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A Predictive Model for Labour Outcomes in Women With Comorbid Diabetes, Insomnia and Hypertension Using Ministry of Health Statistical Bulletin Data

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ABSTRACT

Pregnancy complications, including comorbid diabetes, insomnia, and hypertension, represent a significant public health concern in Nigeria, where a considerable proportion of pregnant women are affected by these conditions. Approximately 15% of pregnant women have hypertension, 5% have diabetes, and up to 78% experience insomnia, all of which exacerbate health risks during labor. This study aims to develop a predictive model to assess labor outcomes in women with these comorbidities using data from the Ministry of Health Statistical Bulletin.

Data from the Osun State Ministry of Health Statistical Bulletin (2011-2022) was analyzed to examine the impacts of diabetes, insomnia, and hypertension on women in labor. Descriptive statistics, including means, standard deviation, and range, were used for data summarization. A multiple regression analysis was conducted using SPSS version 25 to determine the relationship between the health conditions and labor outcomes, with a significance level set at 0.05.The multiple regression analysis resulted in a model that predicts labor outcomes based on the health conditions of the women. The model yielded the following equation: Yi = 2820.686 + 0.265X1 - 0.009X2 - 0.026X3, where X1 represents diabetes, X2 represents insomnia, and X3 represents hypertension. The coefficients indicated that for every diabetic patient, the number of women in labor increased by 0.265 per year, while the number of women in labor decreased by 0.009 per year for each insomnia patient and 0.026 per year for each hypertensive patient. Tests for multicollinearity, autocorrelation, and heteroscedasticity showed no significant issues, confirming the reliability of the model. This study successfully developed a predictive model for labor outcomes in women with comorbid diabetes, insomnia, and hypertension. The findings underscore the importance of targeted healthcare interventions for pregnant women with these conditions, particularly in Osun State. The model provides valuable insights for maternal health strategies, highlighting the relationships between these health conditions and labor outcomes, and affirming the robustness of the data through rigorous statistical tests. These results may guide future healthcare policies to improve maternal outcomes in the region.

Keywords: Pregnancy complications, comorbidities, diabetes, insomnia, hypertension, predictive model

INTRODUCTION

Pregnancy complications are a significant public health concern in Nigeria, with women with comorbid diabetes, insomnia, and hypertension being particularly vulnerable (Federal Ministry of Health, 2020). According to the World Health Organization (2019), approximately 15% of pregnant women in Nigeria have hypertension, while 5% have diabetes. Furthermore, insomnia affects up to 78% of pregnant women, exacerbating existing health conditions (Okogbule-Wonodi et al., 2018). This study aims to develop a predictive model for labour outcomes in women with comorbid diabetes, insomnia, and hypertension using data from the Ministry of Health Statistical Bulletin.

The relationship between diabetes and insomnia has long been established, many diabetics are also hypertensive. In fact, diabetes increases the risk of systolic hypertension by 2.5times. This co-existence worsens the patient's cardiovascular outcome and overall prognosis.

The increase in the prevalence of diabetes mellitus and hypertension in African communities is attributable to the drastic lifestyle changes accompanying urbanization and modernization. There has been an increase in consumption of refined diet and saturated fat with decreased fiber intake and reduced physical activity. Unfortunately prospective approaches to this burden and possible preventive strategies have been hindered by scarcity of data on NCDS in Africa. Only few studies/prevalence, pattern of disease, aeutiopathogenesis and complications have been done on diabetes and hypertension in Nigeria and Africa as a whole despite the fact that they are major health problems.

Diabetes Mellitus, disease in which the pancreas produces insufficient amounts of insulin, or in which the body's cells fail to respond appropriately to insulin. Insulin is a hormone that helps the body's cells absorb glucose (sugar) so it can be used as a source of energy. In people with diabetes, glucose levels build up in the blood and urine, causing excessive urination, thirst, hunger, and problems with fat and protein metabolism. Diabetes mellitus differs from the less common diabetes insipidus, which is caused by lack of the hormone vasopressin, which controls the amount of urine secreted.

Diabetes is most common in adults over 45 years of age; in people who are overweight or physically inactive; in individuals who have an immediate family member with diabetes; and in people of African, Hispanic, and Native American descent. The highest rate of diabetes in the world occurs in Native Americans. More women than men have been diagnosed with the disease.

In diabetes mellitus low insulin levels or poor response to insulin prevent cells from absorbing glucose. As a result, glucose builds up in the blood. When glucose-laden blood passes through the kidneys, the organs that remove blood impurities, the kidneys cannot absorb all of the excess glucose. This excess glucose spills into the urine, accompanied by water and electrolytes—ions required by cells to regulate the electric charge and flow of water molecules across the cell membrane. This causes frequent urination to get rid of the additional water drawn into the urine; excessive thirst to trigger replacement of lost water; and hunger to replace the glucose lost in urination. Additional symptoms may include blurred vision, dramatic weight loss, irritability, weakness and fatigue, and nausea and vomiting

Insomnia

It can be caused by an overactive thyroid gland, diabetes, violent muscle twitching, or drinking caffeine-containing beverages before going to bed, but experts estimate that in three-fourths of all cases the cause is a psychological one. After anxiety-producing events such as the death of a loved one or loss of a job, a person may experience sleep difficulties for a short period. Many persons recover their normal sleep rhythm spontaneously, but others become frustrated and depressed and develop chronic insomnia. Napping during the day may throw off the sleep pattern further.

Predictive Models for Labour Outcomes

Several studies have developed predictive models for labour outcomes in women with comorbid conditions. For example, a study by Al-Ramahi et al. (2018) developed a predictive model for adverse pregnancy outcomes in women with diabetes, using data from the United States. The model included variables such as maternal age, body mass index (BMI), and glycated haemoglobin (HbA1c) levels. Similarly, a study by O'Brien et al. (2017) developed a predictive model for preterm birth in women with hypertension, using data from Canada. The model included variables such as maternal age, BMI, and systolic blood pressure.

Comorbid Diabetes, Insomnia, and Hypertension

Few studies have specifically examined the predictive models for labour outcomes in women with comorbid diabetes, insomnia, and hypertension. However, a study by Okogbule-Wonodi et al. (2018) examined the relationship between insomnia and pregnancy outcomes in Nigerian women. The study found that insomnia was significantly associated with adverse pregnancy outcomes, including preterm birth and low birth weight. Another study by Adeyinka et al. (2017) examined the relationship between hypertension and pregnancy outcomes in Nigerian women. The study found that hypertension was significantly associated with adverse pregnancy outcomes, including preterm birth and stillbirth.

Ministry of Health Statistical Bulletin Data

The Nigerian Ministry of Health Statistical Bulletin provides a rich source of data on pregnancy outcomes, including data on women with comorbid diabetes, insomnia, and hypertension. However, few studies have utilized this data to develop predictive models for labour outcomes. This study aims to fill this knowledge gap by developing a predictive model for labour outcomes in women with comorbid diabetes, insomnia, and hypertension, using data from the Ministry of Health Statistical Bulletin.

LITERATURE REVIEW

Multiple Regression Analysis

Multiple regression analysis is a statistical technique used to model the relationship between a dependent variable and one or more independent variables (Unver & Gangam, 2001). The assumptions of multiple regression analysis include normal distribution, linearity, freedom from extreme values, and no multiple ties between independent variables (Buyukozturk, 2004). Pediatric Endocrinology Review (2005) notes that multiple linear regression is commonly used to investigate how hormones and body composition interact.

Applications of Multiple Regression Analysis

Multiple regression analysis has been applied in various fields, including healthcare, economics, and social sciences. Chiarazzo et al. (2014) define multiple regression as the conventional option for mass housing price appraisal studies for less complex data sets. Mark and Goldberg (2007) state that the significance of the estimated regression coefficient in a multiple regression model can be analyzed by performing a test.

Health-Related Applications

Multiple regression analysis has been used to investigate the relationship between various health-related variables. Uyanik and Guler (2013) used multiple regression analysis to investigate the relationship between psychological counselling and guidance among undergraduate students. Samarawickrama (2015) states that multiple regression is one of the important methods in which the statistical technique is used to build a mathematical model to relate dependent variables to independent variables.

A journal published by Uyanik and Guler (2013) The authors succinctly present the use of multiple regression analysis by way of using 240 undergraduate students pursuing psychological counselling and guidance of sakarya university for the academic year 2011-2012. The introduction of the paper is on substantiate issue of regression, highlighting the types (i.eunivariate and multivariate regression) rationale for their usage, testing of assumptions of linearity and presents a purpose for the usage multiple regression analysis

METHODOLOGY

The method to be used in this project is MULTIPLE REGRESSION.

Multiple Regression

Multiple linear regression (MLR) also known as multiple regression is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. The goal of multiple linear regression is to model the linear relationship between the explanatory (independent) variables and response (dependent) variables.

Multiple Regression Formula

$Y_i = \beta_o + \beta X_1 + \beta X_2 + \beta X_3 + \varepsilon_t$

Where i= n observation

Xi= Explanatory variables

Bo= y-intercept (constant term) when all the independent variables are equal to 0

Bp= slope coefficients for each explanatory variables

£= the model's error term (also known as the residuals)

The model that will analyze the relationship is stated as follows:

$Y_i = \beta_o + \beta X_1 + \beta X_2 + \beta X_3 + \varepsilon_t$

βx1= Diabetes, βx2= Insomnia/any other related sleep disorder, βx3=Hypertension£= Error term

= women in labor= (Diabetes, Insomnia and hypertension,) ……(1)

Women in labor= βo+β1diabetes+β2Insomnia +β3hypertension +£t …..(2)

B1-β3= the coefficient of the explanatory variable

Y= women in labor

£t= Error term

Analysis Of Variance In Multiple Regression

Recall the model again

Yi=β_0+$\beta_1 X_i$1+…$\beta_p X_{ip}$+£I i=1,…n

For the fitted model $\hat{Y}i = b0 + b1Xi1 + ... + bpXip$,

$Yi = \hat{Y}i + ei$i= 1, ..., n

$Yi - \hat{Y}i = \hat{Y}i - \bar{Y} + e_i$

Total deviation Deviation
Duethe regression due to the error

Obs	Deviation of Y_i	Deviation of $\hat{Y}i = b0 + b1Xi1 + \ldots + bpXip$,	Deviation of e_i=Y_i-$\hat{Y}i$
1 2 ⋮ N	Y_1-$\bar{Y}$ Y_2-$\bar{Y}$ ⋮ Y_n-$\bar{Y}$	$\hat{Y}_1$-$\bar{Y}$ $\hat{Y}_2$-$\bar{Y}$ ⋮ $\hat{Y}_n$-$\bar{Y}$	e_1-$\bar{e}$=e_1 e_2-$\bar{e}$=e_2 ⋮ e_n-$\bar{e}$=e_n
Sum of squares	$\sum_{i=1}^{n}(Yi - \overline{Y})^2$ Total sum of squares (SST)	$\sum_{i=1}^{n}(\hat{Y}_1 - \overline{Y})^2$ Sum of squares Due to regression (SSR)	$\sum_{i=1}^{n}(e_i^2$ Sum of squares of error/ residuals (SSE)

We have
$\sum_{i=1}^{n}(Yi - \overline{Y})^2 = \sum_{i=1}^{n}(\hat{Y}_1 - \overline{Y})^2 + \sum_{i=1}^{n}(e_i^2$

SST SSR SSE

[Proof:
$\sum_{i=1}^{n}(Yi - \overline{Y})^2 = \sum_{i=1}^{n}(\hat{Y}_1\text{-}\bar{Y}+Y_i\text{-}\hat{Y}_1)^2$

$=\sum_{i=1}^{n}\{(\hat{Y}_1 - \overline{Y})^2+(Y_i\text{-}\hat{Y}_i)^2+2(\hat{Y}_{i-}\overline{Y})+(Y_i\text{-}\hat{Y}_1)\}$

=SSR + SSE + $2\sum_{i=1}^{n}(\hat{Y}_1 - \bar{Y})(Y_i\text{-}\hat{Y}_i)$

= SSR+SsSE + $2\sum_{i=1}^{n}(\hat{Y}_1 - \bar{Y})\, e_i$

=SSR +SSE

Where $\sum_{i=1}^{n}\hat{Y}_1\, e_i$=0 and $\sum_{i=1}^{n} e_i$=0are used, which follow from the Normal equations.]

•SST =$\sum_{i=1}^{n}(\hat{Y}_1 - \overline{Y})^2$= Y'-Y-$\frac{1}{n}Y'$JY=Y'(I-$\frac{1}{n}$J)Y

Degree of freedom? **n-1**(with n being the number of observations)

•SSE =$\sum_{i=1}^{n}(e_i^2 = e'e = (Y - Xb)'(Y - Xb) = Y'(I - H)\,Y$

Degree of freedom? **n-p-1** (with p+1 being the number of coefficients)

• Let $\mathbf{H} = \mathbf{X}(X'\mathbf{X})^{-1}\mathbf{X}$ and and $\mathbf{J} = 11'/\mathbf{n}$. Note that

$\hat{Y} = \mathbf{HY}$

and by the fact $\sum_{i=1}^{n} e_i = 0$ (see the normal equations)

$\hat{Y} = \bar{Y} = 1'Y/n$

Thus

$$SSR = (\hat{Y} - \bar{Y})' * (\hat{Y} - \bar{Y}) = Y'\ \mathbf{H} - \mathbf{J}/n)'(\mathbf{H} - \mathbf{J}/n)'\mathbf{Y}$$

$= \boldsymbol{Y}'(\mathbf{H} - \mathbf{J}/n)\mathbf{Y}$.

Degree of freedom? **p**(the number of variables).

•It follows that

SST = SSR + SSE

We further define

$MSR = \frac{SSR}{p}$ called **regression mean square**

$MSE = \frac{SSE}{n-p-1}$ called **error mean square (or mean squared error)**

ANOVA Table

Source of variation	Ss	Df	Ms	F-statistic
Regression	SSR= $\boldsymbol{Y}'(\mathbf{H} - \mathbf{J}/n)\mathbf{Y}$	P	$MSR = \frac{SSR}{p}$	$\frac{MSR}{MSE}$
Error	SSE= $\boldsymbol{Y}'(\mathbf{I}-\mathbf{H})\mathbf{Y}$	n-p-1	$MSE = \frac{SSE}{n-p-1}$	
Total	SST= $\boldsymbol{Y}'(\mathbf{I} - \mathbf{J}/n)\mathbf{Y}$	n-1		

***F* test for regression relation**

• $H_0 : \beta_1 = \beta_2 = ... = \beta_p = 0$

H_1: not all β_k ($k = 1, ..., p$) equal zero

• Under H_0, the reduced model: $Y_i = \beta_0 + \text{£}_i$

$SSE(R) = SST = \sum_{i=1}^{n}(\hat{Y}_1 - \bar{Y})^2$

Degrees of freedom $n - 1$

• Full model: $Y_i = \beta_0 + \beta_1 X_i 1 + \ldots + \beta_p X_{ip} + \text{£}_i$

$SSE(F) = SSE = e'e = (\mathbf{Y} - \mathbf{X}b)'(\mathbf{Y} - \mathbf{X}b)$

Degrees of freedom $n - p - 1$

• *F* test statistic (also called F-test for the model)

$F^* = \frac{(SSE(R)-SSE(f))/(df(R)-df(F))}{SSE(F)/df(F)} = \frac{SSR/p}{SSE/(n-p-1)}$

• If $F^* \leq F(1-\alpha; p, n-p-1)$, conclude(accept H_0)
IF $F^* > F(1-\alpha; p, n-p-1)$, conclude Ha (reject H_0)

3.9 R^2 and the adjusted R^2

• $SSR = SST - SSE$ is the part of variation explained by regression model
• Thus, define coefficient of multiple determination

$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}$

Which is the **proportion of variation in the response that can be explained bythe regression model (or that can be explained by the predictors** $X1, ..., Xp$
Linearly)

• $0 \leq R^2 \leq 1$

• With more predictor variables, SSE is smaller and R^2 is larger. To evaluate the contribution of the predictors fair, we define the adjusted R^2

$R_a^2 = 1 - \frac{SSE}{SST} = 1 - (\frac{n-1}{n-p-1})\frac{SSE}{SST}$

PRESENTATION AND ANALYSIS OF DATA

Presentation and analysis of the data obtained from Osun state Ministry of Health Statistical Bulletin (2011 to 2022) Osogbo, Osun State on the impacts of diabetes, insomnia and hypertension on women in labour. Statistical Package for Social Sciences (SPSS) version 25 was used all through. The data was summarized using descriptive statistics such as means, standard deviation and range. Multiple regression model of variables using Simultaneous Multiple Regression analysis to determine the significance of independent variables on the dependent variables. Level of significance was set at 0.05 (95% confidence intervals).

Presentation of Data

Table 4.0

Years	Diabetes	Hypertension	Women in labour	Insomnia/any other type of sleep disorder.
2011	13510	21213	4433	3894
2012	21939	17777	11055	7438
2013	28747	18422	8986	10849
2014	27134	18893	9193	9868
2015	20541	6097	11084	6595
2016	18180	6660	5235	6145
2017	18511	6462	4624	4464
2018	14378	6839	4751	4276
2019	10871	5989	4361	4992
2020	11011	5641	5360	3584
2021	13302	5625	6124	4782
2022	11891	6836	10325	3261

Source: Osun State Ministry of Health Statistical Bulletin (2022)

4.1 Descriptive Statistics Of The Data Under Study

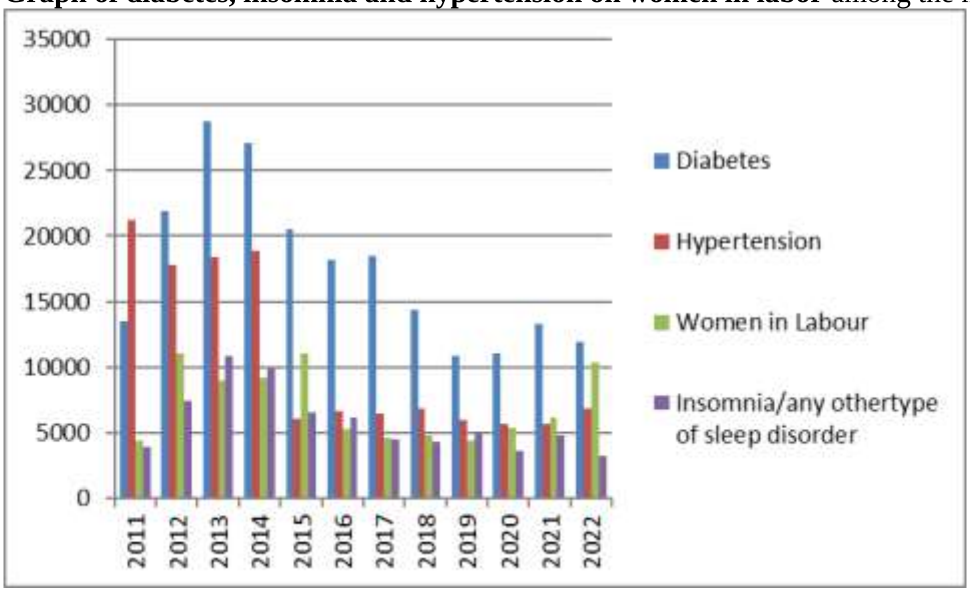
Table 4.1 Descriptive Statistics

Descriptive Statistics

	N	Range	Minimum	Maximum	Sum	Mean	Std. Dev	Variance
Diabetes	12	17876.00	10871.00	28747.00	210015.00	17501.2500	6109.21584	37322518.205
Insomnia/any order form of sleep disorder	12	7588.00	3261.00	10849.00	70148.00	5845.6667	2453.87943	6021524.242
Hypertension	12	15588.00	5625.00	21213.00	126454.00	10537.8333	6366.79134	40536031.970
Women in labour	12	6723.00	4361.00	11084.00	85531.00	7127.5833	2756.23605	7596837.174
Valid N (listwise)	12							

Source: Authors computation, 2024

Graph of diabetes, insomnia and hypertension on women in labor among the mentioned years.



Source: Microsoft Excel

From the descriptive Statistics above, 85531persons are women in labour per year in the study area. Likewise, 210015 diabetic, 126454 are hypertensive and 70148 have insomnia are likely to be reported in a year under the same condition.

4.2 Model Formation

Table 4.2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2820.686	2579.611		1.093	.306		
	Diabetes	.265	.399	.587	.663	.526	.112	8.931
	Insomnia/any order form of sleep disorder	-.009	.988	-.008	-.009	.993	.113	8.811
	Hypertension	-.026	.160	-.059	-.160	.877	.643	1.555

a. Dependent Variable: Women in labour

Source: Authors computation, 2024

$Y= 2820.686+ .265X_1 - .009X_2-.026X_3$

Hypothesis 1

Testing of significance of parameter β_i's of the model

$Y= 2820.686+ .265X_1 - .009X_2-.026X_3$

H_0: $\beta_0 = \beta_1 = \beta_2 = \beta_3 = 0$ i.e. β s are not significant.

H_1: $\beta_0 \neq \beta_1 \neq \beta_2 \neq \beta_3 \neq 0$ i.e. at least one of the β_i's is significant

Decision rule: if p-value > 0.05 accept Ho; otherwise reject Ho.

From table 4.2 above, the p-value for **women in labour** $\beta_1, \beta_2, \beta_3$, are 0.526, 0.993, and 0.877 respectively which are greater than 0.05, therefore, the null hypothesis is rejected and conclude that the B's are significant.

Hypothesis 2

Testing of significance of the formulated model?

H_0: The regression equations (model) is not significant

H_1: The regression equation (model) is significant

Table 4.3

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24896005.716	3	8298668.572	1.132	.393[b]
	Residual	58669203.200	8	7333650.400		
	Total	83565208.917	11			

a. Dependent Variable: Women in labour

b. Predictors: (Constant), Hypertension, Insomnia/any order form of sleep disorder, Diabetes
Source: Authors computation, 2024

α = 0.05
P-value (model) = 0.393

Decision Rule:
Accept H_0 if p-value > 0.05, otherwise reject Ho.
From table 4.3 above, the p-value is 0.393 greater than 0.05 then H_0 is rejected thus the models
$Y_i = 2820.686 + .265X_1 - 0.009X_2 - 0.026X_3$
are statistically significant.

4.3 Predictive Power Of The Model
Table 4.4

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.546[a]	.298	.035	2708.07134	.298	1.132	3	8	.393	1.637

a. Predictors: (Constant), Hypertension, Insomnia/any order form of sleep disorder, Diabetes
b. Dependent Variable: Women in labour
Source: Authors computation, 2024

The coefficient of determination, $R^2 = \frac{SS_{RESIDUAL}}{SS_{TOTAL}}$, R^2 =0.298= 29.8 % for the model Women in labour show the predicting power of the model formed.

4.4. Test Of Multicollinearity, Autocorrelation And Heteroscedasticity.
Test of multicollinearity through Variance inflating factor

Table 4.5 Model		Correlations			Collinearity Statistics	
		Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)					
	Diabetics	.544	.228	.196	.112	8.931
	Insomnia/any order form of sleep disorder	.509	-.003	-.003	.113	8.811
	Hypertension	.283	-.057	-.047	.643	1.555

Source: Authors computation, 2024

Variance Inflating Factor (VIF): If the VIF values lies between 1-10, there is no presence of multicollinearity,If the VIF less than 1 or greater than 10 then there is multicollinearity. The VIF values for the model is between the acceptable ranges thus we conclude that the independent variables are free of multicolinearity.

• **Detection of autocorrelation:** In this section, Durbin Watson d statistic test will be employed in testing for autocorrelation

$d = \frac{\sum(u_t - u_{t-1})^2}{\sum u_t^2}$

Decision rule:

d=2. no autocorrelation.
d=0, perfect +ve autocorrelation
d=>2 presence of-ve autocorrelation
d=4, perfect -ve autocorrelation.
d<2, presence of +ve autocorrelation

Table 4.6

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.546[a]	.298	.035	2708.07134	.298	1.132	3	8	.393	1.637

a. Predictors: (Constant), Hypertension, Insomnia/any order form of sleep disorder, Diabetes
b. Dependent Variable: Women in labour
Source: Authors computation, 2024

From table 4.6 above the Durbin-Watson (d) = $\frac{\sum(u_t - u_{t-1})^2}{\sum u_t^2}$ = 1.637which is approximately = 2

Since d=2 for the model above, independent variables are free of autocorrelations

• **Graphical Method of Detecting Heteroscedasticity,.**

Rule: If there is a regular pattern in the scatter plot of graph of standardized Y and the Studentized residual then there has been a problem of heteroscedasticity. Conversely, if there isno clear pattern, the indication is no heteroscedasticity problem

The above figure are the scatter plot of graph of standardized fitted $\widehat{Y_1}$ with the corresponding the standardized residual.

Interpretation: From the plotted graph above there is no evidence of heteroscedasticity in the error term as the there is no systematic change in the spread of the residuals over the range of measure value.

Summary of the Findings

This research work focus on formulating a predictive model for labour outcomes in women with comorbid diabetes, insomnia and hypertension using ministry of health statistical bulletin data osun state from 2011 to 2021. to verify the relationship between the different categories of disease sustained by the patients, the method of multiple regression analysis was employed along with simple descriptive statistics.

From the multiple regression analysis, this model were derived;

1. Model on the categories of disease sustained by the patients to the number of women in labourY_i= 2820.686+0.265X_1 - 0.009X_2- 0.026X_3

I. The intercept β_0= 2820.686implies that at least 2821patients are in labour within the study areas

ii. The coefficient of X_1 i.e. diabetes suggests that for every patient, the number of Women in labour through diabetes may increase by 0.265per year.

iii. The coefficient of X_2i.e. insomnia suggests that for every patients, the number of women in labour through insomnia may decrease by - 0.009per year.

iv. The coefficient of X_3 i.e. hypertension suggests that for every patient, the number of women in labour through hypertension may decrease by - 0.026per year.

Test of significant difference between the parameter β_0 of the formulated model were conducted and found not significant.

Also, test of multicollinearity through the use of Variance Inflating Factor (VIF) shows that there is no nulticollinearity problem in the data collected since all the VIF values lies between 1 and 10. Likewise, from the Durbin-Watson shows that there is no problem of autocorrelation.

Lastly, there was no evidence of heteroscedasticity in the error term as revealed by the residual plot against fitted plot.

5.1 CONCLUSION

In conclusion, the current literature highlights the need for predictive models that can accurately identify women with comorbid diabetes, insomnia, and hypertension who are at risk of adverse labour outcomes. This study aims to contribute to the existing literature by developing a predictive model for labour outcomes in women with comorbid diabetes, insomnia, and hypertension, using data from the Ministry of Health Statistical Bulletin. The study's models provide valuable insights into the relationships between health conditions and the number of women in labor. The non-significant difference between the formulated models indicates their equal effectiveness in explaining these relationships. Rigorous tests for multicollinearity, autocorrelation, and heteroscedasticity enhance the study's reliability, affirming the robustness of the findings. The result also revealed that there is no presence of multicollinearity, autocorrelation andheteroscedasticity. These results hold practical implications for healthcare strategies in Osun State, facilitating targeted interventions for improved maternal health outcomes. Moreover, the methodology and statistical tests employed offer a blueprint for future research in similar contexts, advancing our understanding of the complex dynamics between health conditions and maternal well-being. The findings of this study have the potential to inform clinical practice and policy decisions aimed at improving pregnancy outcomes in Nigerian women.

Gaps in this research

Despite the availability of predictive models for labour outcomes in women with comorbid conditions, there are several gaps in the current literature. Firstly, few studies have specifically examined the predictive models for labour outcomes in women with comorbid diabetes, insomnia, and hypertension. Secondly, most studies have focused on developed countries, with limited research conducted in low- and middle-income countries like Nigeria. Finally, few studies have utilized data from the Ministry of Health Statistical Bulletin to develop predictive models for labour outcomes.

RECOMMENDATIONS

It's therefore recommended that Government should;

1. Improved access to healthcare: Increase access to quality healthcare services, especially for women in rural areas.
2. Health education and awareness: Provide health education and awareness programs to promote early detection and management of comorbid conditions.
3. Cultural sensitivity and support: Provide culturally sensitive support and care to women with comorbid conditions, addressing their unique needs and concerns.
4. Multidisciplinary care: Ensure multidisciplinary care for women with comorbid conditions, involving obstetricians, endocrinologists, cardiologists, and other relevant specialists.

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