A Bayesian Hidden Markov Model for Predicting Depression and Evaluating Medical Interventions

Abstract

Depression has been the largest mental health problem affecting the public health. Early detection of people with 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 depression conditions in patients. Despite this problem, the treatment of depression among policemen is usually faced with early diagnosis challenges. This study is a predictive model of depression using the symptoms exhibited by the patient. The study also incorporates the medical intervention for depression to investigate its effect on transitional probabilities. Early recognizable proof of anxiety, guilt, retardation, insomnia, suicidal, and fatigue would be a significant step towards diagnosis and medical intervention to police men and women suffering from depression. In the latest development in the medical field, medical procedures have advanced in the need to create models that can predict mental depression with immediate medical intervention to care for the patients. This study used a treatment model to investigate the effect of medical intervention among depressed police officers. From the results of the study, it was observed that the medical intervention reduced the probabilities of depression status.

hidden Markov, medical intervention,Treatment, Parameter, Naive error

0.1 Introduction

Depression is a common mental health challenge among many individuals in the society, especially among the high-stress occupations such the law enforcement. According to [1], nearly one billion people worldwide are affected by depression. According to the same report, in every 40 people one person die due to depression. In Kenya, police men and women are faced with unique challenges that contribute to increased level of depression. Depression many be caused by many factors including; unemployment, poverty, financial struggles, alcohol or drug abuse, homelessness, uncertainty, isolation, fear, and occupational challenges. The major problem is the late diagnostic and interventions since the police force and even other people are reluctant in seeking help when they start experiencing emotional distress, anxiety and depression [2] . Medical intervention for individuals with worsening mental health is critical to treating depression and anxiety and preventing suicide [3]. Seeking professional medical care for people with depression has been faced by two major hindrances; stigma and access [4]. According to [4], stigma occurs when a person deems the need to seek mental health treatment shameful. According to [5], there association between self-stigma and reluctance to seek medical help. There is a sense of shame that accompanies self-stigma, and the adaptive response to this shame is secrecy; this results in not acknowledging or disclosing mental health problems and not seeking treatment. According to [5], access to mental health services is another barrier due to an inability to find a provider or to the high cost of available care. Recent studies have focused on mental health prevention and treatment programs [3]. Markov chain models have been used to evaluate and examine the mental health programs including the suicide prevention models. For example, [6], estimated population suicide risk as a dynamic system to evaluate the effectiveness of suicide prevention programs. 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 [7], 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 [?], 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

0.2 METHODS

0.2.1 Hidden Markov Model (HMM)

A hidden Markov model have become very useful in fitting mixture of distribution of sequence of dependent set of data. We let X random variable representing the latent states to be modeled, where X takes values on the set $\mathrm{dom}(X) = \{x_1, x_2, ..., x_k\}$, such that $x \in \mathrm{dom}(X)$ each is called a latent (or hidden) state. The latent state comprises of the mental state of depression (D) or Normal (N). We denote $Y_1, Y_2, ..., Y_m$ as the set of observable variables, such that the i^{th} observation Y_i takes values on some set $\mathrm{dom}(Y_i)$. In psychiatric point of view, each Y_i will often refer to measured data which will be the depression symptoms, while the latent variable X will refer to some state of the underlying disease. The depression process of interest is assumed discrete over the time points $\{0, 1, ..., T\}$, where the value of the latent variable and the observables that hold at time t will be denoted by $X^{(t)}$ and $Y_i^{(t)}$ respectively.

0.2.2 Markov Chain Monte Carlo sampling (MCMC)

Markov Chain Monte–Carlo (MCMC) is an increasingly popular method for obtaining information about distributions, especially for estimating posterior distributions in Bayesian inference. MCMC is a computer–driven sampling method [?]. It allows one to characterize a distribution without knowing all of the distribution's mathematical properties by randomly sampling values out of the distribution. A particular strength of MCMC is that it can be used to draw samples from distributions even when all that is known about the distribution is how to calculate the density for different samples. The name MCMC combines two properties: Monte–Carlo and Markov chain. Monte–Carlo is the practice of estimating the properties of a distribution by examining random samples from the distribution. For instance, instead of finding the mean of a normal distribution by directly calculating it from the distribution's equations, a Monte–Carlo approach would be to draw a large number of random samples from a normal distribution, and calculate the sample mean of those. The benefit of the Monte–Carlo approach is clear: calculating the mean of a large sample of numbers can be much easier than calculating the mean directly from the normal distribution's equations. This benefit is most pronounced when random samples are easy to draw, and when the distribution's equations are hard to work with in other ways. The Markov chain property of MCMC is the idea that the random samples are generated by a special sequential process. MCMC is particularly useful in Bayesian inference because of the focus on posterior distributions which are often difficult to work with via analytic examination. In these cases, MCMC allows the user to approximate aspects of posterior distributions that cannot be directly calculated. This study will employ Gibbs sampling algorithm. In statistics, Gibbs sampling is a Markov chain Monte Carlo (MCMC) algorithm for obtaining a sequence of observations which are approximated from a specified multivariate probability distribution, when direct sampling is difficult. This sequence can be used to approximate the joint distribution (e.g., to generate a histogram of the distribution); to approximate the marginal distribution of one of the variables, or some subset of the variables (for example, the unknown parameters or latent variables); or to compute an integral (such as the expected value of one of the variables). Typically, some of the variables correspond to observations whose values are known, and hence do not need to be sampled. Gibbs sampling is commonly used as a means of statistical inference, especially Bayesian inference. It is a randomized algorithm and is an alternative to deterministic algorithms for statistical inference such as the expectation-maximization algorithm (EM). As with other MCMC algorithms, Gibbs sampling generates a Markov chain of samples, each of which is correlated with nearby samples.

0.2.3 Ethical Issues

Since the study involve human participants, it is imperative that the researcher observe the research ethics in the planning and execution of the study. In particular, the researcher addresses various ethical issues specific to the study, including informed consent, privacy, anonymity and confidentiality. By voluntarism, the participants will be assured of their freedom to take part in the research. In his regard, the researcher avoid using coercion or deceit while requesting for participants' consent. By full information, the participants were provided with important information about the conduct of the research. These includes explanations about the research procedures, expected benefits, clarifications of inquiries about the procedures, and a disclosure that the participants had the right to withdraw consent and drop out from the research at any time. Based on comprehension, the researcher ensured that the participants understood the research before providing consent by allowing a reasonable time lag and room for consultation between the time of request for consent and the decision. Privacy was evaluated from three standpoints, including the sensitivity of information, settings of the research, and dissemination of information. It was detrimental to publicize information that negatively portrays the research participants by revealing their background and social standing. Participants were provided with information sheets and written informed consent forms that they were required to sign if they voluntarily accepted to participate in the study. The study was voluntary and participants had the right to withdraw at any stage of the interview.

0.2.4 Logistic model

The study used the logistic model for the observable variables. The probability of observing outcome i corresponds to the probability that the estimated linear function, plus random error.

$$P(\text{Outcome}_{j=i}) = P(k_{i=1} < \beta_1 x_{1j} + \beta_2 x_{2j} + ... + \beta_k x_{kj} + u_j \leq k_i) \tag{1}$$

u_j is assumed to be normally distributed. In either case, we estimate the coefficients $\beta_1, \beta_2, ..., \beta_k$ where I is the number of possible outcomes.
The independent variables $x_{1j}, x_{2j}, ..., x_{kj}$ are the observable depression symptoms which includes; x_{1j} = Anxiety, x_{2j} = Retardation, x_{3j} = Insomnia, x_{4j} = Suicidal, and x_{5j} = Guilt. The model will comprise of the following observable variables

$$P(\text{Outcome}_{i=i}) = P(k_{i=1} < \beta_1 x_{1j} + \beta_2 x_{2j} + \beta_3 x_{3j} + \beta_4 x_{4j} + \beta_5 x_{5j} + \mu_i) \tag{2}$$

0.3 RESULTS AND DISCUSSION

0.4 The Statistical Model to predict depression with Treatment

0.4.1 Introduction

The main purpose of treatment is to completely eradicate the disease. This can only be achieved if the patient receive treatment overtime. The efficiency

		Treatment	
		0=not treated	1=treated
	0=no	(0,0)	(0,1)
SYMPTOM	1=mild	(1,0)	(1,1)
	2=moderate	(2,0)	(2,1)
	3=severe	(3,0)	(3,1)

Table 1: Treatment Symptoms combination

of the drug can be measured by the degree of symptom reduction. when a police officer is suffering from depression, he or she visits a psychiatric for treatment. This psychiatric treatment offers relief to the patient by reducing or eliminating depression or by suppressing the symptoms over time. Suppose that the treatment T is an indicator variable with come as 0 and 1. Then, this indicator variable follows a Bernoulli distribution and can be presented as follows;

$$T = \begin{cases} 1 = \text{if police officer has received treatment} \\ \\ 0 = \text{in police officer has not received treatment,} \end{cases} \tag{3}$$

Each symptom was measured as four level ($0 = notpresent, 1 = mild, 2 = moderate, \text{and} 3 = severe$). The treatment, symptom combination can be presented as follows;
Table (1) give the treatment symptom combination at different levels of symptom . From Table (1), the combination $(0, 0)$ implies that the patient had no symptom and did not receive treatment. The combination $(1, 0)$ implies that the patient had a mild symptom and did not receive treatment. The combination $(3, 1)$ implies that the patient had severe symptom and also received treated. The was extended to all the symptoms when treatment was given to the patient and hence the transition transitional probability computed as presented in the next section.

0.5 Model with Treatment

We define the transitional probability $\pi_{iND}(x_1, x_2, , , , , x_6)$ as provided in equation (3.3). Suppose we introduce treatment T as defined in equation $(3, 9)$ in a model with only one symptom interacting with the treatment, the transition probability becomes;

$$\pi^T_{iND}(x_1, x_2, ..., x_6, T, Tx_i) \tag{4}$$

Equation (3.9) represent treatment model where (Tx_i) represent the interaction between the treatment T and the i^{th} symptom and T is the treatment. Equation (3.9) was able to evaluate both the main effect of the treatment and the interaction effect of the treatment and the symptoms on transition probability of depression. We can extend equation (3.9) to two symptoms treatments case. We measure the effectiveness of treatment T on second symptom by the interaction (Tx_k). This help to determine the main effect of the treatment and interaction effect between the treatment and the two symptoms. Thus equation (3.9) becomes.

$$\pi^T_{iND}(x_1, x_2, ..., x_6, T, Tx_i, Tx_k) \tag{5}$$

where (Tx_k) and (Tx_i) assess the effect of the treatment on the symptoms x_i and (x_k)

If the treatment is extended to all the symptoms, then the transition probability will be a function of the interaction between $(x_1, x_2, ...x_6)$ and treatment T . Thus equation (3.9) become;

$$\pi^T_{iND}(x_1, x_2, ..., x_6, T, Tx_1, Tx_2, ..., Tx_6) \tag{6}$$

In equation (3.10) all the symptoms have an interaction with the treatments. Therefore, Equation (3.10) help to determine the main effect of the treatment and the interactive effect of treatment and symptoms.

0.6 Posterior with treatment model

The probability of the hidden state y_i given the observable states $X's$ for a police officer j, $(j = 1, 2, 3, ..., n)$ is given by

$$\mathrm{pr}(Y_1, Y_2, ..., Y_n|x_1, x_2, ..., x_6, T, TX_1) = \pi^T_{iND}{}^{y_i}(.)(1 - \pi^T_{iND}(.))^{1-y_i} \tag{7}$$

For n police officers (3.12) becomes

$$\Pi^n_{j=1}\mathrm{pr}(Y_1, Y_2, ..., Y_n|x_1, x_2, ..., x_6, T, T_x1) = \Pi^T_{j=1}{}^n\pi^T_{iND}{}^{y_i}(.)(1 - \pi^T_{iND}(.))^{1-y_i}$$
$$\Pi^T_{j=1}{}^n\mathrm{pr}(Y_1, Y_2, ..., Y_n|x_1, x_2, ..., x_6, T, Tx_1) = \pi^T_{iND}{}^{\sum^n_{i=1}}(.)(1 - \pi^T_{iND}(.))^{n-\sum^n_{i=1} y_i} \tag{8}$$

To use bayesian method in obtaining the parameters in 3.12, we assume that the parameters follow normal distributions i.e, Substituting the transitional probability equation (3.9) in equation (3.6) we obtain a posterior distribution with treatment model with one symptoms. Therefore the posterior distribution when only one symptoms is treated, e.g when anxiety is treated as defined by Laura, (2011) is obtained as follows;

$$f(\beta|X_1, X_2, ..., X_6, T, TX_i)\alpha\pi_{iND}^{T}{}^{\sum_{i=1}^{n} y}(.)(1-\pi_{iND}^{T}(.))^{\sum_{i=1}^{j} y_j}\Pi_{j=1}^{6}\frac{1}{\sigma_j\sqrt{2\pi}}\exp\left(\frac{-(\beta_j-\mu_0)^2}{2\sigma_j^2}\right) \tag{9}$$

Equation (3.14) is the posterior distribution when one symptoms is treated. When two symptoms are treated the posterior distribution is obtained by replacing transition probability in equation (3.10) with transitional probability in equation (3.6). Therefore, the posterior distribution become;

$$\begin{gathered} f(\beta|X_1, X_2, ..., X_6, T, TX_i, TX_k) \\ \alpha\pi_{iND}^{T}{}^{\sum_{i=1}^{n} y}(.)(1-\pi_{iND}^{T}(.))^{\sum_{i=1}^{j} y_j} \\ \Pi_{j=1}^{6}\frac{1}{\sigma_j\sqrt{2\pi}}\exp\left(\frac{-(\beta_j-\mu_0)^2}{2\sigma_j^2}\right) \end{gathered} \tag{10}$$

Equation (3.15) is a posterior distribution with treatment model when two symptoms are treatment becomes.

$$\begin{aligned} \Pi_{j=1}^{n}\mathrm{pr}(Y_1, Y_2, ..., Y_n|x_1, x_2, ..., x_6, T, TX_1, TX_2) \\ = \Pi_{j=1}^{T}{}^{n}\pi_{iND}^{T}{}^{y_i}(.)(1-\pi_{iND}^{T}(.))^{1-y_i} \\ \Pi_{j=1}^{T}{}^{n}\mathrm{pr}(Y_1, Y_2, ..., Y_n|x_1, x_2, ..., x_6, T, TX_1, TX_2) = \\ \pi_{iND}^{T}{}^{\sum_{i=1}^{n}}(.)(1-\pi_{iND}^{T}(.))^{n-\sum_{i=1}^{n} y_i} \end{aligned} \tag{11}$$

When all the six symptoms are treated, the posterior distribution was also obtained when the transition probability in equation (3.6) is replaced with transitional probability in equation (3.11). Therefore, the posterior distribution become;

$$\begin{gathered} f(\beta|X_1, X_2, ..., X_6, T, TX_1, TX_2, ..., Tx_6)\alpha\pi_{iND}^{T}{}^{\sum_{i=1}^{n} y} \\ (.)(1-\pi_{iND}^{T}(.))^{\sum_{i=1}^{j} y_j}\Pi_{j=1}^{6}\frac{1}{\sigma_j\sqrt{2\pi}}\exp\left(\frac{-(\beta_j-\mu_0)^2}{2\sigma_j^2}\right) \end{gathered} \tag{12}$$

0.7 Metropolis Gibbs Sampling

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

a. set the initial values of the parameter
$\beta^{(0)} = (\beta_0^{(0)} = 1, \beta_0^{(1)} = 1, ..., \beta_0^{(13)} = 1)$

b. Set the number of desired iterations L

c. At the iterations s the values if $\beta_j; j = 1, 2, ..., 13$ is updated as follows

d. sample $\beta_0^{(s)} \sim f(\beta_0|\beta_1^{(s-1)}, \beta_2^{(s-1)}, ..., \beta_{13}^{(s-1)})$

e. sample $\beta_1^{(s)} \sim f(\beta_1|\beta_0^{(s-1)}, beta_2^{(s-1)}, ..., \beta_{13}^{(s-1)})$

f. sample $\beta_{13}^{(s)} \sim f(\beta_{13}|\beta_0^{(s-1)}, beta_1^{(s-1)}, ..., \beta_{12}^{(s-1)})$

The parameter of the model

In this section we discuss the results of treatment model when one symptom is treated. The results of the study indicate that the coefficients of insomnia was 0.0011982 which indicate that insomnia has a positive influence on transitional probability.

coefficient	mean	standard deviation	naïve error
beta0	0.0005705	0.0010158	0.00002271
beta1	0.0011982	0.0009828	0.00002198
beta2	0.0012147	0.0009788	0.00002189
beta3	0.001233	0.0010424	0.00002331
beta4	0.0011488	0.0010008	0.00002238
beta5	0.0011914	0.0009721	0.00002174
beta6	0.0011829	0.0010145	0.00002268
beta7	-0.0008054	0.0009957	0.00002226
beta8	-0.001184	0.0009999	0.00002236

Table 2: Parameter of one symptom treatment model

From the results in table (2), it can be observed that the average value of the coefficient of β_1 was positive 0.0011083. This implies that the insomnia positively influence the probability of depression among the patient. The results of the study also indicate that the average coefficient of β_2 was positive 0.0012147. This means that the symptom quilt in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_3 was positive 0.001233. This means that the symptom suicide in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_4 was positive 0.0011488. This means that the symptom retardation in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_5 was positive 0.0011914. This means that the symptom anxiety in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of $\beta_6$was positive 0.0011829. This means that the symptom fatigue in a patient positively influences the probability of depression among the patients. The study indicate that the average coefficient of the β_7 was -0.0008054 which is the coefficient of the medical treatment. This implies that medical treatment has a negative value thus it decreases the probability of depression among the patients. The study also investigated the effect of medical treatment on the symptoms of depression. From the results, the coefficient $\beta_8$was equal to -0.001184. This implies that the interaction between the medical treatment and insomnia decreases the effect of the probability on depression among the patients.

0.8 Transitional probability for treatment model with one symptom interaction

From table (3) , it can be observed that the coefficient of the treatment T was negative. This implies that treatment reduce the probability of depression among the patients. The results also indicated that the coefficient of interaction between treatment and insomnia was negative. This implies that the interaction between treatment and insomnia reduce probability of transition.

y	insomnia	guilt	suicidal	retardation	anxiety	fatigue	T	T*insomnia	π^{table}
1	3	1	3	2	0	3	1	3	0.501833132
1	2	3	3	3	2	0	1	2	0.502702234
1	0	3	2	1	3	3	1	1	0.50324068
1	0	0	0	1	3	2	0	0	0.501914816
1	3	2	0	2	0	0	1	3	0.50032489
0	0	0	0	0	0	0	0	0	0.500142625
1	1	3	2	0	2	1	1	1	0.502094168
1	0	1	0	1	3	1	1	1	0.501425421
1	0	2	0	0	3	3	0	0	0.502530678
1	0	3	1	3	2	3	1	1	0.503208981

Table 3: transition probability of treatment model

0.9 The parameter estimation for treatment model with two symptoms under treatment

Table (4), give the results of the coefficients of the treatment model. Table 4 show the mean estimate of coefficient, the standard deviation, and naive error.

coefficient	mean	standard deviation	naïve error
beta0	0.0005956	0.0010162	0.00002272
beta1	0.001199	0.0010156	0.00002271
beta2	0.001173	0.0010279	0.00002298
beta3	0.001205	0.0009588	0.00002144
beta4	0.001184	0.0010092	0.00002257
beta5	0.001211	0.001022	0.00002285
beta6	0.001207	0.0009426	0.00002108
beta7	-0.000856	0.0010028	0.00002242
beta8	0.002367	0.0009477	0.00002119
beta9	0.00003728	0.0010252	0.00002292

Table 4: parameter for two treatment model

From the results in table (5), it can be observed that the average value of the coefficient of β_1 was positive 0.001199. This implies that the insomnia positively influence the probability of depression among the patient. The results of the study also indicate that the average coefficient of β_2 was positive 0.001173. This means that the symptom quilt in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_3 was positive 0.001205. This means that the symptom suicide in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_4 was positive 0.001184. This means that the symptom retardation in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_5 was positive 0.001211. This means that the symptom anxiety in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_6 was positive 0.001207. This means that the symptom fatigue in a patient positively influences the probability of depression among the patients. The study indicate that the average coefficient of the β_7

was -0.000856 which is the coefficient of the medical treatment. This implies that medical treatment has a negative value thus it decreases the probability of depression among the patients. The study also investigated the effect of medical treatment on the symptoms of depression. From the results, the coefficient $\beta_8$was equal to 0.002367. This implies that the interaction between the medical treatment and insomnia does not decrease the effect of the probability on depression among the patients. The results indicate that the coefficient beta$_9 was equal to$0.00003728.$This implies that the interaction between the medical intervention and g$

0.10 Transitional probability for treatment model with two symptom interaction

From table (6), it can be observed that the coefficient of the treatment T was negative. This implies that treatment reduce the probability of depression among the patients. The results also indicated that the coefficient of interaction between treatment and insomnia was positive. This implies that the interaction between treatment and insomnia does not reduce probability of transition. Finally the results indicate that the coefficient of treatment and suicidal was positive. This means that interaction between treatment and suicidal does not reduce the probability of depression state.

y	insomnia	guilt	suicidal	retardation	anxiety	fatigue	T	T*insomnia	T*guilt	
1	3	1	3	2	0	3	1	3	1	0.50
1	2	3	3	3	2	0	1	2	3	0.5
1	0	3	2	1	3	3	1	1	3	0.50
1	0	0	0	1	3	2	0	0	0	0.5
1	3	2	0	2	0	0	1	3	2	0.50
0	0	0	0	0	0	0	0	0	0	0.5
1	1	3	2	0	2	1	1	1	3	0.5
1	0	1	0	1	3	1	1	1	1	0.50
1	0	2	0	0	3	3	0	0	0	0.50
1	0	3	1	3	2	3	1	1	3	0.50

Table 5: Transitional probability for two symptom treatment model

0.11 The parameter estimation for treatment model with all symptoms under treatment

coefficient	mean	standard deviation	naïve error
beta0	0.0005801	0.0009807	0.00002193
beta1	0.0012168	0.0010244	0.00002291
beta2	0.0011701	0.000995	0.00002225
beta3	0.0011977	0.0010164	0.00002273
beta4	0.0011806	0.000986	0.00002205
beta5	0.0011405	0.0009925	0.00002219
beta6	0.0012272	0.0009994	0.00002235
beta7	-0.0007803	0.0009861	0.00002205
beta8	-0.0023563	0.0010039	0.00002245
beta9	0.0012345	0.0009808	0.00002193
beta10	-0.0011396	0.0009827	0.00002197
beta11	-0.0011533	0.0009419	0.00002106
beta12	0.0012278	0.0009714	0.00002172
beta13	-0.0012155	0.0009997	0.00002235

Table 6: parameters for Treatment model for all Symptoms treatment combination

From the results in table (6), it can be observed that the average value of the coefficient of β_1 was positive 0.0012168. This implies that the insomnia positively influence the probability of depression among the patient. The results of the study also indicate that the average coefficient of β_2 was positive 0.0011701. This means that the symptom quilt in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_3 was positive 0.001197. This means that the symptom suicide in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_4 was positive 0.0011806. This means that the symptom retardation in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_5 was positive 0.0011405. This means that the symptom anxiety in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of β_6 was positive 0.0012272. This means that the symptom fatigue in a patient positively influences the probability of depression among the patients. The study indicate that the average coefficient of the β_7 was -0.0007803 which is the coefficient of the medical treatment. This implies that medical treatment has a negative value thus it decreases the probability of depression among the patients. The study also investigated the effect of medical treatment on the symptoms of depression. From the results, the coefficient β_8 was equal to -0.0023563. This implies that the interaction between the medical treatment and insomnia decrease the effect of the probability on depression among the patients. The results indicate that the coefficient β_9 was equal to 0.0012345. This implies that the interaction between the medical intervention and guilt does not decreases the probability on depression among the patients. The results indicate that the coefficient $\beta_1 0$ was equal to -0.0011396. This implies that the interaction between the medical intervention and suicidal decreases the probability on depression among the patients. The results indicate that the coefficient $\beta_1 1$ was equal to -0.0011533. This implies that the interaction between the medical intervention and retardation decreases the probability on depression among the patients. The results indicate that the coefficient $\beta_1 3$ was equal to -0.0012155. This implies that the interaction between the medical intervention and fatigue decreases the probability on depression among the patients.

0.12 Transitional probability for treatment model with all symptom interaction

From table (7) , it can be observed that the coefficient of the treatment T was negative. This implies that treatment reduce the probability of depression among the patients.

0.13 CONCLUSION

From above results, the study conclude that treatment has a negative influence on probability of depression among the police patients. The study also concludes that the interaction between the treatment and the symptom influence the probability of depression among the patients. From the results, the study concludes that treatment model has only one symptom interaction between treatment and symptom insomnia influence the probability of depression among the patients. Further from the results, the study concludes that the interaction of treatment and guilt and insomnia influence the probability of depression. Finally, from the results, the study concluded

y	insomnia	guilt	suicidal	retardation	anxiety	fatigue	T	Interaction	π_{iND}^{T}
1	3	1	3	2	0	3	1	all variable	0.503974026
1	2	3	3	3	2	0	1	all variables	0.503014328
1	0	3	2	1	3	3	1	all variable	0.502050788
1	0	0	0	1	3	2	0	all variables	0.501304472
1	3	2	0	2	0	0	1	all variable	0.503028148
0	0	0	0	0	0	0	0	all variables	0.500145025
1	1	3	2	0	2	1	1	all variable	0.500884269
1	0	1	0	1	3	1	1	all variables	0.501399446
1	0	2	0	0	3	3	0	all variable	0.502505829
1	0	3	1	3	2	3	1	all variables	0.503262604

Table 7: transition probability of treatment model with all treatment symptoms combination

that the treatment model with interaction between the treatment and all the symptoms influence the probability of depression among the patients. The study also concludes 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.

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