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Research Article

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The Impacts of Body Mass Index on Gestational Diabetes Pima Indian Heritage Women

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Abstract

*Body mass index (BMI) acts as a casual factor for developing many diseases such as cardiovascular, breast cancer, heart, diabetes etc. The article presents the impacts of BMI on gestational diabetes Pima Indian heritage women with at least 21 years old. It is established here that mean BMI is larger for gestational diabetes mellitus (GDM) women (P=0.0007) than normal. Mean BMI is directly linked with triceps skin fold thickness (TSFT) (P<0.0001), and it is not related with age (P=0.5185), while it is inversely linked with their joint interaction effect TSFT*Age (P=0.0023). In addition, mean BMI is partially inversely linked with insulin (P=0.1813), and it is partially directly linked with diabetes pedigree function (PDF) (P=0.1601). Variance of BMI is larger for normal women (P<0.0001) than GDM women. It is inversely linked with glucose (P<0.0001), and it is not associated with the number of pregnancies (NOP) (P=0.5494), while it is directly linked with their joint interaction effect Glucose*NOP (P=0.0434). Mean and variance of BMI show many complex impacts on GDM women. Gestational women must care on BMI along with TSFT and glucose levels.*

Keywords: Body mass index (BMI); Gestational diabetes mellitus (GDM); Joint generalized linear gamma models; Number of pregnancies (NOP); Triceps skin fold thickness (TSFT).

Introduction

During medical treatment of any individual, mainly four anatomical characteristics such as weight, height, waist and hips are collected to examine that these characteristics may be linked with the diseases of the individual. Using these anatomical characteristics, two composite measures such as body mass index (BMI) and index of fat distribution (IFD) are usually formed which are treated as the risk factors of many diseases such as cancer, diabetes, kidney, breast cancer, heart, cardiovascular diseases etc. [1-4]. Note that BMI is measured by weight(kg)/height(m)2) (=BMI), while IFD is measured by waist/hips (=IFD) ratio. Many articles have shown that BMI & IFD are the risk factors of many diseases [4-6].

Generally, three types of diabetes such as Type-I, gestational and Type-II are observed over the world. For some unusualness of human body parts, if pancreas can't develop insulin, or grows a very small amount of insulin, Type-1 diabetes happens, which is called juvenile diabetes [5-7]. GDM happens in pregnant women during pregnancy with higher glucose levels. Afterwards, the GDM can be turned to Type-II diabetes [8-10]. Type II DM patients generally face the following two problems, or both. One problem is that human body parts can't produce enough insulin, and the other problem is that the enough produced insulin can't work properly, which is termed as insulin resistance [10-12]. The human body produces enough insulin, but its insulin impressibility is undermined and does not work as it should do, and glucose is not entering the body's cells properly. As a result, blood sugar level increases, and the cells are not receiving their needful nutrients for growth and energy [11- 14].

This article focuses on the impacts of BMI on some GDM Pima Indian heritage women. The following hypotheses regarding GDM women are searched in this article with a real data set. The hypotheses are: (1) is there any impact of BMI on GDM Pima Indian heritage women? (2) if it is affirmative, what are the impacts of BMI on the other characteristics of GDM women? The article is arranged as follows. Next section presents materials & methods, followed by statistical & graphical analysis, results & discussion, and finally conclusions.

Materials & Methods

Materials

The article is developed with a real data set related to Pima Indian heritage 768 women with at least 21 years old. The considered dataset was first time collected by the National Institute of Diabetes and Digestive and Kidney Diseases. This data set can be observed in the UCI Machine Learning Repository. It contains 9 interested study characteristics such as age (in years), diastolic blood pressure (BP) (mm Hg) (named as simply BP), study unit type (SUT) (1=non- diabetic, 2= diabetic), triceps skin fold thick-

ness (TSFT) (mm), number of pregnancies (NOP), 2-hours serum insulin (mu U/ml) (Insulin), plasma glucose concentration over 2 hours in an oral glucose tolerance test (Glucose), body mass index (BMI), diabetes pedigree function (DPF). Here all the study characteristics are continuous except SUT, which is an attribute character. Note that DPF is a function which estimates likelihood of diabetes depending on family history.

Statistical Methods

The present GDM data set is physiological data, which is generally non-homogeneous in nature. The response BMI is heteroscedastic continuous and positive. Non-constant variance response BMI can be modeled by treating a suitable transformation if only the BMI variance is stabilized with the transformation, but in practice response variance may not be stabilized in many cases [15]. Note that a positive continuous equal variance response variable should be modeled either by the lognormal, or the gamma model [16]. For an unequal variance positive continuous response variable modeling, joint generalized linear models (JGLM) under the lognormal, or the gamma models can be applied [17, 18]. JGLMs is well illustrated in the book by Lee et al. [18]. The response BMI is modeled properly by the joint gamma models, so they are very shortly illustrated herein.

Joint Generalized Linear Gamma Models

Here the dependent variable BMI is modeled with the rest of the variables. Let us consider BMI=yi as the random response variable with mean μi =E(yi) and unequal variance (σ_i^2), satisfying Var(yi) = σ_i^2 μ_i^2 = σ_i^2 $V(\mu_i)$ say, where $V(.)$ is called as the variance function, which recognizes generalized linear model family distribution. For illustration, if V(μ)= μ, it is Poisson, and it is Normal, or gamma as $V(\mu)$= 1, or $V(\mu) = \mu^2$ etc.

Mean & dispersion JGLMs for BMI with gamma distribution are displayed as

$\eta_i = g(\mu_i) = x_i^t \beta$ and $\varepsilon_i = h(\sigma_i^2) = w_i^t \gamma$,

where $g(.)$ & $h(.)$ are the generalized linear model link functions for the mean & dispersion linear predictors respectively, and x_i^t, $w_i^t\gamma$ are the explanatory variables vectors connected with the mean and dispersion parameters respectively. Maximum likelihood (ML) method is adopted to estimate mean parameters, while the restricted ML (REML) method is used to estimate dispersion parameters [18].

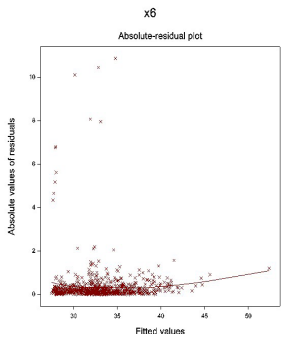
Statistical & Graphical Analysis

The dependent variable BMI is modeled on the rest explanatory variables using JGLMs following gamma distribution only, as the gamma fit gives better results than the Log-normal fit. Here glucose, age, BP, insulin, TSFT, DPF, NOP, SUT are considered as the explanatory variables. Response variable BMI is located as heteroscedastic; therefore, it is modeled adopting JGLMs under gamma distribution. The final BMI fitted joint model is taken based on the lowest Akaike information criterion (AIC=6875.875) value that reduces both the predicted additive errors and squared error loss [19]. The final BMI gamma JGLMs analysis results are shown in Table 1. Following the marginality rule by Nelder, lower order effects (even insignificant) are included in the model if their higher order interaction effects are significant [19]. For better fitting, some partially significant effects are included in the model [19]. For example, in the mean model insulin (P=0.1813) and DPF (P=0.1601) are included, and they are known as confounders in Epidemiology.

Table 1: Joint gamma BMI fitting mean and dispersion models

Model	Covariate	Estimate	S.E.	t-value	P-value
Mean	Constant	3.2864	0.07999	41.088	<0.0001
	Triceps skin fold thickness (TSFT)	0.0103	0.00244	4.211	<0.0001
	Insulin	-0.0001	0.00009	-1.338	0.1813
	DiabetesPedigree Function (DPF)	0.0511	0.03633	1.406	0.1601
	Age	0.0013	0.00194	0.646	0.5185
	TSFT*Age	-0.0002	0.00005	-3.061	0.0023
	Study unit type (SUT)	0.1259	0.03678	3.422	0.0007
DisperSion					
	Constant	3.4976	0.4001	8.741	<0.0001
	No. of Pregnancies (NOP)	-0.0609	0.1016	-0.599	0.5494
	Glucose	-0.0383	0.0034	-11.268	<0.0001
	NOP*Glucose	0.0017	0.0008	2.023	0.0434
	Study unit type (SUT)	-0.8464	0.1499	-5.647	<0.0001
AIC	**6875.875**				

The BMI gamma fitted JGLMs (Table 1) are examined in Figure 1. Figure 1(a) reveals the absolute BMI gamma fitted residuals plot against its predicted values, which is almost a flat straight line, concluding that variance is constant with the running means. Figure 1(b) reveals the BMI gamma fitted mean model (in Table 1) normal probability plot, which does not reveal any fitting discrepancy. The above two plots prove that the BMI gamma fitted JGLMs are appropriate.



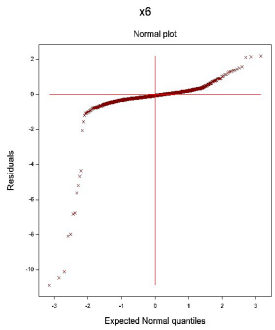


Figure 1(a) **Figure1(b)**

Figure 1: For the JGL gamma BMI fit (Table 1), the (a) absolute residuals plot against the BMI fitted values, and (b) the normal probability plot for the BMI mean model.

Results & Discussions

Summarized outcomes of the BMI gamma fitted JGLMs are displayed in Table 1. It is established here that mean BMI is directly linked with SUT (1=non- diabetic, 2= diabetic) (P=0.0007). Mean BMI is directly linked with TSFT (P<0.0001), and it is not related with age (P=0.5185), while it is inversely linked with their joint interaction effect TSFT*Age (P=0.0023). In addition, mean BMI is partially inversely linked with insulin (P=0.1813), and it is partially directly linked with PDF (P=0.1601). Variance of BMI is inversely linked with SUT (P<0.0001). It is inversely linked with glucose (P<0.0001), and it is not associated with the NOP (P=0.5494), while it is directly linked with their joint interaction effect Glucose*NOP (P=0.0434).

JGL gamma fitted BMI mean ($\hat{\mu}$) model (Table 1) is
$\hat{\mu}$ = exp (3.2864 + 0.0103 TSFT - 0.0001 Insulin + 0.0511 DPF + 0.0013 Age – 0.0002 TSFT*Age + 0.1259 SUT),
and the JGL gamma fitted BMI dispersion ($\hat{\sigma}^2$) model (from Table 1) is
$\hat{\sigma}^2$ = exp (3.4976 –0.0609 NOP – 0.0383 Glucose + 0.0017 NOP*-Glucose – 0.8464 SUT).

From the JGL gamma fitted BMI results (in Table 1) and the above mean & dispersion models, the following can be concluded. Mean BMI is directly linked with SUT (1= non-diabetic, 2= diabetic) (P=0.0007), implying that mean BMI is higher for GDM women than normal. It is always observed in the real fields. The present analysis supports the real facts. Mean BMI is directly linked with TSFT (P<0.0001), interpreting that BMI is higher for gestational women with thick TSFT than women with thin TSFT. It shows that gestational women with thick TSFT may have a higher chance to be affected with GDM as they have higher BMI in general. Mean BMI is not linked with age (P=0.5185), and it is directly linked with TSFT (P<0.0001), while it is inversely linked with their joint interaction effect TSFT*Age (P=0.0023). These results indicate that BMI decreases at older ages along with higher TSFT. But the marginal effect of TSFT shows that BMI increases as TSFT increases. So, even though the TSFT is higher, BMI may not be higher for older women. Mean BMI is partially inversely linked with insulin (P=0.1813), concluding that BMI increases as insulin level decreases. Gestational women with lower insulin levels are affected with GDM, so they have a higher chance of obesity. In the mean BMI model, insulin (P=0.1813), a partially significant effect is considered as a confounder in epidemiology. Mean BMI is partially directly linked with DPF (P=0.1601), indicating that it increases as DPF rises. Note that DPF is also a confounder in the mean model. This outcome shows that BMI and GDM (or DPF) are well linked. It is already shown that BMI is higher for GDM women.

Variance of BMI is inversely linked with SUT (1= non-diabetic, 2= diabetic) (P<0.0001), concluding that BMI is highly dispersed for non-diabetic women. Practically, non-diabetic women have generally low BMI, so the BMI values of these women groups are highly scattered. Thus, the dispersion model also shows a true situation. BMI variance is inversely linked with glucose (P<0.0001), concluding that gestational women with lower glucose levels (non-diabetic) have highly scattered BMI. This result is also established above in the dispersion model. Variance of BMI is independent of NOP (P=0.5494), and it is inversely linked with glucose (P<0.0001), while it is directly linked with their joint interaction effect NOP*Glucose (P=0.0434). These results conclude that women with higher glucose levels along with more pregnancy numbers have highly scattered BMI values.

The present outcomes confirm many real situations as mentioned above. The report also presents many new outcomes such as interaction effects, which are very rare in the earlier published articles. Outcomes of the dispersion model are completely new in the GDM literature as a few articles have considered unequal variance of BMI as the response variable. Most of the earlier articles have used multiple regression, or logistic regression without any dispersion model [8, 10, 12]. The analyses of the earlier articles have not been examined with the diagnostic checking, so the earlier outcomes invite many doubts. The present findings can't be compared with the earlier articles as earlier articles have not considered BMI with unequal variance response variable. One can examine the present analysis outcomes with the data set given in the UCI Machine Learning Repository.

Conclusions

The paper has focused all the outcomes based on JGLMs gamma fit of BMI, while the fitting has been diagnosed by model checking plots. Further, the unknown parameter estimates are very stable as their standard errors (S.E.) are very small (Table 1). The accepted model has been taken based on the lowest AIC criterion value. So, the research has a higher faith on the present outcomes. It is expected that similar data from any source should yield similar results, which has not been verified herein as we have not any similar data in hand. This paper has shown a complex relationship of BMI with the rest explanatory variables. The mean and dispersion models have provided many interesting outcomes, which are completely new to the GDM literature. So, the researchers, GDM practitioners and patients will be benefited by the paper. Gestational women are instructed to take care about their BMI, TSFT, glucose & insulin levels, DPF regularly.

Conflict of Interest: The authors confirm that this article content has no conflict of interest.

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