

Identifying the Risk Factors for Metabolic Syndrome in Bangladesh: Documented from a Nationwide Survey

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SUMMARY

Metabolic syndrome is a complex of interrelated health conditions that pose a significant risk of developing cardiovascular disease, stroke, and type 2 diabetes. Resistance to insulin, genetic predisposition, high blood pressure, inflammation, and excess abdominal fat are the main stimuli of this syndrome. Metabolic syndrome is becoming more widespread due to fast and unplanned urbanization causing changes in lifestyle, such as poor dietary habits and sedentary behavior, that decrease the metabolic rate in the human body. A developing South Asian country like Bangladesh is most vulnerable to components of metabolic syndrome such as obesity, hypertension and diabetes. Consequently, it has become one of the major public health concerns. Prediction of disease status is a key component of community and health service policymaking. A nationally representative cross-sectional survey, the Bangladesh Demographic and Health Survey (BDHS), is used to find statistically significant variables for metabolic syndrome. BDHS datasets do not contain any direct data regarding metabolic syndrome. A binary variable is generated by utilizing the available data on blood pressure, blood glucose level, and body mass index (BMI). Overall, 34.33% of the population has metabolic syndrome. Primarily, bivariate analysis is performed using chi-square testing to find variables that are correlated with metabolic syndrome. Results of binary logistic analysis are presented in terms of coefficients and odds ratios (OR) with 95% confidence intervals (CI). Age, gender, education, division (province), occupation type, and wealth index are found to be important covariates for the syndrome. Age especially is seen as one of the most influential factors, since the prevalence of metabolic syndrome is only 12.17% for the age group younger than 18 years, while for the group older than 65 years it is 62.18%. Residents of Barishal have the highest rate of metabolic syndrome (38.58%). The rate in the country's capital Dhaka is 34.48%. Individuals whose employment primarily involves manual labor are 11.1% less likely to suffer from metabolic syndrome than those doing non-manual work.

Key words: metabolic syndrome, Bangladesh, logistic regression, chi-square test of independence, p-value

1. Introduction

1.1. Background of the study

Metabolic syndrome is a group of health issues which includes high blood pressure, excess abdominal fat, increased level of glycemia, high triglycerides and low HDL cholesterol. Primary causes of metabolic syndrome are excess weight, insulin resistance, less physical activity, genetics and age (see Chowdhury et al., 2018). Diabetes, hypertension and cardiovascular illnesses are more likely to develop in people with metabolic syndrome. Globally, the prevalence of metabolic syndrome is rising almost daily. A diabetic, hypertensive, or obese individual, or a person diagnosed with any mix of these disorders, is a victim of metabolic syndrome and will, as a result, suffer from a number of associated ailments. In 2020, the global prevalence of metabolic syndrome was expected to be 2% for children and 4% for adolescents, equivalent to approximately 25.8 million children and 35.5 million adolescents (see Noubiap et al., 2022). In the presence of metabolic syndrome, the risk of sudden death increases by 68% (see Hess et al., 2017). As the frequency of metabolic syndrome rises, its consequences for cancer become increasingly evident. It has been shown that obese individuals tend to present with more localized tumors, suffer quicker recurrence, and have a worse overall survival rate. It is thought that the elevated endogenous estrogen level in women who are obese has a crucial role in both the prevalence of endometrial cancer and postmenopausal breast cancer (see Braun et al., 2011). Other than affecting a person's bodily health, this condition also negatively impacts mental health. Individuals suffering from diseases such as bipolar disorder and schizophrenia have a higher frequency of metabolic syndrome and its components. As compared to the general population, those with serious mental health problems lose up to 30 years of potential life, mostly owing to early cardiovascular death (see Newcomer et al., 2007).

The prevalence of metabolic syndrome in South Asia was estimated (2015) to range from 14.0% to 32.5% (see Aryal et al., 2016). Bangladesh is a developing South Asian nation, and its economy is steadily growing. Due to rapid urbanization, pollution, and unhealthy lifestyles, noncommunicable diseases are rising in Bangladesh. Noncommunicable diseases account for 67% of all deaths (see Government of Bangladesh, 2018). As indicated previously, cardiovascular disease is the major cause of these deaths, and metabolic syndrome is a significant risk factor for cardiovascular disease (see Galassi et al., 2006). Around 37.0% of Bangladesh's population has

metabolic syndrome, according to estimates (see Chowdhury et al., 2018). This is a critical public health issue that must be addressed immediately. To design effective interventions against metabolic syndrome, it is necessary to have up-to-date estimates of the syndrome's burden and related risk factors. However, there is a deficiency in the evidence supporting national estimates of metabolic syndrome. This study seeks to address that knowledge gap by investigating the prevalence of metabolic syndrome and related variables in a nationally representative sample of Bangladeshis.

In Bangladesh, metabolic syndrome prevalence (8.6–20%) using the ATP III (National Cholesterol Education Program Adult Treatment Panel III), IDF (International Diabetes Federation), and WHO classifications increased with age, more markedly in females, aligning with trends in Indian, South Asian, and American populations (see Rahim et al., 2007). Gupta et al. (2022) linked older age, lower education/income, and smoking to higher metabolic syndrome risk in Bangladesh. Prevalence was 30.4%, higher in women (33.5%) than men (27.1%). High blood pressure was the most common component, followed by central obesity, low HDL cholesterol, high triglycerides, and high fasting glucose. Additionally, Akter et al. (2012) discovered a significant link between age at menarche and metabolic syndrome in rural Bangladeshi women. Early menarche increased the risk of metabolic syndrome, with a prevalence of 25.7%. The main components were central obesity and low HDL cholesterol. In Nepal, Sharma et al. (2011) reported associations of hypertension, obesity, diabetes, and metabolic syndrome with demographics. Metabolic syndrome prevalence was 21.5%, with higher rates in women (24.3%) than men (18.3%). The American Heart Association underscores the significant impact of comorbidities—hypertension, obesity, diabetes mellitus, hyperlipidemia, and metabolic syndrome—on chronic heart failure. Up to 50% of patients with chronic heart failure exhibit obesity, and diabetes mellitus and hypertension are present in up to 40% and 60%, respectively (see Bozkurt et al., 2016). Studies by Huh et al. (2017) revealed that individuals with metabolic syndrome at baseline had a higher risk of developing chronic kidney disease (CKD) than those without. The incidence rate of CKD was 15.6 per 1,000 person-years in participants with metabolic syndrome, while it was 6.7 per 1,000 person-years in those without metabolic syndrome. Such components as hypertension and high fasting blood glucose levels independently increased the risk of developing CKD. In their study, Patton et al. (2010) found that children with metabolic syndrome and non-alcoholic fatty liver disease (NAFLD) exhibited more severe liver histology,

including higher levels of steatosis, inflammation, and fibrosis. For example, 78% had moderate to severe steatosis (vs. 53% among those without the aforementioned conditions), 45% had moderate to severe inflammation (vs. 24%), and 22% had advanced fibrosis (vs. 9%). Patients with metabolic syndrome were shown to have a 33% higher risk of stroke recurrence and a 51% higher risk of all-cause mortality; individual components, like hypertension, were independently associated with elevated risks (see Zhang et al., 2021). According to Limon et al. (2020), individuals with metabolic syndrome have markedly lower mental health-related quality of life than those without, as evidenced by significantly lower mean scores on the relevant scale.

1.2. Objectives of the study

The primary goals of this study are to estimate the prevalence of metabolic syndrome in Bangladesh and to identify the risk factors that are associated with this condition. The following is a list of particular areas of investigation:

- Determination of the prevalence of metabolic syndrome in Bangladesh.
- Identification of risk factors associated with metabolic syndrome in Bangladesh using the chi-square test of independence.
- Evaluation of the impact of variables using logistic regression analysis.

2. Data and variables

This section provides information regarding the data source and the processing of the data, as well as a brief explanation of the variables used in the analysis.

2.1. Source of data

The study utilized data from the 2017–2018 Bangladesh Demographic and Health Survey (BDHS), the eighth national survey funded by USAID (United States Agency for International Development). The sampling frame, based on enumeration areas (EAs) from the 2011 census, ensured national representation. A total of 675 EAs were chosen, with 30 homes randomly selected per EA, resulting in 20,160 responding residential homes. The survey covered 672 sites, and for the Blood Pressure and Diabetes Health Survey (BDHS) 2017–2018, one-fourth of homes (4864 households) underwent blood pressure and glucose testing. Among eligible individuals aged 18 and older, 93% of

women and 85% of men had their blood pressure measured, and 87% of women and 79% of men had their blood glucose levels checked.

2.2. Studied variables

The following sections describe the dependent and explanatory variables used in our study.

2.2.1. Dependent variable

The study examines metabolic syndrome in the form of a binary variable (Yes or No), using BDHS data. Metabolic syndrome is determined based on hypertension (systolic blood pressure ≥ 140 mm Hg or diastolic ≥ 90 mm Hg), diabetes (blood glucose level ≥ 7 mmol/L), and obesity (BMI ≥ 30.0). If at least one condition is met, metabolic syndrome is coded as "1" (Yes); otherwise, it is coded as "0" (No).

2.2.2. Explanatory variables

All of the independent variables are categorical. The details of all categorical variables are given below:

1. **Age group:** Age in years is categorized as "<18", "18-25", "25-35", "35-45", "45-55", "55-65", "65+".
2. **Gender:** This variable is categorized as male and female.
3. **Wealth index:** Wealth index is an important factor behind metabolic syndrome. This variable is coded as poorest, poorer, middle, richer, and richest.
4. **Place of residence:** Place of residence can be considered as a risk factor for metabolic syndrome. Residence is categorized as urban and rural.
5. **Occupation type:** This variable is categorized as physical and non-physical.
6. **Division:** Bangladesh is divided administratively into eight major regions called divisions; these are Dhaka, Sylhet, Khulna, Barishal, Mymensingh, Rajshahi, Rangpur and Chittagong.
7. **Highest level of education:** This variable is coded in four categories, namely no education, up to primary, secondary, and higher.

3. Methodology

This section provides a short description of the theoretical basis of the present study.

3.1. Chi-square test of independence

The chi-square test assesses the association between two categorical variables, employing a contingency table to display the counts of combined variable responses. This test is exclusive to categorical variables and cannot compare continuous variables or measure their association. Conditions for the test include unrelated categories, disconnected subjects in each group, anticipated cell values ≥ 1 , moderate expected frequencies for most cells, a large sample size for comparisons, and no matching of categorical variables. Two valid approaches, one emphasizing relationship and the other independence, yield the same results. For convenience, assumptions are presented with a focus on association. The hypotheses of the chi-square test are as follows:

H_0 : There is no association between the two variables.

H_1 : There is association between the two variables.

$$\chi^2 = \sum_{i=1}^n \sum_{j=1}^n \frac{(O_{ij} - E_{ij})^2}{E_{ij}},$$

where O_{ij} ($i=1, \dots, r$ and $j=1, \dots, k$) denote the observed frequencies, and E_{ij} ($i = 1, \dots, r$ and $j = 1, \dots, k$) denote the expected frequencies. On the assumption that there is no significant difference between the two groups, the test statistic will have $(r - 1) \times (k - 1)$ degrees of freedom and follow a chi-square distribution. In the test statistic, O_{ij} is the observed frequency of the i^{th} row and j^{th} column and E_{ij} is the expected frequency of the i^{th} row and j^{th} column. The expected frequency E_{ij} is calculated as:

$$E_{ij} = \frac{(\text{total of } i^{th} \text{ row}) * (\text{total of } j^{th} \text{ column})}{\text{total number of observations}}.$$

Rejection of the null hypothesis occurs when the chi-square test statistic surpasses the critical value or when the p-value falls below the chosen significance level (e.g., 0.05), signaling a significant association between the variables (see Hogg et al., 2005).

3.2. Binary logistic regression model

In general regression, predictions are made for continuous dependent variables based on covariates. However, when dealing with binary outcomes, binary logistic regression becomes pertinent. This modeling technique is especially suited for scenarios where the response variable is binary (1 for "yes" and 0 for "no"). In our study on metabolic syndrome, we employ binary logistic regression to model the binary response variable, indicating the presence or absence of metabolic syndrome.

For the outcome variable, let Y_i denote the response of the i^{th} observation. Now the response variable Y_i is categorized into

$$Y_i = \begin{cases} 1, & \text{if respondent has metabolic syndrome.} \\ 0, & \text{if respondent does not have metabolic syndrome.} \end{cases}$$

Let $X_{i1}, X_{i2}, \dots, X_{ip}$ be the set of explanatory variables, which may be both quantitative variables or indicator variables presenting different categories, and let $x_{i1}, x_{i2}, \dots, x_{ip}$ be the observed values of the variables $X_{i1}, X_{i2}, \dots, X_{ip}$. For convenience within a study, it may be required to convert continuous random variables into the categories using statistical software, and this conversion often leads to a suitable outcome.

As mentioned earlier, the response variable is a Bernoulli random variable, and so it is clear that this variable follows the Bernoulli distribution with parameter π_i . For the outcome, the probability of success is defined as

$$P(Y_i = 1) = \pi_i = \frac{\exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip})}{1 + \exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip})}.$$

The above equation can be re-expressed using the logit function for a simple expression, as follows:

$$g(X) = \text{logit}(\pi_i) = \log \frac{\pi_i}{1 - \pi_i} = \beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip}.$$

The next step is to estimate the parameters. For this purpose we use the maximum likelihood technique. The likelihood is maximized by finding estimates of the parameters that are most likely to provide the data. The MLE (Maximum Likelihood Estimator) of β_0 and β_1 can be obtained by

maximizing the following likelihood function:

$$L(\beta_0, \beta_1) = \prod_{i=1}^n \frac{\exp(\beta_0 + \beta_1 x_i)}{1 + \exp(\beta_0 + \beta_1 x_i)}.$$

The likelihood equation may be challenging, prompting our use of the log-likelihood function for simplified and more accurate parameter estimations. By maximizing the function below, we obtain results comparable to those based on the likelihood function.

$$l(\pi, \mathbf{y}) = \sum_{i=1}^N [y_i \log(\pi_i) + (n_i - y_i) \log(1 - \pi_i) + \log(n_i C y_i)].$$

3.3. Odds ratio

The odds ratio (OR) is a key measure indicating the relationship between an exposure variable and an outcome. It calculates the likelihood of an event under specific exposure conditions compared with the likelihood when the exposure is absent. It is commonly employed in epidemiological studies. In logistic regression, the coefficient measures the increase in log odds for the outcome with each unit increase in the exposure variable. The odds ratio, also known as relative odds, straightforwardly assesses the impact of an exposure variable on the outcome, facilitating easy interpretation.

4. Analysis and results

A visual representation of the distribution of metabolic syndrome across the various categories of explanatory variables was obtained through exploratory data analysis. To access percentage distributions of the various variables and their associations with metabolic syndrome, a bivariate analysis was then conducted. The simultaneous impacts of all explanatory variables on metabolic syndrome were then investigated.

4.1. Exploratory analysis

In this section, we consider the bivariate analysis. This study employs bivariate analysis to examine whether a result has a statistically significant relationship with many types of variables. We determine, in short, whether a given variable has a meaningful effect on metabolic syndrome.

Table 1. Metabolic syndrome by explanatory variables

Variable	%(Metabolic syndrome)	N	p-value
Age			
<18	12.17	493	<0.001
18-25	13.52	2307	
25-35	25.96	3174	
35-45	38.7	2300	
45-55	48.17	1642	
55-65	55.2	1366	
65+	62.18	870	
Gender			
Male	32.21	5241	<0.001
Female	35.94	6911	
Wealth index			
Poorest	26.63	2366	<0.001
Poorer	29.22	2300	
Middle	32.56	2408	
Richer	36.68	2386	
Richest	45.25	2692	
Residence type			
Urban	37.33	4348	<0.001
Rural	32.66	7804	
Occupation type			
Non-physical	39.67	6304	<0.001
Physical	28.57	5848	
Division			
Barishal	38.53	1264	<0.001
Chittagong	37.34	1647	
Dhaka	34.48	1592	
Khulna	35.94	1678	
Mymensingh	28.49	1376	
Rajshahi	33.5	1591	
Rangpur	35.12	1569	
Sylhet	30	1435	
Level of education			
No education	41.06	2964	<0.001
Primary	33.7	3677	
Secondary	30.78	3518	
Higher secondary	31.76	1993	

This study demonstrates that the respondent's age, wealth index, gender, residence type, occupation type, division, and level of education had a substantial impact on the response. Prevalence of metabolic syndrome and total number of observations (N) were calculated for each category of all of the explanatory variables, as well as their p-values. After completing this analysis variable by variable, the following summary table was created. The above table shows that the rate of metabolic syndrome increases with age, and the association between age and metabolic syndrome is seen to be significant ($p\text{-value} < 0.01$). Hence, older citizens are more vulnerable to this disease. There is a slight difference between the rates of metabolic syndrome in males (32.21%) and females (35.94%). As levels of the wealth index increase from poorest to richest, there is growth in the prevalence of metabolic syndrome. People with the highest socioeconomic status had the highest rate (45.25%), and those from the lowest socioeconomic group had the lowest rate (26.63%). People living in urban areas are more likely than rural dwellers to suffer from obesity, hypertension and diabetes, which are indicators of metabolic syndrome. Urban residents had a 4.67% higher risk of developing metabolic syndrome. Presence or absence of physical work is also related to metabolic syndrome. Manual workers have a lower prevalence than people in non-manual jobs. Manual labor decreases the prevalence by 11.1%. The data reveal that the prevalence of metabolic syndrome is lowest in Mymensingh (28.49%) and highest in Barishal (38.53%). The prevalence in Dhaka falls somewhere between the highest and lowest (34.48%). Those with higher levels of education have a heightened awareness of the importance of health and fitness in their own lives. The results of the bivariate analysis reflect this. Metabolic syndrome is more prevalent among those who have no education (41.06%), and those who have at least secondary education have the lowest rate (30.78%).

4.2. Logistic regression analysis

Logistic regression was necessary for this investigation's binary response variable. In this study, metabolic syndrome is used as the outcome variable, and the relevant factors that relate to it are taken from the previous section.

Table 2. Binary logistic regression analysis

Variable	Coefficient	Odds ratio (OR)	95% CI (OR)		p-value
			Lower	Upper	
Age					
<18 (Ref.)					
18-25	0.139	1.149	0.853	1.549	0.36
25-35	1.05	2.858	2.146	3.805	<0.001
35-45	1.717	5.567	4.163	7.441	<0.001
45-55	2.137	8.471	6.292	11.403	<0.001
55-65	2.44	11.467	8.475	15.516	<0.001
65+	2.724	15.245	11.104	20.929	<0.001
Gender					
Male (Ref.)					
Female	0.312	1.365	1.251	1.489	<0.001
Wealth index					
Poorest (Ref.)					
Poorer	0.162	1.175	1.024	1.348	0.022
Middle	0.311	1.364	1.188	1.566	<0.001
Richer	0.516	1.674	1.448	1.935	<0.001
Richest	0.822	2.274	1.944	2.661	<0.001
Residence type					
Urban (Ref.)					
Rural	-0.02	0.98	0.892	1.077	0.683
Occupation type					
Non-physical (Ref.)					
Physical	-0.335	0.715	0.653	0.783	<0.001
Division					
Barishal (Ref.)					
Chittagong	-0.109	0.896	0.758	1.06	0.203
Dhaka	-0.251	0.778	0.655	0.923	0.004
Khulna	-0.219	0.803	0.679	0.948	0.01
Mymensingh	-0.442	0.642	0.538	0.767	<0.001
Rajshahi	-0.161	0.851	0.719	1.007	0.061
Rangpur	-0.015	0.985	0.833	1.165	0.864
Sylhet	-0.326	0.721	0.605	0.86	<0.001
Level of education					
No education (Ref.)					
Primary	0.173	1.188	1.06	1.332	0.003
Secondary	0.205	1.227	1.079	1.396	0.002
Higher secondary	0.179	1.195	1.016	1.404	0.031

When we take into account all of the different variables to construct the binary logistic regression model, we find that the type of residence is not significant (Table 2). The other variables are significant, however. The regression results show that people in the 18–25 age group have a 14.9% higher odds of having metabolic syndrome than the reference age group (younger than 18 years). The age groups 25 to 35, 35 to 45, 45 to 55, 55 to 65, and over 65 years have 2.858, 5.567, 8.471, 11.467, and 15.245 times higher odds of having metabolic syndrome, respectively, than people under the age of 18 years. The odds of metabolic syndrome are 36.5% higher in females than in males. As can be observed from Table 2, having a higher socioeconomic status increases one's risk of acquiring metabolic syndrome. Poorer, middle-class, and richer groups have higher odds of having metabolic syndrome than the lowest group by 17.5%, 36.4%, and 67.4%, respectively. The richest group had odds that were 2.274 times higher. A person's occupation type has a significant effect on metabolic syndrome. Those doing manual work are less likely to develop metabolic syndrome, as Table 2 shows. The odds for individuals with physical occupations are 28.5% less than for those with non-physical occupations. This can be attributed to the fact that higher levels of physical activity may promote better metabolic health. The effect of division in the logistic regression analysis is quite similar to that found in the bivariate analysis. Here Barishal is set to be the reference group. Compared with Barishal, people living in Chittagong are 10.4% less likely to develop metabolic syndrome (in terms of odds). People residing in Dhaka, Khulna, Mymensingh, Rangpur, Rajshahi, and Sylhet have respectively 22.2%, 19.7%, 35.8%, 14.9%, 1.5%, and 28.9% lower odds of suffering from metabolic syndrome. Completion of primary, secondary, and higher education is associated respectively with 18.8%, 22.7%, and 19.5% higher odds of developing metabolic syndrome. This contradicts the bivariate analysis results, which implied that a higher level of educational attainment lowered the prevalence of metabolic syndrome. This occurs because in this model the odds were adjusted after taking the effects of all other variables into account.

4.3. Discussion and conclusion

In this study, an investigation was made of factors that are associated with metabolic syndrome. Several variables are found to be significant, namely respondent's age, division, wealth index, occupation type, educational qualification, and gender. One other variable that showed a significant

association with metabolic syndrome in the bivariate analysis is residence type; however, this was eliminated in the binary logistic regression as it was found to be insignificant after adjusting for all other variables. Our study demonstrated that, of all the variables considered, the respondent's age is the most sensitive. This variable is separated into seven categories so that the impact of age can be better understood. The likelihood of developing metabolic syndrome is shown to increase with age in both bivariate and logistic regression analyses. Globally, a similar pattern has been observed (see Kelli et al., 2015). Females are more likely to have metabolic syndrome than men, according to the findings of this study. In recent years a change has been observed in the effects of gender on metabolic syndrome. During the last decade, the prevalence of metabolic syndrome has been much higher in women than men (see Regitz et al., 2006). Wealth index and level of educational attainment are also important factors. Higher status or education increases the risk of developing metabolic syndrome, which contradicts the common knowledge that metabolic syndrome is more prevalent amongst the poor (see Perel et al., 2006). This can be explained by an understanding of the lifestyles of different groups. People from higher echelons of society usually lead a very stressful life and are less likely to be involved in physical activities. This is connected to the investigation of the relation between metabolic syndrome and occupation type, which reveals that physical work reduces the risk of having metabolic syndrome. Past studies show that physical activities are beneficial for cardiovascular health and are also effective against metabolic syndrome (see Wang et al., 2014). A great strength of this study is its large and nationally representative dataset. This enables conclusions to be generalized nationwide, and can provide an overview of the prevalence of metabolic syndrome within various categories of age groups, socioeconomic indicators, occupations, gender and division. Despite its merits, the study has a few limitations. The findings indicate only whether an association is present or not; they do not prove causation. This study is limited to the variables available in the dataset, and could not control for all factors that may be associated with metabolic syndrome. The findings of this study indicate a need for government and non-government interventions to increase awareness about metabolic syndrome among Bangladeshis and to identify the most vulnerable groups affected by the syndrome, in order to prevent unnecessary deaths. Initiatives should be undertaken to reduce the high mortality rate of metabolic syndrome and its components. Urbanization should be planned accordingly, so as to provide citizens with sufficient green

space and facilities to encourage them to be more physically active. Rather than encouraging people to follow the Western lifestyle and consume an unhealthy amount of processed food, which leads to various cardiovascular diseases, government and non-government organizations should promote a healthy dietary plan.

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