



Effects of Body Mass Index on Gestational Diabetes Women

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Abstract

It is well known that diabetes mellitus (DM) is a risk factor of many diseases such as breast cancer, heart, diabetes, cardiovascular diseases etc. The current paper focuses the effects of body mass index (BMI) on gestational DM women using a real data set of 768 women. It is identified herein that mean BMI is higher for DM women ($P < 0.01$) than others. Mean BMI is positively associated with skin thickness (ST) ($P < 0.01$), and it is independent of age ($P = 0.52$), but it is negatively associated with their joint interaction effect, that is $ST * Age$ ($P < 0.01$). Mean BMI is partially negatively associated with insulin ($P = 0.18$), while it is partially positively associated with diabetes pedigree function (PDF) ($P = 0.16$). BMI variance is higher for non-diabetic women than diabetic. It is negatively associated with glucose ($P < 0.01$), and it is independent of pregnancy number (PN) ($P = 0.55$), but it is positively associated with their joint interaction effect, that is $Glucose * PN$ ($P = 0.04$). Both mean and variance BMI have very complex effects on gestational DM women. Pregnant women should care on BMI along with glucose level and skin thickness.

Keywords: Pregnancy Number; Skin Thickness

Abbreviations: BMI: Body Mass Index; DPF: Diabetes Pedigree Function; GD: Gestational Diabetes; JGLMs: Joint Generalized Linear Models; DM: Diabetes Mellitus.

Introduction

During clinical investigation of any person, four preliminary anatomical factors such as height, hip, weight and waist are recorded, based on the assumption that these factors may be connected with the diseases of the person. Based on these preliminary anatomical factors, a relative measure known as BMI, which is defined as $BMI = \text{Weight (kg)} / \text{Height (m)}^2$. In medical sciences, mainly BMI is frequently used as a risk factor for many diseases such as breast cancer, heart, diabetes, cardiovascular diseases etc [1-4].

In the society, Type-I, Type-II and gestational diabetes are

observed among the DM patients. For some abnormality of human organs, if pancreas does not yield insulin, or yields a little insulin, Type-1 diabetes occurs, which is termed as juvenile diabetes [5-7]. Gestational diabetes appears in pregnant women with higher glucose levels during pregnancy. Afterwards, the gestational diabetes can be changed to Type-II diabetes [8-10]. This short report focuses the effects of BMI on some gestational DM Pima Indian heritage women. The following questions are investigated in this report based on a real data set.

- Is there any effect of BMI on gestational DM Pima Indian heritage women.
- If it is yes, what are the linkages of BMI on the other factors of gestational DM women.
- What are the effects of BMI on gestational DM Pima Indian heritage women.

Materials & Methods

Materials

These above questions are surveyed in this report with a real data set of 768 Pima Indian DM women with a minimum 21 years containing 9 study variables. The present dataset was collected by the National Institute of Diabetes and Digestive and Kidney Diseases. The data set can be found in the UCI Machine Learning Repository. For our necessary study, the 9 study variables are expressed as follows.

- Body mass index (BMI).
- Number of times pregnancy (Pregnancies).
- Plasma glucose concentration over 2 hours in an oral glucose tolerance test (Glucose).
- Diastolic blood pressure (mm Hg) (Blood Pressure (BP)).
- 2-Hour serum insulin (μ U/ml) (Insulin).

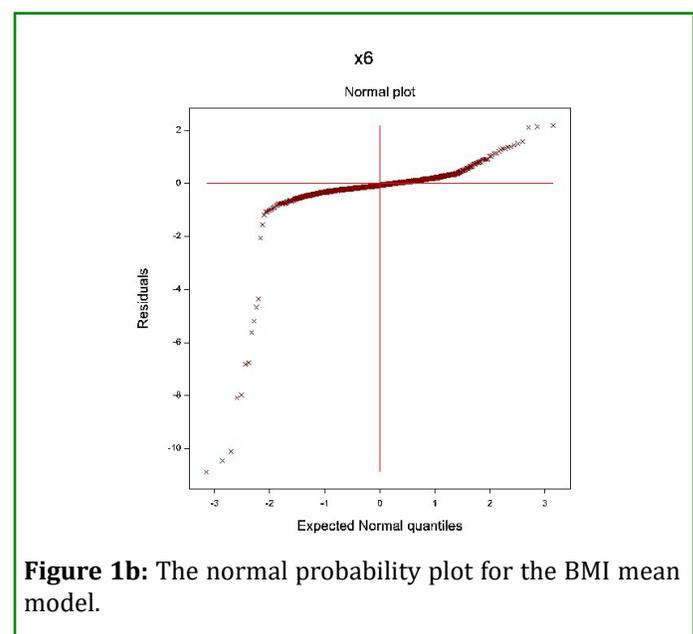
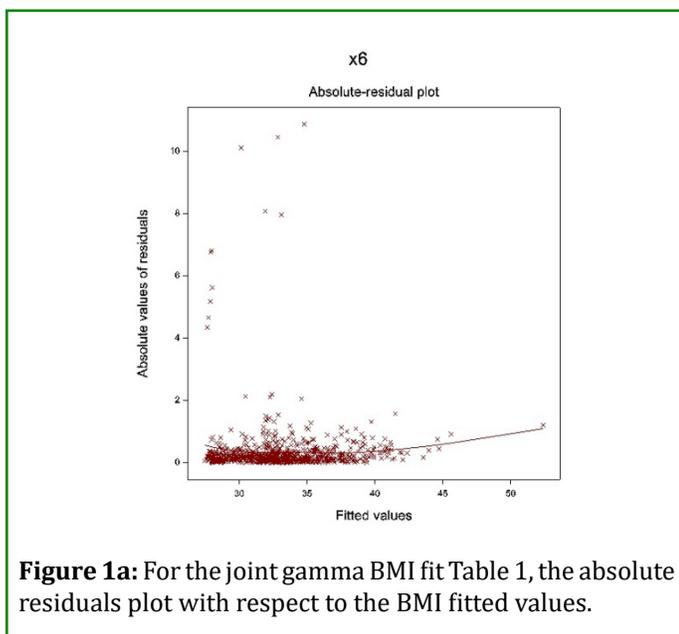
- Triceps skin fold thickness (mm) (Skin Thickness (ST)).
- Age (years).
- Diabetes pedigree function (DPF).
- Types of study unit (1= non-diabetic, 2= diabetic).

Statistical Methods

The above questions can only be investigated by developing an appropriate model of BMI on the rest 8 characters. It is identified that the response BMI is a positive continuous heteroscedastic random variable that can be fitted by joint generalized linear models (JGLMs) using both the lognormal and gamma distributions [11,12]. JGLMs is clearly illustrated in the book by Lee, et al. [12]. It is found herein that joint BMI gamma model fit yields better results than lognormal fit, so the gamma fitted outcomes are displayed in Table 1.

Model	Covariate	Estimate	S.E.	t-value	P-value
Mean	Constant	3.29	0.08	41.09	<0.01
	Skin Thickness (ST)	0.01	<0.01	4.21	<0.01
	Insulin (INS)	-0.01	<0.01	-1.33	0.18
	Diabetes Pedigree Func (DPF)	0.05	0.04	1.41	0.16
	Age	0.01	<0.01	0.65	0.52
	ST*Age	-0.01	<0.01	-3.06	<0.01
	Patient's type	0.13	0.04	3.42	<0.01
Dispersion	Constant	3.50	0.40	8.74	<0.01
	Pregnancies no. (PN)	-0.06	0.10	-0.60	0.55
	Glucose	-0.04	<0.01	-11.27	<0.01
	PN*Glucose	0.01	<0.01	2.02	0.04
	Patient's type	-0.85	0.15	-5.65	<0.01

Table 1: Mean and dispersion model of BMI from joint gamma model fitting.



The present gamma fitted BMI model Table 1 is examined in Figure 1. Figure 1a expresses the absolute gamma fitted BMI model residuals plot with respect to BMI predicted values, which is exactly a flat straight line, interpreting that variance is constant with the running means. Figure 1b expresses the BMI fitted mean model Table 1 normal probability plot, which does not show any discrepancy in fitting. So, the two plots show that BMI gamma fitting is appropriate.

Results & Fitted Models

From Table 1, it is observed that mean BMI is positively associated with the patient's type ($P < 0.01$). Mean BMI is positively associated with ST ($P < 0.01$), and it is independent of age ($P = 0.52$), but it is negatively associated with their joint interaction effect ST*Age ($P < 0.01$). Mean BMI is partially negatively associated with insulin ($P = 0.18$), while it is partially positively associated with DPF ($P = 0.16$). BMI variance is negatively associated with the patient's type ($P < 0.01$). It is negatively associated with glucose ($P < 0.01$), and it is independent of pregnancy number (PN) ($P = 0.55$), but it is positively associated with their joint interaction effect Glucose*PN ($P = 0.04$).

Gamma fitted BMI mean (μ) model from Table 1 is

$$= \exp(3.29 + 0.01 \text{ ST} - 0.01 \text{ Insulin} + 0.05 \text{ DPF} + 0.01 \text{ Age} - 0.01 \text{ ST*Age} + 0.13 \text{ Patient's type}),$$

And the gamma fitted BMI variance (σ^2) model from Table 1 is

$$= \exp(3.50 - 0.06 \text{ PN} - 0.04 \text{ Glucose} + 0.01 \text{ PN*Glucose} - 0.85 \text{ Patient's type}).$$

Conclusion

BMI fitted outcomes are displayed in Table 1. From Table 1, one can interpret the following.

- Mean BMI is positively associated with the patient's type (1= non-diabetic, 2= diabetic) ($P < 0.01$), interpreting that mean BMI is higher for gestational DM women than normal. It reflects the real society situations over the world.
- Mean BMI is positively associated with ST ($P < 0.01$), implying that BMI is higher for gestational women with thick ST than women with thin ST. In other words, it implies that gestational women with thick ST may have a greater chance to be affected with DM along with higher BMI.
- Mean BMI is independent of age ($P = 0.52$), and it is positively associated with ST ($P < 0.01$), but it is negatively associated with their joint interaction effect ST*Age ($P < 0.01$). These imply that BMI decreases as at older ages along with higher ST.
- Mean BMI is partially negatively associated with insulin ($P = 0.18$), implying that BMI decreases as insulin level

increases. Gestational women with higher levels of insulin are free from DM. So, they have a lower chance of obesity. Note that in epidemiology, insulin ($P = 0.18$), a partially significant effect is treated as confounder.

- Mean BMI is partially positively associated with DPF ($P = 0.16$), concluding that it increases as DPF increases. Here DPF is a confounder in the mean model. This result shows that BMI and DM (or DPF) are well connected. It is already established that BMI is higher for DM women.
- BMI variance is negatively associated with the patient's type (1= non-diabetic, 2= diabetic) ($P < 0.01$), implying that BMI is highly scattered for non-diabetic women. Actually, non-diabetic women have low BMI, so they are highly scattered. Therefore, the dispersion model also reflects a practically true situation.
- BMI variance is negatively associated with glucose ($P < 0.01$), interpreting that gestational women with lower glucose level (i.e., non-diabetic) have highly scattered BMI. This is also established in the earlier item of the dispersion model.
- BMI variance is independent of pregnancy number (PN) ($P = 0.55$), and it is negatively associated with glucose ($P < 0.01$), but it is positively associated with their joint interaction effect Glucose*PN ($P = 0.04$). These imply that women with higher glucose level along with more pregnancy numbers have higher BMI.

All the above interpretations have been drawn from the derived BMI gamma fitted mean & dispersion models Table 1, where the standard errors (S.E.) of the estimates are small, interpreting that the estimates are stable. Herein it has been shown that the mean and dispersion of BMI for gestational women are highly linked with many factors, but there is no marginal association of pregnancy number with BMI. It can be concluded that BMI rises for gestational DM women, along with the increase of ST, DPF, and lower value of insulin level, and ST*Age. Medical experts, researchers and gestational women will be benefited from the article. Pregnant women are advised to take care about their BMI, ST, DPF, glucose and insulin levels regularly.

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