



UNIVERSITI PUTRA MALAYSIA

***BAYESIAN LOGISTIC REGRESSION MODEL ON RISK FACTORS OF
TYPE 2 DIABETES MELLITUS***

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FS 2016 45



**BAYESIAN LOGISTIC REGRESSION MODEL ON RISK FACTORS OF
TYPE 2 DIABETES MELLITUS**

By

SANDRA CHIAKA EMENYONU

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in
Fulfilment of the Requirements for the Degree of Master of Science**

April 2016

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DEDICATIONS

*To my wonderful father and mother, for their prayers and supports.
To my lovely siblings, for their patience and encouragements.*



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Master of Science

BAYESIAN LOGISTIC REGRESSION MODEL ON RISK FACTORS OF TYPE 2 DIABETES MELLITUS

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April 2016

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Logistic regression model has long been known and it is commonly used in analysing a binary outcome or dependent variable and connects the binary dependent variable to several independent variables. Estimates of the coefficients for the variables are obtained via the method of maximum likelihood based on the frequentist point of view. However, Bayesian analysis allows the incorporation of the prior information and the coefficients of the logistic regression model are estimated by assuming prior distribution for each of the coefficient of interest, which then combines with the likelihood function for the posterior distribution to be obtained.

The Bayesian logistic regression methods made use of the metropolis hastig (Random walk algorithm) and the Gibbs sampler with the incorporation of non-informative flat prior and non-informative non-flat prior distributions to obtain the posterior distribution for each coefficient of the variables. Although we incorporated the flat prior distribution, it has been shown to be widely used in different fields of study. However, this work also incorporated a non-flat prior, which is our main research and to the best of our knowledge has not been incorporated on any T2DM dataset in Malaysia.

This study evaluates the risk factors such as age, ethnicity, gender, physical activity, hypertension, body mass index, family history of diabetes and waist circumference. The coefficients of the variables mentioned above were estimated by the method of maximum likelihood and significant variables were further identified. The significant variables determined by maximum likelihood method were then estimated using the BLR method. The BLR approach via Gibbs sampler and the random walk metropolis algorithm suggests that family history of diabetes, waist circumference and the body mass index are the significant risk factors associated with the type 2 diabetes mellitus. The model results also show a slight decrease in the posterior standard deviation associated with the parameters generated from the Bayesian analysis with the non-flat prior distribution compared to the results generated from the Bayesian analysis incorporating the non-informative prior. Having seen that the

difference between the models is not much, consequently from all indications, all the models are good and they exhibited model fit.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

MODEL LOGISTIK REGRASI BAYESIAN TERHADAP FAKTOR RISIKO KENCING MANIS JENIS 2

Oleh

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Model regresi logistik telah lama dikenali dan ia biasanya digunakan bagi menganalisis hasil binari atau pembolehubah bersandar dan menghubungkan pembolehubah bersandar binari kepada beberapa pembolehubah bebas. Anggaran pekali bagi pembolehubah diperolehi melalui kaedah kebarangkalian maksimum berdasarkan daripada pemerhatian yang telah diguna pakai sebelum ini. Walau bagaimanapun, analisis Bayesian membolehkan penggabungan maklumat prior dan pekali model regresi logistik dianggar dengan pengandaian taburan prior bagi setiap pekali, yang kemudiannya digabungkan dengan fungsi kebarangkalian untuk mendapatkan taburan posterior.

Kaedah Bayesian regresi logistik menggunakan metropolis hastig (algoritma berjalan secara rawak) dan Gibbs sampler yang menggabungkan taburan prior rata tidak bermaklumat dan prior tidak rata yang tidak bermaklumat untuk mendapatkan taburan posterior bagi setiap pekali pembolehubah. Meskipun kajian ini telah menggunakan prior rata, namun ia juga telah menunjukkan penggunaannya secara meluas dalam pelbagai bidang pengajian. Walau bagaimanapun, kajian ini juga berkait dengan prior tidak rata dimana ia merupakan penyelidikan utama kami dan daripada pengetahuan kami ianya masih belum digunakan di mana-mana dataset T2DM di Malaysia.

Kajian ini menilai faktor-faktor risiko seperti umur, etnik, jantina, aktiviti fizikal, tekanan darah tinggi, indeks jisim badan, sejarah keluarga diabetes dan lilitan pinggang. Pekali pembolehubah yang dinyatakan di atas telah dianggarkan dengan menggunakan kaedah kebarangkalian maksimum dan seterusnya pembolehubah yang berperanan penting akan dikenal pasti dengan lebih teliti. Pembolehubah yang berperanan penting ini ditentukan dengan kaedah kebarangkalian maksimum yang kemudiannya dianggar menggunakan kaedah BLR. Pendekatan BLR melalui Gibbs sampler dan algoritma berjalan secara rawak menunjukkan bahawa sejarah keluarga diabetes, lilitan pinggang dan indeks jisim badan adalah faktor risiko utama yang berkait rapat dengan penyakit kencing manis jenis 2. Hasil keputusan daripada model juga menunjukkan terdapat sedikit penurunan pada sisihan piawai bagi

posterior yang berhubung kait dengan parameter yang dihasilkan daripada analisis Bayesian dengan taburan prior tidak-rata berbanding dengan keputusan yang dihasilkan daripada analisis Bayesian yang menggabungkan prior tidak-bermaklumat. Setelah melihat kepada perbezaan yang tidak ketara di antara model-model, dengan kesinambungan dari semua petunjuk, semua model adalah berkeadaan baik dan ia telah menunjukkan model yang sesuai.



ACKNOWLEDGEMENTS

Firstly, my thanks and praise to God for the wisdom, understanding and knowledge he granted me, I would like to express my deepest and warmest gratitude to my wonderful supervisor, Dr. Mohd Bakri Adam, for his support, guidance and constant encouragement which made me to have focus and direction in my research.

A big thank you to Dr. Isthriyagy Krishnarajah and Dr. Shamarina Shohaimi for their assistance and motivation, I would not have been able to do this research without you. Also I wish to thank the principal investigators Prof. Dr. Anis Safura Ramli, Dr Jamaiyah Haniff, MPH and all the staff of the clinical research centre Kuala Lumpur for providing the data I used in this thesis.

My unending gratitude and appreciation go to my parents (Mr and Mrs D.O Emenyonu), to my siblings (Chidi, Ekeoma, Soro and Ogechi), my cousin brother (Ifeanyi), my nephew (Chisom) and for their support, encouragement, prayers and for believing in me. Finally, thanks to all my friends in mathematics department who contributed in one way or the other, God bless you all.

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science. The members of the Supervisory Committee were as follows:

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LIST OF ABBREVIATIONS

BA	Bayesian Approach
BMI	Body Mass Index
BLR	Bayesian Logistic Regression
C.I	Credible Interval
CVDs	CardioVascular Diseases
DIC	Deviance Information Criterion
FA	Frequentist Approach
FDM	Family History of Diabetes
FLR	Frequentist Logistic Regression
FPG	Fasting Plasma Glucose
GDM	Gestational Diabetes Mellitus
GLMS	Generalized Linear Models
HbA1C	Glycated Hemoglobin
2HPG	2Hours Plasma Glucose
HYPERT	Hypertension
IFG	Impaired Fasting Glycemia
IGT	Impaired Glucose Tolerance
MCMC	Markov Chain Monte Carlo
MLE	Maximum Likelihood Estimation
OR	Odds Ratio
PA	Physical Activity
POST DIST	Posterior Distribution
STD	Standard Deviation
SSR	Soybean Sclerotinia Stem Rot
T2DM	Type 2 Diabetes Mellitus
WC	Waist Circumference
WHO	World Health Organization

CHAPTER 1

INTRODUCTION

1.1 Section

Alberti et al. (1998) define diabetes mellitus as a class of metabolic disorders characterized by excess sugar in the blood over a long period of time which is caused by inadequate secretion of insulin, insulin activity or the two. In a study on global prevalence of diabetes, Wild et al. (2004) estimate the total number of people with type 2 diabetes mellitus (T2DM) in the year 2000 at 171 million and anticipate it to rise to 366 million in 2030. The rise in the prevalence of diabetes has been of great concern globally but is higher in the developing nations compared to the developed nations. This rapid rise in the prevalence of diabetes has been reported to be more in Asia, especially the South East Asian countries like Malaysia. With Mafauzy (2006) revealing that the prevalence of diabetes in Malaysia within the period of 1986 to 1996 showed a rise from 6.3 percent to 8.2 percent. Further predictions by the world health organization, suggests that there will be a total number of 2.48 million people with diabetes by 2030 as compared to 2000, where a figure of 0.94 million was estimated thus, showing a 164 percent increase in prevalence rate. Similarly, Mafauzy et al. (2011) predict that by 2025, the prevalence of diabetes will be higher by 170 percent in the developing world, compared to a 42 percent increase in prevalence rate in the developed nations. In conclusion, T2DM is seen to be the commonest form of diabetes which has taken hold of over 90% of the diabetic community through out the world and the fast upswing in the number of people with diabetes is prominent in the urban and rural regions Valliyot et al. (2013).

Diabetes consists of type 1 diabetes, type 2 diabetes mellitus, and gestational diabetes mellitus (GDM). For type 1, which is known as insulin dependent occurs when no insulin is produced at all because the insulin producing cell in the pancreas has been destroyed. While the T2DM occurs when the body either does not produce enough insulin or the insulin being produced cannot be used by the body, also known as insulin resistance. GDM occurs during pregnancy, but can be resolved after the baby has been delivered, and if not taken care of, can result to type 2 diabetes. Moreover, diabetes type 2 has different symptoms. American diabetes association et al. (2013) reveal that the symptoms of high blood sugar include polyuria which is frequent urination, polydipsia, which is an increase in thirst, polyphagia also known as increased hunger, weight loss and blurred vision, and these symptoms of the type 2 diabetes are shown in Figure 1.1.

Diagnosis of diabetes can be done through a test of Glucose level. Organization (1999) investigates several ways for the measurement of glucose which have been built, and the standard measurement for diabetes have been reconsidered for more than ten years. Consequently the following test are used to this effect.

- **Fasting Plasma Glucose Test:** The fasting plasma glucose test (fasting blood sugar) measures the glucose level from a blood sample of an individual for atleast eight hours

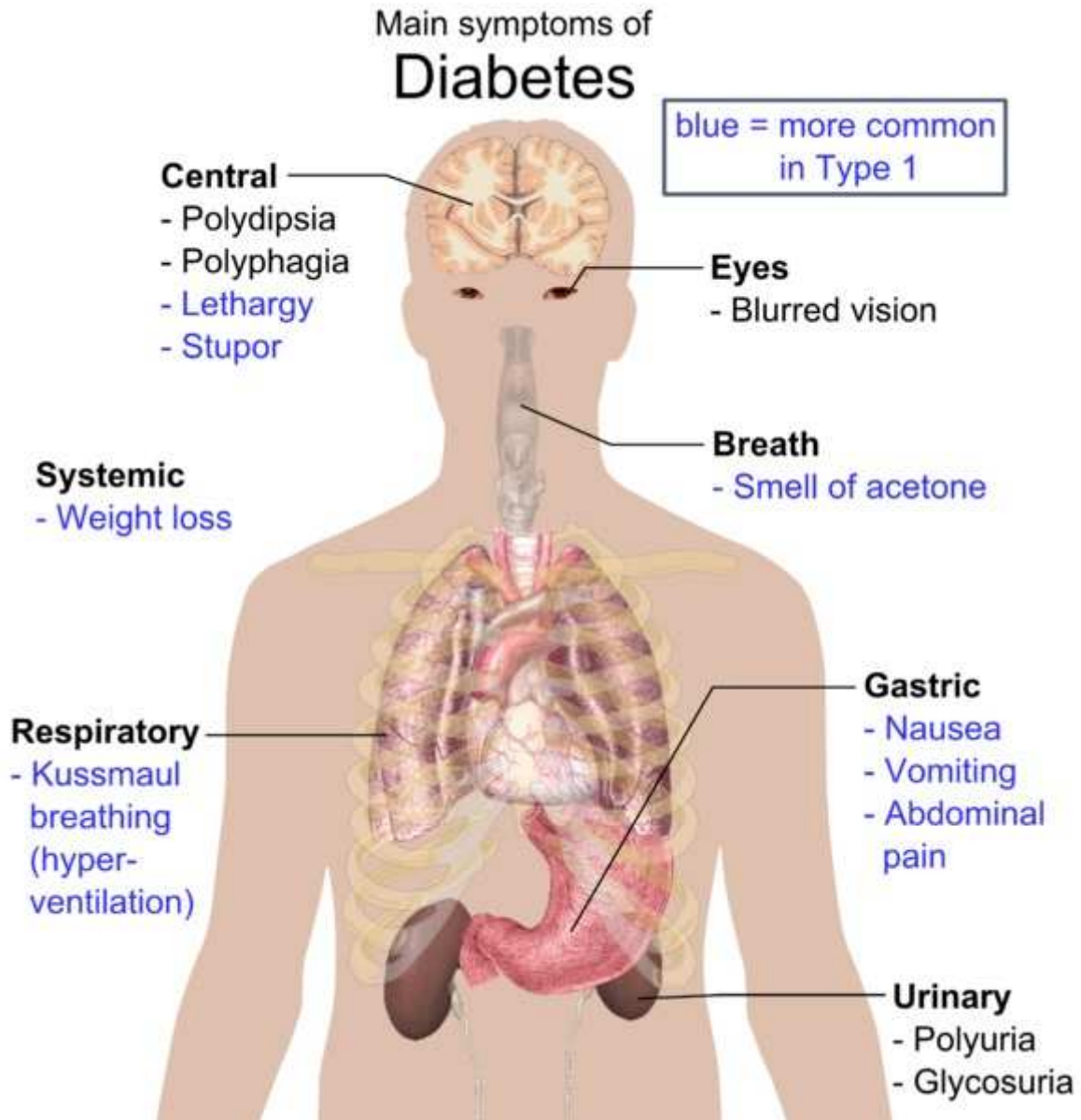


Figure 1.1: Symptoms of type 2 diabetes mellitus (T2DM)

(Mikael Häggström, 2014)

of not eating. It is frequently used to check for prediabetes and diabetes. National diabetes data group et al. (1979) reveal that both fasting plasma glucose and the 2-hour plasma glucose concentration have been approved to check for diabetes and impaired glucose tolerance (IGT) since the year 1979.

- **Glycated Haemoglobin (HbA1C):** Nathan et al. (2007) show that HbA1C measures

the amount of glucose in the red blood cells for the last 2 -3 months and can be used to detect the presence of diabetes.

- **Oral Glucose Tolerance Test (OGTT)** measures the blood glucose after a person fasts not less than eight hours, then 2 hours after the person consumes glucose dissolved in water. American diabetes association et al. (2013) recommend the test to be done as reported by the world health organisation, using a glucose solution which contains 75 grams of anhydrous glucose dissolved in water. This test can be used in diagnosing pre-diabetes and diabetes.

Confirmation using a second test should be carried out on a different day, if the test result indicates that a subject has diabetes. Reason being that, the repeated test serves as a confirmatory test, which when done is checked with the previous test result to know if the two different test results available are above the diagnostic cut-off points and having seen that affirms the diagnosis of diabetes.

This study evaluates both the frequentist and Bayesian approaches on logistic regression model. Frequentist Logistic regression model has long been known and it is commonly used in analyzing a binary outcome. However, one of the major difference between the Bayesian and the frequentist is that, the Bayesian allows the incorporation of prior information.

The estimation of the coefficients of the variables being considered, will be estimated via the method of maximum likelihood and Bayesian logistic regression method making use of the Gibbs sampler and the Random walk Metropolis algorithm. Further, these variables which include both the significant and non-significant being considered in the present study, have been considered in some literatures but mostly from the frequentist point of view. Although, some of these variables, in different studies were found to be significant risk factors of type 2 diabetes mellitus. Therefore, we decided to consider these variables in our work to see if they are also significant risk factors of type 2 diabetes mellitus.

On the other hand several fields of study in different countries have applied the Bayesian logistic regression model via the Gibbs sampler and the Random walk metropolis algorithm, incorporating mostly the non- informative prior (flat) distribution. However, there have not been many studies on the risk factor of type 2 diabetes mellitus employing the Bayesian logistic regression model via the Gibbs sampler and the Random walk metropolis algorithm, assuming a non-flat prior distribution. In as much as the flat prior will be incorporated, it has been shown to be widely used in different fields of study. However, this work suggests a new prior distribution, which is our main research and to the best of our knowledge has not been incorporated on any T2DM dataset in Malaysia.

In other words, the Bayesian logistic regression method incorporating our suggested prior distribution will be applied on the significant risk factors associated with type 2 diabetes melitus to obtain the posterior distribution for each parameter of the variables.

Therefore, our research's main contributions are

- estimating the parameters of the variables of T2DM, that is those factors that can influence the development of type 2 diabetes mellitus,

- different methods were employed in estimating of these risk factors and these are the Frequentist and the Bayesian methods,
- the frequentist approach made use of the method of maximum likelihood, while the Bayesian analysis was via two MCMC approaches incorporating the flat and non-flat prior distribution. for the non-flat prior distribution, a weakly informative prior was specified which is our newly suggested prior for the estimation of the coefficients of variables of T2DM.

1.2 Problem Statement

The Frequentist Logistic Regression (FLR) method has been applied in different fields of study. However, the Bayesian Logistic Regression (BLR) method can also be used to analyse various distributions. One of the key advantage of the Bayesian over Frequentist approach is the incorporation of the prior information. Further, the non-informative flat prior distribution has been incorporated and applied to different fields of research. For instance, Bayesian logistic regression model via Random walk metropolis algorithm incorporating a non-informative prior distribution has been applied in economic related field, like the study carried out by Acquah (2013). Similarly, the Bayesian logistic regression method has also been applied in environmental related field using a non-informative prior distribution. This Bayesian analysis was performed via the Gibbs sampler as reported by Das et al. (2012). However, to the best of the author's knowledge, there have not been studies incorporating non-flat prior distributions on T2DM dataset in Malaysia. Thus, this research aims at carrying out the Bayesian analysis via the Metropolis algorithm and the Gibbs sampler incorporating our newly suggested prior distributions.

1.3 Objectives of the Research

The objectives of this study are

- to determine risk factors associated with T2DM using maximum likelihood estimation,
- to determine risk factors associated with type 2 diabetes mellitus via the Gibbs sampler using flat and non-flat prior distribution, and
- to determine risk factors associated with type 2 diabetes mellitus via Random walk metropolis algorithm using flat and non-flat prior distribution.

1.4 Expected Outcome

After the completion of this research, we expect to achieve the following:

1. The development of model from this research can be used in real life situations in

determining probability. More so, the systematic use of prior information can improve long term accuracy.

2. The result will provide information on the application of Bayesian logistic regression method incorporating a non-informative prior and a non-flat prior distribution in several fields of research.
3. This research can enable analyst and decision makers to establishing a consistent set of decision about the assesment of risks and how to manage them properly.

1.5 Limitations of the Study

Due to time and financial constraints, two Markov Chain Monte Carlo (MCMC) methods of estimation were considered, also few variables were chosen in this study, as the capacity to explore other variables and the use of other MCMC approaches being considered in other studies were limited.

1.6 Organization of the Thesis

The thesis is classified under five chapters. Chapter 1 deals with the background of the thesis, objective, expected outcome and limitations of the study. Relevant literature reviews including different approaches used in this thesis are discussed in Chapter 2. Chapter 3 explains the mathematical methods applied, data type, data source and procedures for the data analysis. Chapter 4 introduces the Bayesian inference. Chapter 5 includes results and discussion. While the findings, conclusion and future work are in Chapter 6.

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