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Research article

Examining the risk factors for overweight and obesity among women in Ghana: A multilevel perspective

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A R T I C L E I N F O

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A B S T R A C T

Overweight/obesity prevalence is on the increase in epidemic proportions across Low- and Middle-Income countries (LMICs). The public health burden associated with obesity/overweight cannot be underestimated due to its association with chronic health outcomes. This study investigated the individual- and community level risk factors for obesity/overweight among reproductive women. The data used consist of 4393 reproductive women and form part of the 2014 Ghana Demographic and Health Survey (GDHS). Information on these women are clustered within 427 communities. A 2-tier random intercept multilevel logistic model was used to assess the effect of individual- and community level factors on the likelihood of a woman to be obese/overweight. The obesity/overweight prevalence among reproductive women was estimated to be 35.5% (95% CI: 34.04, 36.90%), which significantly differed across clusters. Most at risk were women from middle-income households (aOR = 2.85; 95% CI: 2.28, 3.56), upper-income households (aOR = 5.019, 95% CI: 3.85, 6.55), attaining secondary education (aOR = 1.74; 95% CI: 1.41, 2.16), and higher (aOR = 1.63; 95% CI: 1.14, 2.33), old age (20–29 years (aOR = 4.26; 95% CI: 3.142,5.78); 30–39 years (aOR = 8.59; 95% CI: 6.15, 12.00); 40–49 years (aOR = 12.81; 95% CI: 9.10, 18.16)). Significant differences in the probability of being overweight/obese between different communities were observed (MOR = 1.39). The high prevalence of overweight/obesity requires urgent public health interventions to prevent future public health crises. Efforts to strengthen the healthcare system, encourage lifestyle modification, and public health education are needed to solidify the gains of ensuring a healthy population by 2030 (SDG 3).

1. Introduction

There is a sharp increase in the prevalence of obesity and overweight among adult populations around the world, which has had a negative impact on public health, particularly in developing nations like Ghana [1]. Overweight/obesity is an abnormal accumulation of fat in humans which poses severe health risk [2]. According to Refs. [2–5], findings suggests that overweight/obesity trends around the world have sharply reached epidemic proportions across all age groups and much so very alarming in developing countries [2–5]. According to findings in Refs. [2,6], overweight/obesity are major predisposing factors for several chronic conditions and diseases

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such as diabetes, cardiovascular diseases, cancer, and many others, which are further associated with high mortality rates [7–9].

The World Bank estimated an increase in mortality associated with non-communicable diseases in Sub-Saharan Africa (SSA) by 64% between 2008 and 2030, of which overweight/obesity are major risk factors [3,9,10]. Again [11], projected an increase in overweight and obesity prevalence by 23.2% and 9.8%, respectively, between 2005 and 2030. In addition, the population of overweight/obese individuals around the world will surpass 2.1 billion/1.1 million, respectfully, by the end of 2030. The burden of overweight/obesity were initially observed in developed economies but has in recent decades assumed very alarming proportions in developing countries [6,12]. The increasing trend of overweight and obesity across populations, most especially in urban areas, is attributed to improved livelihoods and standards of living compared to rural communities [7,13–15].

The body mass index (BMI), which helps in the categorization of body weight, is used to examine and identify body size categories for related health burden [2]. The significant increase in overweight and obesity prevalence coupled with its associated morbidity and public health burden has significant consequences on efforts toward achieving Sustainable Development Goal 3 (SDG 3); ensuring healthy lives and promoting well-being for all persons across all ages by 2030. Additionally, failure to achieve SDG 3 will further impede attempts to promote gender equity (SDG 5), quality education (SDG 4), and the supply of decent jobs for economic growth (SDG 8). The effect of healthy reproductive women in the community is very critical for the development of communities, economies, and the world at large. Moreover, the concept of gender cutting across all sustainable development goals was proposed and adopted in 2015 to spearhead efforts towards meeting the SDGs with gender as the main propelling cornerstone.

Studies have been conducted to identify potential risk factors for overweight and obesity at the individual level [7,14,16–19]. However, there was a renewed commitment by Heads of State and governments after the high-level United Nations General Assembly in October 2018 to adequately set up robust health care systems to respond appropriately to the health needs of populations with respect to non-communicable diseases of which overweight and obesity are predisposing risk factors [14,20–22]. It is therefore important to investigate how both community and individual level characteristics influence the likelihood of a woman from a given community to be overweight/obese relative to another woman from a different community. The hierarchical nature of the Ghana Demographic and Health Survey (GDHS) cross-sectional data employed in this study requires robust statistical methods to account for the variations in the likelihood of a selected woman to be overweight/obese given some community and individual attributes. This has not been investigated in the study setting. This study sought to provide insights into the overweight/obesity dynamics in Ghana through a multilevel perspective to identify covariates that explain the likelihood of a woman to be overweight/obese. Insights from this study will help inform and educate the general population on significant risk factors for obesity/overweight. Moreover, the findings will further inform the policy directions targeted at reducing the health burden associated with overweight/obesity. And will also enhance Ghana's efforts towards achieving SDG 3.

2. Materials and methods

2.1. Study population and data description

This study is based on the 2014 national cross-sectional GDHS in Ghana carried out between September and November of 2014. The study data comprise of information from 427 enumeration areas (EAs) called clusters, which are made up of 216 urban and 211 rural areas respectfully [23]. The multistage sampling process used for the selection of EAs and subsequently, households (HHs) systematically within the preselected EAs of the survey was outlined by the implementing agency, Ghana Statistical Service (GSS). The random selection of HHs was performed with an average of thirty (30) from each cluster to constitute the total number of HHs obtained. In all, information was obtained on 4,393 women in their reproductive age (15–49 years) out of a total of 9,396 women randomly selected from 11,835 HHs. The extracted GDHS data has a hierarchical structure where the sampled women are considered as lower-level units and are nested within predefined clusters as the higher level of the hierarchy.

2.2. Study variables

The dependent variable is the body weight status based on the measured BMI values. According to Ref. [2], BMI between 25 kgm^{-2} and 30 kgm^{-2} is classified as overweight whereas BMI values greater than 30 kgm^{-2} indicate obese body weight category. In line with WHO standards, women with BMI of 25 kgm^{-2} and above are overweight/obese (BMI $>$ 25 kgm^{-2} as overweight/obese coded 1, and $BMI < 25\ \mathrm{kg}m^{-2}$ as 0).

The risk factors considered in this study are significant determinants for increased body size among women based on literature. The risk factors considered in this study include; maternal age, number of children ever born (CEB), type of place of residence (rural or urban), marital status (single, married, cohabiting, and divorced/separated/widowed) and educational background (no formal education, primary, secondary and higher) and household wealth index category (poor, middle, rich). The built-up index of clusters which ranges from 0.00 (extremely rural) to 1.00 (extremely urban) for clusters within 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey buffer location. The built-up index of an area is expressed as a proportion of occupied foot print within each cell derived from high-resolution data using remote sensing image collections [24].

2.3. Ethical consideration

The ICF International Institutional Review Board (IRB) together with the Ghana Health Service Ethical Committee reviewed and approved the protocol for the 2014 GDHS. Moreover, informed consent of eligible women was duly sought prior to the interviews and data collection. Dataset was accessed for free after a simple registration process with the DHS Program.

2.4. Multilevel model specification

Multilevel models (MLMs), also known as mixed-effects or random effects models, are extensions of the classical regression models which are gaining much popularity in recent times, motivated by the ability to model variations among individuals belonging to different groups [25,26]. In this study, MLMs are required to assess the variability and relationships between variables taking into account population structure and the associated dependencies on both individual and cluster level characteristics which have influence on the outcome (body weight status) in this study [27]. It is worth noting that the presence of dependencies among observations at lower level results in the violates of the independence assumption required in classical linear regression analysis. This consequently leads to inefficient and inappropriate inferences on the generated parameter estimates [28–30].

The multilevel logistic model is adopted in this study due to the hierarchical structure of the GDHS data, where women (lower level) are nested within clusters (higher level), and women living in the same community share similar characteristics than those living in different communities. This violates the assumptions of independence of observations and constant variance across clusters required in the classical binary logistic model [31]. According to Refs. [32,33], modelling within multilevel frameworks places more importance on cluster-level differences in the risk of being overweight/obese among women and the extent of nesting of overweight/obesity within a cluster, which the classical binary logistic model cannot accomplish.

We hereby, we propose a multilevel binary logistic model which permits clustering in the dataset. We let $P_{ij} = P(y_{ij} = 1 | x_{ij})$ denote the probability of woman i from cluster j being overweight/obese, x_{ij} is the observed attribute of the i^{th} woman in the j^{th} cluster, and $1-P_{ij} = P(y_{ij} = 0 | x_{ij})$ is the probability that the i^{th} woman in the j^{th} cluster is not overweight/obese. The P_{ij} therefore assumes a Bernoulli distribution. Similar to the standard logistic regression model, P_{ij} is modelled with the logit link function. Our two-level multilevel model formulation is given as follows:

$$Logit(P_{ij}) = log\left(\frac{P_{ij}}{1-P_{ij}}\right) = \alpha + \sum_{h=1}^{k} X_{hij}\gamma_{hj} + \mu_{oj} + \sum_{h=1}^{k} X_{hij}\mu_{hj} \tag{1}$$

where, $X_{hij} = (X_{1ij}, X_{2ij}, \cdots, X_{kij})$ denote the lower (individual) and higher (community) level covariates for the k variables, $\gamma = (\gamma_0, \gamma_1, \cdots, \gamma_k)$ are the fixed effects parameters coefficients, and $\mu_{oj}, \mu_{1j}, \ldots, \mu_{kj}$ are the higher level random effects parameter coefficients which follow a normal distribution with mean zero (0) and variance σ_u^2. It follows that, conditional on $\mu_{oj}, \mu_{1j}, \ldots, \mu_{kj}$, the y_{ij} are independently distributed, and α is the intercept [34].

We begin with the empty (null) (M_0) two-level model for the dichotomous response (overweight/obese or not), which is the variance component model of the form;

$$Logit(P_{ij}) = log\left(\frac{P_{ij}}{1-P_{ij}}\right) = \gamma_{oj} + \mu_{oj} + \varepsilon_{ij} \tag{2}$$

Where, y_{ij} refers to the overweight/obese status of the i^{th} woman in the j^{th} cluster; γ_{oj} is the overall mean; μ_{oj} is the cluster random effects which are normally distributed with zero mean and constant variance σ_u^2 and the ε_{ij} is also identically and independent distributed with mean zero and variance σ_ε^2. The ε_{ij} and μ_{oj} are, however, uncorrelated. The null model separates the total variance into two; cluster and woman levels, which represent between and within cluster variations of being overweight/obese or not [30,35,36]. The interclass correlation coefficient (ICC) measure used to quantify the proportion of total variance attributed to observations (women) within a cluster is expressed in the form;

$$ICC = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_\varepsilon^2}$$

Where σ_ε^2 and σ_u^2 are the "between-women" and "between-cluster" variances respectfully. For a binary outcome, woman -level variance (σ_ε^2) follows the standard logistic distribution with variance $\pi^2/3$ and mean zero (0).

After the null model, we considered a random intercept logistic multilevel model (M_1) in which only the intercept is allowed to vary with respect to the cluster, suggesting that only clusters differ regarding the average response whereas, the covariates do not vary among groups. Thus, the random intercept represents the heterogeneity between clusters in the outcome [34]. Suppose there are a set of variables serving as potential predictors for a randomly selected woman to be overweight/obese or not. Let these variables be represented by $X_h = \{X_{hij}, i = 1, 2, \ldots, n_j, h = 1, 2, \ldots, k \text{ and } j = 1, 2, \ldots, N\}$ where, k is the number of predictors under consideration. The random intercept logistic model expresses the log-odds, $\left[log\left(\frac{P_{ij}}{1-P_{ij}}\right)\right]$ as the sum of the random cluster dependent variation μ_{oj} and the linear function of the covariates in the form;

$$Logit(P_{ij}) = \gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij} + \mu_{oj} \tag{3}$$

Where, $\gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij}$ is the fixed part, whereas, μ_{oj} is the random part [30,36] and the probability of success (overweight/obese) is

$$P_{ij} = \frac{e^{\gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij} + \mu_{oj}}}{1 + e^{\gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij} + \mu_{oj}}} \tag{4}$$

Next, the random intercept and slope model (M_2) in which both lower- and higher-level covariates are modelled. These models explain the unobserved heterogeneity in the effects of both cluster- and women-level covariates on the response under study. It is important to note that part or all of these covariates could be from the lower level, hence the probability of being overweight/obese cannot be the same for women sampled from the same community. Thus, a woman's probability of being overweight/obese depends on the woman and her community characteristics, which is defined as:

$$Logit(P_{ij}) = \gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij} + \mu_{oj} + \mu_{1j} X_{ij} \tag{5}$$

Where the fixed and random parts are captured in the model respectively as $\gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij}$ and $\mu_{oj} + \mu_{1j} X_{ij}$. And (μ_{oj}, μ_{1j}) are bivariate normally distributed such that $\mu_{0j} \sim N(0, \sigma_{u0}^2)$, $\mu_{1j} \sim N(0, \sigma_{u1}^2)$ and $Cov(\mu_{0j}, \mu_{1j}) = \sigma_{\mu 01}$. The likelihood of (5) is of the form;

$$L = \prod_{i=1}^{n_j} \prod_{j=1}^{N} (P_{ij})^{y_{ij}} (1 - P_{ij})^{1 - y_{ij}} \tag{6}$$

Where,

$$P_{ij} = \frac{e^{\gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij} + \mu_{oj} + \mu_{1j} X_{ij}}}{1 + e^{\gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij} + \mu_{oj} + \mu_{1j} X_{ij}}} \text{ and}$$

$$(1 - P_{ij}) = \frac{1}{1 + e^{\gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij} + \mu_{oj} + \mu_{1j} X_{ij}}}$$

Substituting expressions for P_{ij} and $(1 - P_{ij})$ into (6) yields;

$$L = \prod_{i=1}^{n_j} \prod_{j=1}^{N} \left(\frac{e^{\gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij} + \mu_{oj} + \mu_{1j} X_{ij}}}{1 + e^{\gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij} + \mu_{oj} + \mu_{1j} X_{ij}}} \right)^{y_{ij}} \left(\frac{1}{1 + e^{\gamma_{00} + \sum_{h=1}^{k} \gamma_{hj} X_{hij} + \mu_{oj} + \mu_{1j} X_{ij}}} \right)^{1 - y_{ij}} \tag{7}$$

Parameters of the proposed multilevel model are obtained using the method of maximum likelihood estimation (MLE) through the Laplace approximation [37,38]. The goodness-of- fit of the fitted models were assessed by means of model deviance [39,40], Akaike information criterion (AIC) [41], Bayesian Information Criterion (BIC; [42,43]), and intraclass correlation Coefficient (ICC) determined to measure the variation between clusters [31]. The AIC and BIC measures are determined by;

$$AIC = d + 2k$$

$$BIC = d + k\log(n)$$

Where, $d = -2loglikelihood$, k is the number of model parameters to be estimated and n is the number of observations. The model with the associated minimum AIC or BIC is adjudged the most attractive model for the data [36,44–46].

According to Refs. [31,33], the ICC also known as variance partition coefficient, which is mostly difficult to interpret practically. Hence, to overcome this drawback, the median odds ratio (MOR) is determined to quantify the cluster-level heterogeneity in the outcome. The MOR refers to the ratio between the community with the high likelihood of overweight/obesity and the community with lower likelihood when the two communities are randomly selected. The MOR is estimated as [47–49].

$$MOR = \exp\left(\varphi^{-1}(0.75)\sqrt{2\sigma_u^2}\right) \cong \exp(0.9549\sigma_\mu)$$

Where σ_u^2 is the cluster level variance. Adjusted odds ratio (AOR) together with 95% confidence interval (CI) and p-values <0.05 in the multivariable multilevel model were used to declare a significant association with overweight/obesity status of the sampled reproductive aged women [50,51].

3. Results

Table 1 presents the summary statistics and the measure of the association between overweight/obesity status and some socio-demographic characteristics of respondents. All analysis were conducted in R (version 4.0.4) at 5% level of significance. Out of the 4,393 reproductive women considered, 35.5% were obese or overweight (BMI >25 kgm^{-2}). The prevalence of overweight/obese is higher among urban women (45.8%), women with higher (tertiary) level of education (53.5%), women from rich households (45.6%), widowed/divorced women (55.2%), women aged between 40 and 49 years (51.8%), and multi-parous women (43.9%). The results further showed that place of residence, marital status, household wealth category, educational attainment of women, age, and number of children ever born are significantly associated ($p < 0.01$) with the chance of a woman being overweight/obese in the study setting.

3.1. Multilevel model results

The 0.15 ICC of the null model (M_0) signifies that 15% of the total variance of a woman to be overweight/obese is attributable to the community differences. Thus, the likelihood of a woman being overweight/obese is significantly clustered by the community. Moreover, the significant clustering of the overweight/obese status of reproductive women further supports the need for multilevel modelling of the data. The introduction of individual level and cluster level attributes into the model reduced the ICC by almost three quarters from 0.15 (15%) to 0.03 (3%). The model deviance, AIC, and BIC indices of the final model are significantly lower than the null model, which signify better-fit model to the data. The 1.390 MOR for the final model suggests that the overweight/obesity prevalence among reproductive women varies significantly across clusters in Ghana. A reproductive woman from a community with a high chance of being overweight/obese has 39% odds to be overweight/obese compared to a woman from a community with a low likelihood of being overweight/obese.

Both the fixed effects model and the random intercept multilevel model generated similar estimates for model parameters, but the fixed effects model relatively underestimated the associated standard errors often associated with ignoring the hierarchical structure in survey data [30].

Based on the multilevel logistic model results (Table 2 and 3), educated women have a significantly higher risk of being overweight/obese than women with no formal education. Women with primary education were 63% more at risk of overweight/obese than those with no education. Those with secondary and higher (tertiary) educational attainment were 1.73 and.

12.46 times, respectively, more likely to be overweight/obese than women with no form of formal education. Household wealth category of women was also found to be a significant risk factor associated with overweight/obese body weight status among reproductive women in Ghana. Women from households in the middle and rich wealth categories were 2.85 and 5.65 times more probable to be overweight/obese compared to women from poor households.

The odds of overweight/obesity in the setting were observed to increase with an increase in the age of women. While women aged 20–29 years were 4 times at risk of being overweight/obese than reproductive women aged below 20 years, women in the 30-39- and 40-49-year groups were at least 8- and 12-times at higher risk of being overweight or obese, respectively. The risk of overweight or

Table 1
Overweight/obesity status and background characteristics.

Variables	Categories	Overweight/Obese Status		Df	Chi-Square
		Yes n (%)	No n (%)		
Type of Residence	Rural	561(25.3)	1657(74.7)	1	202.543[a]
	Urban	997(45.8)	1178(54.2)		
Educational Attainment	No Formal Education	275(26.0)	782(74.0)	3	86.645[a]
	Primary	280(33.3)	560(66.7)		
	Secondary	881(38.8)	1387(61.2)		
	Higher	122(53.5)	106(46.5)		
Wealth Status	Poor	342(17.9)	1566(82.1)	2	509.325[a]
	Middle	358(39.5)	549(60.5)		
	Rich	720(45.6)	858(54.4)		
Marital Status	Never Married	337(21.1)	1261(78.9)	3	256.082[a]
	Cohabiting	205(37.1)	347(62.9)		
	Married	837(43.6)	1082(56.4)		
	Widowed/Divorced	179(55.2)	145(44.8)		
Age Group	<20	68(7.9)	789(92.1)	3	473.546[a]
	20–29	443(31.5)	964(68.5)		
	30–39	559(47.1)	628(52.9)		
	40–49	488(51.8)	454(48.2)		
Children Ever Born	None	274(19.9)	1102(80.1)	3	224.593[a]
	1–3	709(43.5)	921(56.5)		
	4–6	467(43.8)	598(56.2)		
	7+	108(33.5)	214(66.5)		

[a] Significant at $p < 0.01$.

Table 2
Multilevel logistic Modelling of risk factors.

	Null Model (M_0)	Fixed Effects Model(M_1)	Final Model (M_1)
		Individual and Household level variables	
Constant	0.519(0.469, 0.574) *	0.007(0.005, 0.009) *	0.018 (0.013, 0.025) *
Type of Residence			
Rural		1	1
Urban		0.95(0.78, 1.16)	0.8427(0.670, 1.059)
Educational Attainment			
No Formal Education		1	1
Primary		1.68(1.34, 2.11) *	1.66 (1.31, 2.10) *
Secondary		1.77(1.44, 2.18) *	1.74 (1.41, 2.13) *
Higher		1.61 (1.14, 2.29) *	1.63 (1.14, 2.33) *
Wealth Status			
Poor		1	1
Middle		2.92(2.36, 3.60) *	2.845 (2.277, 3.555) *
Rich		5.75(4.52, 7.32) *	5.019 (3.849, 6.546) *
Marital Status			
Never Married		1	1
Cohabiting		1.38(1.07, 1.77) *	1.423(1.100, 1.840) *
Married		1.63 (1.33, 2.01) *	1.702 (1.375, 2.107) *
Widowed/Divorced		2.01(1.49, 2.72) *	2.062 (1.516, 2.804) *
Age Group			
<20		1	1
20-29		4.10 (3.04, 5.52) *	4.26 (3.142, 5.776) *
30-39		8.33(6.0, 11.56) *	8.59 (6.151, 12.00) *
40-49		12.30(8.78, 17.23) *	12.81 (9.096, 18.162) *
Cluster level Variable			
Built Population			1.631 (1.194, 2.248) *
Random Effects			
Cluster-level variance	0.599		0.1187
ICC	0.15		0.03
MOR	2.094		1.39

*Significant at $p < 0.01$.

Table 3
Model fit statistics.

Statistic	Null Model (M_0)	Fixed Effects Model(M_1)	Multilevel Model (M_2)
Loglikelihood	−2766.2	−2283.15	−2274
Model Deviance	5532.4	4566.3	4548.1
AIC	5536.4	4592.3	4578.1
BIC	5549.2	4675.4	4673.9

obesity among reproductive aged women is significantly linked to the built-up index of the cluster in which these women dwell. This shows that an increase in the built-up index of clusters leads to an increase in the risk of being overweight or obese by at least 60% among women of child bearing age in Ghana.

Additionally, with respect to marital status, married women have an increased risk of being overweight/obese compared to single women, and widowed or divorced reproductive aged women had an 83% increase in the odds of being overweight/obese relative to single women. Although women with at least a child ever born had slightly higher odds of being overweight/obese. The increased odds were insignificantly associated with overweight or obese status among women in their reproductive age in the Ghanaian setting.

4. Discussion

The overall overweight/obesity prevalence of 35.5% (12.54% obese and 22.94% overweight) among women between 15 and 49 years in Ghana is relatively high and differs significantly across communities in Ghana. The reported prevalence of overweight or obesity in this study is similar to that of 33.7% and 30% observed in South Africa and Nigeria, respectively [52,53] but, lower than the 50.1% prevalence observed in Cameroun [54]. As reported in Ref. [1], there is continuous upsurge in overweight/obesity prevalence among adult populations, especially women living in urban communities in SSA. The disparity in overweight or obesity prevalence is attributed to the disparity in wealth status, marital status, and educational attainment, especially in urban settings [13,55]. The present study found educational attainment, age, household wealth, place of residence, marital status of reproductive women, and the built-up index of the cluster where reproductive aged women live as significant risk factors for overweight/obesity among women in Ghana. We observed a significant positive association between overweight/obesity and educational attainment of reproductive women. Similar findings were observed and noted elsewhere in Tanzania and Botswana [56,57] but, contradicts the findings in Refs.

[17,58] where no association or the reverse were observed between educational attainment and overweight/obese body status.

Wealth status of households of women in Ghana was a significant determinant of large body size and its associated socio-cultural perception which is consistent with findings in Refs. [13,59] where gaining more weight may be considered as a sign of high social status and wealth of one's family and background. Interestingly, bigger body size and image in most African settings and traditions including Ghana are associated with wealth status, beauty, and other socio-cultural perceptions [8,16]. Moreover, improvements in living conditions in urban areas coupled with rapid westernization of lifestyle such as dietary modifications and sedentary work environments are possibly driving the rise in overweight/obesity prevalence in major parts of SSA [6,8,10,12].

In addition, women who are married, widowed, or divorced have increased odds of gaining weight, which consequently results in overweight/obese relative to women who are single. This is could be as a result of the "model of attractiveness" of body image and marriage in society where single women in general are very particular about their body image and shape compared to married women who are not in search for marriage partners or suitors [60–62]. This further affirms conclusions in Refs. [17,62], where being married with more than two (2) children increased the odds of a woman to be overweight/obese than their counterparts who are unmarried and have no children.

The prevalence of overweight or obesity as a global health concern has multifaceted determinants at the individual, community, and national levels [63]. Community level characteristics such as neighborhood-built environment are important to decreasing or increasing the risk of overweight or obesity. Findings in Refs. [12,64] established a positive relationship between one's body mass index and the distribution of fast-food restaurants in most built-up environments. According to Ref. [10], easy access to fast-food restaurants may increase the risk of overweight or obesity due to the excess calorie intake and low diet quality associated with most of these restaurants. Moreover, rapid urbanization is highly linked to lack of physical activity in most sub-Saharan African countries. This may be due to the easy access to energy-dense food as a result of nutrition transition and reduced strenuous jobs in urban areas [12,58]. Findings in this study further support the high risk of overweight or obesity associated with urban areas compared to rural settings in past studies [12,65].

Furthermore, another significant risk factor for overweight or obesity among women is an increase in age. The study observed that women aged above 30 years are at a significantly higher risk of being overweight/obese than those below 20 years. This observation was noted in Refs. [14,66–68] where the risk of overweight/obesity increased significantly with advancement in age. This finding could be linked to reduced physical activity of women as the age and coupled with the intake of more energy-dense foods, which could in overweight and obesity [69,70]. The reason could be that, as women grow, their body composition undergoes modifications, which can result in an increased in fat mass and a decrease in fat-free mass [71]. The continuous increase in overweight and obesity prevalence among women in their reproductive age in Ghana and across SSA poses a serious public health threat to lives and health systems [7,14,23]. The high prevalence of overweight and obesity pose a growing public health threat, especially among reproductive aged women in Sub-Saharan Africa and could derail efforts instituted to meet the United Nations' SDG 3, which could also affect other SDGs by the end of 2030 [72–74]. On the other hand, the burden of the continuous upsurge in the prevalence of overweight/obesity in the adult population could further worsen the already weak public health system, which requires government commitment to strengthen. Public health education on lifestyle modification and healthy dietary as well as encouraged physical activity among couples could minimize overweight/obesity prevalence within the settings as recommended in Refs. [1,54].

The increase in the prevalence of overweight or obesity among women of childbearing age in Ghana has substantial ramifications for the country's healthcare system. This pattern has been seen in a number of low- and middle-income (LMIC) countries, and it results in a steadily rising need for the treatment of chronic illnesses typically associated with being overweight or obese, such as cancer, diabetes, and cardiovascular diseases [7–9]. Targeted interventions are needed to combat the public health threat because women in reproductive age who have at least basic education and live in urban areas are at a high risk of being overweight or obese. Stakeholders at many levels should be involved in these intended interventions to control for nutrition transitions, sedentary lifestyle adjustment for the person, community, and diverse socioeconomic status in order to ensure commitment and support from everyone.

4.1. Strengthen and limitations of the study

It is important to highlight some strengths and limitations of this study. First and foremost, the use of national cross-sectional survey data which is representative of all women guarantees the validity of generalization of the findings to all women of child bearing age in Ghana. In addition, the DHS program ensured that all forms of error or bias were minimized through the use of a validated questionnaire, well-defined protocols, and highly experienced data collectors. The study also presents findings on the risk of overweight or obesity among women in their reproductive age based on individual and cluster level characteristics. Despite the important findings in this study, these findings were interpreted in the midst of some few limitations. The first limitation has to do with large amount of missing/incomplete data on the sampled women, which drastically reduced the sample size used for the final analysis. Secondly, the limited complete cluster/community level characteristics to present more insight on the risk of overweight and obesity among reproductive age women limited the scope of findings. Moreover, the wealth status variable categorizations were not measured in figurative terms (eg dollars) but were determined using easy-to-collect data on the household's ownership of a few selected assets.

5. Conclusion

The prevalence of overweight and obesity among women in their reproductive age in Ghana is very high and is influenced by the older age group (>30 years), from a rich household, attainment of higher education and being married, divorced or widowed. This finding is significant and requires urgent public health measures targeting young and single women in their reproductive age to help reduce the risk of overweight/obesity and avert the public health burden in the country.

Author contribution statement

Killian Asampana Asosega: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Eric Nimako Aidoo: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Atinuke Olusola Adebanji: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Ellis Owusu-Dabo: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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