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Missingness of Height Data from the Demographic and Health Surveys in Africa between 1991 and 2016 Was Not Random but Is Unlikely to Have Major Implications for Biases in Estimating Stunting Prevalence or the Determinants of Child Height

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Abstract

Background: Obtaining accurate information on child height is essential for targeting interventions to reduce stunting. Thus, large-scale nutrition surveys must ensure that samples are representative of underlying populations of interest. Without accurate representation, resources for combating child stunting may be inefficiently allocated.

Objective: This study examined differences between children with (92.7%) and without (7.3%) complete and biologically plausible height data available from the Demographic and Health Surveys.

Methods: A total of 116 Demographic and Health Surveys conducted between 1991 and 2016 from 35 countries in sub-Saharan Africa were merged. Differences between children with and without biologically plausible height data were examined with the use of chi-square tests, *t* tests, and bivariate and multivariate logistic regression with survey cluster-level fixed effects.

Results: Of the whole sample, 97.9% of children had complete height data and 92.7% of children had complete and biologically plausible height data. There were sociodemographic and socioeconomic differences between those with and those without complete and biologically plausible height data. Children with usable height data were more likely to have a health card seen by the survey enumerator [mean height-for-age *z* score (HAZ): −1.32] than not (mean HAZ: −1.44) ($P < 0.001$), be older (mean HAZ: −1.63) than younger (mean HAZ: −1.11) ($P < 0.001$), have been ill in the previous 2 wk (mean HAZ: −1.43) than not ill (mean HAZ: −1.33) ($P < 0.001$), live in urban areas (mean HAZ: −1.13) than in rural areas (mean HAZ: −1.44) ($P < 0.001$), have literate mothers (mean HAZ: −1.16) than illiterate mothers (mean HAZ: −1.53) ($P < 0.001$), have mothers with more education (mean HAZ: −1.23) than not (mean HAZ: −1.54) ($P < 0.001$), and have more household wealth (mean HAZ: −0.82) than not (mean HAZ: −1.56) ($P = 0.038$).

Conclusions: Missing data from the DHS anthropometry questionnaires may affect research on child height, but overall effects are likely small. Given the trends in nutritional epidemiology toward the use of large-scale national surveys, understanding the ways in which biases arise as sample sizes increase is essential. *J Nutr* 2018;148:781–789.

Keywords: national surveys, child height-for-age, data quality, selection bias, stunting

Introduction

This study explores selection bias in child height data in 116 Demographic and Health Surveys (DHSs) from 35 countries conducted between 1991 and 2016 in sub-Saharan Africa (1). As of 2016, 22.9% of children around the world were stunted, an encouraging reduction from 32.7% in the year 2000 (2). Obtaining accurate information on child height is a critical task because child height serves as a cumulative metric of child health,

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cognitive development (3), the risk of noncommunicable diseases in adulthood (4), and future economic potential (5).

The group of children selected to be measured in each DHS was representative of the overall study population in each survey. However, not every child selected for the anthropometry questionnaire ended up with complete and biologically plausible anthropometric data available for nutrition researchers to analyze, given the normal logistical challenges of large-scale surveys. Some respondents refused to be measured, some data were lost or recorded incorrectly, and some measurements were outside of the normal parameters for height as defined by the WHO (1, 6).

Measuring the heights of children is challenging to do correctly and consistently (6, 7). Nonetheless, nationally representative surveys such as the DHS have relatively high data quality and enumerators receive training as to proper procedures (1, 6). Previous work has scrutinized the quality of child anthropometric data that use indicators such as the SDs of z scores, heaping measures, and the percentage of flagged measurements (6–10). However, these studies did not examine which child, mother, and community characteristics are associated with the likelihood of a selected child having usable anthropometric data.

The concern of potentially random measurement error is present for many health indicators collected during nationally representative surveys, including child height. Random measurement error typically attenuates the estimated relations between child height and the determinants of child height. Misreported age is another source of random and systematic error (11). Incorrect procedures used to measure height, improperly calibrated instruments, errors in data entry or recording, observer error, or the difficulty of getting children to stand still, lie still, or stretch out could cause random measurement error or nonrandom measurement error if these challenges differ on the basis of child characteristics.

Random measurement error is an important issue. However, the present study is not focused on random measurement error, the investigation of which would require carrying out repeated anthropometric measurements on the same children and then comparing the results, or conducting Monte Carlo simulations, or analyzing the SDs of z scores (6, 7). Instead, we address the question of whether there are systematic differences between the children with complete and biologically plausible (i.e., usable) height data and those without these data.

The objective of this study was to explore the possibility of selection bias in child height data, which could affect estimated prevalence rates of stunting and the validity of research studies that incorporate information on child heights (10). Many studies have utilized nationally representative microdata on child height to examine risk factors and potential solutions to the problem of child stunting (12–16). If there is nonrandom missingness or selection bias in the sample of children who have complete and biologically plausible height data in the DHSs, studies that utilize these data without adjusting for the presence of bias may misidentify associations or causal effects.

Methods

Data. The data set for this study was constructed from a collection of 116 DHSs from 35 countries in sub-Saharan Africa conducted between 1991 and 2016 (1). The DHSs are cross-sectional, nationally representative health surveys that contain detailed information on maternal and child nutritional status (1, 6). With rigorous standardization, the DHSs are comparable over time and across countries (1, 6). Sub-Saharan Africa was selected as the study region because of the widespread prevalence of child stunting there, because the African continent has wide coverage by the DHSs, and because data quality in the region is low compared with other regions (**Supplemental Table 1**). Of the 10 countries with the largest SDs in height-for-age z scores (HAZs), 9 were in Africa; and of the 10 countries with the most height observations outside of biologically plausible limits, 7 were in Africa (6). The DHS data sets on all births to interviewed women were used. A total of 559,790 children in this collection had been selected for the anthropometric questionnaires. Because this study used only previously de-identified secondary data, it was considered exempt from full review by the Allegheny College Institutional Review Board.

Three outcome variables were constructed for analysis. The first was a binary indicator of whether a child selected for the anthropometric subsample had missing data for his or her height measurement ("complete height data"). The second was a binary indicator of whether the child's height measurement was flagged by the DHS as being outside of biologically plausible ranges, defined by the WHO (17) as >6 SDs from the median, or as <45 cm or >120 cm ("biologically plausible height data"). The third outcome variable was a combination of these 2 indicators ("usable height data"). HAZs were calculated by the DHS program with the use of the CDC reference curves (1).

To understand whether certain children were likely to have usable height data available for analysis in the final DHS data sets, we examined a set of covariates expected to influence the likelihood of a child eventually having usable height data available. To select these variables, we considered which characteristics of children and mothers may have made it either more or less difficult for survey enumeration teams to obtain anthropometric data. The child-level characteristics selected included child age, sex, recent illness in the past 2 wk or in the past 24 h, and whether the child had a health card that was seen by the survey enumerator. Recent illness was defined as manifesting as fever, cough, or diarrhea. The maternal and household-level characteristics included the mother's educational attainment, wealth, age, literacy, pregnancy status, the number of children in the household, whether she was the head of the household at the time of the survey, and urban or rural residence. The survey year entered regressions as a linear time trend.

We expected that it would be more difficult to obtain accurate measurements from younger children, and that there would be no differences between the sexes for ease of measurement. Recent illness was included because it may be easier to measure children who are feeling ill, given that they may not be as inclined to move around as much during the measuring process. A child's health card in possession of the family may have indicated that the child had been seen by health professionals previously for vaccinations, vitamin A supplements, or for previous anthropometric measurement, and may have been relatively more accustomed to being measured, compared with children who did not have health cards. Thus, we expected that children with health cards seen by the survey enumerator would be more likely to have complete and biologically plausible height data available. Children with health cards are may also be more likely to have had their ages recorded accurately.

We also expected that it would be easier for survey enumerators to measure children when their mothers had more education, were literate, were the head of the household, or were wealthier, due to the potential need for increased time required for explaining the survey procedures to women without literacy or with less educational attainment. In contrast, we expected that it would be more difficult for survey enumerators to obtain accurate measurements from women who had more children in the household or from women who were pregnant, perhaps due to survey fatigue or high levels of activity in the household. Last, we expected that, for rural areas, survey enumerators may have been less likely to obtain complete and biologically plausible anthropometric measures, perhaps due to the strenuousness of traveling to rural compared with urban areas, or other logistical challenges that arise with conducting surveys in remote areas.

Statistical techniques. The DHS survey sample design, survey weights, and stratification were incorporated into all estimates. We calculated the percentages of children with incomplete or biologically implausible data, then used chi-square tests, t tests, as well as bivariate and multivariate logistic regression models to analyze the data in Stata 14/MP (StataCorp) (18). First, by using chi-square tests and *t* tests, we examined differences between the children with and without usable height data for analysis. Next, we estimated the unadjusted bivariate associations between the selected covariates and each of the 3 outcomes of interest. Logistic regression was used because we had access to a large sample size and the dependent variables were binary by construction. We expected that observations were independent, although within families or within survey enumerators, this assumption may have been violated. Finally, we calculated variance inflation factors to ascertain the degree of multicollinearity and found that they ranged from 1.00 to 2.50, indicating that there was not a high degree of collinearity between the independent variables (**Supplemental Table 2**).

Each estimated association was determined to potentially overestimate or underestimate the prevalence of child stunting in the population on the basis of the available HAZ scores of children with and without the selected characteristics. Estimated associations between child HAZs themselves and each covariate (**Supplemental Table 3**) were also compared with the results of **Table 1**, which indicated whether children with certain characteristics were likely to have complete and biologically plausible height data. Next, multivariate associations were estimated and included survey cluster-level fixed effects, taking the DHS sampling design and strata into account. Controlling for survey cluster-level fixed effects was necessary because previous work showed substantial heterogeneity in anthropometric data quality across survey clusters (6). Results were estimated for the whole sample, then split by time period and by region. These *P* values may be small simply due to large sample sizes. Therefore, we estimated upper and lower bounds on stunting prevalence by survey to conceptualize the potential magnitude of the problem. To do this, we calculated what stunting prevalence would have been if all of the children with incomplete data had been stunted and defined this as the "upper bound." Then, we calculated what stunting prevalence would have been if all of the children with incomplete data had not been stunted and defined this as the "lower bound". Further investigation is needed to determine the actual directions and magnitudes of bias in the case of each individual survey.

Results

Tables 1–4 present the main results. A list of included countries, surveys, survey years, and a summary of the outcome measures can be found in Supplemental Table 1. Table 2 presents descriptive statistics of the sample of children, stratified by age. Of the whole sample, 97.9% of children had complete height data available and 92.7% of children had complete and biologically plausible height data available from the DHSs.

Table 3 compares the groups of children with and without usable height data in the final DHS data sets. The 2 groups differed in several respects. Children with usable height data were more likely to have a health card than were children in the total group that was originally selected ($P < 0.001$). Older children were more likely to have usable data as well ($P < 0.001$), as were children with literate mothers ($P < 0.001$). Children who were recently ill were more likely than those not recently ill to have usable height data than were urban children ($P < 0.001$ and $P = 0.003$ for the past 2 wk and past 24 h, respectively). Rural children, although they represented a greater proportion of the sample, were less likely to have usable height data than were urban children ($P < 0.001$). Children with older mothers ($P < 0.001$), who had more education ($P < 0.001$), and who were wealthier ($P < 0.001$) were also more likely to be included in the final usable sample. Finally, children with mothers who were pregnant at the time of the survey were more likely to have usable height data ($P < 0.001$). Children in female-headed households ($P < 0.001$) or with mothers who were pregnant at the time of the survey ($P < 0.001$) were less likely to have nonmissing height data. The group of children with missing height data had a higher mean number of children aged <5 y in the household ($P < 0.001$). There were no differences across child sexes.

Table 1 presents unadjusted bivariate estimates of associations between the usability of child height data and 13 key child, household, and community characteristics. **Supplemental Tables 4** and **5** present bivariate estimates for data completeness and biological plausibility as outcomes separately. Three of the selected characteristics were negatively associated with whether the height data were usable: whether the child had a health card that was seen by the survey enumerator (OR: 0.552; 95% CI: 0.534, 0.570), the mother's illiteracy (OR: 0.672; 95% CI: 0.645, 0.700), and living in a rural area (OR: 0.742; 95% CI: 0.701, 0.785). For these characteristics, children without health cards had a lower mean HAZ (−1.44) than children with health cards (−1.32), children with illiterate mothers had a lower mean HAZ (−1.53) than children with literate mothers (−1.16), and children living in rural areas had a lower mean HAZ (−1.44) than children living in urban areas (−1.13). Therefore, the differences in observed HAZ between these groups were small and unlikely to lead to major biases.

Eight of the selected characteristics were positively associated with the usability of the child height data: mother's age in years (OR: 1.012; 95% CI: 1.010, 1.014), mother's education in years (OR: 1.029; 95% CI: 1.023, 1.034), household wealth (OR: 1.038; 95% CI: 1.021, 1.056), and female-headed households (OR: 1.138; 95% CI: 1.092, 1.186). Children who were born to mothers with more education had a higher mean HAZ (−1.23) than children of mothers with less education (−1.54), and children living in wealthier households also had a higher mean HAZ (−0.82) than those living in poorer households (−1.56). Older children were more likely to have usable height data in the DHS (OR: 1.018; 95% CI: 1.017, 1.019), as were children whose mothers were pregnant at the time of the survey (OR: 1.329; 95% CI: 1.266, 1.395) and children who were recently sick, either within the past 2 wk (OR: 1.590; 95% CI: 1.542, 1.640) or the past 24 h (OR: 2.125; 95% CI: 1.890, 2.388). For these characteristics, children who lived in a female-headed household had a higher mean HAZ (−1.31) than those in a male-headed household (−1.39), children with a pregnant mother at the time of the survey had a lower mean HAZ (−1.71) than children with a nonpregnant mother at the time of the survey (−1.33), and children who were recently ill had a lower mean HAZ (−1.43) than children who were not ill recently (−1.33).

Finally, 2 characteristics were found to not be associated with the usability of the child height data: the number of children in the household being surveyed (OR: 0.995; 95% CI: 0.981, 1.009) and the sex of the child (OR: 1.011; 95% CI: 0.986, 1.035). Overall, given these patterns in observed HAZ between groups, HAZ prevalence may be misestimated, or coefficient estimates between HAZ and these selected characteristics may be biased toward or away from the null, but these consequences likely would not be substantial.

Table 4 presents 3 models estimating the adjusted multivariate relations between the outcomes of interest and the characteristics that may be associated with the usability of child height data in the DHSs. The first 2 columns present models in which the completeness and the biological plausibility of the height

TABLE 1 Unadjusted bivariate estimates of associations between the completeness and biological plausibility of child height data and key child, household, and community characteristics for children aged <5 y in sub-Saharan Africa[1]

Outcome: Child had complete and plausible height data in the DHSs	Unadjusted bivariate coefficient estimates, OR (95% CI)	Height data that are incomplete or not plausible,[2] %	HAZ for when binary characteristic = 1[3]	HAZ for when binary characteristic = 0[3]
Characteristics that are negatively associated with height data completeness and feasibility[4]				
Child's health card (1 = no health card, 0 = health card seen)	0.552*** (0.534, 0.570)	7.08	−1.44 ± 1.77[5]	−1.32 ± 1.49
Mother's literacy (1 = illiterate, 0 = literate)	0.672*** (0.645, 0.700)	7.71	−1.53 ± 1.73	−1.16 ± 1.52
Type of place of residence (rural = 1, urban = 0)	(0.742*** (0.701, 0.785)	7.05	−1.44 ± 1.63	−1.13 ± 1.55
Characteristics that are positively associated with height data completeness and feasibility				
Mother's age[6] (single years)	1.012*** (1.010, 1.014)	7.03	−1.37 ± 1.60	−1.37 ± 1.63
Child's age[7] (single months)	1.018*** (1.017, 1.019)	7.03	−1.11 ± 1.63	−1.63 ± 1.56
Mother's education (single years)[8]	1.029*** (1.023, 1.034)	7.02	−1.54 ± 1.71	−1.23 ± 1.52
Wealth index (1 = poorest, 5 = richest)[9]	1.038*** (1.021, 1.056)	8.19	−1.56 ± 1.68	−0.82 ± 1.55
Sex of household head (1 = female, 0 = male)	1.138*** (1.092, 1.186)	7.02	−1.31 ± 1.57	−1.39 ± 1.63
Pregnancy during survey (1 = pregnant, 0 = not)	1.329*** (1.266, 1.395)	7.02	−1.71 ± 1.58	−1.33 ± 1.62
Child illness (1 = ill in past 2 wk, 0 = not ill)	1.590*** (1.542, 1.640)	7.02	−1.43 ± 1.58	−1.33 ± 1.66
Child illness (1 = ill in past 24 h, 0 = not ill)	2.125*** (1.890, 2.388)	7.02	−1.51 ± 1.51	−1.37 ± 1.63
Characteristics that are not associated with height data completeness and feasibility				
Children aged <5 y in household,[10] *n*	0.995 (0.981, 1.009)	7.02	−1.29 ± 1.58	−1.41 ± 1.63
Sex of child (1 = male, 0 = female)	1.011 (0.986, 1.035)	6.81	−1.44 ± 1.61	−1.31 ± 1.63

[1]Coefficients were estimated with the use of a bivariate logistic regression model that incorporated survey weights, clustering, and sampling strata. ***$P < 0.01$. DHS, Demographic and Health Survey; HAZ, height-for-age z score.
[2]The number of children included in each model varied due to data availability of each covariate; not all households across all surveys were asked the same questions, which is why the percentage of missing data differs depending on the covariate.
[3]These summary statistics are for children for whom height data were available.
[4]ORs are presented in ascending order of distance from 1 in each category: negatively associated, positively associated, and not associated.
[5]Mean ± SD (all such values).
[6]For maternal age, the HAZ estimates were split by the median respondent age, which was 28 y. Thus, column 3 shows the HAZ for children born to mothers who were strictly younger than 28 y at the time of the survey, and column 4 shows the HAZ for children born to mothers who were ≥28 y old at the time of the survey.
[7]For child age, the HAZ estimates were split by the median child age, which was 26 mo. Thus, column 3 is the HAZ for children strictly younger than 26 mo, and column 4 shows the HAZ for children ≥26 mo of age.
[8]For maternal education, the HAZ estimates were split by the median years of education for the mother, which was 2 y. Thus, column 3 shows the HAZ for children with mothers who have strictly <2 y of education, and column 4 shows the HAZ for children who have ≥2 y of education.
[9]For wealth, columns 3 and 4 present estimates of HAZ for the poorest and richest quintiles, respectively.
[10]For number of children in the household, column 3 presents HAZ for those children living in households with strictly fewer than the median number of children across the whole sample, and column 4 presents HAZ for those children living in households with greater than or equal to the median (the median number of children aged <5 y in the household was 2).

data were separated as outcomes, and the last column combines the indicators. Multivariate estimates mirror the bivariate estimates presented in Table 1 and are consistent with the patterns of differences between the groups of children with and without usable height data presented in Table 3.

Tables 5 and **6** present the same estimates as in column 3 of Table 4, split by survey period and region, respectively. Overall, the associations between the selected characteristics and the likelihood of having complete and biologically plausible height data have become larger in magnitude over time (Table 5). Across regions, different characteristics were associated with the likelihood of having complete and biologically plausible height data (Table 6). Recent child illness is strongly and positively associated with having complete data, with the largest

TABLE 2 Descriptive statistics stratified by child age for children aged <5 y in sub-Saharan Africa

	All children (*n* = 559,790)	Children <24 mo old (*n* = 256,762)	Children ≥24 mo old (*n* = 303,028)	*P*[1]
Child				
Has a health card, *n* (%)	301,795 (53.91)	160,376 (62.46)	141,419 (46.67)	
Has no health card, *n* (%)	249,151 (44.51)	95,793 (37.31)	153,358 (50.61)	<0.001
Age, mo	26.98 ± 17.12[2]	11.07 ± 6.67	40.47 ± 10.37	<0.001
Male sex, *n* (%)	281,678 (50.32)	129,115 (50.29)	152,563 (50.35)	
Female sex, *n* (%)	278,112 (49.68)	127,647 (49.71)	150,465 (49.65)	0.653
Mother was literate, *n* (%)	196,014 (35.02)	88,445 (34.45)	107,569 (35.50)	
Mother was illiterate, *n* (%)	247,665 (44.24)	105,798 (41.20)	141,867 (46.82)	<0.001
Ill in past 2 wk, *n* (%)	242,405 (43.30)	126,922 (49.43)	115,483 (38.11)	
Not ill in past 2 wk, *n* (%)	317,385 (56.70)	129,840 (50.57)	187,545 (61.89)	<0.001
Ill in past 24 h, *n* (%)	10,676 (1.91)	6604 (2.57)	4072 (1.34)	
Not ill in past 24 h, *n* (%)	549,114 (98.09)	250,158 (97.43)	298,956 (98.66)	<0.001
Rural residence, *n* (%)	448,174 (80.06)	203,898 (79.41)	244,276 (80.61)	
Urban residence, *n* (%)	106,111 (18.96)	50,325 (19.60)	55,786 (18.41)	<0.001
Mother				
Age, y	28.83 ± 6.94	27.51 ± 6.83	29.95 ± 6.84	0.003
Education, y	3.72 ± 4.13	3.77 ± 4.14	3.69 ± 4.41	<0.001
Wealth index, *n* (%)				
Poorest	95,996 (17.15)	41,833 (16.29)	54,163 (17.87)	
Poorer	84,230 (15.05)	36,801 (14.33)	47,429 (15.65)	
Middle	78,416 (14.01)	34,074 (13.27)	44,342 (14.63)	
Richer	73,012 (13.04)	31,778 (12.38)	41,324 (13.64)	
Richest	63,416 (11.33)	27,567 (10.74)	35,849 (11.83)	0.438
Male household head, *n* (%)	461,369 (82.42)	212,212 (82.65)	249,157 (82.22)	
Female household head, *n* (%)	98,420 (17.58)	44,550 (17.35)	53,870 (17.78)	<0.001
Mother was pregnant, *n* (%)	59,000 (10.54)	10,895 (4.24)	48,105 (15.87)	
Mother was not pregnant, *n* (%)	500,790 (89.46)	245,867 (95.76)	254,923 (84.13)	<0.001
Children, *n*	2.18 ± 1.25	2.19 ± 1.29	2.17 ± 1.24	0.067

[1] *P* values are for tests of differences in characteristics between older and younger children, with the use of a *t* test for continuous variables and a test for equality of proportions for binary variables.
[2] Mean ± SD (all such values).

magnitude OR estimated for Central Africa (OR: 1.665; 95% CI: 1.495, 1.855). Not having a health card is most strongly and negatively associated with having complete data in Eastern Africa (OR: 0.582; 95% CI: 0.550, 0.615). Maternal age, maternal literacy, and pregnancy status at the time of the survey are slightly associated with data completeness in Eastern and Western Africa only. Household wealth is positively associated with data completeness in Western Africa only (OR: 1.064; 95% CI: 1.039, 1.089). **Supplemental Table 6** presents estimates for the upper and lower bounds of stunting prevalence by survey if all missing data had been from children who were stunted or not stunted, respectively.

Discussion

Anthropometric measures such as height and weight are especially useful for planning resource allocations because they are comparably easier to measure than other indicators of nutritional status, such as those that would require biochemical or in-depth clinical analyses (19). At national levels, measuring child heights is also key to monitoring progress toward eliminating undernutrition and food insecurity. Despite their immense value to the nutrition research community, there has been limited research on the data quality of large-scale surveys, even though the utility of these surveys depends on whether the populations in question are accurately represented. In cross-sectional surveys like the DHSs, selection bias can occur if the sample selected is not representative of the underlying population.

The purpose of this study was not to criticize the procedures of the DHS program. Instead, we sought to outline the potential issue of selection bias into the sample of children with usable anthropometric data in the DHSs. Given the patterns found and the differences in mean observed HAZ between groups, overall impacts of the nonrandom missingness on stunting prevalence or on estimating the relations between child height and the determinants of child height are likely small. However, determining the net effects of the patterns found here on the estimated prevalence of stunting and on estimated associations with socioeconomic factors requires further investigation, and previous work has shown that large numbers of biologically implausible measurements result in overestimating the prevalence of stunting (7). Regardless of whether these patterns would result in an over- or underestimation of stunting prevalence, misallocation of resources for reducing undernutrition could occur.

In the subsample of children selected for the DHS anthropometric questionnaire, we found sociodemographic and socioeconomic differences between those with and without usable height data. It is possible that implementing the survey with illiterate mothers or in households in rural areas takes longer than with literate mothers or with households in urban areas, and survey enumeration teams end up feeling rushed. Older children may be easier to coax into being measured, and less struggle potentially leads to less chance of obtaining an implausible measure. Children who had recently been ill may be more likely to

TABLE 3 Comparisons between the groups of children with and without usable height data for children aged <5 y in sub-Saharan Africa[1]

	Sample population: Children with usable height data for analysis ($n = 518,886$)	Missing data: Children without usable height data for analysis ($n = 40,904$)	P[2]
Child			
Has a health card, n (%)	285,166 (55.88)	16,629 (40.97)	
Has no health card, n (%)	225,188 (44.12)	23,963 (59.03)	<0.001
Age, mo	27.33 ± 17.00[3]	22.56 ± 18.05	<0.001
Male sex, n (%)	261,159 (50.33)	20,519 (50.16)	
Female sex, n (%)	257,727 (49.67)	20,385 (49.84)	0.515
Mother was literate, n (%)	183,804 (45.03)	12,210 (34.38)	
Mother was illiterate, n (%)	224,355 (54.97)	23,310 (65.63)	<0.001
Ill in past 2 wk, n (%)	229,014 (44.14)	13,391 (32.74)	
Not ill in past 2 wk, n (%)	289,872 (55.86)	27,513 (67.26)	<0.001
Ill in past 24 h, n (%)	10,298 (1.98)	378 (0.92)	
Not ill in past 24 h, n (%)	508,588 (98.02)	40,904 (99.08)	<0.001
Rural residence, n (%)	413,374 (80.49)	34,800 (85.42)	
Urban residence, n (%)	100,173 (19.51)	5938 (14.58)	<0.001
Mother			
Age, y	28.87 ± 6.94	28.33 ± 6.95	<0.001
Education, y	3.78 ± 4.40	3.21 ± 4.51	<0.001
Wealth index, n (%)			
Poorest	86,917 (24.04)	9079 (27.00)	
Poorer	77,004 (21.30)	7226 (21.49)	
Middle	72,130 (19.95)	6286 (18.69)	
Richer	67,434 (18.65)	5668 (16.85)	
Richest	58,044 (16.06)	5372 (15.97)	<0.001
Male household head, n (%)	426,931 (82.28)	34,438 (84.19)	
Female household head, n (%)	91,954 (17.72)	6466 (15.81)	<0.001
Mother was pregnant, n (%)	55,622 (10.72)	3378 (8.26)	
Mother was not pregnant, n (%)	463,264 (89.28)	37,526 (91.74)	<0.001
Children, n	2.17 ± 1.24	2.23 ± 1.39	<0.001

[1] Usable height data were complete and biologically plausible.
[2] P values are for tests of differences in characteristics between the children with and without usable height data with the use of a t test for continuous variables and a test for equality of proportions for binary variables. The table is split into 2 groups: those children with complete and biologically plausible height data are in the left-hand column and children without complete and biologically plausible height data are in the middle column.
[3] Mean ± SD (all such values).

have been nearby the house on the day of the survey, or they may have struggled less when measured because they were tired or still not feeling well.

The nonrandom missing data found in this study were measurable even after controlling for survey cluster-level fixed effects to capture the heterogeneity across survey enumeration teams (6). Over time, the biases appear to become larger in magnitude, but this could be the result of increasing sample size over the course of the study period. Results suggest that there was bias present in the selection of children who eventually had biologically plausible height data available for analysis. Overall, for the individual socioeconomic and sociodemographic characteristics, these biases are toward the null, as in these biases could create an attenuation of estimated associations between each given characteristic and child height. However, these would likely be small attenuations given the differences in mean HAZ between groups.

When studying child height and its determinants with the use of large-scale survey data, researchers should consider utilizing conventional imputation methods to correct for selection on observable characteristics, or utilizing Heckman-type selection models to correct for selection on observable and unobservable characteristics (20). Researchers should also take care to not make claims of generalizability without examining the demographic and economic profiles of surveyed children without usable height data.

This study focused on the DHSs, but policy suggestions would apply to any organization that conducts nationally representative health and nutrition surveys. More training of survey enumerators on anthropometric measurement as well as measurement of age could assuage the problem of selection bias, especially for infants and young toddlers (6). Recent efforts to improve birth registration will help with the goal of measuring age accurately (21, 22). Technological advancements in anthropometric equipment and investments in existing technology could also improve the data quality and reduce selection bias, such as having on-site digital data entry and spot checks.

Unfortunately, training and technology—however comprehensive and innovative—are not sufficient to guarantee the validity of anthropometric measures. Having a well-structured and organized working environment for survey enumeration teams, including a mechanism for team members to suggest improvements to logistical procedures, is also essential. Survey enumeration in remote areas, often in communities at risk of undernutrition, infectious disease, environmental hazards, and

TABLE 4 Adjusted multivariate estimates of associations between 3 indicators of child height data quality and key child and household characteristics, with community fixed effects for children aged <5 y in sub-Saharan Africa[1]

Covariates	Units/Type	Child had complete data[2]	Child had biologically plausible height data[3]	Child had complete and biologically plausible height data[4]
Child's age	Months	1.001* (1.000, 1.003)	1.027*** (1.026, 1.027)	1.024*** (1.023, 1.025)
Male child	Binary (1 = male)	1.031 (0.984, 1.079)	1.014 (0.988, 1.041)	1.008 (0.982, 1.035)
Child ill within 2 wk	Binary (1 = yes)	1.397*** (1.323, 1.475)	1.319*** (1.279, 1.360)	1.324*** (1.284, 1.365)
Health card	Binary (1 = no card)	0.478*** (0.452, 0.505)	0.694*** (0.671, 0.717)	0.613*** (0.593, 0.633)
Number of kids	Count	0.967*** (0.948, 0.986)	1.005 (0.993, 1.018)	0.999 (0.987, 1.011)
Mother's education	Years	1.000 (0.992, 1.008)	1.000 (0.995, 1.005)	1.001 (0.996, 1.006)
Mother's age	Years	1.007*** (1.003, 1.010)	1.006*** (1.004, 1.008)	1.005*** (1.003, 1.007)
Illiterate	Binary (1 = yes)	0.831*** (0.767, 0.901)	0.929** (0.886, 0.973)	0.894*** (0.853, 0.937)
Pregnant	Binary (1 = yes)	0.996 (0.921, 1.076)	1.118*** (1.065, 1.174)	1.122*** (1.071, 1.176)
Wealth	Categorical	1.064*** (1.033, 1.095)	1.034*** (1.017, 1.052)	1.047*** (1.030, 1.064)
Female head	Binary	0.968 (0.904, 1.037)	1.007 (0.967, 1.048)	1.008 (0.968, 1.049)
Survey year	Trend	1.481* (1.066, 2.059)	0.950 (0.874, 1.033)	0.957 (0.881, 1.039)
Observations[5]	*n*	72,871	206,407	208,893
Percentage affected	%	2.67	7.96	8.62
Clusters	*n*	4374	12,447	12,658

[1]Values are ORs (95% CIs) unless otherwise indicated. Coefficients were estimated with the use of a multivariate logistic regression model that incorporated survey weights, clustering, and sampling strata and survey cluster-level fixed effects. $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$.
[2]Outcome in column 1: child had complete height data available.
[3]Outcome in column 2: child's recorded height data were biologically plausible.
[4]Outcome in column 3: the combination of indicators for columns 1 and 2.
[5]Sample size differed across models because of missing data across covariates and because survey clusters with all positive or all negative outcomes could not be analyzed within survey clusters and were automatically dropped.

civil conflict, is a challenging and sometimes dangerous task. Understanding the processes by which enumeration teams work together and make day-to-day decisions requires in-depth economic, anthropological, and sociological analyses.

Limitations and possible extensions. This was a secondary analysis of a collection of complex, large-scale surveys over a long time period. We used the CDC growth reference to keep consistent across all DHSs, including those that occurred

TABLE 5 Adjusted multivariate estimates of associations between child height data quality by time period of survey, with community fixed effects for children aged <5 y in sub-Saharan Africa[1]

Covariates	Units/Type	1991–1997[2]	1998–2003[3]	2004–2009[4]	2010–2016[5]
Child's age	Months	1.032*** (1.026, 1.039)	1.025*** (1.023, 1.028)	1.024*** (1.023, 1.026)	1.023*** (1.022, 1.024)
Male child	Binary (1 = male)	1.152 (0.942, 1.409)	0.978 (0.899, 1.065)	0.990 (0.951, 1.032)	1.025 (0.987, 1.064)
Child ill within 2 wk	Binary (1 = yes)	1.274 (0.995, 1.631)	1.295*** (1.181, 1.420)	1.308*** (1.249, 1.370)	1.355*** (1.294, 1.418)
Health card	Binary (1 = no card)	0.692* (0.513, 0.934)	0.702*** (0.631, 0.781)	0.678*** (0.644, 0.713)	0.551*** (0.526, 0.577)
Number of kids	Count	0.917 (0.789, 1.067)	1.032 (0.989, 1.076)	1.030** (1.010, 1.051)	0.975** (0.959, 0.991)
Mother's education	Years	1.056 (0.966, 1.153)	0.982 (0.961, 1.003)	1.006 (0.999, 1.013)	0.997 (0.990, 1.004)
Mother's age	Years	1.004 (0.988, 1.019)	1.004 (0.998, 1.011)	1.007*** (1.004, 1.011)	1.003* (1.000, 1.006)
Illiterate	Binary (1 = yes)	0.989 (0.598, 1.635)	0.791* (0.661, 0.947)	0.928* (0.866, 0.995)	0.870*** (0.812, 0.933)
Pregnant	Binary (1 = yes)	1.570* (1.033, 2.387)	1.215* (1.035, 1.427)	1.098* (1.021, 1.180)	1.118** (1.045, 1.196)
Wealth	Categorical	1.083 (0.964, 1.216)	1.048 (0.995, 1.104)	1.033* (1.007, 1.060)	1.060*** (1.034, 1.086)
Female head	Binary	1.007 (0.729, 1.390)	0.948 (0.830, 1.082)	1.026 (0.963, 1.093)	1.003 (0.948, 1.061)
Observations[6]	*n*	2874	23,445	83,889	98,647
Percentage affected	%	4.19	5.76	9.82	7.93
Clusters	*n*	295	1340	4652	6372

[1]Values are ORs (95% CIs) unless otherwise indicated. Coefficients were estimated with the use of a multivariate logistic regression model that incorporated survey weights, clustering, and sampling strata and survey cluster-level fixed effects. $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$.
[2]Outcome: child had complete and biologically plausible height data. Estimated for surveys that took place between 1991 and 1997.
[3]Outcome: child had complete and biologically plausible height data. Estimated for surveys that took place between 1998 and 2003.
[4]Outcome: child had complete and biologically plausible height data. Estimated for surveys that took place between 2004 and 2009.
[5]Outcome: child had complete and biologically plausible height data. Estimated for surveys that took place between 2010 and 2016.
[6]Sample size differed across models due to survey availability.

TABLE 6 Adjusted multivariate estimates of associations between child height data quality by region of survey, with community fixed effects for children aged <5 y in sub-Saharan Africa[1]

Covariates	Units/Type	Eastern[2]	Central[3]	Western[4]	Southern[5]
Child's age	Months	1.030*** (1.028, 1.032)	1.021*** (1.018, 1.024)	1.020*** (1.019, 1.021)	1.045*** (1.036, 1.055)
Male child	Binary (1 = male)	1.033 (0.985, 1.084)	1.095 (0.993, 1.208)	0.987 (0.954, 1.022)	0.912 (0.708, 1.176)
Child ill within 2 wk	Binary (1 = yes)	1.406*** (1.332, 1.484)	1.665*** (1.495, 1.855)	1.221*** (1.172, 1.273)	1.388* (1.042, 1.849)
Health card	Binary (1 = no card)	0.582*** (0.550, 0.615)	0.638*** (0.561, 0.725)	0.620*** (0.593, 0.647)	0.712* (0.519, 0.976)
Number of kids	Count	1.018 (0.989, 1.049)	1.005 (0.961, 1.051)	0.994 (0.980, 1.008)	1.012 (0.891, 1.151)
Mother's education	Years	1.004 (0.994, 1.014)	0.998 (0.982, 1.015)	0.998 (0.991, 1.004)	0.992 (0.941, 1.045)
Mother's age	Years	1.004* (1.001, 1.008)	1.007 (1.000, 1.015)	1.006*** (1.003, 1.008)	0.994 (0.975, 1.013)
Illiterate	Binary (1 = yes)	0.885** (0.818, 0.958)	0.944 (0.800, 1.114)	0.875*** (0.817, 0.937)	0.628 (0.379, 1.042)
Pregnant	Binary (1 = yes)	1.121* (1.022, 1.230)	1.127 (0.949, 1.337)	1.134*** (1.069, 1.203)	0.587 (0.305, 1.128)
Wealth	Categorical	1.027 (0.999, 1.055)	1.011 (0.953, 1.074)	1.064*** (1.039, 1.089)	1.164 (0.984, 1.376)
Female head	Binary	0.975 (0.916, 1.037)	1.015 (0.885, 1.165)	1.049 (0.987, 1.114)	0.888 (0.666, 1.185)
Survey year	Trend	0.953 (0.877, 1.037)	1.248 (0.533, 2.920)	0.720 (0.325, 1.594)	—
Observations[6]	*n*	68,603	17,382	112,344	2285
Percentage affected	%	5.14	5.82	10.56	3.7
Clusters	*n*	4815	1042	5883	268

[1]Values are ORs (95% CIs) unless otherwise indicated. Coefficients were estimated with the use of a multivariate logistic regression model that incorporated survey weights, clustering, and sampling strata and survey cluster-level fixed effects. $*P < 0.10$, $**P < 0.05$, $***P < 0.01$.
[2]Outcome: child had complete and biologically plausible height data. Estimated for surveys that took place in Eastern Africa as defined by the United Nations.
[3]Outcome: child had complete and biologically plausible height data. Estimated for surveys that took place in Central Africa as defined by the United Nations.
[4]Outcome: child had complete and biologically plausible height data. Estimated for surveys that took place in Western Africa as defined by the United Nations.
[5]Outcome: child had complete and biologically plausible height data. Estimated for surveys that took place in Southern Africa as defined by the United Nations.
[6]Sample size differed across models due to survey availability.

before 2006, but the use of the updated WHO standards instead would allow for standardization in the determinants of nutritional status, such as child illness, maternal smoking, infant and young child feeding practices, breastfeeding, and environmental conditions. Furthermore, examining mechanisms for the findings would be difficult without detailed information about the behaviors of survey enumeration teams and other on-the-ground conditions at the time of each survey in each community. As part of their methodologic reports, the DHS program could consider interviewing or conducting focus groups with survey enumeration teams and analyzing the resulting qualitative data. Without qualitative information about actual survey conditions on the ground, it will be difficult to develop improved procedures.

A way in which the present study could be extended would be to analyze DHS data quality for each country individually. In conjunction with the aggregated analysis, a deeper country-level analysis could bring to light which places need the most attention for improvement. Substantial heterogeneity in data quality across countries has already been shown (6). It is possible that, within many countries, there are no differences between the subsample of children selected for the anthropometric questionnaire and the final sample of children with usable data, but these selection biases compound as the sample sizes increase. Future work could also seek to measure and correct for overdispersion in these data. Finally, the use of Heckman-type selection models could account for this selection bias when calculating prevalence rates of stunting or when modeling the determinants of child height, such as those models often used to control for selection bias in HIV testing (23).

Conclusions. In the DHSs, children with missing data or biologically implausible data are different from those children for whom we have complete and plausible measurements. Most of the incomplete height data for children in the DHSs are due to biological implausibility of the measurements and not due to missing data. To ascertain the net effects of the biases found in this study, a reference population would be needed for comparison, or the Heckman-corrected prevalence estimates for stunting could be estimated. Reference populations could be obtained from other large-scale surveys such as the Multiple Indicators Cluster Survey from UNICEF (24) or the Living Standards Measurement Survey from the World Bank (25), but these surveys may have similar issues with selection bias.

Studies that use the DHS anthropometric microdata directly for analyses may be affected by the selection biases found here if independent variables are correlated with error terms, or if claims are made by researchers about the generalizability of findings. Other types of epidemiologic studies or government reports, such as those that aggregate the data into regional or country-level prevalences, would also be affected because the sample of children with usable height data is not necessarily representative of the underlying population. Given the trends in nutritional epidemiology toward the use of large-scale national surveys, understanding the way in which biases change as sample size increases is essential (7). Last, nutrition policymakers should strive to develop policies that could apply to a wider CI for stunting prevalence in their communities.

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