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Mothers' Lifestyle Characteristics Impact on Her Neonates' Low Birth Weight

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Abstract

Objective: Epidemiological research often seeks to identify a causal relationship between the risk factors and the disease. Earlier researches suggest that mother age, her weight at last menstrual period, race, the number of physician visit during the first trimester of pregnancy, may affect on her neonate birth weight. Mechanisms of mother lifestyle characteristics on her neonate weight are intricately complicated. These mechanisms, however, can be easily interpreted through an appropriate mathematical relationship. The present study aims to identify the factors of mother's lifestyle characteristics which have statistical significant effects on her neonate birth weight based on statistical (or probabilistic) modeling.

Materials and Methods: The present study is based on the secondary data collected at Baystate Medical Center, Springfield, Massachusetts during 1986. It was a routine data set. There was not any specific setting. Study subjects were 189 mothers, 59 of which had low birth weight babies and 130 of which had normal birth weight babies. Joint generalized linear log-normal statistical modeling of mean and variance is used.

Results: The present analysis identifies that mother age (p= 0.063), her weight at last menstrual period (p= 0.019), race (p= 0.017, p= 022), smoking status (p= 0.014), history of premature labor (p= 0.008), history of hypertension (p= 0.031, 0.039) and presence of uterine irritability (p= 0.002) are statistically significant on her neonate birth weight. It has been detected that the variance of neonatal birth weight is non-constant, which invites the present study.

Conclusion: Impacts of mother's lifestyle characteristics on her neonate weight are explained based on mathematical relationships. This analysis supports many earlier research findings. However, the present analysis also has identified many additional casual factors that have explained the mean and variance of neonatal birth weight, which was not reported by the earlier investigators. In addition, some conflicts about the earlier research findings are attempted to be removed.

Keywords: Ethnic Groups, Joint Generalized, Linear Log-normal Models, Lifestyle Characteristics, Low Birth Weight, Premature Labor, Uterine Irritability, Last Menstrual Period Regularity

Introduction

Neonatal death is a serious concern, both in the developing and in the developed worlds. While infant mortality rates have been decreasing steadily all over the world, changes in neonatal mortality rate have been much slower. One of the commonest causes of neonatal mortality in the world is prematurity and low birth weight (1-4). Generally, it is recognized that low birth weight can be caused by many factors (5-7). Because many questions and conflicts still remain, however, about which factors exert independent causal effects, as well as the magnitude of these effects, a critical assessment and meta-analysis of the medical literature published from 1970 to till the date were carried out.

Neonate low birth weight has long been a subject of clinical and epidemiological investigations and a target for public health intervention. Low birth weight is defined by WHO as a birth weight less than 2500 g (before 1976, the WHO definition was less than or equal to 2500 g), since below this value birth-weight-specific infant mortality begins to rise rapidly (2,8-11). In particular, considerable attention has been focused on the causal determinants of birth weight, and especially of low birth weight (LBW), in order to identify potentially modifiable factors. Many researches have focused on factors with well-established direct causal impacts on intrauterine growth include infant sex, racial/ethnic origin, maternal height, pre-pregnancy weight, paternal weight and height, maternal birth weight, parity, history of prior low-birth-weight infants, gestational weight gain and caloric intake, general morbidity and episodic illness, malaria, cigarette smoking, alcohol consumption, and tobacco chewing (1,7,10). Note that these factors were identified based on preliminary statistical methods such as frequency distribution, odds ratio, simple regression

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analysis, logistic regression etc. These methods may not identify the determinants correctly in medical systems, demography and quality engineering process, as the variance of the response may be non-constant, and the variance may have some relationship with the mean (12-18). Generally, the above methods identify insignificant factors as significant and vice versa (12-14), which is a serious error in any data analysis.

The present study analyzes the relationship of neonate birth weight (response) to the mother's lifestyle explanatory variables. It has been identified that the response is non-constant variance. Consequently, two models (mean and variance) are derived. This particular analysis identifies the following: Mean neonate birth weight is explained by the statistically significant factors, mother weight at last menstrual period, her race, smoking status during pregnancy, history of premature labor, history of hypertension and presence of uterine irritability. Mother weight at last menstrual period is positively associated with her neonate mean weight, indicating that if mother weight at last menstrual period increases, her neonate birth weight will increase. Mother race is negatively associated with her neonate birth weight. It indicates that neonate birth weight will be lower for black women than white. Mother smoking status during pregnancy is negatively associated with her neonate birth weight. This implies that higher smoking status of mother during pregnancy decreases her neonate birth weight. Mother history of premature labor is negatively associated with her neonate birth weight. It indicates that if the mother number of premature labor increases, her neonate birth weight will decrease. Mother history of hypertension and presence of uterine irritability are negatively associated with her neonate birth weight. This implies that if mother hypertension and presence of uterine irritability increase, her neonate birth weight will decrease. Variance of neonate birth weight is positively associated (statistical significant) with mother age, her history of hypertension and presence of uterine irritability. Thus, the neonate birth weight variance will increase with the increased of mother age, her hypertension and presence of uterine irritability. Therefore, the neonate birth weight variance will be lower for a mother with lower age, without hypertension and uterine irritability.

Hosmer and Lemeshow (19) studied that the mother's lifestyle characteristics on her neonate birth weight based on the data described in Results Section. Similar study has been done by many researchers (1,2). To identify the appropriate model, the earlier investigators used logistic regression techniques. Hosmer and Lemeshow (19) also noted that the variance of the response (neonate birth weight) was non-constant, and its distribution was non-normal. Therefore, the researchers used logistic regression techniques by changing the responses (neonate birth weight) 0 (= birth weight ≥2500 g) and 1 (= birth weight <2500 g). Original responses are neglected, consequently, early researchers might loose many important information. For heteroscedastic data, log-transformation is often recommended to stabilize the variance (20). In practice, though, the variance is not always stabilized by this method. For example, Myers et al. analyzed "The Worsted Yarn Data" (13) using a usual (errors are uncorrelated and homoscedastic) second-order response surface design. Myers et al. (13) treated the response (y = T) as the cycles to failure (T), and also noticed that the variance was non-constant and the analysis was inappropriate. Then using log transformation of the cycles to failure (i.e., y= lnT), the final data analysis had been done, and it was found that log model, overall, was an improvement over the original quadratic fit. The researchers noticed, however, that there was still some indication of inequality of variance. Recently, Das and Lee (14) showed that simple log transformation was insufficient to reduce the variance constant, and the investigators analyzed the data using joint generalized model. Das and Lee (14) found that many factors were significant and the log-normal distribution was more appropriate. For non-constant variance of response, classical regression technique gives inefficient analysis, often resulting in an error so that the significant factors are classified as insignificant. In addition, positive data are generally analyzed by log-normal and gamma models (12,13,21). For instance, the analysis by Myers et al. (13) missed many important factors. This fault is very serious in every data analysis. The present authors notice that the original data set is positive, variance of the response is non-constant, distribution is non-normal, and original responses are neglected. These observations have motivated us to take up this .

Materials and Methods

The class of generalized linear models includes distributions useful for the analysis of some continuous positive measurements in practice which have non-normal error distributions. The problem of non-constant variance in the response variable (y) in linear regression is due to the departure from the standard least squares assumptions. Transformation of the response variable is an appropriate method for stabilizing the variance of the response. Box (22) proposed for using linear models with data transformation. For example, when

$$E(y_i) = \mu_i \text{ and } Var(y_i) = \sigma_i^2 \mu_i^2$$

the transformation Z_i = log (Y_i) gives stabilization of variance $Var(Z_i) \approx \sigma_i^2$. However, if a parsimonious model is required, a different transformation is needed. Thus, a single data transformation may fail to meet various model assumptions. Nelder and Lee (23) proposed to use joint generalized linear models (JGLMs) for the mean and dispersion.

If the response Y_i is constrained to be positive, log transformation $Z_i = \log Y_i$ is often used. Under the log-normal distribution a joint modeling of the mean and dispersion is such that

$E(Z_i) = \mu_i, Var(Z_i) = \sigma_i^2$ and

$$\mu_i = x_i^t \beta, \log(\sigma_i^2) = g_i^t \gamma,$$

where and g_i^t are respectively the row vectors for the regression coefficients ß and γ in the mean and dispersion models. Cox and Reid (24), Lee and Nelder (25,26) studied the parameter estimation of joint modeling of the mean and dispersion. These researchers have proposed to use the maximum likelihood (ML) estimator for the mean parameters ß and the restricted maximum likelihood for dispersion parameters γ. The restricted likelihood estimators have proper adjustment of the degrees of freedom by estimating the mean parameters, which is important in the analysis of data from quality-improvement experiments because the number of parameters of ß is often relatively large compared with the total sample size. More detailed discussions of joint generalized liner models is given in (14,25-29).

Results

Data

Neonate low birth weight data set contains 189 observations on 10 variables. Study subjects (N= 189) were women (mothers), 59 of which had low birth weight babies and 130 of which had normal birth weight babies. This data set was collected at Baystate Medical Center, Springfield, Massachusetts during 1986. This is a complete data set which is given in the book written by Hosmer and Leme show (19). A paired data set created from this low birth weight data may be found in the website lowbwtm11.dat and 3 to 1 matched data set created from the low birth weight data may be found in the website mlowbwt.dat.

Variables

1. Dependent variable: The dependent variable in the present study is the neonate birth weight. 2. Independent variables: There are two sets of independent variables, qualitative and quantitative. Six independent variables (coded low birth weight, mother race, her smoking status during pregnancy, history of premature labor, history of hypertension, presence of uterine irritability) are qualitative, two are continuous (mother age and her weight at the last menstrual period) and one is discrete (number of physician visits during the first trimester) variables. The present study has neglected the coded low birth weight as an independent variable, as the original neonate birth weight is treated as the response variable. Thus, the coded low birth weight is not shown in Table 1. Table 1 presents a description of each set of items and how they are operationalized for the present study. A detailed data description is given in Hosmer and Lemeshow (19).

Analysis and Interpretation

Generally, positive data are analyzed by log-normal and gamma models (12-14,18,21), as the variance of some positive data set may have relation with the mean. Recently, log-normal and gamma models (13) are of interest in fitting positive data arising from quality-improvement experiments. Das and Lee (14) studied positive data for quality-improvement experiments, under both the log-normal and gamma joint generalized linear models.

The present subsection displays the analysis of the above mentioned neonatal birth weight data using the joint log-normal models, where the neonatal birth weight is treated as the response variable, and the remaining other eight covariates are used as explanatory variables. Table 1 displays the independent variables and their levels. There are five factors, two continuous variables and one discrete variable. For factors, the constraint that the effects of the first levels are zero is accepted. Therefore, it is taken that the first level of each factor as the reference level by estimating it as zero. Suppose that αi fori = 1, 2, 3 represents the main effect of A. It is taken $\hat{\alpha}_1 = 0$, so that $\hat{\alpha}_2 = \hat{\alpha}_2 - \hat{\alpha}_1$. For example, the estimate of the effect A2 means the effect of difference between the second and the first levels in the main effect A, i.e., $\hat{\alpha}_2 - \hat{\alpha}_1$.

The present article aims to examine the effects of mother different personal (lifestyle) characteristics (explanatory variables) on her neonate birth weight, treated as the response variable. Thus, joint log-normal models as in METHODS Section is fitted, and the results are displayed in Table 2. The selected models have the smallest Akaike information criterion (AIC) value in each class. It is well known that AIC selects a model which minimizes the predicted additive errors and squared error loss (30). The AIC value of the selected models (Table 2) is 2980 + 2 ×14= 3008 (is presented here for verification of the present models).

Figure 1(a) displays the histogram of residuals. It does not show any lack of fit for missing variables. Figure 1(b) presents the absolute residuals plot with respect to

Table 1. Operationalization of variables in the analysis

Variable Name	Operationalization
AGE(x_1)	Age of mother (in years)
LWT(x_2)	Weight of mother at the last menstrual period (in pounds)
RACE(R)	Race of mother (1=White, 2=Black, 3=Other)
SMOKE(S)	Smoking status during pregnancy (1=Yes, 0=No)
PTL(P)	History of premature labor (0=None, 1=one , etc.)
HT	History of hypertension (1=Yes, 0=No)
UI	Presence of uterine irritability (1=Yes, 0=No)
FTV	No. of physician visits during the first trimester (0=none, 1=one, 2=two, etc.)
BWT	Neonate birth weight in grams (dependent variable)

Table 2. Results for mean and dispersion models of neonate low birth weight data from log-normal fit

	Covariate	Estimate	s.e.	t	P-value	95% C.I.
Mean Model	Constant	7.9153	0.08719	90.78	<0.001	7.7440-8.0861
	LWT	0.0014	0.00060	2.36	0.019	0.0002-0.0026
	RACE2	−0.1182	0.04910	−2.41	0.017	−0.2144-−0.0228
	RACE3	−0.0904	0.03929	−2.30	0.022	−0.1674-−0.0134
	SMOKE2	−0.0913	0.03678	−2.48	0.014	−0.1633-−0.0192
	PTL2	−0.1407	0.05303	−2.65	0.008	−0.2446-−0.0367
	PTL3	−0.0063	0.11143	−0.06	0.952	−0.2247-0.2121
	PTL4	0.4541	0.36137	1.26	0.209	−0.2461-1.1623
	HT2	−0.2275	0.10436	−2.18	0.031	−0.4320-−0.0229
	UI2	−0.2144	0.06717	−3.19	0.002	−0.3460-−0.0827
Dispersion Model	Constant	−4.0130	0.4802	−8.357	<0.001	−4.9542-−3.0718
	AGE	0.0380	0.02050	1.870	0.063	−0.0022-0.0782
	UI2	0.9790	0.3078	3.179	0.002	0.3757-1.5822
	HT2	0.9800	0.4726	2.074	0.039	0.0537-1.9063

the fitted values. This is a flat diagram with the running means, indicating that the variance is constant under the joint GLM log-normal fitting. Figure 2(a) and Figure 2(b), respectively, display the normal probability plot for the mean and the variance model in Table 2. Neither figure shows any systematic departures, indicating no lack of fit of the selected final models. The standard error of all the estimates (Table 2) are very small, indicating that the estimates are stable (29).

Table 2 shows the parameters mother weight at the last menstrual period, her race, smoking status during pregnancy, history of premature labor, history of hypertension, and presence of uterine irritability are statistically significant factors on her neonate mean birth weight. Mean neonatal birth weight will increase with the increase of mother weight at the last menstrual period, as it is positively associated with the neonatal birth weight. The race (1= White, 2= Black, 3= Others) of mother is negatively associated with her neonate birth weight. This indicates an inverse relationship between the mother race and her neonate weight. Thus, the neonate birth weight will be minimum at black and other race, but it will be maximum at white race. The smoking status (0= No, 1= Yes) of mother during pregnancy is negatively associated with her neonate birth weight. This indicates a reciprocal relationship of the smoking status of mother during pregnancy, and her neonate birth weight. So, the birth weight will be lower for a neonate coming from a smoker (smoking status, i.e., 1= Yes) mother during pregnancy than a non-smoker. Mother history of premature labor (0= none, 1= one, etc.) is negatively associated with her neonate birth weight. Therefore, neonate birth weight will be decreasing with the increasing value of premature of labor of mother. Mother history of hypertension (0= No, 1= Yes) is negatively associated with her neonate birth weight. Thus, the birth weight will be lower for a neonate coming

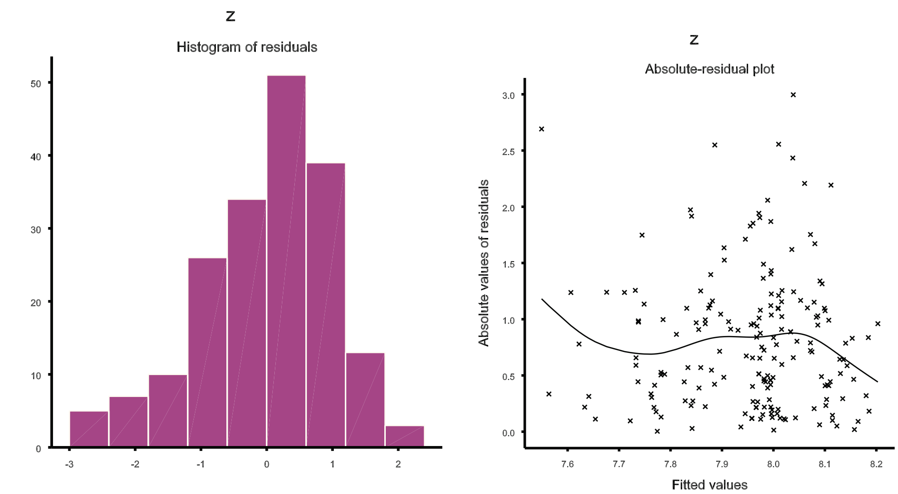

Figure 1. (a) The Histogram plot of residuals and (b) the absolute residuals plot with respect to fitted values (Table 2)

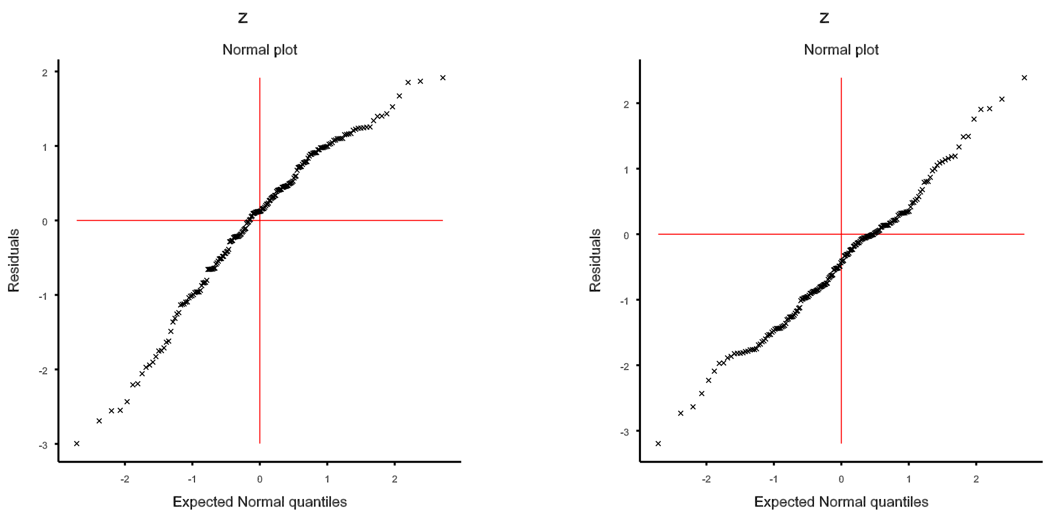

Figure 2. The normal probability plot of the (a) mean, and (b) variance model (Table 2).

from a hypertension mother than a non-hypertension. Mother presence of uterine irritability (1= Yes, 0= No) is negatively associated with her neonate birth weight. So, the birth weight will be lower for a neonate coming from a mother with the presence of uterine irritability than a normal mother (free of uterine irritability).

Table 2 shows that the mother age, her hypertension and presence of uterine irritability are positively statistical significant with the variance of her neonate birth weight. Thus, higher mother age, her higher hypertension and presence of uterine irritability increase the variance of her neonate birth weight. Table 2 indicates that higher mother weight at the last menstrual period, her white race, non-smoker status, no premature labor, no hypertension, absence of uterine irritability, lower age will increase her neonate birth weight and decrease its variance.

Discussion

This article focuses on the determinants of neonatal low birth weight. Response data are positive, so the probability model is log-normal or gamma (21). The response neonatal low birth weight is identified as non-constant variance (Table 2). Thus, joint models of mean and variance are derived from log-normal distribution. The present article have examined both the joint log-normal and gamma models (14). Observation indicates that the joint log-normal models fit much better than the gamma models, therefore, only the results of joint log-normal models are reported.

Early researches pointed out that the variance of neonatal low birth weight was non-constant and its distribution is non-Normal (1,2,4,19). Early researchers have derived the mean model using logistic regression techniques based on coded responses. However, in the present study, both the mean and the variance models of neonatal low birth weight have been derived based on original responses.

Some of the present results are supported by early researches (1,2,19). However, some of the present results are little cited in the literature. For example, the present analysis first derived the determinants (mother age, her history of hypertension, presence of uterine irritability) of the variance of neonatal low birth weight. Moreover, some additional factors (such as mother smoking status during pregnancy, her history of premature labor, history of hypertension, presence of uterine irritability) have been identified in the mean model. As a result of this approach, this report attempts to remove some conflicts of earlier research reports. For instance, in the literature, there is a conflicting report of the age which effects on neonatal mean low birth weight (1,2,19) . However, Table 2 shows that age is partially significant (p= 0.063) with the variance of neonatal weight, but it is independent of mean. In epidemiology, partially significant factors (treated as confounders) may have some effects on the responses. Rich-Edwards et al. (2), pointed (based on odds ratio) that the interaction effect of mother age and her race (or ethnic groups) is significant on her neonatal low birth weight. The present analysis shows that mother age is independent of mean neonatal weight but it is partially dependent on the variance (Table 2). To examine the interaction effect of mother age with her race, the results of an additional analysis are displayed in Table 3. Table 3 shows that the interaction effect of mother age with her race is statistically insignificant. Confidence interval of the estimates are shown in Table 2, as they are the final estimates, but these are not shown in Table 3 as they are not the final estimates.

In addition, the earlier researches have identified that the number of physician visits during the first trimester of pregnancy is significant on neonatal mean low birth weight, but the present study has shown that it is independent of both the mean and the variance. The present analysis agrees with the effects of weight of mother at her last menstrual period and her race. This study shows that all the covariates (included in the data set) are important to explain the neonatal low birth weight except the mother number of physician visits during the first trimester of pregnancy. Finally, the determinants of

Table 3. Results for mean and dispersion models (with interaction effects) of neonate low birth weight data from log-normal fit

	Covariate	Estimate	s.e.	t	P-value
Mean Model	Constant	7.8908	0.1354	58.268	<0.001
	LWT	0.0016	0.00060	2.519	0.012
	RACE2	0.0414	0.2412	0.172	0.863
	RACE3	0.0054	0.1777	0.031	0.975
	AGE	0.0000	0.0046	0.006	0.995
	AGE.RACE2	−0.0079	0.0113	−0.699	0.485
	AGE.RACE3	−0.0043	0.0077	−0.555	0.579
	SMOKE2	−0.0849	0.0381	−2.230	0.027
	PTL2	−0.1368	0.0547	−2.501	0.013
	PTL3	0.0027	0.1130	0.024	0.981
	PTL4	0.4550	0.3591	1.267	0.207
	HT2	−0.2197	0.1007	−2.181	0.030
	UI2	−0.2123	0.0664	−3.195	0.001
Dispersion Model	Constant	−4.091	0.4906	−8.340	<0.001
	AGE	0.043	0.0211	2.029	0.044
	UI2	0.932	0.3116	2.992	0.003
	HT2	0.875	0.4859	1.800	0.073

the variance of neonatal low birth weight identified in this study are completely new findings.

To fill the gaps in the neonatal low birth weight research literature, this study derives the relationships (mean and variance models) of neonatal low birth weight with the mother's lifestyle characteristics. The mathematical models (Table 2) in this report show that the mean and variance relationships of neonatal birth weight with the mother's lifestyle characteristics. The models reported here illuminate the complex relationships. Fortunately, a true mathematical model can open the truth that is covered by the complex relationships.

Conclusion

An important conclusion has to do with the use of earlier used statistical models. While further research is called for, we find that the joint log-normal models (with non-constant variance) are much more effective than either traditional simple, multiple, logistic regression and Log-Gaussian models (with constant variance), because they better fit the data. In short, research should have greater faith in this results than those emanating from the simple, multiple, logistic regression and Log-Gaussian (with constant variance) models.

To reduce the infant mortality due to low birth weight, this study suggests that a white mother with lower age should be a non-smoker, free of hypertension, free of uterine irritability, with higher weight at the last menstrual period and without any premature labor.

Ethical issues

The local ethics committee approved the study.

Conflict of interests

The authors declare no conflict of interests.

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