Research Article

BIOSTATISTICS AND BIRTH OUTCOME IN ENUGU STATE TEACHING HOSPITAL PARK LANE, ENUGU, NIGERIA

ABSTRACT

Biostatistics is an important field of study, both to statisticians, medical/ health and environmental scientists. Its application has been very useful in solving some critical health issues. In health issue like pregnancy, birth outcome is usually expected with a lot of anxiety. This study aimed at applying Biostatistics to examine some possible factors that can influence the birth outcome in a pregnancy; ranging from the number of pregnancies by a mother, to the gestational age of a mother. To achieve this aim, data on birth outcome based on these factors were collected from records Unit of Enugu State University Teaching hospital. Linear Discriminant Analysis (LDA); a Multivariate strategy use for classifying observations, into known groups was used to classify the Birth outcome into Stillbirth and Alive birth. From the analysis, Prior Probabilities result of 0.50 indicated that the two birth outcomes were given equal probability. Also the descriptive statistics indicated that the weight of infants was highest with a mean value of 3.1934 while the number of pregnancies by mothers was highest with a standard deviation of 1.84269. The result of this study identified infant weight to be influencing the birth outcome. The analysis result also pointed out an important process that often posses a big challenge in data collation; the case of misclassification.

Keywords: *Birth outcome, classifications, Still-birth, Discriminant analysis, Expectant mothers Misclassification. Multivariate strategy,*

INTRODUCTION

Birth outcomes in every pregnancy is usually preceded by a lot of uncertainties and also seen to vary across geographical areas due to woman's personal and behavioral characteristics, environmental exposures, access to and level of care[1]. In Enugu state, this is a worrisome trend that needs attention of both health practitioners and the general public as those concerned always anxiously await the birth outcome of each pregnancy. There is the need to be aware of possible factor(s) that could influence the birth outcome. This is an important medical issue in the society which ought to be examined. Biostatistics is the branch of applied statistics that applies statistical methods to medical and biological problems. It can be defined as “the application of the mathematical tools used in statistics to the fields of biological sciences and medicine”. It is a growing field with applications in many other areas apart from biology and medical/ health sciences, such as epidemiology, educational research and environmental sciences[2]. Further definitions has it that biostatistics is "the science of obtaining, analyzing and interpreting data in order to understand and improve human health"[3].

For decades, biostatistics has played an integral role in modern medicine holistically; from analyzing data to determine if a treatment will work to developing clinical trials. In line with this, a good knowledge of the subject is of utmost importance for research scholars, medical students, and nursing students as this will enable them design epidemiological study accurately and draw meaningful conclusions[4]. It helps researchers utilize collected data to decide whether a treatment is working or to find factors that contribute to diseases. Biostatistics is used to determine how diseases develop, progress and spread. For example, biostatisticians use statistics to predict the behavior of an illness like the flu. It is used to help predict the mortality rate, the symptoms and even the time of year people might get it[5]. Furthermore, Medical research that employs the application of biostatistics as a vital tool is being encouraged in some part of the world particularly in India. Also it is considered an important tool that will aid medical doctors to understand and make use of available data to analyze findings and engage in meaningful research activities[4]. It is very useful in finding treatment for new drugs for diseases like cancer. Biostatisticians developed a sequential design that allows them to quit a study as soon as a clear treatment effect is observed. They also help to design, manage and analyze cancer clinical trials as well as helping to identify the causes and characteristics of cancer. Oncologists rely on these numbers to recommend treatments for their cancer patients. Since cancer is not a "one-size fits all" disease; it varies. They work closely with oncologists to identify how factors such as drug interaction, diet and nutrition play a role in cancer. They also examine the traits of cancer and how it occurs in various ages, genders and racial groups to work on prevention and treatment. These underscore why this study is seen as a Biostatistics study. For pregnant mothers the birth outcome of their babies whether alive or still-birth is usually a thing of great concern to them and indeed to the family concerned. This view is supported by Krissi who stated that “Giving birth to a stillborn baby is a fear of many pregnant women[6]. When it does happen, it's natural to want to understand what caused the stillbirth. Unfortunately, sometimes doctors don't have an answer to this question”. A study found that in approximately one-quarter of stillbirths, there is no known probable or possible cause. The causes tend to shift depending on gestational age, and unexplained stillbirth is more common late in pregnancy[6]. However, some common factors have been attributed to causes of stillbirth and they include: Placenta problems, Birth defects, Pregnancy and labor complications, Umbilical cord problems, Infection, Maternal health[7].

In line with other studies in Biostatistics, it is worthwhile to examine how some other possible factors could influence the birth outcome; still-birth or alive birth in a pregnancy.

The aim of this study is to examine the influence of some factors on birth outcome with respect to still-birth and alive birth. This is a retrospective study therefore to achieve the stated aim, the following factors: number of pregnancies by a mother, number of births by a mother, first pregnancy status of a mother, number of pregnancy plus miscarriages experienced by a mother, sex of infant, weight of baby, age of a mother, gestational age of a mother; were considered.

Materials and Methods

Study area:

As earlier stated that this is a retrospective study; data for the study were collected from records unit of Enugu State University Teaching Hospital (ESUTH), Park Lane, Enugu in Nigeria. The period covered under this study was from 2006-2019. This research project was conducted from 2/3/2019-20/11/2019. The data comprised of infant birth outcome status, number of pregnancy, number of births, first pregnancy status, number of pregnancy plus miscarriages, sex of infant, weight of baby, age of mother, gestational age.

Linear Discriminant Analysis:

The multivariate statistical method employed as earlier stated is the Linear Discriminant Analysis (LDA). LDA is a method used to discriminate between two or more groups of samples. In principle, any mathematical function may be used as a discriminating function. In case of the LDA, a linear function of the form

$$y = a_0 + a_1x_1 + a_2x_2 +..., + a_nx_n \quad \text{................[1]}^8$$

is used, with x_i being the variables describing the data set. The parameters a_i have to be determined in such a way that the discrimination between the groups is at its best state. Note that this linear discriminating function is formally equivalent to the multiple linear regressions. One can directly use multiple linear regressions if the response variable y is replaced by the weighted class numbers c_1 and c_2:

$$c_1 = n_2/(n_1+n_2) \quad and \quad c_2 = - n_1/(n_1+n_2) \quad \text{.....................[2]}$$ Derived from Basic Statistics

In some cases one may be decide to use multiple linear regression analysis in a retrospective study of this nature, especially as the equations are similar thus

$$y = b_0 + b_1x_1 + b_2x_2 +..., + b_nx_n \equiv y = a_0 + a_1x_1 + a_2x_2 +..., + a_nx_n \quad \text{................[3]}^8$$

However for this study to achieve the desired result, linear discriminant analysis is considered most appropriate.

Discriminant analysis (DA) is used to distinguish distinct sets of observations and allocate new observations to previously defined groups and also in situations where the clusters are known a priori[8]. Discriminant analysis aims to classify an observation, or several observations, into known groups. In other words, DA can be said to be a set of methods and tools used to distinguish between groups of population's π_i and to determine how to allocate new observations into groups. To use this tool it is pertinent to check if the data conforms to its assumptions.

Assumptions of Linear discriminant analysis

Multivariate Normality and Outliers: Discriminant analysis does not make the strong normality assumptions like MANOVA because emphasis is on classification. A sample size of at least twenty observations in the smallest group is usually adequate to ensure the robustness of any inferential tests that may be made. Outliers can cause severe problems that even the robustness of discriminant analysis will not overcome. One should ensure that the data are screened carefully for outliers using the various univariate and multivariate normality tests and plots to determine if the normality assumption is reasonable.

Homogeneity of Covariance Matrices: Discriminant analysis assumes that the group covariance matrices are equal. This assumption may be tested with Box's M test in the Equality of Covariances procedure or looking for equal slopes in the Probability Plots. If the covariance matrices appear to be grossly different, corrective action should be taken. Although the inferential part of the analysis is robust, the classification of new individuals is not. These will tend to be classified into groups with larger covariances. Corrective action usually includes the close screening for outliers and the use of variance-stabilizing transformations such as the logarithm.

Linearity: Discriminant analysis assumes linear relations among the independent variables. The scatter plots of each pair of independent variables should be studied, using a different color for each group. Observe for curvilinear patterns and possible outliers. The occurrence of a curvilinear relationship will reduce the power and the discriminating ability of the discriminant equation.

Multicollinearity and Singularity: Multicollinearity occurs when one predictor variable is almost a weighted average of the others. This collinearity will only show up when the data are considered one group at a time. Forms of Multicollinearity may show up when the number of observations is less than the number of variables. In this case, the number of independent variables has to be reduced. Multicollinearity is easily controlled during the variable selection phase. Only the variables that show an R^2 with other X's of less than 0.99 should be included [9].

In linear discriminant function; the discriminant rule was based on a projection $a^{\tau}x$ such that a good separation can be achieved[10].
Suppose

$$y = x_a \qquad \text{…………….[4)]}^{10}$$

is a linear combination of observations, then the total sum of squares of y,

$$\sum_{i=1}^{n}(y_i - \bar{y})^2 \qquad \text{………………….[5]}$$

can be represented as

$$y^{\tau}H\, y = a^{\tau}X^{\tau}HXa = a^{\tau}Ta \qquad \text{………………..…[6]}^{11}$$

where the centering matrix

$$H = I - n^{-1}\, I_{n_n}\, I_n^{\tau} \;\; and\; T = X^{\tau}HX \qquad \text{…………..[7]}^{11}$$

Considering, $X_j, j = 1,2,3, \dots, j,$ samples from j populations, the linear combination $a^{\tau}x$ which maximizes the ration of the between-group-sum of squares to the within-group-sum of squares. The within-group-sum of squares is given by

$$\sum_{j=1}^{n} y_j^{\tau} H_j y_j = \sum_{j=1}^{j} a^{\tau} X_j^{\tau} H_j X_j a_{-a^{\tau}}\; Wa \qquad \text{…………………[8]}^{11}$$

where y_j denotes the j^{th} sub-matrix of y corresponding to observations of group j and H_j denotes the (n_j x n_j) centering matrix. The within-group-sum of squares measures the sum of variations within each group.

The between-group-sum of squares is given by

$$\sum_{j=1}^{J} n_j(\bar{y}_j - \bar{y})^2 = \sum_{j=1}^{J} n_j\{a^\tau(\bar{X}_j - \bar{X})\}^2 = a^\tau \; Ba \qquad \text{.................. [9]}$$ [11]

where $\bar{y}_j$ and $\bar{x}_j$ are the means of y_j and x_j and $\bar{y}$ and $\bar{x}$ are the sample means of Y and X respectively. The between-group-sum of squares measured the variation of the means across groups.

The total sum of squares represented in (9) is the sum of the within-group-sum of squares and the between-group-sum of squares.

$$a^\tau Ta = a^\tau Wa + a^\tau Ba \qquad \text{........................[10]}$$

To select the projection vector *a* that maximizes the ratio

$$\frac{a^\tau Ba}{a^\tau Wa} \qquad \text{........................[11]}$$

The vector *a* that maximizes (10) is the eigenvector of $W^{-1}B$ that corresponds to the largest eigen value. Hence, the corresponding discriminant rule is

$$X \to \pi_1 \text{ if } a^\tau\left\{X - \tfrac{1}{2}(\bar{X}_1 + \bar{X}_2)\right\} > 0$$

$$X \to \pi_2 \text{ if } a^\tau\left\{X - \tfrac{1}{2}(\bar{X}_1 + \bar{X}_2)\right\} \le 0$$ (Derived equations based on fisher's proposal[10].)

To illustrate this concept we now use the medical data collected from records unit of Enugu State University Teaching hospital Park lane. The data are as tabulated below in table 1 and 2.

Table 1: Data on Alive Births in Enugu State for the Period under Study

YEAR	**Live Birth**	**NPM**	**NB**	**NCA**	**NPPM**	**Male**	**Female**	**Weight**
2006	103	367	267	216	366	47	56	352.1
2007	87	168	186	138	268	48	39	292.8
2008	77	297	198	174	277	42	35	248.9
2009	49	180	135	127	180	28	22	168.8
2010	60	221	161	132	221	24	36	203.8

2011	95	344	248	225	344	49	46	297.9
2012	60	220	166	156	60	32	28	209.2
2013	99	329	229	229	329	50	49	330.6
2014	51	149	96	96	149	26	25	167.6
2015	112	293	185	179	293	60	52	370.0
2016	43	126	84	79	126	17	26	134.6
2017	97	226	123	98	226	55	42	297.9
2018	144	327	181	173	227	92	52	485.2
2019	266	678	383	354	686	160	106	897.1
TOTAL	1343	3925	2642	2376	3842	730	614	4456.5

Source: ESUTH, 2020[12]

Key: BO= Birth Outcome, NPM=Number of Pregnancy by Mother, NB=Number of Births, NCA=Number of Children Alive, NPPM=Number of Pregnancy plus Miscarriages, Sex= Sex of infant, and Weight=Weight of infant.

Table 2: Data on Stillbirths in Enugu State for the Period under Study

Year	**Stillbirth**	**NPM**	**NB**	**NCA**	**NPPM**	**Male**	**Female**	**Weight**
2006	41	123	93	63	124	24	17	87.4
2007	36	219	93	75	119	24	12	96.8
2008	27	72	68	39	92	16	11	84.6
2009	22	54	34	24	54	13	8	58.2
2010	27	83	63	49	83	16	11	74.2
2011	36	113	84	63	113	24	12	97.9
2012	28	66	40	30	66	18	10	72.2
2013	0	0	0	0	0	0	0	0.0
2014	3	6	3	3	6	0	3	8.1
2015	10	44	34	34	38	6	4	31.8
2016	11	52	41	37	51	11	0	35.2
2017	1	5	3	3	5	1	0	3.2
2018	10	27	14	14	27	0	10	16.4
2019	23	38	8	8	38	6	17	44.0
TOTAL	275	902	578	442	816	159	115	710

Source: ESUTH, 2020[12]

Key: BO= Birth Outcome, NPM=Number of Pregnancy by Mother, NB=Number of Births, NCA=Number of Children Alive, NPPM=Number of Pregnancy plus Miscarriages, Sex= Sex of infant, and Weight=Weight of infant.

RESULTS

Result obtained as shown in Table 3 presents the mean and the standard deviation of the variables for the category of birth outcome (Alive and Stillbirth). The result revealed that the weight of infants recorded the highest mean with a measure of 3.1934 while the number of pregnancies by mother recorded the highest standard deviation with a value of 1.84269.

Table 3: Summary of Group Statistics of the variables

Birth Outcome		Mean	Std. Deviation	Valid N (list wise) Unweighted	Valid N (list wise) Weighted
Alive	Number of Pregnancy by Mother	2.9821	1.84931	1343	1343.000
	Number of Births	1.9687	1.76628	1343	1343.000
	Number of Children Alive	1.7692	1.70045	1343	1343.000
	Number of Pregnancy plus Miscarriages	2.9806	1.85131	1343	1343.000
	Sex of Infant	1.4572	.49835	1343	1343.000
	Weight of Infant	3.3186	.50119	1343	1343.000
Stillbirth	Number of Pregnancy by Mother	2.9891	1.81334	275	275.000
	Number of Births	2.0945	1.55383	275	275.000
	Number of Children Alive	1.6073	1.61379	275	275.000
	Number of Pregnancy plus Miscarriages	2.9636	1.77743	275	275.000
	Sex of Infant	1.4182	.49416	275	275.000
	Weight of Infant	2.5818	.85877	275	275.000
Total	Number of Pregnancy by Mother	2.9833	1.84269	1618	1618.000
	Number of Births	1.9901	1.73220	1618	1618.000
	Number of Children Alive	1.7417	1.68665	1618	1618.000
	Number of Pregnancy plus Miscarriages	2.9778	1.83843	1618	1618.000
	Sex of Infant	1.4506	.49770	1618	1618.000
	Weight of Infant	3.1934	.64036	1618	1618.000

The result as shown in Table 4 revealed that the mean weight of the infant recorded a Wilks' Lambda (^) of 0.813 and a p-value of 0.000 showing that the test is significant.

Table 4: Result of Test of Equality of Group Means

Parameter	Wilks' Lambda(^)	F	df1	df2	Sig.
Number of Pregnancy by Mother	1.000	.003	1	1616	.955
Number of Births	.999	1.204	1	1616	.273
Number of Children Alive	.999	2.105	1	1616	.147
Number of Pregnancy plus Miscarriages	1.000	.020	1	1616	.889
Sex of Infant	.999	1.402	1	1616	.237
Weight of Infant	.813	371.379	1	1616	.000

The result as shown in Table 5 indicated that the two birth outcomes were given equal probability i.e 0.50. Also, it was observed that 1343 infants were alive while 275 were recorded as stillbirth during the period under study.

Table 5: Prior Probabilities for Groups

Birth Outcome	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Alive	.500	1343	1343.000
Stillbirth	.500	275	275.000
Total	1.000	1618	1618.000

The result as obtained in Table 6 revealed that the weight of the infant recorded the highest coefficient in the first and second functions with a coefficient of 13.366 and 10.472, respectively than the other variables.

Table 6: Classification Function Coefficients

Parameters	Birth Outcome	
	Alive	Stillbirth
Number of Pregnancy by Mother	-3.866	2.603
Number of Births	-7.802	-5.870
Number of Children Alive	1.425	.353
Number of Pregnancy plus Miscarriages	9.980	2.790
Sex of Infant	10.554	9.299
Weight of Infant	13.366	10.472
(Constant)	-33.250	-22.965

The result obtained in Table 7 revealed that 14.4% of birth outcomes recorded as alive were misclassified as stillbirth, while 23.3% of birth outcomes recorded as stillbirth were misclassified as alive. Hence, it was revealed that 84.1% of the original grouped cases were correctly classified.

Table 7: Classification Result of Birth outcome

		Birth Outcome	Predicted Group Membership		Total
			Alive	Still Birth	
Original	Count	Alive	1150	193	1343
		Stillbirth	64	211	275
	%	Alive	85.6	14.4	100.0
		Stillbirth	23.3	76.7	100.0
a. 84.1% of original grouped cases correctly classified.					

DISCUSSIONS

The analysis results showed that weights of infants recorded the highest mean value with a value of 3.1934 while the number of pregnancy by mother recorded the highest standard deviation with a value of 1.84269 for the independent variables. This is in line with the literature; because Low Birth Weight is seen as an important predictor of perinatal morbidity and mortality which can also be used to evaluate the effectiveness of public health actions and interventions for preventing LBW[1].
The Wilks' Lambda (^) of 0.813 obtained for the mean weight of the infant clearly shows that the groups were poorly separated; given that the value is a bit close to 1; this indicates that the group dispersion is small[13]; although the p-value of 0.000 that was recorded shows that the test is significant.
The coefficient for weights of infants in the first and second function is greater in magnitude than the coefficients for the other variables with a coefficient of 13.366 and 10.472, respectively; this implies that weights of infants have the greatest impact for the discriminant function which confirmed the result obtained earlier.
Prior Probabilities of 0.5 for the groups shows that birth outcomes were given equal chances of occurrence; implying that there was no biasness in classifying the birth outcome into alive or stillbirth.
The analysis result shows that 14.4% of birth outcomes recorded as live births were misclassified as stillbirth, while 23.3% of birth outcomes recorded as stillbirth was misclassified as live birth. Therefore, it was observed that 84.1% of the original grouped cases were correctly classified this shows that about 15.9% of birth outcomes of the original cases were misclassified.
The mean weights of infants are significantly different from the other independent variables, implying that the weights of infants are expected to impact more on the classification of the birth outcome.
The highest mean recorded for the weights of infants implies that the weight of infants is expected to impact more on the classification of the birth outcome. This is similar to a study that stated that children with low birth weight are more likely to die during infancy compared to those born with normal weight[14].
Most times the choice of using regression analysis in a study of this nature is preferred to the choice of discriminant analysis because of the flexibility of the assumptions; however the result obtained in this study with respect to the classification of the birth outcome under alive and still-birth is considered to be acceptable given the variables being examined[15]. Also identifying infant birth weight as being significant among other recorded variables has shown how well the chosen statistical tool the linear discriminant analysis has performed as against using linear regression analysis as earlier stated[8]. It is imperative to know that the choice of statistical tool should also be based on the peculiarity of a study and not just on the general assumption of the model and its conformity with the data collected for the study.

This study implies that weight of infants can be used to check birth outcome among other already established factors; this is in line with the result of the study by Hong and Ruiz-Beltran[16] However, another study has it that birth weight may not result in reduced infant mortality.[17]; although existing literature shows that birth outcome cannot be predicted nor attributed to a known particular cause[6]
The limitation of this study is that the variables considered based on the data collected for this study may likely be affected by Multicollinearity given the respective values of the Wilks' Lambda(^); ranging from 0.813 to 1.000. Although weight of infant recorded a smaller value 0.813 compared to other variables; the dispersion is small.

This study therefore recommends inclusion of more variables in order to eliminate possible effect of multicollinearity and improve proper classification. This could enhance a better and more reliable result in the analysis of birth outcome in a teaching hospital.

CONCLUSION

This study has examined some possible factors that can influence the birth outcome in a pregnancy; ranging from the number of pregnancies by a mother, to the gestational age of a mother. However, literature has it that there is no known probable or possible cause and that unexplained stillbirth is more common late in pregnancy. The result of this study has attributed the birth outcome to the weight of babies. The analysis result pointed out an important process that often posses a big challenge in data collation; the case of misclassification. This case of misclassification could be misleading in giving out information in a given process; therefore should be taken seriously.

SIGNIFICANCE STATEMENTS

This study discovered that weight of infants could be used to evaluate birth outcome; although existing study has stated that there is no known probable or possible cause. This can be beneficial to both the antenatal care givers and pregnant mothers. Being aware of this fact can influence the nutritional habits of pregnant mothers which will in turn impact on the weights of their babies. Thus guideline on desired weights of infants which could be achieved through the a guided diet of mothers during pregnancy can be proposed.

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