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Research Article

# Predictive Model for Depression Without Medical Intervention

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## Abstract

Depression has been the largest mental health problem affecting the public health. Early detection of persons suffering from depression is crucial for effective mitigation and treatment. The key to this can only be achieved when clear symptoms of depression are used to detect patients' depression conditions. The objective of this study is to develop a predictive model for depression that uses the symptoms. The study used both simulated data and real data from the hospitals. The study developed hidden markov model that help to compute the transitional probabilities. The study also used the logistic regression to assess the predictive power of the symptoms of depression. The study found that insomnia positively influence the probability of depression among the patients. The study also found that guilt positively influence the probability of depression among the patients. From the results, the study found that suicidal positively influence the probability of depression among the patients and also fatigue influence the probability of depression. From the study it was also found that retardation positively influence the probability of depression. Finally, found that the change in anxiety negatively influence the probability of depression among the patients. The study also conclude that the predictive model can be used to predict the depression status of the patients by a medical doctor given that the observable symptoms are present.

## Keywords

Depression, Transition Probability, Hidden Markov, Logistic

## 1. Background

It has been noted that depression is among the common chronic diseases that human being are suffering from due to changes in social economic conditions. A study by world health organization found that approximately 350 millions people globally suffer from depression. In the clinical environment, the prevalence of depression among the world population is close to 20% of the population. According the diagnostic and statistical manual for mental disorders, for a psychiatrist to declare a patient has depression five or more symptoms should be present for at least 2 weeks. One symptoms that must be present is the depression mood or loss of pleasure (Anhedonia). The other symptoms are; sleep difficult (insomnia or hypersomnia), psychomotor agitation or retardation, diminished ability to think, Fatigue or loss of energy, excess guilt, and suicidal.

According to DSM, to determine the presence or absence of depression, the symptoms are summed. According to Elliot et al [3], a two factor model fit better than unidimensional mode. The

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found the depression symptoms are represented using somatic and non somatic factors. The depression symptoms that are classified as somatic are; sleep difficulties (SD), appetite or weight changes, poor concentration, fatigue, and psychomotor agitation/retardation while those that are classified as non somatic are depressed mood, anhedonia, feelings of worthless, and thoughts of death. There has been to study that has highlighted the number of symptoms that can indicate the severity of the depression or the even if the degree of each symptom can be used to classify depression as mild, moderate or severe.

According to Morin and Benca [7], Insomnia or sleep difficult has been classified as a major public health problem associated with depression and anxiety. The study found that a person suffering from depression is a high risk of experiencing Insomnia during the period. According to Pellson [10], the preference of insomnia is higher when a person is suffering from depression and anxiety. In a study conducted by Pellson over 10-years period among the Norwegian adult population, it was observed that maintain of sleep was a common characteristics among the population suffering from depression. According to Parthasarathy, [11], the presence of insomnia is greatly attributed to both physical and mental problem. According to lallukka [6], many people who are suffering from depression are likely to report the presence on insomnia over a period of even 4 week or 3 months.

According to Mars, Burrows, Hjelmel and and Gunnell [13], suicidal attempts are major problems that are associated with psychiatric problems specifically depression. According to a study conducted by Mars, Heron, Crane, Hawton, Kidger, and Lewis [13], 80% of the patients who where being treated on depression problems admitted having attempted suicide. According to Bryan [2] in the study on behavioral among the patient suffering from depression shame and guilt positively correlates with the depression episodes. According to Bi et al, [1] the major public health problem of mental patients was the guilt and suicide. The study further indicated that guilt strongly relate with the suicidal thoughts.

According to Grahek [5], retardation was found to be one of problem which is attributed to major depressive disorder. The study also found that retardation is usually a clear indication of depression. According to Grahek [5], it was observed that there was significant relationship between the physical impairment of the functioning and the depression. According to Fried [4], psychosocial functioning, and triggering life events as the risk factors for depression.

The Major depression disorder has been modeled and analyzed using the Markov chain model. Several Markov models that were developed successfully captured the salient characteristics of patient state of mind. According to Oskooyee, Rahmani, and Kashani, [9], Markov chain model was introduced to deal with various sequence of information All the daily commotion causes disturbances in an individual life which is sufficient in creating a disturbance in his normal state of mind. The magnitude of these disturbances determine the probability of shifting a normal person to depression state. According to Katrina and Meadows [14], two state Markov chain model was used in modelling the mental health of patients who visited the psychiatric hospital. The Two state Markov model was also used in modelling the long term behavior of the depressed state. Despite the use of the Markov model being popular, one weakness of Markov model is the assumption the state of mind of the person in observable and can be determined. This assumption is not always the case, hence there is need to determine the best method to model the mental health. This study therefore develop a bayesian hidden Markov model for modeling the mental health. The study will use both the numerical simulation and mathematical analysis in validation of the model.

## 2. Methods

*Bayesian Estimation Approach*

This study will employ a Bayesian approach in the estimation of the model parameters which implies that if $\theta$ is the vector of the parameters describing the model, all the required inference will be based on the posterior distribution of $\theta$. Given the data set *y*, from the Bayes' theorem:

$$p(\theta|y) \propto p(y|\theta)\, p(\theta)$$

where $p(y|\theta)$ is the likelihood and $p(\theta)$ is the prior distribution of the parameters. Depending on the choice of the loss function, inference about the parameter $\theta$ is based on the posterior distribution. For instance if the squared loss function is used then the posterior mean is the estimator for the parameter $\theta$. i.e $\widehat{\theta}_\pi = E_\pi[\theta \mid \underline{X}]$.

*Hidden Markov Model (HMM)*

A hidden Markov model have become very useful in fitting mixture of distribution of sequence of dependent set of data.

Let us denote by S the random variable representing the latent states to be modeled, where S takes values on the set $dom(s) = \{s_1, s_2, \ldots\ldots, s_k\}$, such that each $s \in dom(s)$ is called a latent (or hidden) state. We denote by $\{Y_1, Y_2, \ldots\ldots, Y_m\}$ the set of observable variables, such that the i$^{th}$ observation $Y_i$ takes values on some set $dom(Y_i)$. In medical domains, each $Y_i$ will often refer to measured data such as symptoms, while the latent variable S will refer to some state of the underlying disease (i.e disease remitting mental wellbeing). The disease process of interest is assumed discrete over the time points $\{0, 1, \ldots\ldots, T\}$, where the value of the latent variable and the observables that hold at time t will be denoted by $s^{(t)}$ and $Y_i^{(t)}$ respectively. The hidden Markov model comprises of the bivariate discrete time process of the form $\{s_t, y_t\}_{t\geq 1}$ where $\{s_t\}$ consist of unobservable Markov chain states and conditional on $\{s_t\}, \{y_t\}$

being sequence of random variables that are independent and that conditional distribution of $Y_t$ only depend on $s_t$. Sequence $\{s_t\}, and \{y_t\}$ are referred to as the state and observed sequences respectively [12]. Figure 1 show Hidden Markov Model showing the dependence structure of the state sequence and the observed sequence is represented as

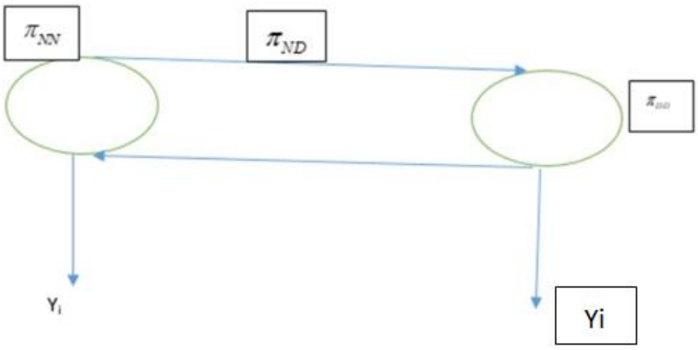


***Figure 1.*** *Transitional probabilities.*

Assuming the first order Markov chain represented by $S_t(t=1,2,...,n)$ which assume on the m values in the transitional matrix $T=\left(p_{ij}\right)_{m\times m}$ and probability of being in the first state or the initial probability distribution

$$\pi=\left(\pi_i, i=1,2,..m\right)^T, where$$
$$p_{ij}=p(x_t=j\,|\,x_{t-1}=i)i,\ j=1,2,..m;t=1,2,..n$$
$$\pi_i=p(s_1=i)i=1,2,...,m$$

And the conditional distribution of $Y_t / s_t$ has a parametric form $f_i(y_t,\theta_i)$ with $\theta_i$ being a vector consisting of unknown parameters. In fitting the hidden markov chain model the parameters will be estimated including both the transitional, initial probabilities and the probability distribution parameters. The transitional matric in the hidden state is a square matrix in which each probabilities in the row is modelled using the ordered probit logit model. In estimation of the distribution parameters, the study can use Bayesian method with the assumption that the parameters of the distribution follows a distribution called the prior distribution. The hidden markov chain models have been used by many research in modeling real life phenomenon. Hidden Markov models (HMM) can be seen as an extension of Markov models to the case where the observation is a probabilistic function of the state, i.e. the resulting model is a doubly embedded stochastic process, which is not necessarily observable, but can be observed through another set of stochastic processes that produce the sequence of observations. Let $y=\left(y_t\right)_{t=1}^T$ be the vector of observed variables, indexed by time. HMMs assume that the distribution of each observed data point $y_t$ depends on an unobserved (hidden) variable, denoted $s_t$, that takes on values from 1 to *k*. The hidden variable $s=\left(s_t\right)_{t=1}^T$ characterizes the "state" in which the generating process is at any time *t*. HMMs further postulate a Markov Chain for the evolution of the unobserved state variable and, hence, the process for $s_t$ is assumed to depend on the past realizations of $y$ and $s$ only through $s_{t-1}$:

$$p\left(s_t=j\middle|s_{t-1}=i\right)=\lambda_{ij}$$

where $\lambda_{ij}$ is the generic element of the transition matrix $\Lambda=\left(\lambda_{ij}\right)$

## 2.1. The Observed Symptoms and Latent State of Depression

Considering data on N different individuals who self-report on daily bases over several months. The data will therefore correspond to the depression patients related symptoms, report by N different patients. In this study, six symptoms related to depression were recorded. They include: insomnia, guilt, suicidal, retardation, anxiety, and fatigue. All these symptoms are record by the psychiatric in a scale of 0, 1, 2, and 3 where 0 is taken a no depression sign, 1 show presence of mild, 2 an indication of moderate depression and 3 an indication of severe symptoms of depression.

Let $y_{nt}\in\{0,1,2,...,M\}^j$ where the j symptoms scores reported by individual $n\in\{1,2,...,N\}$ on event t, where for our study J=6 and M=2; we use generalized notation because the basic modelling strategy may be applied to other types of related. The study assume that at any given time, any individual is either in a depressed state D or in a Normal state N. the study assume that a person in state N does not show symptom of depression. The study also indicate that a person in state D exhibit the symptoms of depression. This study used a logistic model to link the observed symptoms J to the latent state.

The study classified the symptoms for the patients in vector form as

$$X_i = \{x_1 = \text{insomnia},\ \text{x}_2\text{=guilt},\ \text{x}_3\text{=suicidal},\ \text{x}_4\text{=retardation},\ \text{x}_5\text{=anxiety},\ \text{and x}_6\text{=fatigue}\}$$

The observed state of depression symptoms are also defined as according Morin Belleville, [8] to in with scale (0=no symptom, 1=mild, 2= moderate, 3= severe).

Assumptions of the model

The model apply the following assumptions;

1. Individuals are exposed to depression due to social economic pressure
2. Its assumed that the person can move from normal to depressed

## 2.2. The Latent State

A police officer is said to be in depression if he/she exhibit at least one of these symptoms. Since depression is not observable, we model the presence of depression in two progression states: 1 the state where no symptom of depression is observed, 2- the state where depression symptom are observed. This is a two state model as described in Figure 2. The states are normal (N) and illness or depressed (D) as show in Figure 2.


***Figure 2.*** *Transitional diagram.*

A normal police Officer is the one whom all the observed symptoms are all showing 0's meaning the absence of depression. Thus, the transition probabilities $\pi_{NN}, \pi_{ND}, \pi_{DD}$ and $\pi_{DN}$ are functions of the $x_1, x_2, \ldots\ldots, x_6$. Simply written as $\pi_{NN}(x_1, x_2, \ldots\ldots, x_6), \pi_{ND}(x_1, x_2, \ldots\ldots, x_6)$, $\pi_{DD}(x_1, x_2, \ldots\ldots, x_6)$ and $\pi_{DN}(x_1, x_2, \ldots\ldots, x_6)$, without loss of generality simply write as $\pi_{NN}(x_1, x_2, \ldots\ldots, x_6) = \pi_{NN}(.)$,

$\pi_{ND}(x_1, x_2, \ldots\ldots, x_6) = \pi_{ND}(.)$,

$\pi_{DD}(x_1, x_2, \ldots\ldots, x_6) = \pi_{DD}(.)$

and $\pi_{DN}(x_1, x_2, \ldots\ldots, x_6) = \pi_{DN}(.)$ now if atleast on of the $x_1, x_2, \ldots\ldots, x_6$ is greater than 0, then

$\pi_{ND}(.) > 0$ if at least one of the $x_1, x_2, \ldots\ldots, x_6 > 0$ or

$\pi_{ND}(x_1 > 0, or, x_2 > 0, \ldots\ldots, x_6 > 0) > 0$

The probabilities $\pi_{NN}, \pi_{ND}, \pi_{DD}$ and $\pi_{DN}$ are transitional probabilities which they form a $2 \times 2$ transitional matrix

$$T = \begin{bmatrix} \pi_{NN}(.)\pi_{ND}(.) \\ \pi_{DN}(.)\pi_{DD}(.) \end{bmatrix}$$

Notice that, we do not observe the depression in the police officer but the symptoms $x_1, x_2, \ldots\ldots, x_6$ to guide the as this state of the police officer. Suppose that the state of the police officer us N-no depression and D-depressed as presented in Figure 2, this is a binary output.

$$\text{If } y = \begin{cases} 1 = D \\ 0 = N \end{cases} \text{ as this binary results}$$

$$y = \begin{cases} 1 - \text{at least one of the } x_1, x_2, \ldots\ldots, x_6 > 0 \\ 0 - x_1 = 0, x_2 = 0, \ldots\ldots, x_6 = 0 \end{cases}$$

This implies that

$$\pi_{ND}(.) = pr(y=1) \text{or } \pi_{NN}(.) = pr(y=0)$$

Therefore

$$\pi_{ND}(.) = \frac{e^{\beta_0 + \beta_1 x_{t1} + \ldots\ldots\ldots + \beta_k x_{t6}}}{1 + e^{\beta_0 + \beta_1 x_{t1} + \ldots\ldots\ldots\ldots + \beta_k x_{t6}}} \qquad (1)$$

Firstly, note that (Equation 1) has parameters which the present

$$\pi_{ND}(x_1, x_2, \ldots\ldots, x_6 \mid \beta_0, \beta_1, \ldots, \beta_6) = \frac{e^{\beta_0 + \beta_1 x_{t1} + \ldots\ldots\ldots + \beta_k x_{t6}}}{1 + e^{\beta_0 + \beta_1 x_{t1} + \ldots\ldots\ldots\ldots + \beta_k x_{t6}}} \qquad (2)$$

The next step is to estimate the parameters of (Equation 2).

# 3. Results and Discussion

## 3.1. Parameter Estimation

In this section, our objective is to obtain the estimates of these parameters in (Equation 2). We shall use the Bayesian approach due to the lack of closed form of (Equation 2).

For any modeling population of size N police officers. Suppose a sample of size n is randomly selected from the population N, the $j^{th}$ police officer is either depressed (D) or not depressed (N). This is a binary outcome $Y_j$.

We use this $x_1, x_2, \ldots\ldots, x_6$ to predict the y's. Y's are the hidden state where as X's are the observed state. The probability of the hidden state $y_j$ given the observable states X's for a police officer j, j=1, 2, 3,…., n is given by

$$pr(Y_1, Y_2, ........, Y_n \mid x_1, x_2, .....x_6) = \pi_{ND}{}^{y_j}(.)\left(1-\pi_{ND}(.)\right)^{1-y_j} \quad (3)$$

For n police officers (equation 3) becomes

$$\prod_{j=1}^{n} pr(Y_1, Y_2, ........, Y_n \mid x_1, x_2, .....x_6) = \prod_{j=1}^{n} \pi_{ND}{}^{y_j}(.)\left(1-\pi_{ND}(.)\right)^{1-y_j}$$

$$\prod_{j=1}^{n} pr(Y_1, Y_2, ........, Y_n \mid x_1, x_2, .....x_6) = \pi_{ND}{}^{\sum_{j=1}^{n} y}(.)\left(1-\pi_{ND}(.)\right)^{n-j\sum_{j=1}^{n} y_j} \quad (4)$$

Equation 4 give the joint density for n police officers.
Assuming that the distribution beta follow is normal distribution and in equation 5.

$$f(\beta_j) = \frac{1}{\sigma_j\sqrt{2\pi}} \exp\left(-\frac{\left(\beta_j - \mu_0\right)^2}{2\sigma_j{}^2}\right) \quad (5)$$

Equation (5) combine with 4 to obtain the posterior distribution

$$f\left(\underline{\beta} / x_1, x_2, ....., x_6\right) \alpha \pi_{ND}{}^{\sum_{j=1}^{n} y}(.)\left(1-\pi_{ND}(.)\right)^{n-j\sum_{j=1}^{n} y_j} \prod_{j-1}^{6} \frac{1}{\sigma_j\sqrt{2\pi}} \exp\left(-\frac{\left(\beta_j - \mu_0\right)^2}{2\sigma_j{}^2}\right) \quad (6)$$

Equation 6 give the posterior distribution and does not have a closed form of any particular distribution. Hence the study used the computational technique to obtain the bayes estimators. The MCMC simulation was applied in obtaining the bayes estimators.

## 3.2. Metropolis Gibbs Sampling

Given that $\underline{\beta}$ represent a vector of the logistic regression parameters to be estimated, and using the Bayesian method, the information about the parameters $\underline{\beta}$ can only be found from posterior distribution $f\left(\underline{\beta} / data\right)$ This study used the Gibbs sampler algorithm to produce the estimate of the parameters $\beta^s$ from the previous estimate $\beta^{s-1}$ using the following steps

a. Set the initial values of the parameter $\beta^{(0)} = \left(\beta_0^{(0)} = 1, \beta_0^{(1)} = 1, \beta_0^{(2)} = 1, \beta_0^{(3)} = 1, \beta_0^{(4} = 1, \beta_0^{(5)} = 1, \beta_0^{(6)} = 1\right)$

b. Set the number of desired iterations L

c. At the iteration s the value of $\beta_j; j = 1,2,3,4,5,6$ is updated as follows

d. Sample $\beta_0^{(s)} \sim f(\beta_0 \mid \beta_1^{(s-1)}, \beta_2^{(s-1)}, ......, \beta_6^{(s-1)}; data)$

e. Sample $\beta_1^{(s)} \sim f(\beta_1 \mid \beta_0^{(s-1)}, \beta_2^{(s-1)}, ...., \beta_6^{(s-1)}; data)$

f. Sample $\beta_6^{(s)} \sim f(\beta_6 \mid \beta_0^{(s-1)}, \beta_1^{(s-1)}, \beta_2^{(s-1)}, ......., \beta_5^{(s-1)}; data)$

g. $\beta_6^{(s)} \sim f(\beta_6 \mid \beta_0^{(s-1)}, \beta_1^{(s-1)}, \beta_2^{(s-1)}, \beta_3^{(s-1)}, \beta_4^{(s-1)}, \beta_5^{(s-1)}; data)$

The above steps are repeated until the completion of all the iterations.

Since the estimation of the logistic regression parameter coefficient using Bayesian method lead to a posterior distribution that does not have a closed form. A computation technique is applied to obtain the needed estimators of the parameters and hence the MCMC with gibbs sampling.

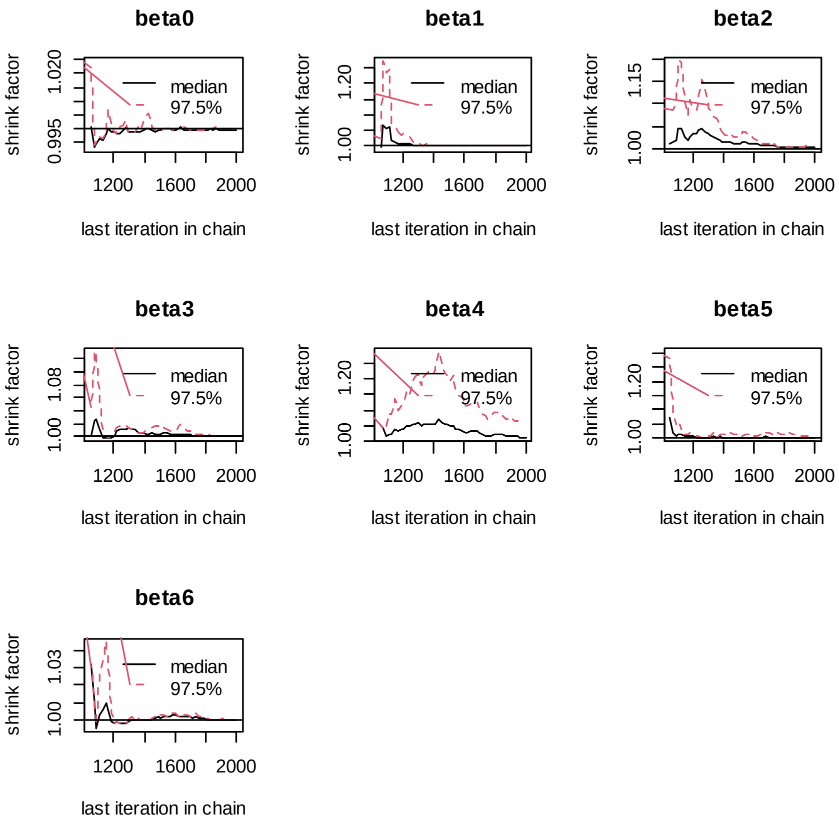


***Figure 3**. Parameter estimates.*

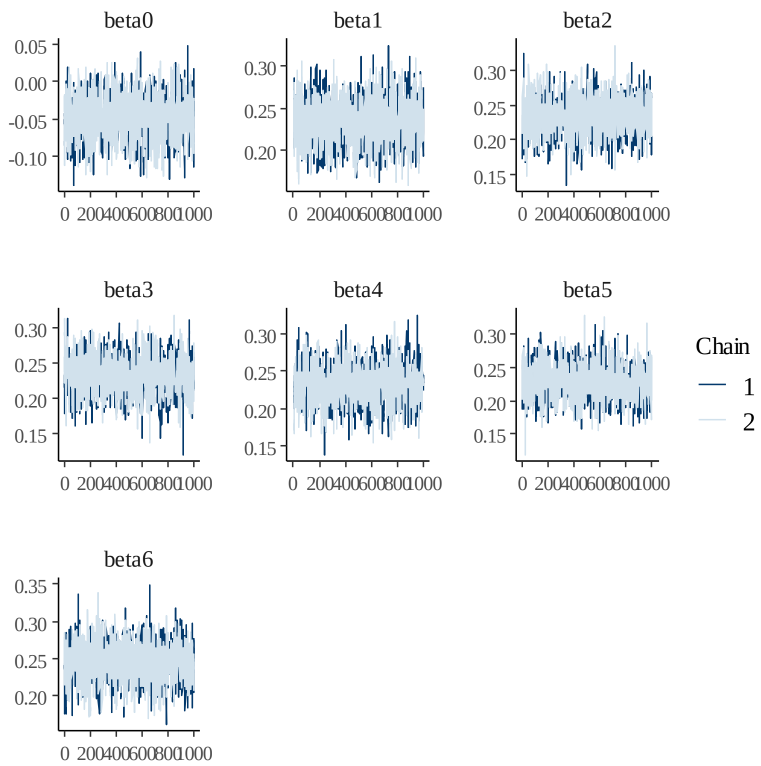


***Figure 4**. Parameter convergence.*

# 4. Results and Discussion

## 4.1. Convergence of the Algorithms and Model Diagnostics

This section describe the convergence of each parameter though analysis of the scale reduction parameter. From the results in figure 3, the parameter beta 0, beta 1, beta 3, beta 5 and beta 6 had a factor of 1 or close to 1 when the number of chain iteration was at 1200. This mean that between variance and within chain variance are equal. The results also indicate that the parameters beta 2 and beta 4 had not converged at 1200 iteration. From the results in figure 4, the study can conclude that the parameters beta 0, beta 1, beta 2, beta 3, beta 4, beta 5 and beta 6 converges at the 1600 iteration. This was because they all attain a factor on 1 or very close to one which mean that between variance and within chain variance are equal.

## 4.2. Parameter

This section discuss the estimate of the parameters in the model. The results in Figure 4 indicate that the red line which give the true value of the estimate and the black line which give the estimated value. The result indicate that the true value of beta 0 was -0.034842 which is denoted by red while the black line the estimated value (-0.034841). The results also indicate that the true value for beta 1 was 0.23501 as indicated by the red line, while the black line which give the estimated value was 0.24144. The plot of the density show that the insomnia coefficient indicated better combination of the MCMC chains and stationary a good indication of the convergence.

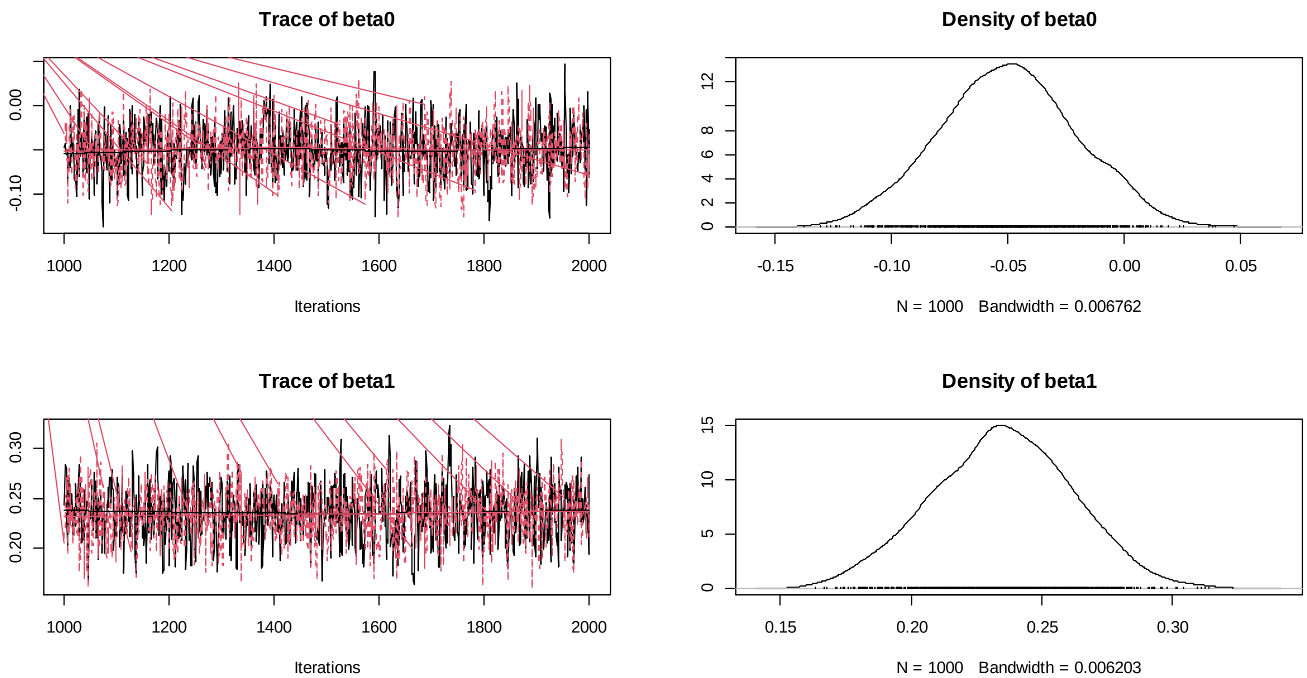


***Figure 5.*** *Estimates for beta 0 and beta 1.*

The results in figure 6 below indicate that the red line which give the true value of the estimate and the black line which give the estimated value. The result indicate that the true value of beta 2 was 0.23380 which is denoted by red while the black line the estimated value (0.23365). The results also indicate that the true value for beta 3 was 0.23271 as indicated by the red line, while the black line which give the estimated value was 0.22998. The plot of the density show that the guilt coefficient as well as suicidal coefficient indicated better combination of the MCMC chains and stationary a good indication of the convergence.

The results in figure 7 indicate that the red line which give the true value of the estimate and the black line which give the estimated value. The result indicate that the true value of beta 4 was 0.23525 which is denoted by red while the black line the estimated value (0.23863). The results also indicate that the true value for beta 5 was 0.2287 as indicated by the red line, while the black line which give the estimated value was 0.23863. The plot of the density show that the retardation coefficient as well as anxiety coefficient indicated better combination of the MCMC chains and stationary a good indication of the convergence.

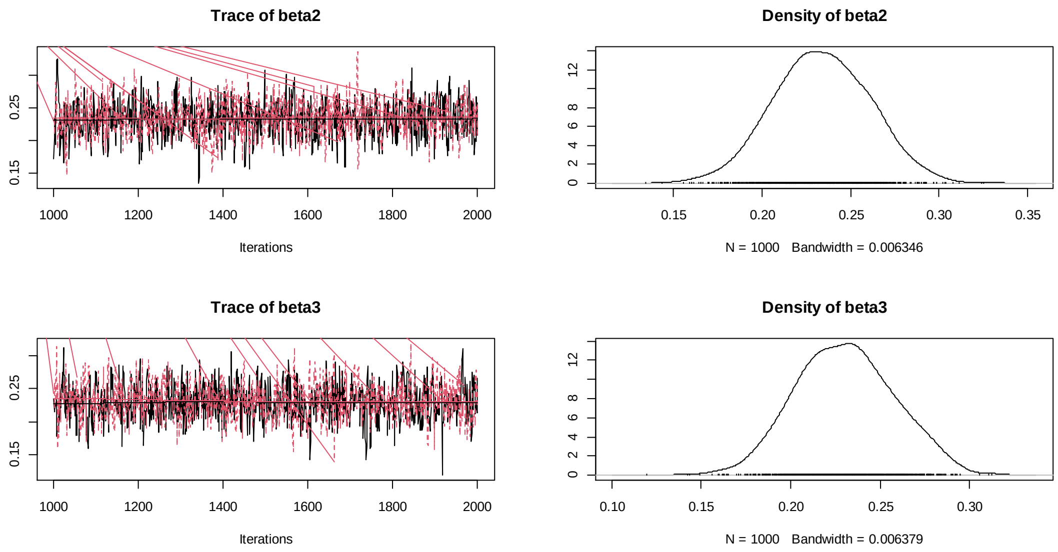


***Figure 6.*** *Estimates for beta 2 and beta 3.*

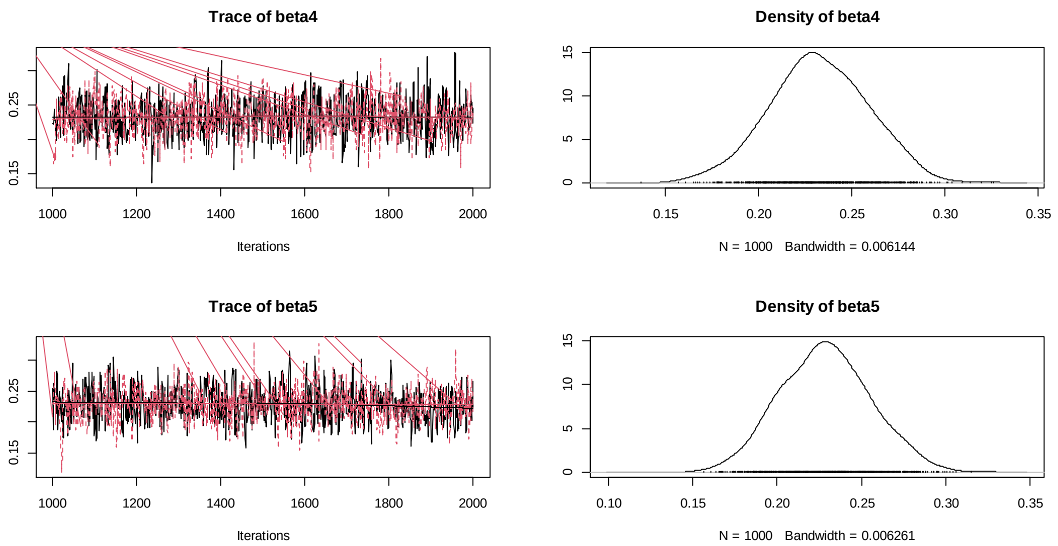


***Figure 7.*** *Estimates for beta 4 and beta 5.*

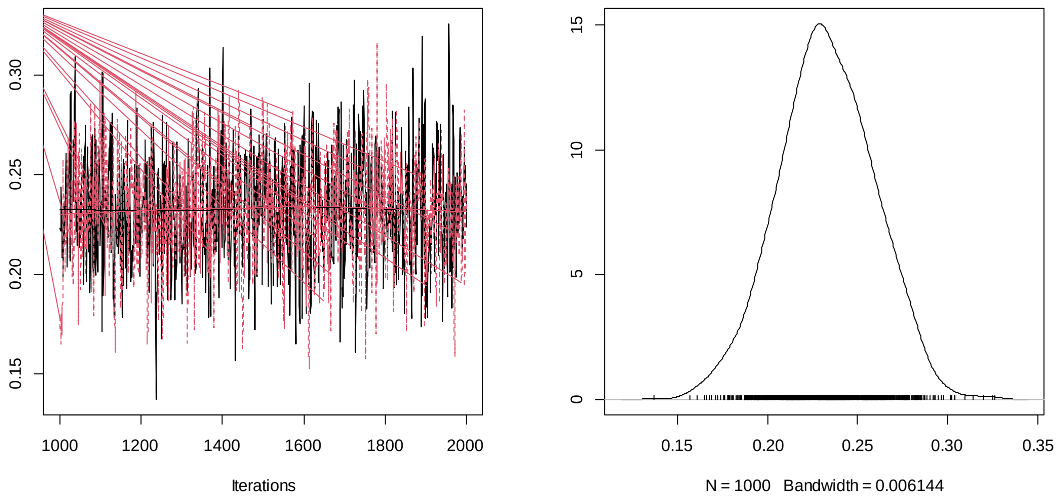


***Figure 8.*** *Estimates for beta 8.*

The results in figure 8 also indicate that the true value for beta 6 was 0.24456 as indicated by the red line, while the black line which give the estimated value was 0.24495. The plot of the density show that the fatigue coefficient indicated better combination of the MCMC chains and stationary a good indication of the convergence.

## 4.3. The Parameter Estimation Summary

***Table 1**. Parameter estimates.*

| coefficient | mean | standard deviation | na ïve error |
|---|---|---|---|
| beta0 | -0.03484 | 0.0301 | 0.0006731 |
| beta1 | 0.24144 | 0.02628 | 0.0005875 |
| beta2 | 0.23969 | 0.02691 | 0.0006017 |
| beta3 | 0.23525 | 0.02739 | 0.0006125 |
| beta4 | 0.23863 | 0.02868 | 0.0006413 |
| beta5 | 0.23662 | 0.02669 | 0.0005967 |
| beta6 | 0.25061 | 0.02866 | 0.0006409 |

## 4.4. The Transitional Probabilities

From table 1 above, the Bayes estimated of the parameters $\widehat{\beta}_J$= 0, 1, 2, 3, 4, 5, 6 are

$$\widehat{\beta}_J = \begin{bmatrix} -0.03484 \\ 0.24144 \\ 0.23969 \\ 0.23525 \\ 0.23862 \\ 0.26620 \\ 0.25061 \end{bmatrix}$$

Therefore the logistic linear component is given by

$$\hat{\eta} = -0.03484+0.24144\times1+0.23969\times2+0.23525\times3+0.23862\times4+0.23662\times5+0.25061\times6$$

This implies that the logistic transitional model is given as follows

$$\pi_{ND} = \frac{e^{-0.03484+0.24144x1+0.23969x2+0.23525x3+0.23862x4+0.23662x5+0.25061x6}}{1+e^{-0.03484+0.24144x1+0.23969x2+0.23525x3+0.23862x4+0.23662x5+0.25061x6}}$$

While the logistic transitional model of the patient remaining normal state is given as

$$\pi_{NN} = \frac{1}{1+e^{-0.03484+0.24144x1+0.23969x2+0.23525x3+0.23862x4+0.23662x5+0.25061x6}}$$

## 4.5. Example

This section give an example of the transition probabilities by considering a sample of 20 depressed patients. From table 2, state=1 implies that the $i^{th}$ person id depressed and the state =0 implies the $i^{th}$ person is not depressed. From the table, consider the patient (1) and (2) which indicate that they show that the person has a depression symptoms. The probability that the person will transit from normal to depression is 0.946156 and 0.955395 respectively. This show that the likelihood of transiting from the normal state to depression state when the no medical intervention is applied by the psychiatrist is very high. The study clearly show that the transiting from normal to depression for medical students is very high 94.6156% and 95.5395% of transiting from normal state to depressed state. The study also indicate that the transitional probability of remaining normal despite the social economic challenges was 0.500136.

***Table 2.*** *Model outcomes and probabilities predictions.*

| Y | insomnia | guilt | suicidal | retardation | anxiety | fatigue | prob |
|---|---|---|---|---|---|---|---|
| 1 | 3 | 1 | 3 | 2 | 0 | 3 | 0.946156 |
| 1 | 2 | 3 | 3 | 3 | 2 | 0 | 0.955395 |
| 1 | 0 | 3 | 2 | 1 | 3 | 3 | 0.945698 |
| 1 | 0 | 0 | 0 | 1 | 3 | 2 | 0.804895 |
| 1 | 3 | 2 | 0 | 2 | 0 | 0 | 0.838676 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.500136 |
| 1 | 1 | 3 | 2 | 0 | 2 | 1 | 0.893054 |
| 1 | 0 | 1 | 0 | 1 | 3 | 1 | 0.803173 |
| 1 | 0 | 2 | 0 | 0 | 3 | 3 | 0.870855 |
| 1 | 0 | 3 | 1 | 3 | 2 | 3 | 0.945974 |

## 5. Conclusion

From above results, the study conclude that insomnia positively influence the probability of depression among the patients. The study also conclude that symptom of guilt positively influence the probability of depression among the patients. From the results, the study conclude that the symptom of suicidal positively influence the probability of depression among the patients. Further that from the results, the study conclude that symptom of fatigue influence the probability of depression. From the results, it was concluded that symptom of retardation positively influence the probability of depression. Finally, from the results, it can be concluded that the change in anxiety negatively influence the probability of depression among the patients.

The study also conclude that the predictive model can be used to predict the depression status of the patients by a medical doctor given that the observable symptoms are present.

## Author Contributions

**Charles Mwangi:** Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing

**Kennedy Nyongesa:** Investigation, Resources, Supervision

**Everlyne Akoth Odero:** Project administration, Supervision

## Conflicts of Interest

The authors declare no conflict of interest.

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## Research Fields

**Charles Mwangi:** Disease modeling, Hidden markov models, Machine learning, Longitudinal analysis, Mixture model

**Kennedy Nyongesa:** Statistical modelling, Longitudinal data analysis, Data science, Group testing

**Everlyne Akoth Odero:** Statistical modelling, Longitudinal data analysis, Data science