
51+ years	1535 (20.5)	21.5	1401 (20.60)	20.19	2035 (22.8)	22.35	1072 (22.45)	20.54
ANC visits								
Below 4 visits	1892 (37.7)	38.5	2587 (55.62)	56.29	3104 (49.6)	48.36	657 (27.17)	26.78
4+ visits	3130 (62.3)	61.5	2064 (44.38)	43.71	3150 (50.4)	51.64	1761 (72.83)	73.22
Place of delivery								
Home	4090 (57.8)	54.6	3519 (51.77)	50.57	3382 (40.5)	38.72	523 (18.29)	18.50
Health facility	2986 (42.2)	45.4	3278 (48.23)	49.43	4976 (59.5)	61.28	2337 (81.71)	81.50
Skilled birth attendant								
No	498 (9)	10.1	268 (3.94)	4.57	2579 (53.6)	56.57	71 (1.48)	1.67
Yes	5056 (91)	89.9	6538 (96.06)	95.43	2232 (46.4)	43.43	4726 (98.52)	98.33
Type of birth								
Normal	7282 (97.4)	97	6501 (95.81)	95.68	8469 (94.9)	94.43	2712 (88.92)	90.29
Caesarean	196 (2.6)	3	284 (4.19)	4.32	460 (5.15)	5.57	338 (11.08)	9.71
Prenatal services by skilled								
No	1317 (26.1)	20.1	647 (13.65)	9.99	5133 (80.3)	81.3	389 (14.12)	14.15
Yes	3727 (73.9)	79.9	4093 (86.35)	90.1	1260 (19.7)	18.7	2365 (85.88)	85.85
Mother's age								
15 – 24	2222 (29.7)	31.4	1842 (27.06)	29.48	2597 (29.1)	30.21	1310 (27.31)	28.33
25 - 34	3634 (48.5)	48.8	3111 (45.71)	45.11	3953 (44.3)	44.2	2180 (45.45)	45.95
35 - 49	1636 (21.8)	19.8	1853 (27.23)	25.41	2379 (26.6)	25.59	1307 (27.25)	25.72
Mother's education								
Uneducated	2088 (27.9)	26.4	1741 (25.58)	25.63	1947 (21.8)	21.42	1033 (21.53)	21.56
Primary	4811 (64.2)	69.4	4290 (63.03)	68.23	5368 (60.1)	64.55	2517 (52.47)	57.83

Secondary	593 (7.9)	4.2	775 (11.39)	6.14	1614 (18.1)	14.03	1247 (26.00)	20.62
Mother's age at first birth								
< 25	6829 (94.4)	94.6	6207 (94.02)	94.79	8046 (92.4)	92.83	4227 (90.26)	91.58
25 - 30	367 (5.1)	4.8	352 (5.33)	4.55	597 (6.9)	6.41	396 (8.46)	7.41
31+	40 (0.5)	0.6	43 (0.65)	0.66	67 (0.77)	0.76	60 (1.28)	1.01
Mother currently working								
No	1309 (17.5)	13.4	1141 (16.78)	13.1	1967 (22)	21.33	1918 (39.98)	40.66
Yes	6182 (82.5)	86.6	5660 (83.22)	86.9	6962 (78)	78.67	2879 (60.02)	59.34
Marital status								
Single	287 (3.8)	4.4	283 (4.16)	4.99	418 (5.7)	5.35	275 (5.73)	6.45
Married	6584 (87.9)	87.4	5937 (87.23)	85.46	7622 (85.4)	84.2	4075 (84.95)	84.36
Separated	621 (8.3)	8.1	586 (8.61)	9.55	889 (9.96)	10.45	447 (9.32)	9.19
Number of births in 3 years								
None	970 (13)	13	1012 (14.87)	14.79	1296 (14.5)	15.63	805 (16.78)	17.67
Once	4990 (66.4)	66.7	4553 (66.9)	67.62	5995 (67.1)	67.42	3275 (68.27)	68.20
Twice or more	1532 (20.4)	20.3	1241 (18.23)	17.59	1638 (18.3)	16.95	717 (14.84)	14.13
Decision making								
Not participate	1036 (13.8)	11.6	4030 (67.93)	65.01	4475 (58.7)	57.52	1601 (39.29)	39.96
Participates	6456 (86.2)	88.4	1903 (32.07)	34.99	3147 (41.3)	42.48	2474 (60.71)	60.04
Mother's BMI (kg/m^2)								
Below 18.5	636 (8.5)	6.9	666 (9.82)	9.25	642 (7.21)	6.92	332 (6.94)	7.31
18.5 – 29.9	5642 (75.8)	78	4793 (70.64)	73.54	5995 (67.4)	68.65	3025 (63.23)	65.87
25+	1161 (15.6)	15.1	1326 (19.54)	17.21	2264 (25.4)	24.43	1427 (29.83)	26.83
Media access								
No	1714 (22.9)	24.8	1740 (25.57)	27.94	1821 (20.4)	19.9	1733 (36.13)	37.41
Yes	5778 (77.1)	75.2	5066 (74.43)	72.07	7108 (79.6)	80.1	3064 (63.87)	62.59
Fever								
No	4900 (72.1)	74.3	5270 (77.51)	75.81	7326 (82.1)	81.3	4284 (89.42)	88.94
Yes	1897 (27.9)	25.7	1529 (22.49)	24.19	1598 (17.9)	18.7	507 (10.58)	11.06
Twin								
No	7178 (95.8)	96.1	6646 (97.65)	97.63	8654 (96.9)	97.01	4663 (97.21)	97.50
Yes	314 (4.2)	3.9	160 (2.25)	2.37	275 (3.08)	2.99	134 (2.79)	2.50

We evaluated the cross-tabulation of stunting status by each of the study variables under consideration; results are presented in Table 2. We revealed that out of 2697 stunted children in TDHS 2010, majority were 660 (53.2%) among aged between 24 -35 months, 1447 (45%) among males, 252 (51%) among born with small size at birth, 982 (40%) among those born to mothers who attended less than 4 ANC visits, 1514 (45%) among those born at home and 756 (45%) among those born to uneducated mothers. Furthermore, the study revealed that, of the 2991 stunted children in 2015/16, majority were; 2491 (37.3%) among those living in rural areas, 739 (45.2%) among those aged 24 – 35 months, 1591 (35.4%) among males, 418 (47%) among those born with small size at birth, 1036 (34%) born to mothers who attended less than 4 ANC visits, 1263 (39%) among those delivered at home and 747 (39%) among those born to uneducated mothers.

Table 2: Distribution of participant characteristics across stunting status

Variable	TDHS 2004/5		TDHS 2010		TDHS 2015/16		TDHS 2022	
	Stunted - yes	p-value	Stunted - yes	p-value	Stunted - yes	p-value	Stunted - yes	p-value
Area of residence								
Urban	1040		643		500 (24.9)		277 (19.58)	

Variable	TDHS 2004/5		TDHS 2010		TDHS 2015/16		TDHS 2022	
	Stunted - yes	p-value	Stunted - yes	p-value	Stunted - yes	p-value	Stunted - yes	p-value
	(41.6)		(41.2)					
Rural	2129 (45.3)	0.0165	2054 (41.44)	0.907	2491 (37.25)	<0.001	1112 (33.34)	<0.001
Child age in months								
0 - 11	668 (43.8)		291 (21.14)		344 (15.93)		200 (17.92)	
12 - 23	616 (43)		700 (49.24)		786 (38.04)		369 (36.32)	
24 - 35	563 (42.6)		660 (53.22)	<0.001	739 (45.22)	0.001	337 (38.50)	<0.001
36 - 47	525 (45.4)		599 (47.69)		629 (40.88)		259 (30.95)	
48 - 59	506 (44.8)	0.6887	447 (37.68)		493 (32.45)		224 (25.18)	
Child sex								
Male	1559 (43.7)		1447 (44.98)		1591 (35.44)		768 (33.33)	
Female	1610 (43.9)	0.8845	1250 (37.83)	0.001	1400 (31.06)	<0.001	621 (25.82)	0.0001
Child size at birth								
Small	369 (43.5)		252 (50.85)		418 (46.98)		98 (46.61)	
Average	2114 (43.4)		1885 (41.4)	0.001	2104 (33.95)	<0.001	494 (29.03)	0.0005
Large	678 (45.3)	0.4764	445 (36.25)		443 (27.72)		256 (28.96)	
Childbirth order								
First – second order	185 (44)		978 (40.51)		1175 (33.38)		577 (29.11)	
Third - fourth order	827 (42.2)		771 (41.12)	0.4214	769 (32.19)	0.013	400 (27.43)	0.0232
Fifth or more order	1057 (45.2)	0.2315	948 (42.65)		1047 (36.67)		412 (33.23)	
Diarrhea status								
No	2475 (43.8)		2303 (41.34)		2611 (33.9)		1272 (29.59)	
Yes	408 (45)	0.5815	393 (41.75)	0.83	377 (35.22)	0.468	117 (30.45)	0.7847
Duration of breastfeeding								
< 6 months	432 (43.6)		144 (19.62)		129 (12.15)		94 (17.34)	
6 – 12 months	627 (43.8)		451 (34.43)	<0.001	229 (19.35)	<0.001	109 (19.70)	<0.001
13 – 24 months	1704 (43.4)		1763 (46.08)		485 (37.72)		209 (37.23)	
25+ months	281 (48)	0.2913	239 (53.6)		49 (50.89)		16 (42.12)	
Sex of household head								
Male	2607 (43)		2252 (41.17)		2477 (33.5)		1101 (30.37)	
Female	562 (48)	0.0021	445 (42.48)	0.553	514 (36.82)	0.041	288 (27.20)	0.1096
Age of household head								
<24 years	171 (48.2)		86 (39.45)		143 (41.27)		71 (34.30)	
25 – 30 years	682 (41.9)		509 (43.09)		541 (37.41)		275 (30.06)	
31 – 40 years	1117 (46.3)		979 (41.6)	0.644	1006 (33)	0.009	462 (30.49)	0.3355
41 – 50 years	550 (41)		606 (41.68)		655 (33.74)		287 (29.43)	
51+ years	646 (43.4)	0.0357	516 (39.49)		642 (32.22)		285 (26.54)	
ANC visits								

Variable	TDHS 2004/5		TDHS 2010		TDHS 2015/16		TDHS 2022	
	Stunted - yes	p-value	Stunted - yes	p-value	Stunted - yes	p-value	Stunted - yes	p-value
<= 4 visits	818 (45)		982 (39.57)		1036 (33.65)		213 (34.64)	
4+ visits	1302 (42.5)	0.1244	756 (38.44)	0.567	942 (30.45)	0.034	454 (26.47)	0.0030
Place of delivery								
Home	1780 (46.1)		1514 (44.73)		1263 (39.42)		172 (36.42)	
Health facility	1279 (41.7)	0.0029	1178 (37.83)	0.0001	1598 (31.36)	<0.001	680 (29.52)	0.0096
Skilled birth attendant								
No	230 (46.9)		106 (36.88)		1002 (40.04)		29 (41.70)	
Yes	2141 (42.8)	0.1416	2591 (41.6)	0.2078	691 (30.99)	<0.001	1360 (29.44)	0.0620
Type of delivery								
Normal	3078 (43.8)		2596 (41.8)		2870 (34.69)		796 (30.41)	
Caesarean	86 (44.9)	0.8084	93 (32.64)	0.016	121 (23.35)	<0.001	110 (32.05)	0.6122
Prenatal services by skilled								
No	525 (43.5)		240 (38.06)		1630 (31.63)		119 (28.97)	
Yes	1601 (43.5)	0.9974	1540 (39.27)	0.661	404 (33.68)	0.271	655 (28.73)	0.9313
Mother's age								
15 – 24	984 (44.8)		743 (41.61)		908 (35.45)		403 (32.56)	
25 - 34	1509 (43)		1183 (39.47)	0.023	1244 (32.09)	0.02	610 (27.40)	0.0280
35 - 49	676 (44.4)	0.5279	771 (44.53)		839 (35.82)		376 (30.46)	
Mother's education								
Uneducated	866 (43.4)		756 (44.65)		747 (39.13)		361 (36.28)	
Primary	2112 (44.6)		1755 (41.96)	<0.001	1868 (34.75)	<0.001	767 (30.51)	<0.001
Secondary	191 (33.4)	0.0057	186 (21.41)		376 (23.13)		261 (20.31)	
Mother's age at first birth								
< 24	2917 (44.1)		2469 (41.4)		2715 (34.31)		1236 (30.15)	
25 - 30	134 (40.5)		131 (37.95)	0.4152	165 (28.68)	0.113	104 (22.46)	
31+	18 (40.5)	0.522	15 (32.13)		20 (29.91)		20 (37.76)	0.0436
Mother currently working								
No	502 (39.2)		367 (36.45)		584 (30.27)		519 (27.78)	
Yes	2667 (44.6)	0.0051	2327 (42.1)	0.0079	2407 (35.08)	0.003	870 (30.93)	0.0966
Marital status								
Single	123 (42.6)		103 (36.23)		139 (31.04)		86 (30.99)	
Married	2777 (43.8)		2342 (41.3)	0.153	2514 (33.67)	0.02	1172 (29.49)	0.8765
Separated	269 (44.8)	0.8350	252 (44.87)		338 (38.72)		131 (30.21)	
Number of births in 3 years								
None	417 (44.2)		404 (41.26)		459 (34.96)		220 (27.95)	

Variable	TDHS 2004/5		TDHS 2010		TDHS 2015/16		TDHS 2022	
	Stunted - yes	p-value	Stunted - yes	p-value	Stunted - yes	p-value	Stunted - yes	p-value
Once	2131 (44.5)		1822 (41.98)	0.3895	2033 (34.76)	0.035	949 (29.54)	0.4195
Twice or more	621 (41.4)	0.1891	471 (39.21)		499 (30.44)		220 (32.28)	
Decision making								
Not participate	432 (44.5)		1599 (41.55)		1512 (34.75)		466 (29.61)	
Participates	2737 (43.8)	0.7548	740 (40.77)	0.6718	1002 (32.21)	0.0849	706 (29.40)	0.9096
Mother's BMI (kg/m^2)								
Below 18.5	257 (44.4)		317 (47.6)		253 (39.38)		90 (27.11)	
18.5 – 29.9	2426 (44.1)		1958 (40.85)	0.448	2136 (36.15)	<0.001	970 (32.86)	<0.001
25+	463 (42.3)	0.6207	415 (31.3)		595 (26.0)		323 (22.44)	
Media access								
No	767 (44.9)		748 (43.67)		697 (38.12)		595 (34.46)	
Yes	2402 (43.5)	0.4983	1949 (40.5)	0.0469	2294 (33.05)	0.0001	794 (26.77)	<0.001
Fever								
No	2080 (43.6)		2079 (41.15)		2411 (33.11)		1246 (29.65)	
Yes	799 (44.7)	0.4438	617 (42.28)	0.5277	578 (38.18)	0.0025	143 (29.99)	0.9109
Twins								
No	3030 (43.6)		2594 (40.83)		2854 (33.6)		1307 (28.76)	
Yes	139 (50.3)	0.0522	103 (64.36)	<0.001	137 (48.98)	0.0002	82 (64.12)	<0.001

Factors associated with stunting

We evaluated stunting factors independently for TDHS 2004/5, 2010, 2015/16, and 2022, as presented in Table 3. Based on child characteristics for TDHS 2010, the study found that female children had 20% lower odds of stunting than males (AOR=0.8; 95% CI: 0.75, 0.84). Children born with average and larger size at birth had 16% [AOR=0.84; 95% CI: 0.79, 0.9] and 29% [AOR=0.71; 95% CI: 0.65, 0.77] lower odds of stunting, compared with children born with small size at birth, respectively. Children born in the second, third, fourth, and above orders had 1 [AOR= 1.1; 95% CI: 1, 1.11] and 1 [AOR=1.1; 95% CI: 1.01, 1.12] times higher odds of stunting as compared to children born in the first order. Other child characteristics associated with higher odds of stunting were duration of breastfeeding, child age, and being born as a twin, while lower odds of stunting were observed among singleton children.

Based on TDHS 2015/16, the study found that female children had 13% [AOR=0.87; 95% CI: 0.8, 0.94] lower odds of stunting than males. Children born at the second-third and at least fourth order had 33% [AOR=0.67; 95% CI: 0.62, 0.72] and 46% [AOR=0.54; 95% CI: 0.49, 0.6] lower odds of stunting, respectively, than children born with small size. Children with diarrhoea had 1.2 [AOR=1.2; 95% CI: 1.06, 1.34] times higher odds of stunting as compared to children without diarrhoea. Furthermore, the study found statistically significantly lower odds of child stunting as the household head ages, while statistically significantly higher odds of stunting as the child ages.

Based on maternal characteristics, using TDHS 2010, children born to a working mother had 1.2 [AOR=1.25; 95% CI: 1.12, 1.38] times higher odds of stunting than children born to non-working mothers. Children born to mothers who were attended by skilled personnel during antenatal visits had 1.01 [AOR=1; 95% CI: 1.01, 1.14] times higher odds of stunting as compared to mothers attended by non-skilled personnel. Children born to mothers aged 25-34 and 35-49 had 17% [AOR=0.83, 95% CI: 0.76, 0.9] and 15% [AOR=0.85, 95% CI: 0.77, 0.96] lower odds of stunting, as compared to children born to mothers aged below 15 years, respectively. Children born to mothers aged 25-30 and at least 31 years at first birth had 1.2 [AOR=1.16; 95% CI: 1.04, 1.26] and 1.12 [AOR=1.12; 95% CI: 1.04, 1.22] times higher odds of stunting as compared to children whose mother's age at first birth was below 15 years. For the TDHS 2015/16, the study revealed that children born to mothers whose age at first birth was 25-30 years had 1.1 [AOR=1.14; 95% CI: 1.05, 1.22] times higher odds of stunting as compared to children born to mothers aged below 25 years at first birth.

Based on household characteristics, the TDHS 2010 study found that for each 1-point increase in WAMI, odds of stunting were 64% lower [AOR=0.36, 95% CI: 0.33, 0.38]. Children born to households with moderate and severe food insecurity had 10% [AOR=0.9; 95% CI: 0.85, 0.95] and 8% [AOR=0.92; 95% CI: 0.84, 0.99] lower odds of stunting as compared to children born to households with secure food. For the TDHS 2015/16, the study found that for each 1-unit increase in the household's MPI, the odds of stunting were 1.1 times higher [AOR=1.1; 95% CI: 1.06, 1.15]. Furthermore, there was 28% [AOR=0.73; 95% CI: 0.66, 0.82], 24% [AOR=0.76; 95% CI: 0.7, 0.83] and 26% [AOR=0.74; 95% CI: 0.65, 0.82] lower odds of stunting among children living in households headed by a person aged 31–40, 41–50, and 51+ as compared to children living in households headed by a person aged <24 years respectively.

For the random effects, the study found that stunting variances differed significantly between regions [AOR= 0.03; 95% CI: 0.01, 0.07] and between clusters [AOR=0.01; 95% CI: 0.002, 0.013]. Regional-specific effects showed statistically significant variability in odds of stunting in the Dodoma region for TDHS 2010. Similar results for statistical significance in variability in odds of stunting were observed for TDHS 2015/16; however, we found no statistically significant regional-specific variability in odds of stunting. We found statistically significant effects at the enumeration area level.

Table 3 B-MGLM estimating the factors associated with stunting

	Survey year			
	2004/5	**2010**	**TDHS 2015/16**	**TDHS 2022**
Factors	**AOR (95% CI)**	**AOR (95% CI)**	**AOR (95% CI)**	**AOR (95% CI)**
A: Fixed factors				
MPI	0.99 [0.9, 1]		1.1 [1.1, 1.2]	
WAMI		0.36 [0.3, 0.4]		0.88 [0.85, 0.92]
Child age in months (reference = 0 – 11)				
12 - 23	1.02 [0.9, 1]	2.02 [1.9, 2.2]	2.39 [2.1, 2.7]	1.91 [1.76, 2.08]
24 - 35	0.97 [0.9, 1]	2.15 [2, 2.3]	3.11 [2.9, 3.4]	1.85 [1.68, 2.02]
36 - 47	1 [1, 1.1]	1.74 [1.7, 1.8]	2.88 [2.5, 3.3]	*Omitted*
48 - 59	1.1 [1, 1.2]	1.46 [1.4, 1.6]	2.32 [2.1, 2.6]	*Omitted*
Child sex (reference = Male)				
Female	1 [0.9, 1]	0.8 [0.8, 0.8]	0.87 [0.8, 0.9]	0.80 [0.73, 0.88]
Child size at birth (reference = Small)				
Average	0.97 [0.9, 1]	0.84 [0.8, 0.9]	0.67 [0.6, 0.7]	0.60 [0.54, 0.66]
Large	0.98 [0.9, 1.1]	0.71 [0.7, 0.8]	0.54 [0.5, 0.6]	0.58 [0.52, 0.63]
Child birth order (reference = First – second)				
Third - fourth		1.05 [1, 1.1]		
Fifth+		1.07 [1, 1.1]		
Diarrhea status (Yes)	1.1 [1, 1.2]		1.2 [1.1, 1.3]	
Birth type (reference = Single)				
Multiple (twins)	0.83 [0.7, 0.9]	1.68 [1.5, 1.9]		2.31 [2.08, 2.53]
Duration of breastfeeding in months (reference = < 6)				
6 – 12	1 [0.9, 1.1]	1.31 [1.2, 1.4]		
13 – 24	0.97 [0.9, 1.1]	1.4 [1.3, 1.5]		
25+ months	1.2 [1.2, 1.3]	1.7 [1.6, 1.8]		
Sex of household head (reference = Male)				
Female	1 [0.9, 1.1]	1.02 [1, 1.1]	1.01 [0.9, 1.1]	0.88 [0.78, 0.98]
Age of household head (reference = <24 years)				
25 – 30 years	0.87 [0.8, 0.9]		0.99 [0.8, 1.1]	1.11 [0.98, 1.25]
31 – 40 years	0.97 [0.9, 1]		0.73 [0.7, 0.8]	1.02 [0.90, 1.15]

Factors	Survey year 2004/5 AOR (95% CI)	2010 AOR (95% CI)	TDHS 2015/16 AOR (95% CI)	TDHS 2022 AOR (95% CI)
41 – 50 years	0.9 [0.8, 0.9]		0.76 [0.7, 0.8]	1.15 [1.02, 1.29]
51+ years	0.94 [0.9, 1]		0.73 [0.7, 0.8]	0.95 [0.80, 1.10]
ANC visits (reference = "Less than 4 visits)				
4+ visits	0.97 [0.9, 1.1]	1 [0.9, 1.1]	0.93 [0.8, 1.1]	0.83 [0.77, 0.91]
Skilled ANC attendant				1.36 [1.12, 1.60]
Place of delivery (reference = Home)				
Health facility	0.99 [0.9, 1.1]	0.94 [0.9, 1]	0.98 [0.9, 1.1]	
Skilled birth attendant (Yes)	1 [0.9, 1.1]		0.92 [0.8, 1]	1.02 [0.86, 1.20]
Type of delivery (reference = Normal)				
Caesarean	0.98 [0.9, 1.1]	0.9 [0.8, 1]	0.98 [0.9, 1.1]	1.21 [1.05, 1.37]
Prenatal services by skilled (Yes)		1.08 [1, 1.1]	1.05 [0.9, 1.2]	
Mother's age (reference = 15 – 24)				
25 - 34		0.83 [0.8, 0.9]	0.94 [0.9, 1.1]	0.99 [0.90, 1.08]
35 - 49		0.85 [0.8, 1]	1.1 [1, 1.2]	0.98 [0.88, 1.08]
Mother's age at first birth (reference = < 24)				
25 - 30	1.04 [1, 1.2]	1.16 [1, 1.3]	1.14 [1.1, 1.2]	1.14 [1.00, 1.32]
31+	1.07 [1, 1.1]	1.12 [1, 1.2]	1.09 [0.9, 1.4]	1.23 [1.10, 1.38]
Mother currently working (Yes)		1.25 [1.1, 1.4]		1.19 [1.07, 1.33]
Decision making (Yes)	1.1 [1, 1.2]		0.98 [0.9, 1.1]	
Number of under-fives (<5s)		1.03 [1, 1.1]		
Number of births	1.08 [1, 1.14]	0.96 [0.9, 1]		
Household size	1 [0.9, 1]	0.99 [0.9, 1]		
Residence area (reference = Urban)				
Rural	1.09 [1, 1.2]	0.97 [0.9, 1]		1.06 [0.95, 1.18]
Access to media (Yes)			0.91 [0.9, 1]	0.99 [0.91, 1.07]
Fever (Yes)	0.94 [0.89, 0.98]		1.09 [1, 1.2]	
B: Random factors				
Variance (region)	0.07 [0.02, 0.14]	0.03 [0.01, 0.067]	0.03 [0.008, 0.075]	0.03 [0.01, 0.07]
Variance (enumeration area)	0.007 [0.003, 0.013]	0.007 [0.002, 0.013]	0.012 [0.003, 0.026]	0.01 [0.00, 0.02]

Key: COR - means Crude Odds Ratio

AOR - means Adjusted Odds Ratio

CI - means credible intervals

* - represents statistical significance at 5% level

Discussion

The study aimed to compare SES indices in predicting stunting, thereby elucidating the association between SES indices and stunting, while controlling for random factors using Bayesian multilevel generalised mixed methods for TDHS 2010 and 2015/16. We formulated simple and complex SES indices using both the score and PCA methods. We formulated the assets index, the WAMI, WEO, and MPI indices, with the latter being more complex than the others. The study found that PCA methods are more robust than score methods. Furthermore, indices constructed using the RF approach showed stronger predictive power for stunting than when assets are not selected based on the outcome under consideration.

The study found that WAMI and MPI had better predictive capacity for stunting than HWI for the TDHS 2010 and 2015/16, respectively. These findings are similar to a multicountry study conducted in Africa (Psaki et al., 2014).

After controlling for other variables, the study found that for each unit increase in WAMI, odds of stunting decrease. These results are similar to a multicountry study (Psaki et al., 2014), being supported by the ability of educated mothers to have, better health-seeking behaviour, feeding practices and decision-making power (Taleke et al., 2022). The role of safe water and sanitation facilities in reducing contamination and the outbreak of diseases through repeated episodes of diarrhoea, which further hinders child food intake and absorption (Joseph et al., 2019) should be acknowledged. Furthermore, households with safe water and sanitation and educated mothers may have higher purchasing power and, therefore, better access to nutritious foods, which are the backbone of child growth.

It should be considered that WAMI and MPI are similar, although they work in different directions, and that MPI is more comprehensive because it includes additional variables such as maternal nutrition status and under-five deaths in a household. The findings that for each score increase in MPI, the odds of stunting increase are underlined by other studies, which revealed that poor water and toilet facilities increase stunting, poor maternal nutrition as measured by BMI (Haile et al., 2016) and children born to uneducated mothers (Abeway et al., 2018; Takele et al., 2020) are prone to stunting. Furthermore, higher values of MPI imply the presence of poor water and toilet facilities, which in turn are associated with communicable diseases like diarrhoea (Joseph et al., 2019) as explained above.

Based on child characteristics, the study found lower odds of stunting among female children than among male children. These findings are similar to those of other scholars in different countries and multi-country studies (Taleke et al., 2022). The agreement of findings from this study and others might be attributable to the fact that, mostly, males undergo preterm births as compared to females, which hinder early breastfeeding and hence untimely growth (Hansen Pupp et al., 2004). Preterm births require initial respiratory and circulatory support. Furthermore, male children are affected by acute respiratory tract infections and diarrhoea as compared to females (Fink et al., 2011). Contrary to the findings of the current study, the study conducted in Northern Ethiopia (Abeway et al., 2018) reported that females had higher odds of stunting than males. The observed differences may be due to methodological differences, as the study by Abeway et al. (2018) was a community–based cross–sectional study conducted in one district; the results lack generalizability.

The study found that children aged above 11 months (in their corresponding age categories) had higher odds of stunting than children aged below 11 months. These findings were in agreement with another study conducted in Bangladesh (Das et al., 2022). These findings are in support of the fact that as the child ages, he/she increases body movements and starts to crawl and walk, thereby increasing the possibility of contamination with germs (Prüss-Üstün et al., 2008). If a child lives in poorly sanitised areas, he/she may eat whatever comes their way, increasing the likelihood of infections. Another finding was that children suffering from diarrhoea had higher odds of stunting is underlined by other country and multi-country studies (Taleke et al., 2022). The justification is that a child suffering from diarrhoea has poor appetite and a lower amount of food intake, malabsorption and hence loss of nutrients needed for growth and development (Martorell et al., 1980).

This study also revealed that children with medium/average and larger size at birth had lower odds of stunting than children born with smaller size. These findings were consistent with other studies (Takele et al., 2020). The observed consistency might be due to the fact that a mother's good nutrition status and better health during pregnancy facilitate child intrauterine growth, and that small size at birth is normally associated with different morbidities like diarrhoea and acute febrile illness, which hinder child linear growth (Adedokun & Yaya, 2020). In this manner, children with small size are prone to poor growth outcomes compared with their counterparts. Furthermore, the study findings that children born at the second to third and fourth orders had higher odds of stunting as compared to children born to the first order were consistent with other studies (Takele et al., 2020).

The current study findings that children born at an interval of 24-47 and at least 48 months and above had lower odds of stunting as compared to children born at an interval of less than 24 months were consistent with other studies (Takele et al., 2020). The observed similarity might be due to the fact that the shorter birth intervals undermine the mother's body resettlement and intrauterine growth, as well as womb readiness to carry a new pregnancy (Dewey & Cohen, 2007). The findings that children born to working mothers had higher odds of stunting as compared to non-working mothers were consistent with other scholars (Glenn et al., 2022) but contrary to other scholars (Kedir et al., 2022). This consistency may be because working mothers do not have enough time to care for their children; most child-rearing activities are left to relatives and house girls. Thus, a child lacks enough breastfeeding, which is paramount for child growth and survival (Jahanpour et al., 2022).

The findings that children born to mothers aged 25 – 34 and 35-49 years had lower odds of stunting as compared to children born to mothers aged below 25 years were contrary to other studies (Taleke et al., 2022). These findings may imply that as the mother ages, she gets enough experience of child caring and rearing and hence provides all requirements and accurate responsibility for child growth and survival. Furthermore, the study findings that twins had higher odds of stunting as compared to single births were consistent with other studies (Taleke et al., 2022). The fact that multiple births are associated with preterm births, perinatal as well as neonatal morbidities (Ananth & Chauhan, 2012) which in turn hinders child linear growth.

Based on the random effects model, the study found that variances in odds of stunting were statistically significant between enumeration areas. These findings are consistent with other studies (Takele et al., 2020; Taleke et al., 2022) who reported significant variability in stunting across geographical areas.

CONCLUSION

Stunting is still a major problem in Tanzania, varying significantly across regions and enumeration areas. The fact that individual child, maternal and household characteristics influencing child stunting are known still alarms us about the possibility of designing interventions which may reach each individual. Contextual factors, driven by social and cultural norms related to stunting, emphasise the need to design well-targeted interventions that are specific to particular regions and enumeration areas. Initiatives should focus on ensuring safe water, sanitation facilities, maternal education, and housing facilities are in place in lower administrative areas.

Furthermore, household wealth assets, including dwellings, should be a critical factor in improving the living environment for under-fives. The observed contextual factors associated with stunting call for further studies, principally aimed at exploring spatial variability in stunting at lower administrative levels such as enumeration areas and districts. The results align with parent–offspring conflict theory, life history theory, and the ecological model. This study emphasises that other researchers use these theories and that the WAMI showed a consistent negative relationship with stunting, hence revealing it as an important intervention towards reducing stunting by 2030.

The current study has several strengths: it provides concrete estimates because of its sufficient sample size and larger DHS datasets, which are generalizable to Tanzania as a whole, compared with Psaki et al. (2014), an area-based study with limited generalizability. Second, the study shows that SES is truly multidimensional, and its effect on stunting varies over time. Instead of using the common measure of SES across different health outcomes over time, a corresponding SES index associated with stunting should be established, as SES indicators vary over time. Lastly, the study accounted for correlation between observations and quantified contextual factors associated with stunting using Bayesian multilevel generalised mixed regression models.

Despite these strengths, the study was limited in causal inference and was subject to self-report bias, as the DHS is typically cross-sectional; thus, we could not establish a causal relationship (Savitz & Wellenius, 2022) between stunting and the independent variables considered. Furthermore, most research questions, such as birth size and fever and diarrhoea status, are self-reported, which increases the chance of biased estimates (Rosenman & Tennekoon, 2011). Furthermore, self-reported answers are prone to misclassification bias (Althubaiti, 2016); however, they have been used in various studies. Further studies should investigate the spatial and spatio-temporal effects of these SES indicators to account for space and time, given the shifting trend of stunting over time. To end all forms of malnutrition, including wasting and underweight, by 2030, multivariate models may provide promising evidence for developing targeted interventions by identifying overlapping factors.

ACKNOWLEDGEMENTS

We acknowledge the DHS efforts to ensure these large datasets are freely available to researchers and academicians.

CONFLICT OF INTEREST

The authors have no financial, non-financial, or competing interests relating to this paper.

AUTHOR’S CONTRIBUTION

EM designed the study, downloaded the dataset from the DHS Measure website, and conducted statistical analysis and manuscript writing. TM and JM provided guidance from study design through analysis and manuscript write-up.

DATA AVAILABILITY

The dataset is freely available from the DHS website at http://www.dhsprogram.com/data/dataset_admin/login_main.cfm

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