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Logistic Modeling of Normal Ovulation in Selected Women

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ABSTRACT

The aim of this paper was to accurately model the ovulation interval of selected women in Ika North-East and Ika South Local Government Areas of Delta State in order to estimate the probabilities of normal ovulation amongst them. Data were collected from reproductive women (women that are still ovulating and experiencing menstrual cycles) in the two Local Government Areas. Data Dimension span through their Age, Height, Weight, Work Time, Menstrual Duration, Number of Conceptions, Number of Births, Exposure to Sun and Ovulation Interval. Interviews and questionnaires were administered to the two hundred women considered in the study. The Binary Logistic Regression Model was applied in the analysis of data. A random variable, y_i, was defined as the event that a randomly selected woman was ovulating normally thus, the logistic model estimated the probability, P_i, that the randomly selected woman was ovulating normally. 54 of the 92 women experiencing normal were erroneously estimated to be experiencing non-normal ovulation, giving 41.3% accuracy in this group; 75 of the 108 women experiencing non-normal ovulation were correctly estimated to be actually experiencing non-normal ovulation while 33 of them were erroneously estimated to be experiencing normal ovulation giving 69.44% accuracy in this group. A total of 113 of the 200 women were correctly estimated to be experiencing their actual ovulation while 87 of them were erroneously estimated giving a 56.5% accuracy.

INTRODUCTION

The process by which eggs are released from the ovary of a reproductive woman at monthly interval is called ovulation. This occurs when the ovarian follicles rupture and release the secondary oocyte ovarian cells (Duke, 2011). In humans, ovulation takes place at half the interval of the menstrual cycle. The few days surrounding ovulation (from approximately day 10 to 18 of a 28-day cycle) constitute the most fertile period (Chaudhuri, 2007). The half way period is estimated at 14.6 days but with substantial variation between females and between cycles in any single female, with an overall 95% prediction interval of 8.2 to 20.5 days (Geirsson, 1991). The substantial variation between females has made it difficult if not impossible for accurate estimation of the ovulation interval of women in certain populations.

A statistical method that may be used to model the variation in ovulation interval is the Logistic Regression Model. It is commonly used to model the mathematical chance that a particular experimental outcome occurs. Logistic regression is a statistical model which is used to model a dependent variable that has two or more possible outcomes (Tolles & Meurer, 2016). A logistic model in which the dependent has two possible outcomes is called a binary logistic model. The logistic model does not classify observations but only models the probability that an observation falls into one of two defined groups (Walker & Duncan, 1967).

It is therefore the aim of this study to model the ovulation of selected women in Ika North-East and Ika South-West Areas of Delta State in Nigeria in order to estimate the probabilities of normal ovulation. Hence, fertilization and fecundity will be appropriately and properly planned.

MATERIALS AND METHODS

The data for this study were collected from reproductive women (women that are still ovulating and experiencing their menstrual cycle) in Ika North-East and Ika South-West Local Government Areas of Delta State. The multidimensional data were collected on their Age, Height, Weight, Work Time, Menstrual Duration, Number of Conception, Number of Births, Exposure to Sun and Ovulation Interval. Interviews and questionnaires were administered to the women that would be addressed as volunteers because they decided to participate in the exercise against the majority’s opinion that most of the questions were digging too deep into their privacy. A total of two hundred participants were involved in the study.

The data for this study shall be analyzed using the Binary Logistic Regression Model. Let y_i be defined as the event that a randomly selected woman in the study is experiencing normal ovulation. Here, a value of 1 shall be assigned to those women that experience normal ovulation (every 24 to 30 days) and a value of 0 shall be assigned to those women experiencing non normal ovulation (every less than 24 days or above 32 days).

In that case, $$y_i = \begin{cases} 1 \; if \; the \; i^{th} \; woman \; experiences \; normal \; ovulation \\ 0 \; if \; the \; i^{th} \; woman \; experiences \; non \, normal \; ovulation. \end{cases} \quad (1)$$

If P_i is the probability that the i^{th} woman is experiencing normal ovulation (that is, the probability that $y_i = 1$) then,

$$P_i = \frac{1}{1 + e^{-y_i}} \quad (2)$$

where

$$y_i = b_0 + b_1 x_{1i} + b_2 x_{2i} + \cdots + b_p x_p + e_i \quad (3)$$

That is,

$$y_i = \sum_{j=0}^{p} b_j \, x_{ji} + e_i \quad (4)$$

(Neter, William, & Michael, 1983)

The b_j's are estimated using the maximum likelihood method (NCSS, 2019).

This implies an assumption of a linear relationship between the predictor variables and the log-odds of the event $y_i = 1$. However, the assumptions of conventional regression analysis are violated. Though the dependent variable is Bernoulli, the logit is on an unrestricted scale (Hosmer & Stanley, 2000).

If $P_i \geq 0.5$, the i^{th} observation is more likely to take a value of 1 (normal ovulation in this case) and if $0 \leq P_i \leq 0.5$, the i^{th} observation is more likely to take a value of 0 (nonnormal ovulation).

ANALYSIS OF DATA

Equation 2 was applied for the analysis of data and the probability (P_i) of each i^{th} woman experiencing normal ovulation was determined. A value equal to or greater than 0.5 imply that the i^{th} woman is more likely to be ovulating normally while a value less than 0.5 imply that i^{th}

woman is more likely to experience non normal ovulation than normal ovulation. Applying Equations 3 and 4 gave the logit model of the distribution as

$$\begin{aligned} y_i = -0.45 - 0.0144 Age - 0.08 Height + 0.01010 Weight + 0.0443(Work\ Tme) \\ - 0.0066(Menstrual\ Duration) - 0.0818\ (number\ of\ Conception) \\ + 0.108\ (Number\ of\ Births) - 0.0059(Exposure\ to\ Sun) \end{aligned} \quad (5)$$

Of the 200 women considered for the study, 92 are those who actually experience normal ovulation while 108 experience non normal ovulation. 54 out of those 92 women experiencing normal ovulation were erroneously estimated to experience non-normal ovulation by the logistic model while 38 of them were correctly estimated to be experiencing normal ovulation giving 41.3% correct estimation rate in this group. Also, 75 out of those 108 women experiencing non-normal ovulation were correctly estimated to be actually experiencing non-normal ovulation while 33 of them were erroneously estimated to experiencing normal ovulation giving 69.44% rate of correct estimation in the group. A total of 113 out of the 200 women were correctly estimated to be experiencing their actual ovulation while 87 of them were erroneously estimated to be experiencing the wrong ovulation. In total, the logistic model achieved 56.5% correct classification. This, actually, is a good performance.

RESULTS AND DISCUSSION

54 out of those 92 women experiencing normal ovulation were erroneously estimated to experience non-normal ovulation by the logistic model; 38 of the 92 women were correctly estimated to be experiencing normal ovulation; there is a 41.3% rate of correct estimation in the group of women experiencing normal ovulation; 75 out of 108 women experiencing non-normal ovulation were correctly estimated to be actually experiencing non-normal ovulation; 33 of the 108 women experiencing non-normal ovulation were erroneously estimated to be experiencing normal ovulation; there a 69.44% rate of correct estimation in the group of women experiencing non-normal ovulation; 113 out of the 200 studied women were correctly estimated to be experiencing their actual ovulation; 87 of the 200 studied women were erroneously estimated to be experiencing the wrong ovulation; the logistic model achieved 56.5% correct estimation in general and the specificity rate being 69.44% shows that the model is more effective in detecting those women that are not ovulation normally.

CONCLUSION

It is deemed logical to make the following conclusions:

with a 41.3% rate of correct estimation in the group of women experiencing normal ovulation the Binary Logistic Regression model was fairly sensitive for estimating the normal ovulation interval in the population of women in Ika Local Government Areas; with a 69.44% rate of correct estimation in the group of women experiencing non-normal ovulation, the Binary Logistic Regression Model was good in terms of specificity; with a general rate of correct classification being 56.5%, the Binary Logistic regression Model performed well in terms of correct classification and; the Binary Logistic Regression Model having recorded a fair level of accuracy in the selected women may be applied to their entire population or a representative of the population for effective family planning (natural child spacing and conception planning).

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