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Assessing the Effect of Anaemia Severity on Child Stunting in Malawi using a Generalised Propensity Score Method

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Abstract

Child stunting remains a significant public health challenge in Malawi, reflecting chronic undernutrition in the country. It is among the areas of focus for the 2030 Global Nutrition Targets and the Sustainable Development Goals. Understanding drivers of child stunting help decision makers in aligned implementation of relevant interventions. Thus, this study aimed to assess the causal effect of anemia severity on child stunting in Malawi. Data of 4080 children aged 6 to 59 months was drawn from the 2024 Malawi Demographic and Health Survey. Stunting was defined as a height-for-age z-score below -2 standard deviations, and anaemia was classified as not anaemic, mild, or moderate/severe. The prevalence of stunting among children was 36.9%. Generalised propensity scores were used to match children across anemia categories. Propensity scores were estimated using multinomial logistic regression, and inverse propensity weights were applied to adjust for socio-demographic and socio-economic differences across anaemia categories. The graphical balance assessment showed an improvement in covariate balance after weighting, with absolute standardised differences for Occupation, ethnicity, age, religion, sex, household size, and educational residence falling below 0.1. Weighted logistic regression results indicated that children with moderate/severe anaemia had 30.7% higher odds of being stunted (AOR = 1.307, 95% CI: 1.116–1.532), compared to non-anaemic children, whereas mild anaemia remains non-significant. Sensitivity analysis using E-values suggested that moderate/severe anaemia had a relatively robust association with stunting (E-value = 1.317). These findings highlight the importance of integrated interventions that address anaemia and child undernutrition to reduce the burden of stunting in Malawi.

Keywords: Anaemia, Child stunting, Propensity score weighting, Causal inference

1 Introduction

Child stunting remains a major global public health challenge, affecting approximately 148 million children under five years of age (22%) in 2023 and contributing to impaired cognitive development, poor educational attainment, reduced economic productivity, and increased risks of morbidity and mortality [1–4]. Despite global efforts, progress towards achieving Sustainable Development Goal (SDG) 2.2 has been uneven, particularly in low- and middle-income countries [2, 5]. Sub-Saharan Africa bears more than 30% of the global burden of child stunting [3]. In Malawi, the prevalence of child stunting declined from 47% in 2010 to 37% in 2021 but increased slightly to approximately 38% in 2024, indicating stalled progress despite previous gains [6, 7]. Child stunting is driven by multiple interrelated factors, including food insecurity, inadequate dietary diversity, recurrent climate shocks, socioeconomic disadvantage, and poor health outcomes [8, 9].

Among these factors, anaemia is an important contributor to impaired child growth and development [10, 11]. Anaemia is defined as a haemoglobin (Hb) concentration below 11 g/dL among children aged 6–59 months, resulting in reduced oxygen-carrying capacity to body tissues and organs [12]. In Malawi, anaemia remains a major public health concern. The 2024 Malawi Demographic and Health Survey reported that approximately 56% of children aged 6–59 months were anaemic, representing only a modest decline from 63% reported in the 2015–16 survey [6, 7]. Given the persistently high burden of both anaemia and child stunting in Malawi, understanding their relationship is critical for informing integrated nutrition and child health interventions.

Numerous studies have reported a significant association between anaemia and child stunting, with anaemic children being more likely to experience impaired linear growth than their non-anaemic counterparts [13–16]. However, achieving SDG 2.2 requires evidence-based interventions informed by causal rather than associative evidence. While randomized controlled trials (RCTs) are the gold standard for estimating causal effects, they are often impractical or unethical for evaluating conditions such as childhood anaemia [17–19]. Consequently, researchers rely on observational data, where anaemia and child stunting share several common determinants—including socioeconomic disadvantage, poor nutrition, recurrent infections, and limited healthcare access—that may confound the estimated relationship [20–25]. As a result, conventional analyses that estimate associations may yield biased estimates of the causal effect of anaemia on child stunting.

Causal inference methods, particularly propensity score (PS) approaches, are widely used to estimate causal effects from observational data by reducing confounding through balancing observed covariates across exposure groups [19, 26, 27]. However, the traditional PS is designed for binary exposures, whereas anaemia is a multi-level condition classified as mild, moderate, and severe according to haemoglobin concentration [12]. Consequently, dichotomising anaemia into anaemic and non-anaemic groups

may obscure differences in risk across severity levels and potential dose–response relationships [28–31]. To address this limitation, [32] introduced the generalized propensity score (GPS), which balances observed covariates across multiple exposure levels to facilitate causal effect estimation [17, 32]. Despite its methodological advantages, the application of GPS to estimate the causal effect of anaemia severity on child stunting remains limited. Therefore, this study estimates the causal effect of anaemia severity on child stunting among Malawian children using a generalized propensity score approach.

2 Data and Methods

2.1 Data

This study utilized data from the 2024 Malawi Demographic and Health Survey (MDHS), conducted by the National Statistical Office. The 2024 MDHS represents the sixth Demographic and Health Survey implemented in Malawi and employed a nationally representative, stratified two-stage cluster sampling design. A total of 792 clusters and approximately 23,760 households were selected for the survey. Within a subsample comprising every second household selected for the women’s survey, all men aged 15–54 years who were usual residents or who spent the night preceding the survey in the selected households were eligible for interview. In the same subsample, all children under five years of age were eligible for height and weight measurements as well as anaemia testing. The survey provides nationally representative estimates for both urban and rural populations across all 28 districts of Malawi.

2.2 Study Variables

The primary outcome was child stunting, defined as a binary variable based on the height-for-age z-score (HAZ). Children with a HAZ below -2 standard deviations from the 2006 WHO Child Growth Standards reference population [33] were classified as stunted ($Y = 1$). While those with a HAZ of at least -2 standard deviations were classified as not stunted $Y = 0$ for not stunted. The primary exposure variable was anaemia severity, categorized into three levels: $T = 0$ (not anaemic), $T = 1$ (mild), and $T = 2$ (moderate/severe anaemia). Potential confounders included household size, maternal education (none, primary, secondary, or tertiary), parental occupation, ethnicity, maternal age, child’s sex (male or female), religion (none, Christian, or Muslim), region (Northern, Central, or Southern), and place of residence (urban or rural). Potential confounders were selected a priori based on previous literature and subject-matter knowledge.

2.3 Unadjusted Outcome Model

To examine the association between anaemia severity and child stunting before adjusting for confounders, a logistic regression model was first estimated as:

$$\log \left(\frac{P(Y = 1)}{P(Y = 0)} \right) = \beta_0 + \beta_1 T_1 + \beta_2 T_2 + \beta_3 T_3 + \beta_4^\top \mathbf{X}, \quad (1)$$

where Y is the binary stunting outcome, T_1 , T_2 , and T_3 are dummy indicators for not anaemic, mild, and moderate/severe anaemia (with not anaemic as reference), and $\mathbf{X}$ represents the vector of covariates.

2.4 Inverse Probability Weighting (IPW)

Treatment assignment in this study was not random, making confounding a potential source of bias when estimating the effect of anaemia on stunting. Although PS works well with binary treatments, the problem arises with multiple treatments, because this method cannot adequately balance covariates across multiple treatment levels. To address this problem, [32] developed the concept of generalized PS for applications in which the number of treatments exceeds two. Unlike the conventional PS, the GPS gives several estimated probabilities for different treatment conditions.

In this study, anaemia status comprised three categories (non-anaemic, mild, moderate/severe anaemia). Consequently, generalized propensity scores were estimated using a multinomial logistic regression model, where the probability of belonging to each anaemia category was modelled as a function of the observed covariates. The generalized propensity score is defined as;

$$e_t(X_i) = P(T = t | X_i) = \hat{e}_t(X_i) = P(T_i = t | X_i) = \frac{\exp(\beta_t + \mathbf{X}_i^\top \mathbf{T}_t)}{\sum_{k=1}^K \exp(\beta_k + \mathbf{X}_i^\top \mathbf{T}_k)}, \quad (2)$$

where $e_t(X_i)$ is the probability that child i belongs to treatment level t , and X_i is the vector of observed covariates. The estimated GPS were then used to construct inverse probability weights (IPW). Each child was weighted by the inverse of the probability of receiving the anaemia category that they actually experienced,

$$w_i = \frac{1}{e_{T_i}(X_i)}. \quad (3)$$

These weights create a pseudo-population in which baseline covariates are balanced across anaemia levels, like in a randomized experiment [34].

2.5 Covariate Balance Assessment

$$SMD = \frac{\bar{X}_t - \bar{X}_c}{\sqrt{\frac{s_t^2 + s_c^2}{2}}}, \quad (4)$$

where $\bar{X}_t$ and $\bar{X}_c$ represent the means of a given covariate in the treatment and control groups, respectively, and s_t^2 and s_c^2 are their corresponding variances. For categorical variables, balance was assessed by comparing group proportions using the following formula:

$$SPD = \frac{p_t - p_c}{\sqrt{\frac{p_t(1-p_t) + p_c(1-p_c)}{2}}}, \quad (5)$$

where p_t and p_c denote the proportions of individuals with the given characteristic in the treatment and control groups, respectively. An absolute SMD value of less than

0.1 was considered indicative of adequate covariate balance between treatment groups. Additionally, propensity score overlap was examined using boxplots. Adequate overlap indicates that every individual has a non-zero probability of receiving each treatment level, satisfying the positivity assumption.

2.6 Weighted Outcome Model

After confirming covariate balance, a weighted logistic regression model was estimated to assess the effect of anaemia severity on child stunting:

$$\log \left(\frac{P(Y = 1 | T)}{1 - P(Y = 1 | T)} \right) = \beta_0 + \beta_1 T_1 + \beta_2 T_2 + \beta_3 T_3, \quad (6)$$

where the model was fitted using inverse probability weights to produce unbiased treatment effect estimates. Results were reported as odds ratios (ORs) with 95% confidence intervals (CIs). All analyses were performed in **R version 4.5.1** using the **glm**, **mnp** (from the **twang** package), and **svyglm** (from the **survey** package) functions.

3 Results

3.1 Data summary

Table 1 presents the distribution of socio-demographic and health characteristics by stunting status among children. The total number of children sampled from the 2024 MDHS for analysis was 4,080. Overall, 40.0% of the children were classified as stunted. Anaemia status was strongly associated with stunting ($p < 0.001$). The proportion of stunted children increased with anaemia severity, ranging from 34.9% among those not anaemic to 36.3% and 42.1% among those with moderate/severe anaemia, respectively. Household size, however, did not show a statistically significant association with stunting ($p=0.287$), although a slight increase in stunting was observed in larger households.

Child sex and place of residence were significantly associated with stunting. Male children showed a higher prevalence of stunting (39.6%) compared to females (34.3%) ($p<0.001$). Similarly, children residing in rural areas had a higher likelihood of being stunted (38.0%) compared to their urban counterparts (32.0%) ($p = 0.003$). Regional differences were also evident ($p < 0.001$), with the Southern region recording the highest prevalence of stunting (39.6%), followed by the Central region (38.3%), while the Northern region had the lowest (29.7%).

Ethnicity and religion were both significantly associated with stunting. Children from the Lomwe/Yao/Sena ethnic group had the highest prevalence of stunting (40.3%), whereas those from Tumbuka/Tonga/other groups had comparatively lower levels (33.0%) ($p < 0.001$). In terms of religion, children from Muslim households had a higher prevalence of stunting (42.1%) compared to Christians (36.1%), with the highest levels observed among those reporting no religion or other affiliations (51.3%) ($p = 0.006$).

Parental education showed a strong inverse relationship with stunting ($p < 0.001$). Children of parents with no education had the highest prevalence (44.7%), which

progressively declined with increasing education level, reaching the lowest among those with tertiary education (19.3%). In contrast, working status of the parent was not significantly associated with stunting ($p = 0.708$), as similar proportions were observed between working and non-working groups. The mean maternal age was 28.5 years (SD = 7.06).

3.2 Outcome analysis without the use of propensity scores

In the first step, outcome analysis was done without the use of propensity scores. The two logistic regression tables present the association between anaemia levels and child stunting, with Table 2 showing an unadjusted model that only examines the relationship between anaemia and stunting, and Table 3 showing an adjusted model that includes several confounding variables.

The unadjusted model (Table 2) showed that children with moderate or severe anaemia had significantly higher odds of being stunted compared to non-anaemic children (OR = 1.355, 95% CI: 1.159–1.582, $p < 0.001$), while mild anaemia was not significantly associated with stunting ($p = 0.467$). These estimates, however, do not account for potential confounding factors such as parent education level, residence, and regional differences.

After adjusting for confounders in the multivariable model (Table 3), the odds ratios for all anaemia levels decrease slightly but remain generally consistent in direction. moderate/severe anaemia remained a significant predictor of stunting (AOR = 1.307, 95% CI: 1.115–1.530, $p = 0.001$), whereas mild anaemia continued to show no significant association. The adjusted model also highlights the importance of other predictors of stunting. Male children had higher odds of being stunted compared to females (AOR = 1.242, $p = 0.001$). In contrast, residing in the Northern region was associated with lower odds of stunting (AOR = 0.737, $p = 0.003$). Higher maternal education demonstrated a strong protective effect, with secondary (AOR = 0.568, $p < 0.001$) and tertiary education (AOR = 0.344, $p = 0.001$) significantly reducing the likelihood of stunting. Additionally, increasing maternal age was associated with a slight reduction in the odds of stunting (AOR = 0.989, $p = 0.033$). Other factors, including residence, ethnicity, religion, and maternal employment status, were not statistically significant.

3.3 Estimating the Weights Results

After estimating propensity scores, the study computed Inverse Probability Weights (IPW) using a multinomial logistic regression model to adjust for differences in treatment assignment across children with anaemia. Weights were derived by taking the inverse of the probability of treatment group membership. A key diagnostic step involved assessing the balance of covariate distributions across treatment groups through graphical evaluation. The covariate balance plot (Figure 1) showed absolute standardized differences before (in red) and after (in blue) applying IPW, highlighting considerable imbalances pre-adjustment, particularly for covariate such as age, which exceeded the 0.1 threshold. Post-adjustment, all covariates fell below this threshold, indicating improved balance.

Table 1: Distribution of Children Stunting by Socio-demographic and Socio-economic Characteristics in Malawi

Characteristic	Not Stunted n (%)	Stunted n (%)	Overall Total n (%)	χ^2 -p-val
Overall Sample	2572 (63.1)	1508 (36.9)	4080 (100)	
Anaemia status				< 0.001
Not anaemic	1372 (65.1)	736 (34.9)	2108 (51.7)	
Mild	633 (63.7)	360 (36.3)	993 (24.3)	
Moderate/Severe	567 (57.9)	412 (42.1)	979 (24.0)	
Household members				0.287
≤5	1651 (63.9)	933 (36.1)	2584 (63.3)	
6–10	868 (61.7)	538 (38.3)	1406 (34.5)	
≥11	53 (58.9)	37 (41.1)	90 (2.2)	
Sex				< 0.001
Female	1346 (65.7)	704 (34.3)	2050 (50.2)	
Male	1226 (60.4)	804 (39.6)	2030 (49.8)	
Residence				0.003
Rural	2088 (62.0)	1280 (38.0)	3368 (82.5)	
Urban	484 (68.0)	228 (32.0)	712 (17.5)	
Region				< 0.001
Central	886 (61.7)	549 (38.3)	1435 (35.2)	
Northern	634 (70.3)	268 (29.7)	902 (22.1)	
Southern	1052 (60.4)	691 (39.6)	1743 (42.7)	
Ethnicity				< 0.001
Chewa/Ngoni	787 (62.5)	473 (37.5)	1260 (30.9)	
Lomwe/Yao/Sena	853 (59.7)	576 (40.3)	1429 (35.0)	
Tumbuka/Tonga/other	932 (67.0)	459 (33.0)	1391 (34.1)	
Religion				0.006
Christian	2257 (63.9)	1273 (36.1)	3530 (86.5)	
Muslim	296 (57.9)	215 (42.1)	511 (12.5)	
None/Other	19 (48.7)	20 (51.3)	39 (1.0)	
Education				< 0.001
No education	166 (55.3)	134 (44.7)	300 (7.4)	
Primary	1613 (60.4)	1056 (39.6)	2669 (65.4)	
Secondary	726 (70.6)	302 (29.4)	1028 (25.2)	
Tertiary	67 (80.7)	16 (19.3)	83 (2.0)	
Working status				0.708
Not working	1233 (63.4)	713 (36.6)	1946 (47.7)	
Working	1339 (62.7)	795 (37.3)	2134 (52.3)	
Parent's Age				
Mean (SD)	28.6 (7.02)	28.3 (7.14)	28.5 (7.06)	

The overlap of propensity score distributions was used to assess the positivity assumption. Figure 2 shows a lot of overlap, which means that the groups probably have a lot of common support. For the non-anemic propensity scores, the median values are fairly similar across all treatment categories. The central values are a little higher in the non-anemic group, but the interquartile ranges overlap and the spread is

Table 2: Pre-analysis assessment of the balance for a categorical (Child Stunting) variable

Predictors	Odds Ratios	Std. Error	95% CI	p-value
Intercept	0.536	0.025	0.490 – 0.586	< 0.001
Anaemia Level				
Not anaemic*				
Mild	1.060	0.085	0.905 – 1.240	0.467
Moderate/Severe	1.355	0.107	1.159 – 1.582	< 0.001

similar. A similar trend is seen in the mild propensity scores, where the medians and distributions of all three groups are very close to each other. This means that people in all three groups have similar chances of being classified as mildly anaemic based on the covariates that were observed. For the moderate/severe propensity scores, the moderate/severe group has a central tendency that is a little higher than the other groups, but the distributions still overlap a lot.

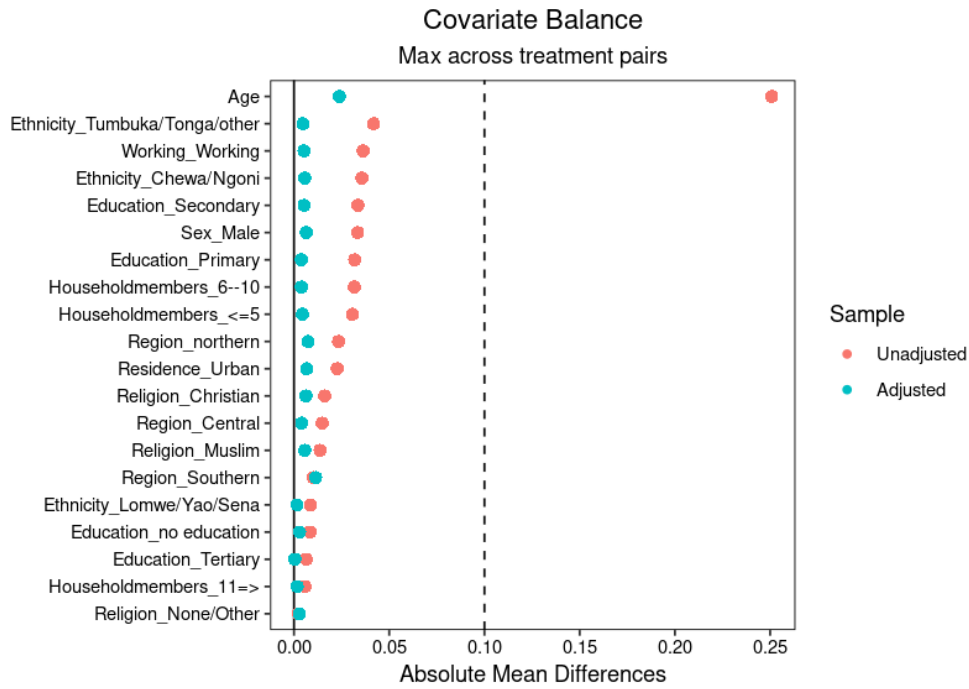


Fig. 1: Absolute standardised differences for before and after balancing the covariates.

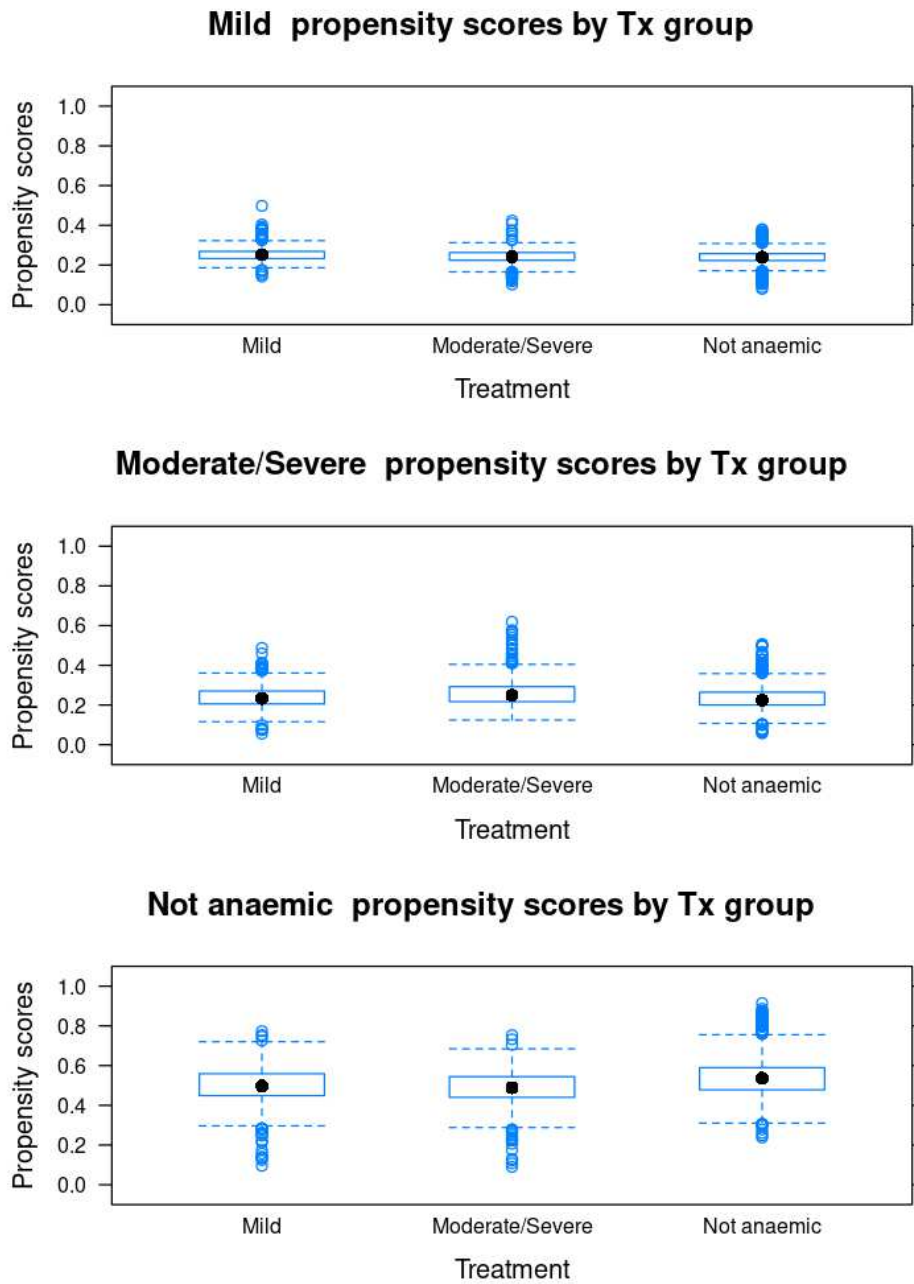


Fig. 2: Overlap Assessment. Each panel presents box plots by treatment group of the estimated propensity scores for one of the treatments.

Table 3: Multivariable Logistic Regression Results for Factors Associated with Stunting

Predictors	Odds Ratios	Std. Error	95% CI	p-value
Intercept	0.823	0.174	0.543–1.245	0.357
Anaemia Level				
Not anaemic*				
Mild	1.031	0.084	0.878–1.209	0.709
Moderate/Severe	1.307	0.105	1.115–1.530	0.001
Household size				
≤5				
6–10	1.155	0.086	0.999–1.336	0.052
≥11	1.310	0.291	0.842–2.018	0.224
Sex				
Female*				
Male	1.242	0.082	1.091–1.413	0.001
Residence				
Rural*				
Urban	0.935	0.087	0.779–1.121	0.472
Region				
Central*				
Northern	0.737	0.075	0.603–0.900	0.003
Southern	0.976	0.101	0.797–1.194	0.815
Ethnicity				
Chewa/Ngoni*				
Lomwe/Yao/Sena	1.128	0.127	0.905–1.406	0.283
Tumbuka/Tonga/Other	0.996	0.092	0.831–1.193	0.963
Religion				
Christian*				
Muslim	1.082	0.112	0.883–1.324	0.445
None/Other	1.607	0.524	0.845–3.067	0.146
Education				
No education*				
Primary	0.841	0.107	0.656–1.079	0.172
Secondary	0.568	0.081	0.430–0.750	0.001
Tertiary	0.344	0.106	0.183–0.616	0.001
Working				
No Working*				
Working	1.051	0.070	0.922–1.197	0.459
Respondent's age	0.989	0.005	0.980–0.999	0.033

3.4 Balance analysis after implementing propensity scores

Table 4 presents the results of the balance assessment after applying propensity score weights estimated through logistic regression. Following the application of propensity score weighting to improve covariate balance, the results remain largely consistent. However, the magnitude and statistical significance of the associations were generally reduced relative to the unweighted (Table 2) results. In the weighted analysis,

moderate/severe anaemia continues to be significantly associated with increased odds of stunting (OR = 1.307, 95% CI: 1.116–1.532, $p = 0.001$), whereas mild anaemia remains non-significant (OR = 1.030, $p = 0.717$). The similarity between unweighted and weighted estimates suggests that baseline imbalances in observed covariates had limited influence on the association. endfor

Table 4: Post-weighting balance assessment using propensity score weights estimated via logistic regression

Predictors	Odds Ratio	Std. Error	95% CI	p-value
Intercept	0.549	0.025	0.501 – 0.601	< 0.001
Anaemia Level				
Not anaemic*				
Mild	1.030	0.083	0.879 – 1.207	0.717
Moderate/Severe	1.307	0.106	1.116 – 1.532	0.001

3.5 Sensitivity analyses

The E-value sensitivity analysis was conducted to assess the robustness of the observed associations to potential unmeasured confounding. The findings indicate that the association between mild anaemia and child stunting was weak and highly sensitive to unmeasured confounding (OR = 1.170; 95% CI: 1.001–1.367; E-value = 1.14; lower CI E-value = 1.00), suggesting that even a very small unmeasured confounder could explain away this effect. In contrast, moderate/severe anaemia was significantly associated with increased odds of stunting (OR = 1.317; 95% CI: 1.140–1.521), and this relationship was more robust to unmeasured confounding (E-value = 1.55; lower CI E-value = 1.30). This implies that a moderately strong unmeasured confounder would be required to fully attenuate the observed association.

Table 5: E-value sensitivity analysis for the association between anaemia level and child stunting

Anaemia Level	OR	95% CI	E-value (Point)	E-value (Lower CI)
Not anaemic*	–	–	–	–
Mild	1.170	1.001–1.367	1.137	1.000
Moderate/Severe	1.317	1.140–1.521	1.548	1.301

507 4 Discussion

508
509 The study set out to assess the causal association between anaemia severity and child
510 stunting in Malawi using data from the 2024 MDHS. The findings reveal a clear
511 gradient where the prevalence and odds of stunting increase alongside the severity of
512 anaemia. These results align with broader nutritional literature indicating that chronic
513 iron deficiency and functional anaemia often coexist with the long-term nutritional
514 deficits that lead to linear growth faltering[4, 8, 10, 12].

515 The results align with previous research emphasizing the need for integrated inter-
516 ventions to address both the biological and socio-economic drivers of stunting. Studies
517 by Clark et al. [35] and UNICEF 2020 [36] advocate for comprehensive programs com-
518 bining iron supplementation, deworming, malaria prevention, and improved dietary
519 practices with poverty reduction and maternal education initiatives. The slight reduc-
520 tion in odds ratios after weighting underscores the importance of tackling underlying
521 socio-economic disparities. For instance, Ekholuenetale et al. [37] found that chil-
522 dren from wealthier households or those with more educated mothers had lower risks
523 of both anaemia and stunting, supporting the idea that structural factors must be
524 addressed. A significant strength of the study was the application of Inverse Probability
525 Weighting (IPW) to account for baseline imbalances in socio-demographic and health
526 characteristics. Before weighting, significant differences were observed across anaemia
527 groups regarding child parents age. The propensity score weighting successfully bal-
528 anced these covariates, as evidenced by all absolute standardized differences falling
529 below the recommended threshold [17, 19, 26]. The substantial overlap in propen-
530 sity score distributions provides further assurance that the positivity assumption was
531 satisfied, supporting valid estimation of average treatment effects. [27, 38]

532 The consistency of the findings across the unadjusted, multivariable-adjusted,
533 and inverse probability weighting (IPW)-weighted models provides some reassur-
534 ance regarding the observed association between anaemia and stunting. In the
535 IPW-weighted analysis, moderate/severe anaemia remained significantly associated
536 with stunting, whereas no statistically significant association was observed for mild
537 anaemia. The similarity of the estimates across conventional regression adjustment
538 and propensity score weighting suggests that the association between moderate/severe
539 anaemia and stunting was not substantially altered by adjustment for the measured
540 socioeconomic and regional characteristics available in the 2024 MDHS.

541 Nevertheless, the E-value analysis highlights an important distinction in the
542 strength of evidence across anaemia categories [39, 40]. The greater sensitivity of
543 the mild anaemia association to potential unmeasured confounding suggests that this
544 finding should be interpreted cautiously. In contrast, the moderate/severe anaemia
545 association appears less sensitive to residual confounding, although the possibility of
546 bias from unmeasured factors cannot be excluded. Overall, these findings support the
547 robustness of the observed relationship for more severe anaemia while underscoring
548 the need for caution when interpreting associations involving mild anaemia.

549 Despite the strengths of using nationally representative data and propensity score
550 weighting, several limitations should be acknowledged. Firstly, the analysis is based
551 on the assumption of no confounding factors but, for example, dietary diversity, and
552 food security of the family may not be entirely reflected in the MDHS survey. Finally,

while using inverse probability weighting, good covariate balance was obtained but it can be affected by misspecification of the model and extreme weights	553 554 555
5 Conclusion	556 557
This study provides robust empirical evidence that anaemia, particularly in its moderate/severe forms, is significantly associated with stunting among children in Malawi, even after adjusting for a wide range of socio-demographic and socio-economic factors using Inverse Probability Weighting. The use of propensity score-based weighting improved covariate balance and enhanced the validity of the estimated associations. In conclusion, reducing childhood anaemia could yield substantial gains in growth and development outcomes in Malawi. Efforts to combat anaemia must therefore be embedded within broader nutrition and poverty reduction initiatives, ensuring that no child's growth potential is constrained by preventable nutritional deficiencies.	558 559 560 561 562 563 564 565 566 567
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Declarations	571 572
Funding	573 574
Not applicable	575 576
Competing interests	577 578
The authors declare that they have no competing interests.	579 580
Ethics approval and consent to participate	581 582
The data used in this study were collected by the Malawi National Statistical Office (NSO) in partnership with the Measure DHS program. The data owners have reported in the 2024 Malawi Demographic and Health Survey (MDHS) report that they adhered to proper ethical guidelines during the data collection [6]. After receiving online consent from the Measure DHS program, these data were accessed, through . Every method was used in compliance with the applicable rules and regulations.	583 584 585 586 587 588
Consent for publication	589 590
All authors read and approved the final manuscript.	591 592
Data availability	593 594
The dataset generated and analysed during the current study are not publicly available since we received a data access letter from the DHS team https://dhsprogram.com/ specific to our project but are available from the DHS team upon request.	595 596 597 598

599 **Author contribution**

600 This is a masters thesis done by SM. HST conceptualised and supervised and provided
601 insights and guidance. The paper was drafted by SM and was critically revised by
602 HST before submission.
603

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