TETF/DESS/POLY/UGBOKOLO/ARJ/2019/VOL.1 BSP Adv. Sci. Eng. Technol. Maiden Edition, December, 2024

Innovative Academia Hub International IAHI
EMPOWERING MINDS INSPIRING EXCELLENCE DRIVING INNOVATIONS

BSP ADVANCES IN SCIENCE, ENGINEERING AND TECHNOLOGY

www.iahiservices.com

A Binary Logistic Regression Model for Assessing Predisposing Factors of Obesity among Urban Traders in Benue State

Simon Shir Usu[1*], Jonathan Atsua Ikughur[2] and Enobong Francis Udoumoh[3]

[1]Department of Computer Science and Statistics, Akperan Orshi Polytechnic, Yandev-Gboko, Benue State-Nigeria

[2,3]Department of Statistics, Joseph Sarwuan Tarka University, Makurdi-Nigeria

*Corresponding Author: Email: ususimonshir@gmail.com, ususimonshir@aopoly.edu.ng Phone: +2348065217993.

ABSTRACT-The study investigated the predisposing factors to obesity among adult urban traders in four selected towns in Benue State-Nigeria using binary logistic regression modeling procedure. The study utilized a cross -sectional design and a stratified random sampling technique using structured questionnaire to elicit responses from 400 selected traders considering their lifestyle, habits and socio-economic factors, anthropometric measurements and physical exercise. Sensitivity and specificity tests were also performed. Sensitivity and specificity tests results showed 99.2% and 97.9% respectively, indicating the extent to which the obese and non -obese cases were correctly classified. Results showed that increase in health challenges (= 0.000), household income (= 0.000), body weight (= 0.018), parental history (= 0.027), alcohol intake (= 0.001), educational level (= 0.034) were associated with the increased likelihood of traders being obese, whereas increase in physical exercise (= 0.000) was associated with the decreased likelihood of traders being obese. The prevalence of obesity was found to be 61.75% among thetraders in the study area. The study recommends that promoting healthy dietary and weight management practices as well as encouraging regular physical exercise and other healthy life style changes like not drinking alcohol might be of great importance to the adult urban traders in the study area.

Keywords: Binary Logistic Regression, Lifestyles, Obesity, Odds Ratio, Overweight, Traders, Nigeria.

1. INTRODUCTION

Overweight and obesity have become a major public health problem in the last two decades in the world. Lavie *et al.* [1] defined overweight and obesity as possessing abnormal excessive body fat accumulation that can cause harm to one's health. The worldwide problem of overweight and obesity has affected individuals, families, societies, and nations. The prevalence of obesity worldwide nearly tripled between 1975 and 2016. According to WHO [2], about two billion adults currently live with overweight, of which 650 million are considered to be affected by obesity (BMI≥30 kg/m²). Equivalently, about 39% of men and 40% of women of adults aged 18 years and above are living with overweight and 13% living with obesity. It is estimated that most of the world's population now lives in countries where overweight and obesity are a bigger risk to health than underweight [2]. The World Obesity Federation estimated that by the year 2020, around 770 million adults globally will be affected by obesity, and that figure is anticipated to exceed one billion by the year 2030 unless serious measures are taken [3]. In Nigeria, a meta-analysis of 75 published articles revealed that the prevalence of overweight individuals ranged from 20.3%–35.1%, while the prevalence of obesity ranged from 8.1%–22.2% [4].

The most common method of identifying, estimating, and monitoring overweight or obesity is the body mass index (BMI), which is cost-effective, easy to calculate, suitable for all ages and genders, and very popular in clinical practices. Obesity is associated with some chronic diseases including hypertension, Type 2 diabetes mellitus (T2DM), cardiovascular diseases (CVDs), arterial stiffening dyslipidemia, chronic liver disease, bronchial asthma, musculoskeletal disorders, sub-fertility, renal failure, psychosocial disorders, and some types of oncological diseases [5]. Obesity has been declared a global epidemic as its prevalence is on the rise in both industrialized advanced economies and middle to low-income countries. This declaration has made overweight and obesity a clinical and public health concern worldwide. The prevalence of overweight and obesity among older adults has been considered high in the systematic analysis of the global burden of obesity disease [6].

Several empirical studies have documented that overweight and obesity are the major reasons for co-morbidities, diabetes, heart disease, cancer, and other health challenges. The associated healthcare cost is also a significant factor, for example, Olufemi *et al.* [7] found in a study conducted in Abuja-Nigeria that many cardiovascular risk factors such as overweight, obesity, hypertension, and higher anthropometric indices were significantly prevalent among the urban population compared to the rural population while smoking and alcohol intake were more prevalent among the rural population. Ukegbu *et al*. [8] found the prevalence of overweight and obesity to be 25% and 31.7% respectively from a cross-sectional study of 240 market women in the Umuahia market in Nigeria. In a related development, Mawaw *et al*. [9] conducted a study and reported a prevalence of 13.26% of obesity among 430 women selling in the central market of Lusonga in Lubumbashi. Marital status, education level, residence, use of oral birth control pills, and consumption of fruit and vegetables were found to be significant factors associated with the prevalence of obesity in this category of women.

The prevalence of obesity was also found to be relatively high (36.8%) among University of Botswana students in a study conducted by Tapera *et al*. [10] to determine the prevalence and factors associated with overweight/obesity among University of Botswana (UB) students. By analyzing physical measurements and physical activity index to assess the likelihood of overweight and associated factors among young students, Noora (2019) found the prevalence of overweight to be higher in female students (27.8%) than in males (14.7%). The odds ratio for gender revealed that the likelihood of subjects falling into the overweight category was 2.6 times higher in females as compared to male subjects. Kabore *et al*. [11] determined the prevalence and predictors of overweight and obesity in Burkina Faso using a population-based countrywide sample of 4800 and found that the prevalence of overweight and obesity in Burkina Faso were 13.82% and 4.84% respectively.

The urban lifestyle, overreliance on technology, and less focus on physical exercise bring health-related problems such as overweight or obesity among adult urban traders. This raises the question about the prevalence and contributing factors of obesity using simple and cost-effective screening methods in adults. The present study attempts to assess the likelihood of obesity and its associated factors among adult urban traders in some selected towns in Benue State using a binary logistic regression model.

2. MATERIALS AND METHODS

2.1 Population of the Study

The data used in this study is the primary data obtained from an urban-based cross-sectional survey through the use of structured questionnaires, individual interviews, and anthropometric measurements. The population of the study covers four towns in Benue State, namely, Makurdi, Gboko, Otukpo, and Katsina-Ala towns. About 557814 township traders were involved. The urban-based cross-sectional survey for November 2021 was carried out by the researcher.

2.2 Sampling Technique and Sample Size Determination

The researcher purposively selected four local government areas considered to have high urban economic and business activities. These are Makurdi, Gboko, Otukpo and Katsina-Ala LGAs. The sample size consists of 400 town traders including 74, 181, 99, and 46 respondents from Makurdi, Gboko, Otukpo, and Katsina-Ala LGAs respectively.

2.3 Measurements of Variables

The physical measurements for the subjects were recorded by the researcher to negate any inter-observer variability. Some of the explanatory variables such as height, weight, and body mass index (BMI) were measured by the researcher based on the report of WHO expert consultation (WHO, 2008). Body Mass Index (BMI) was calculated by dividing weight in kg by height in m^2. This study considered a dichotomous outcome variable obese or no obese. For the subjects whose BMI<18.5kg/m^2 corresponds to being underweight, a BMI of 18.5-24.99kg/m^2 represents a normal range, BMI≥25kg/m^2 corresponds to the overweight group, a BMI range of 25-29kg/m^2 corresponds to the pre-obese group whereas BMI ≥30.00kg/m^2 corresponds to the obese group [12].

2.4 Methods of Data Analysis

The following statistical tools are employed for analysis in this study.

2.4.1 Binary Logistic Regression

A binary logistic regression analysis is used in this work to predict the likelihood that a subject falls into any one of the two groups of a dichotomous dependent variable (obese or no obese) based on the independent variables that are categorical and continuous. Let us assume that a sample of n independent observations of the pair $(x_i, y_i), i = 1,2, \dots, n$. The probability distribution of the outcome variable is Binomial i.e. $y_i \sim Bin(n_i, \pi(x_i))$ where, y_i denote the value of a dichotomous response variable, and x_i denotes the value of the independent variable for the ith subject. Now,

$$y_i = \begin{cases} 1, \text{if the subject is obese} \\ 0, \quad \text{otherwise} \end{cases}$$

If we consider the conditional mean, as $\pi(x)$, the expected value of y given the value of x in logistic regression:

$$\pi(x) = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}$$

In fitting a binary logistic regression model in equation (1) to a given dataset, the unknown parameters β_0 and β_1 have to be estimated and for dichotomous data, $0 \leq \pi(x) \leq 1$. The binary regression model predicts the logit, which is the natural log of the odds of subjects to be obese or not obese with predictors such as, physical measurement, and physical exercise, level of education etc. The logit transformation in this model is the transformation of $\pi(x)$ which is defined as:

$$\text{logit}\,\pi(x) = \ln\left(\frac{\pi(x)}{1-\pi(x)}\right) = \beta_0 + \beta_1 x \quad (2)$$

Here, $\pi(x)$ is the predicted probability of the event which is coded with "1" obese rather than "0" no obese. $1-\pi(x)$ is the predicted probability of the other decision and x is the independent variable. The logit value may be continuous and range from $-\infty$ to $+\infty$. The expression for $\pi(x)$ in equation (1) provides the conditional probability $Pr(Y=1|x)$ and the term $1-\pi(x)$ gives the conditional probability $Pr(Y=0|x)$ for an arbitrary parameter $\beta=\beta_0$ and β_1, the vector parameters. For those pairs (x_i, y_i), if $y_i=1$, the contribution to the likelihood function is $\pi(x_i)$, and if $y_i=0$, it is $1-\pi(x_i)$; where $\pi(x_i)$ is the value of $\pi(x)$ computed at x_i[13]. It can be expressed as:

$$\pi(x_i)^{y_i}[1-\pi(x_i)]^{1-y_i} \quad (3)$$

For logistic regression, the observations are assumed to be independent, so the likelihood function is obtained as follows:

$$l(\beta)=\prod_{i=1}^{n}\pi(x_i)^{y_i}[1-\pi(x_i)]^{1-y_i} \quad (4)$$

For ease of mathematical calculations, log of equation (4), log likelihood, can be written as:

$$L(\beta)=\ln[l(\beta)]=\sum_{i=1}^{n}\{y_i\ln[\pi(x_i)]+(1-y_i)\ln[1-\pi(x_i)]\} \quad (5)$$

Differentiating equation (5) with respect to β_0 and β_1 for maximizing the likelihood function, $L(\beta)$ and solving for β we get the two likelihood equations as:

$$\sum[y_i-\pi(x_i)]=0 \quad (6)$$

$$\sum x_i[y_i-\pi(x_i)]=0 \quad (7)$$

For binary logistic regression, the terms in equations (6) and (7) are nonlinear in β_0 and β_1, and hence require iterative methods for solution which is obtained by using an iterative weighted least squares technique. Then, the value of the maximum likelihood estimate will be obtained [14]. In the present study, there are few major independent variables such as health challenges, weight, physical exercise, educational level, etc for which the expression of the binary logistics regression model ($i=1,2,\dots,n$ subjects) is given by:

$$\ln\left[\frac{\pi(x_i)}{1-\pi(x_i)}\right]=\beta_0+\beta_1x_{i1}+\beta_2x_{i2}+\beta_3x_{i3}+\cdots+\beta_nx_{in} \quad (8)$$

where, $x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}$ are categorical or continuous independent variables [15]. From equation (8), the equation for the prediction of the probability can be derived and solved the logit equation for $\pi(x_i)$ to obtain:

$$\pi(x_i)=\frac{e^{(\beta_0+\beta_1x_{i1}+\beta_2x_{i2}+\beta_3x_{i3}+\cdots+\beta_nx_{in})}}{1+e^{(\beta_0+\beta_1x_{i1}+\beta_2x_{i2}+\beta_3x_{i3}+\cdots+\beta_nx_{in})}}$$

2.4.2 The Odds Ratio

If an event A has probability P(A) of occurring, the odds of A occurring are defined as

$$Odds(A)=\frac{Pr(A)}{1-Pr(A)}$$

which implies that

$$\Pr(A)=\frac{Odds(A)}{1+Odds(A)}$$

Suppose that X denotes the event that an individual is exposed to a risk of being obese and that D denotes the events that the individual becomes obese, we denote the complementary events as $\overline{X}$ and $\overline{D}$. The odds of an individual becoming obese given that he is obsessed are

$$Odds\left(\frac{D}{X}\right)=\frac{Pr(D/X)}{1-Pr(D/X)}$$

and the odds of an individual becoming obsessed given that he is not obsessed are

$$Odds\left(\frac{D}{\overline{X}}\right)=\frac{Pr(D/\overline{X})}{1-Pr(D/\overline{X})}$$

The ratio is

$$\Delta = \frac{Odds(D/X)}{odds(D/\overline{X})} \quad (14)$$

is a measure of the influence of exposure on subsequent obesity conditions.

3. RESULTS AND DISCUSSION

3.1 Socio-Demographic Characteristics and Summary Statistics of the Respondents

The result of the socio-demographic characteristics and summary statistics of the respondents are computed and presented in Tables 1 and 2.

Table 1: Socio-Demographic Characteristics of the Respondents

Respondent's Characteristics		Frequency	Percentage
Gender	Male	145	36.25
	Female	255	63.75
	Total	**400**	**100**
Age (in years)	20-29	75	18.75
	30-39	152	38.00
	40-49	106	26.50
	50-59	44	11.00
	60-69	23	5.75
	Total	**400**	**100**
Marital Status	Married	279	69.75
	Single	121	30.25
	Total	**400**	**100**

Table 2: Summary Statistics of the Respondents ($n = 400$)

	Minimum	Maximum	Mean	Standard Deviation
Age (years)	25	65	39.43	9.79
Height (m)	1.30	1.90	1.70	0.17
Weight (kg)	28.8	104.1	55.44	16.55
BMI (kg/m^2)	12.65	71.50	32.69	9.71

The result of the socio-demographic characteristics of the respondents reported in Table 1 showed that 145(36.25%) respondents of the total respondents were male while 255(63.75%) were female. This clearly shows that they were more female traders in the study area than their male counterparts.

The age distribution of the respondents shows that 75(18.75%) respondents were between the age of 20-29 years, 152(38%) respondents fall in the age range of 30-39, while 106(26.5%) were between the age range of 40-49 years; 44(11%) of the total respondents were between the age of 50-59 years whereas, 23(5.75%) were between the age of 60-69 years of age. The age distribution of the respondents clearly shows that traders in the age brackets of 30-39 and 40-49 years dominated the study area.

Regarding the marital status of the respondents, 279(69.75%) of the respondents were married while 121(30.25%) were single in the study area. The marital status distribution of the respondents clearly shows that traders who were married dominated the study area. The socio-demographic characteristics of the respondents showed that all the respondents were conversant with the concept of obesity and its implications on human health and trading activities. Therefore, the information gathered from this category of respondents could be deemed reliable.

The summary statistics of the respondents reported in Table 2 indicate that the mean age of the respondents was 39.43 years with a standard deviation of 9.79 years. The minimum and maximum ages of the respondents in the study area were 25 and 65 years respectively. The mean height of the respondents was 1.70 meters with a standard deviation of 0.17 meters. The minimum and maximum heights of the respondents in the study area were 1.30 and 1.90 meters respectively. The mean weight of the respondents was 55.44kg with a standard deviation of 16.55kg. The minimum and maximum weights of the respondents in the study area were 28.8kg and 104.1kg respectively. Whereas, the mean body mass index (BMI) of the respondents was 32.69kg/m^2 with a standard deviation of 9.71kg/m^2. The minimum and maximum BMI of the respondents in the study area were 12.65kg/m^2 and 71.50kg/m^2 respectively. The mean BMI of 32.69kg/m^2 clearly shows that the study population was at risk of being obese or was dominated by people who are obese.

Table 3: Anthropometric Characteristics of the Respondents

BMI	Range	Frequency	Percentage (%)
Underweight	<18.49kg/m^2	7	1.25
Normal	18.50-24.99kg/m^2	132	33.00
Overweight	25.00-29.99kg/m^2	14	3.50
Obese	≥30kg/m^2	247	61.75
	Total	**400**	**100**

Note: BMI = Body mass index

The result of the prevalence of underweight, normal weight, overweight and obesity among the market traders in the study area reported in Table 3 is based on the World Health Organization Classification (WHO, 2008). The result shows that 7(1.25%) respondents were underweight ($BMI < 18.49kg/m^2$), about 132(33%) respondents had normal weight ($BMI = 18.50 - 24.99kg/m^2$), the number of respondents with overweight (possibility of being obese) was 14(3.5%) of the total respondents ($BMI = 25.00 - 29.99kg/m^2$) whereas, the prevalence of obesity among the respondents was 247(61.75%) respondents ($BMI > 30kg/m^2$). The higher prevalence of obesity among the market traders might be as a result of the sedentary lifestyle of the traders since the better parts of their days are made up of sitting activities.

The rate of obesity reported in this study is higher than 31.7% reported among female traders in Umuahia [8].

3.2 Result of Binary Logistic Regression Model

The result of the classification table for the null model is presented in Table 4. The result of the null model (the intercept-only model) is reported in Table 5. The result of Omnibus Tests of Model Coefficients is reported in Table 6. The result of the model summary comprising -2Log likelihood, Cox & Snell R Square, and Nagelkerke R Square is reported in Table 7. The Hosmer and Lemeshow test result is presented in Table 8. The classification table which represents the level of predictive accuracy achieved by the fitted model is presented in Table 9. The parameter estimates of the fitted binary logistic regression model is presented in Table 10 and the result of the final model in step 7 which contains all the significant predisposing factors of obesity among adult urban traders in Benue state is presented in Table 11. The odds predictions for the absence/low or presence/high for the occurrence of an attribute is computed individually for the independent variables based on the final prediction equation reported in Table 11 and presented in Table 12.

Table 4: Classification Table for the Null Model

	Observed		Predicted		
			Obese		Percentage
			No	Yes	Correct
Step 0	Obese	No	0	145	0.00
		Yes	0	255	100.0
	Overall Percentage				63.8

a. Constant is included in the model
b. The cut value is 0.500

The result of Table 4 reports the classification table for the null model (the constant-only model) which displayed the output of 400 selected cases used in the analysis with no missing cases. There are two decision options, the majority 255/400 = 63.8% of subjects were in the yes obese group, coded as "1" whereas, 145/400 = 36.2% of cases were considered as no obese coded as "0".

Table 5: Block 0 Null Binary Logistic Regression Model

	B	S.E.	Wald	Df	P-value	Exp(B)
Constant	0.565	0.104	29.459	1	0.000	1.759

The result reported in Table 5 presents, Block 0, beginning block output variables in the binary logistic regression model, the null, intercept, or constant-only model which is estimated as $\ln(odds) = 0.565$. By taking the exponents on both sides of the expression, the predicted odds $(\exp(B)) = \exp(0.565) = 1.759$. This means the predicted odds of the subjects being obese is 1.759. Since 255 subjects were from the "yes obese" group and 145 subjects were from the "no obese" group, the observed odds are $255/145$ = 1.759. In this constant-only model, the other variables are not included in the model.

Table 6: Omnibus Tests of Model Coefficients

		Chi-Square	Df	P-value
	Step	470.152	1	0.000
Step 1	Block	470.152	1	0.000
	Model	470.152	1	0.000
	Step	53.723	1	0.000
Step 2	Block	523.874	2	0.000
	Model	523.874	2	0.000
	Step	47.842	1	0.000
Step 3	Block	523.874	1	0.000
	Model	523.874	1	0.000
	Step	59.397	1	0.000
Step 4	Block	523.874	2	0.000

	Model	523.874	2	0.000
	Step	64.628	1	0.000
Step 5	Block	544.775	2	0.000
	Model	544.775	2	0.000
	Step	56.638	1	0.000
Step 6	Block	537.566	1	0.000
	Model	537.566	1	0.000
	Step	61.715	1	0.000
Step 7	Block	526.328	2	0.000
	Model	526.328	2	0.000

The Omnibus tests of model coefficients reported in Table 6 give the result of the likelihood ratio (LR) test which indicates whether the inclusion of an additional block of variables contributes significantly to model fit. A p-value of less than 0.05 for block means that the block 1 model is a significant improvement to the block 0 model; the block 2 model is a significant improvement to the block 1 model, and so on. The Chi-square test values in Table 6 are statistically significant showing that the null (the intercept only) model was significant and a good fit for the data. The Chi-square values in the rows showed an increase in fit as a result of adding more predictors to the model. The null hypothesis that all the coefficients are not significantly different from zero was rejected in favor of the alternative hypothesis and a conclusion was made that the fitted model was significantly different from the null model.

Table 7: The Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	53.723	0.691	0.847
2	51.127	0.718	0.877
3	49.652	0.755	0.894
4	46.396	0.779	0.918
5	43.817	0.792	0.936
6	39.907	0.812	0.953
7	37.775	0.847	0.975

It can be observed from Table 7 that the final estimated binary logistic regression model has a relatively larger pseudo R^2 ranging from 0.847 for the Cox and Snell R Square to 0.975 for the Nagelkerke R Square. That is the fitted model can explain or account for about 84.7% to 97.5% of the total variation in the dependent variable. This is an indication of a good model fit. The final model also exhibits the -2Log Likelihood statistic of 37.775. This statistic measures how poorly the model predicts the decision; the smaller the -2Log Likelihood statistic the better the model.

Table 8: Hosmer and Lemeshow Test Result

Step	Chi-Square	Degree of freedom	P-value
1	25.751	3	0.098
2	19.008	3	0.101
3	13.311	3	0.107
4	11.719	3	0.285
5	9.998	3	0.471

6	12.297	3	0.218
7	6.355	3	0.635

The Hosmer and Lemeshow test results reported in Table 8 show insignificance for the fitted model (step 7) since p-values are greater than 0.05 for all steps, indicating that insignificant differences remain between the actual and expected values. This is a strong indication of a good model fit.

Table 9: Classification Table on the Model Predictive Accuracy

	Observed		**Predicted**		
				Obese	**Percentage**
			No	**Yes**	**Correct**
Step 1	Obese	No	128	52	71.1
		Yes	29	191	86.8
	Overall percentage				**79.8**
Step 2	Obese	No	138	34	80.2
		Yes	40	188	82.5
	Overall percentage				**81.5**
Step 3	Obese	No	135	47	74.2
		Yes	23	195	89.4
	Overall percentage				**82.5**
Step 4	Obese	No	155	33	82.4
		Yes	25	187	88.2
	Overall percentage				**85.5**
Step 5	Obese	No	143	28	83.6
		Yes	10	219	95.6
	Overall percentage				**90.5**
Step 6	Obese	No	125	25	83.3
		Yes	5	245	98.0
	Overall percentage				**92.5**
Step 7	Obese	No	142	3	97.9
		Yes	2	253	99.2
	Overall percentage				**98.8**

Table 9 demonstrates the result of the classification of subjects, unlike multiple regression, the binary regression model estimates the probability of a subject falling into as yes obese or no obese group. The cut value in the classification table is 0.500. The output classification table presents the grouping of the subject as yes obese if the projected probability of the event happening is ≥ 0.5. If the probability of the event occurring is < 0.500, the subject is classified as no obese. In the classification table, it can be observed that the overall success rate of the model has increased from 63.8% in block 0 to 98.8% in block 7. We shall therefore base our discussion on step 7, which is the final model.

The classification on Table 9 shows that the percentage accuracy in classification is 98.8%. In addition, this value shows that 98.8% of cases are correctly classified as yes obese from the added independent variables. The sensitivity = Pr (correct prediction|event did occur) = 253/255 = 99.2% or true positive value is the percentage of cases that are obese and were acceptably anticipated by the model.

The specificity = $\Pr(\text{correct prediction}|\text{event did not occur}) = 142/145 = 97.9\%$ or true negative value is the percentage of cases that are not obese and were appropriately projected as no obese cases. The false positive value = $\Pr(\text{incorrect prediction}|\text{predicted occurrence}) = 3/253 = 1.2\%$ or false positive value is the percentage of suitably expected cases with the detected feature of no obese compared to the total number of cases predicted as yes obese.

The false negative value
$= \Pr(\text{incorrect prediction}|\text{predicted non} - \text{occurrence})$
$= 2/145 = 1.4\%$
or false negative is the percentage of accurately forecasted cases without the detected feature of obesity compared to the total number of cases forecasted as no obesity. A false negative rate tells the subjects predicted as not obese but actually, they are obese.

From the results of Table 9, it is observed that the overall predictive accuracy of the model kept increasing at each step. The overall predictive accuracy of the model was 79.8% in step 1, 81.5% in step 2, 82.5% in step 3, 85.5% in step 4, 90.5% in step 5, 92.5% in step 6 and finally peaked with 98.8% in step 7. This is a significant improvement from the null model predictive accuracy of 63.8%, hence coupled with the statistically based measure of model fit, the model is deemed acceptable in terms of both statistical and practical significance.

Table 10: Parameter Estimates of the Fitted Binary Logistic Regression Model

Step	Var.	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Step 1	HC	0.842	0.092	83.762	1	0.000	2.321	1.227	5.159
	Constant	-0.455	0.069	43.484	1	0.000	0.634		
Step 2	HC	0.847	0.093	82.947	1	0.000	2.333	1.127	5.059
	HI	1.612	0.178	82.014	1	0.000	5.013	3.417	8.710
	Constant	-0.453	0.068	44.379	1	0.000	0.636		
Step 3	HC	0.845	0.092	84.360	1	0.000	2.328	1.225	5.175
	HI	1.615	0.176	84.201	1	0.000	5.028	3.419	8.779
	PE	0.912	0.109	70.006	1	0.000	2.489	1.251	5.873
	Constant	-0.461	0.069	44.638	1	0.000	0.631		
Step 4	HC	0.839	0.092	83.166	1	0.000	2.314	1.135	5.039
	HI	1.599	0.177	81.611	1	0.000	4.948	3.007	8.558
	PE	0.898	0.099	82.278	1	0.000	2.455	1.247	5.986
	WT	0.332	0.145	5.243	1	0.019	1.394	1.017	3.777
	Constant	-0.457	0.065	49.432	1	0.000	0.633		
Step 5	HC	0.837	0.092	82.770	1	0.000	2.309	1.129	5.789
	HI	1.587	0.171	86.131	1	0.000	4.889	2.968	8.157
	PE	0.885	0.098	81.552	1	0.000	2.423	1.246	5.889
	WT	0.337	0.146	5.328	1	0.018	1.401	1.016	3.807
	PH	0.551	0.132	17.424	1	0.023	1.735	1.024	4.008
	Constant	-0.449	0.066	46.281	1	0.000	0.607		
Step 6	HC	0.799	0.089	80.596	1	0.000	2.223	1.127	5.691
	HI	1.475	0.169	76.175	1	0.000	4.371	2.963	7.985

	PE	0.881	0.097	82.491	1	0.000	2.413	1.237	5.755
	WT	0.341	0.145	5.531	1	0.016	1.406	1.019	3.827
	PH	0.549	0.133	17.039	1	0.025	1.732	1.098	3.998
	ALC	0.074	0.009	67.605	1	0.001	1.077	1.022	3.418
	Constant	-0.45	0.067	45.110	1	0.000	0.638		
Step 7	HC	0.685	0.088	60.592	1	0.000	1.984	1.194	4.162
	HI	1.445	0.168	73.981	1	0.000	4.242	2.942	7.509
	PE	-0.877	0.096	83.456	1	0.000	2.404	1.269	5.557
	WT	0.339	0.143	5.620	1	0.018	1.404	1.017	3.761
	PH	0.533	0.131	16.554	1	0.027	1.704	1.097	3.995
	ALC	0.071	0.009	62.235	1	0.001	1.074	1.021	3.283
	EL	0.306	0.143	4.579	1	0.034	1.358	1.118	3.709
	Constant	-0.443	0.068	42.441	1	0.000	0.642		

Table 11: Parameter Estimates of the Final Binary Logistic Model

Variable	**B**	**S.E.**	**Wald**	**Df**	**Sig.**	**Exp(B)**	**95% C.I. for Exp(B)**	
							Lower	**Upper**
HC	0.685	0.088	60.592	1	0.000	1.984	1.194	4.162
HI	1.445	0.168	73.981	1	0.000	4.242	2.942	7.509
PE	-0.877	0.096	83.456	1	0.000	2.404	1.269	5.557
WT	0.339	0.143	5.620	1	0.018	1.404	1.017	3.761
PH	0.533	0.131	16.554	1	0.027	1.704	1.097	3.995
ALC	0.071	0.009	62.235	1	0.001	1.074	1.021	3.283
EL	0.306	0.143	4.579	1	0.034	1.358	1.118	3.709
Constant	-0.443	0.068	42.441	1	0.000	0.642		

Note: HC=health challenges, HI= household income, PE = physical exercise, WT= body weight, PH= parental history, ALC=alcohol consumption, EL= educational level

Table 11 illustrates the influence of each predictor variable on the binary logistic model and statistical significance ($p < 0.05$) of Wald Chi-Square test, which is obtained by squaring the ratio of each coefficient to its standard error. Wald Statistics tests the unique contribution of each independent variable, in the context of the other variables with significant p-values. The variables health challenges (HC) with p-value (p = 0.000), household income (HI) with p-value (p = 0.000), physical exercise (PE) with p-value (p = 0.000), parental history (PH) with p-value (p = 0.027), alcohol consumption (ALC) with p-value (p = 0.001), educational level (EL) with p-value (p = 0.034) and body weight (WT) with p-value (p = 0.018) have added significant contributions to the model.

From Table 11, the fitted binary logistic regression model using the stepwise forward selection method is given by:

$$\ln\left[\frac{\pi(x_i)}{1-\pi(x_i)}\right] = -0.443 + 0.685hc + 1.445hi - 0.877pe + 0.339wt + 0.533ph + 0.071alc + 0.306el \qquad (15)$$

The odd prediction equation is

$$\frac{\pi(x_i)}{1-\pi(x_i)} = e^{-0.443+0.685hc+1.445hi-0.877pe+0.339wt+0.533ph+0.071alc+0.306e}$$

This function can be used to predict the odds that a subject of a given health challenge (hc), household income (hi), physical exercise (pe), body weight (wt), parental history (ph), alcohol consumption (alc) and educational level (el) will be obese.

The analyzed result in Table 11 showed a positive relationship between health challenges (hc) and obesity. The coefficient for health challenges (hc) is 0.685 with a significant p-value of 0.000. This implied that the odds ratio Exp(B) = Exp(0.685) = 1.984 with confidence interval of 1.194 and 4.162 explaining that the odds of traders experiencing health challenges will fall between 1.194 and 4.162 (95%) of the time. Thus a unit increase in health challenges leads to increase in obesity among traders in the study area. The odds of being obese in the study area are higher for an increasing health challenge. For an additional health challenge among traders in the study area, the odds of being obese is higher by a factor of 1.984. Alternatively, the odds of being obese by a trader with health challenge are 1.984 times more when compared with the odds of not being obese by a trader with no health challenge in the study area.
The model formulated can be used to predict the odds that a trader with health challenge in the study area will be obese. Converting odds to probability for health challenges of respondents, we have that:

$$\text{odds ratio} = \frac{\text{odds}}{1+\text{odds}} = \frac{1.984}{1+1.984} = \frac{1.984}{2.984} = 0.6649$$

the model predicts that about 66.49% of the traders in the study area experiencing health challenges such as hypertension, diabetes Miletus, etc., are liable to becoming obese.

The odds prediction equation for traders with no health challenges/health challenges is given as:

$$\text{Odds} = e^{\beta_0+\beta_1 hc}$$

The absence of health challenge is coded 0 while the presence of health challenge is coded 1.
The odds that a trader experiencing no health challenge will become obese is given as

$$\text{Odds} = e^{-0.443+0.685(0)} = 0.6421$$

The odds that a trader experiencing health challenges will become obese is given as

$$\text{Odds} = e^{-0.443+0.685(1)} = 1.2738$$

Similarly, the other contributing factors are computed and the odds predictions are presented in Table 12.

Table 12: Odds Predictions for Absence/Occurrence of an Attribute for Individual Independent Variables

Independent variables	Low(Absence)	High(Presence)
HC	0.6421	1.2738
HI	0.6421	2.7237
PE	0.6421	0.2671*
WT	0.6421	0.9012
PH	0.6421	1.0942
ALC	0.6421	0.6894
EL	0.6421	0.8720

Note: *the odds of being obese with high physical exercise are less than the odds of being obese with low physical exercise. The results are computed from: $\text{Odds} = e^{\beta_0+\beta_i x_i}$.

3.3 Discussion of Findings

The study found that health challenges; household income; physical exercise; weight; parental history; alcohol consumption level and educational level of the respondents affect obesity among adult urban traders in the study area. From the study;

The odds of being obese by a trader with a health challenge are 1.984 times higher when compared with the odds of not being obese by a trader with no health challenge in the study area. The model predicted that about 66.49% of the traders in the study area experiencing health challenges such as hypertension, diabetes Miletus, etc., are liable to becoming obese. The model predicted that about 84.4% of the traders in the study area having higher household income will experience obesity whereas the remaining 15.6% of the traders in the study area having lower household income will not be experiencing obesity. The odds that a trader having high household income will experience obesity are 2.7237 times more than the traders having low household income in the study area

The model predicted that about 70.62% of the traders in the study area having high physical exercise are not liable to becoming obese. The odds that a trader having high physical exercise will not experience obesity are 0.2671 times less than the traders having low physical exercise in the study area. Weight was also seen as a significant factor contributing to an increasing number of obesity cases among traders in the study area. The model predicted that about 58.4% of the traders in the study area experiencing abnormal weight (weight increase) are liable to become obese. The odds that a trader having high or abnormal weight will experience obesity are 0.9012 times more that the traders having low or normal in the study area.

There is also a positive relationship between parental history and obesity. The model predicted that about 63.02% of the traders in the study area whose parents are obese are also liable to become obese. the odds that a trader whose parents were obese will also experience obesity are 1.0942 times more than the traders whose parents were not obese in the study area. An increase in alcohol consumption of respondents leads to an increase in obesity cases among traders in the study area. The odds of being obese in the study area are higher for increasing alcohol consumption. The model predicted that about 51.78% of the traders in the study area who consume alcohol in excess are liable to become obese whereas the remaining 48.22% of the traders will not be liable to obesity.

The educational level of respondents was also seen as a significant factor contributing to an increasing number of obesity cases among traders in the study area. The model predicted that about 57.59% of the traders in the study area having high educational qualifications are liable to become obese. The odds that a trader having a high educational level will experience obesity are 0.8720 times more than the traders having a low educational level in the study area.

This study is in agreement to what Otang-Mbeng et al. [3] reported in South Africa, that 70% of the prevalence of obesity was recorded among people who did not engage in any form of physical activity. The work is in confirmatory with the work of Puciato *et al.* [16] in Poland that exercise, household income, income per capital and gender are predictors of obesity. The odds on parental history is high in this study. The model predicts that about 63.02% of the traders in the study area whose parents were/are obese are also liable to become obese. This study also agreed with the findings of Kamaruddina *et al.* [17] who found that the odds of a student being overweight and obese are high for students having a family history of obesity. The high risk of obesity in this study agrees with the work done by Saddiqui *et al.* [18] that obesity prevalence is high in urban settings. The present study also agrees with the empirical findings of Chantal *et al.* [19] that overweight and obese participants with high levels of physical activity were not at increased risk of cardiovascular diseases compared with normal-weight counterparts. Alcohol consumption and educational level in this work are also associated with obesity similar to the results of Kabore *et al.* [11] on the determination of the prevalence and predictors of overweight and obesity in Burkina Faso. This work is also in line with what Makambi and Adam-Campbell [20] reported in Washington DC that physical activity and education among other factors predicting overweight and obesity can reduce the menace.

This study contradicts the study conducted by Peralta *et al*. [21] for older European adults (age ≥ 50 years), since the socio-demographic characteristics of respondents in this study are between the ages of 25-65 years. This clearly shows that people of less than 50 years (young people) are liable to become obese. This work also contradicts the work of Tapera *et al*. [10], that gender, faculty of study, family history of obesity, and alcohol consumption were not significantly associated with obesity.

4. CONCLUSION

This study set out to identify the predisposing factors associated with obesity among adult urban traders in Benue State using a binary logistic regression model. A cross-sectional study design was utilized. The study population consisted of adult urban traders in some selected local government areas in Benue State who were between the ages of 25-65 years. Stratified random sampling was adopted in selecting 400 adult urban traders for this study. A structured questionnaire was administered to consenting traders. Anthropometric measurements such as weights and heights of the respondents to determine body mass index were also taken. The binary logistic regression model using a forward stepwise selection procedure was executed to determine the influences of the independent variables such as health challenges, household income, physical exercise, body weight, parental history, alcohol intake, and educational level on the likelihood that the subjects are associated with obesity. The sensitivity and specificity described by the final model are 99.2% and 97.9% respectively. The increase in the values of health challenges, household income, body weight, parental history, alcohol intake, educational level, and a decrease in physical exercise are associated with the increased likelihood of subjects being obese. The prevalence of obesity was found to be 61.75% among the subjects in the study area.

Based on the empirical findings of this study, the following recommendations/suggestions are hereby presented:

1. To reduce the risk of overweight and obesity, there is every need for broad-based strategies encouraging physical exercise among traders in the study area as well as different socioeconomic groups.
2. Promoting healthy dietary and weight management practices might be of great importance to the adult urban traders in the study area.
3. Excess alcohol consumption should be reduced by the traders in the study area as this will in turn minimize obesity cases.
4. An Enlightenment campaign should be carried out by both government and non – governmental organizations on income management practices for urban traders to reduce the menace.
5. Having the knowledge of obesity history cases in the family will reduce the tension whenever the obesity case arises.

REFERENCES

[1] Lavie, C., Pandey, A., Lau, D. H., Alpert, M. A., and Sanders, P. (2017). Obesity and Atrial Fibrillation Prevalence, Pathogenesis, and Prognosis: Effects of Weight Loss and Exercise. *Journal of the American College of Cardiology,* 70(16): 2022-2035.

[2] WHO (2008). Waist Circumference and Waist-hip ratio: Report of a WHO expert consultation. Switzerland: World Health Organization.

[3] Otang-Mbeng, W., Otunola, G. A., and Afolayan, A. J. (2017). Lifestyle Factors and Comorbidities Associated with Obesity and Overweight in Nkonkobe Municipality of the Eastern Cape, South Africa. *Journal of Health, Population and Nutrition,* 36: 22-36.

[4] Chukwuonye, I. I., Chuku, A., John, C., Ohagwu, K. A., Imoh, M. E., Isa, S. E., Ogah, O. S., and Oviasu, E. (2013). Prevalence of Overweight and Obesity in Adult Nigerians-A Systematic

Review, *Diabetes, Metabolic Syndrome and Obesity*, 6: 43-47.

[5] Djalalinia, S., Qorbani, M., Peykari, N., and Kelishadi, R. (2015). Health Impacts of Obesity. *Pakistan Journal of Medical Sciences*, 31(1): 239-242.

[6] Ng, M., Fleming, T., Robinson, M., Thomson, B., Graetz, N., Margono, C., and Gakidou, E. (2014). Global, Regional, and National Prevalence of Overweight and Obesity in children and Adults during 1980-2013: A Systematic Analysis for the Global Burden of Disease Study 2013. *Lancet,* 384:766-781.

[7] Olufemi, S. A., Philip, B. A., and Adeseye, A. A. (2013). Anthropometric Differences Among Natives of Abuja Living in Urban and Rural Communities: Correlations with Other Cardiovascular Risk Factors. *Journal of Empirical Research*, 2(3): 118-129.

[8] Ukegbu, P. O., Uwaegbute, A. C., and Emezue, A. G. (2015). Nutritional Status and Market Activities of Female Traders in a Major City South East, Nigeria. *Rwanda Journal Series F: Medicine and Health Sciences,* 2(1): 47-52.

[9] Mawaw, P., Yav, T., Lukanka, O., Mukuku, O., Kakisingi, C., Jean-Baptiste Kakoma, J. B., and Luboya, O. N. (2017). A cross-sectional study on obesity and related risk factors among women of the central market of Lusonga in Lubumbashi, Democratic Republic of Congo. *Pan African Medical Journal*, 28(157): 1-9.

[10] Tapera, R., Merapelo, M. T., Tumoyagae, T., Maswabi, T. M., Erick, P., Letsholo, B., and Mbongwe, B. (2017). The Prevalence and Factors Associated with Overweight and Obesity Among University of Botswana Students. *Cogent Medicine*, 4: 135-153.

[11] Kabore, S., Millogo, T., Soubeiga, J. K.,Lanou, H., Bicaba, B., and Kouanda, S. (2020). Prevalence and Risk Factors for Overweight and Obesity: A Cross-Sectional Countrywide Study in Burkina Faso. *BMJ Open,* 10: 1-9.

[12] Hung, S. P., Chen, C. Y., Guo, F. R., Chang, C. I., and Jan, C. F. (2017). Combine Body Mass Index and Body Fat Percentage Measures to Improve the Accuracy of Obesity Screening in Young Adults. *Obesity Research and Clinical Practice*, 11(1): 11-18.

[13] Hosmer, D. W., Hosmer, T., Le Cessie, S., and Lemeshow, S. (1997). A Comparison of Goodness of Fit Test for the Logistic Regression Model. *Statistics in Medicine*, 16: 965-980.

[14] Cox, D. R., and Snell, E. J. (1989). Analysis of Binary Data (2nd ed.). London: Chapman and Hall.

[15] Hosmer, D. W. and Lemeshow, S. (2000). Applied Logistic Regression (2nd ed.). New York: John Wiley & Sons.

[16] Puciato, D., Rozpara, M., Olesniewics, P., Markiewicz-Patkowska, j., and Jandova, S. (2019). Physical Activity of Working Age Wroclaw Residents with Reference to their income. Baltic Journal of Health and Physical Activity, 11(1):96-105.

[17] Kamaruddina, A. A., Ali, Z., Noora, N. M., Baharuma, A., and Ahmad, W. M. A. W. (2014). Modelling of Binary Logistic Regression for Obesity among Secondary Students in a Rural Area of Kedah. *AIP Conference Proceedings*, 1605: 856-861.

[18] Siddiqui, S. T., Kandala, N. B., and Stranges, S. (2015). Urbanisation and Geographical Variation of Overweight and Obesity in India: A Cross- Sectional Analysis of the Indian Demographic Survey 2005-2006. *International Journal of Public Health*, 60(6): 717-726.

[19] Chantal, M. K., Klodian, D., Josje, D. S., Arfan, I. M., Maryam, K., and Oscar, H. F. (2017). Impact of Physical Activity on the Association of Overweight and Obesity with Cardiovascular Disease: The Rotterdam Study. SAGE *Serial Analysis of Gene Expression Journal*, 24(9): 934-94.

[20] Makambi, K. H. and Adams-Campbell (2017). Mediation Effect Of Physical Activity on Obesity in Black Women. *Journal of the National Medical association*, 110(5): 513-521.

[21] Peralta, M., Ramos, M., Lipert, A., Martins, J., and Marques, A. (2018). Prevalence and Trends of Overweight and Obesity in Older Adults from 10 European Countries from 2005 to 2013. *Scandinavian Journal of Public Health,* 46: 522-529.