

## Logistic Regression Model for Depression with Treatment

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### Abstract

The purpose of this study was to develop a logistic regression model for depression with treatment. Depression has been the largest mental health problem affecting public health. Early detection of people with depression is crucial for effective mitigation and treatment. This can only be achieved when clear symptoms of depression are used to detect depression in patients. Despite this problem, the treatment of depression among policemen usually faces early diagnosis challenges. To achieve this, a population of 10000 was simulated and used in this study. This study developed a logistic predictive model for police officers using the symptoms exhibited by the patient. The study also incorporated the medical intervention for depression to investigate its effect on transition probabilities. The results indicated that there were reduced transition probabilities when treatment was added to the model. The study clearly shows that the transition from normal to depression for police officers is very high: 50.3974026 per cent, and 50.3014325 per cent of transitions from the normal state to the depressed state. This means that the treatment reduces the level of transition probabilities by lowering the depression effect. The study developed a logistic regression model with treatment that was able to reduce the transition probability of depression from 0.9461 to 0.5040.

**Key terms:** Bayesian, depression, logistic, treatment, transition probability.

## 1.0 INTRODUCTION

Depression is a common mental health challenge among many individuals in society, especially among high-stress occupations such as law enforcement. According to the World Health Organisation (2020), nearly one billion people worldwide are affected by depression. According to the same report, in every 40 people, one person dies due to depression. In Kenya, police men and women are faced with unique challenges that contribute to increased levels of depression. Depression may 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 diagnosis and intervention, since the police force and even other people are reluctant to seek help when they start experiencing emotional distress, anxiety and depression (Călin et al., 2023).

Medical intervention for individuals with worsening mental health is critical to treating depression and anxiety and preventing suicide (Goldstein et al., 2021). Seeking professional medical care for people with depression has been hindered by two major barriers: stigma and access (Usmani et al., 2016). In the Kenyan context, depression represents a significant source of morbidity (Patel et al., 2019). According to Nyongesa et al. (2019), Kenya has approximately 1.9 million cases of depression, ranking 5th after South Africa, whose cases are reported to be 2.4 million; the Democratic Republic of Congo with 2.9 million cases; Ethiopia with 4.5 million cases; and Nigeria with 7.1 million cases. According to the Kenya National Commission on Human Rights, approximately 25 per cent and 40 per cent of the outpatients (individuals who visit health facilities for consultations or treatment without being admitted overnight) and inpatients (individuals who are admitted and stay in health facilities for continued care) suffer from mental illness, of which the majority of the diagnoses are depression, stress, and anxiety disorders (Marangu et al., 2021). According to Usmani et al. (2016), stigma occurs when a person deems the need to seek mental health treatment shameful. According to Ceschi et al. (2022), there is an 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 Ceschi et al. (2022), access to mental health services is another barrier due to an inability to find a provider or the high cost of available care. Recent studies have focused on mental health prevention and treatment programs (Goldstein et al., 2021).

Markov chain models have been used to evaluate and examine mental health programs, including suicide prevention models. For example, Yip et al. (2014) estimated population suicide risk as a dynamic system to evaluate the effectiveness of suicide prevention programs. Major depressive disorder has been modelled and analysed using the Markov chain model. Several Markov models successfully captured the salient characteristics of patients' states of mind. According to Oskooyee et al. (2011), the Markov chain model was introduced to handle sequences of information. Daily commotion disrupts an individual's life, which can disturb their normal state of mind. The magnitude of these disturbances determines the probability of shifting a normal person to a depressed state. According to Long and Meadow (2018), a 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 to model long-term behaviour in the depressed state.

Despite the use of the Markov model being popular, one weakness of the Markov model is the assumption that the state of mind of the person is observable and can be determined. This assumption is not always true; therefore, it is necessary to determine the best method for modelling mental health. This study

therefore develops a Bayesian hidden Markov model for modelling mental health. The study will use both numerical simulation and mathematical analysis in validation of the model. The main objective of the study was to develop a logistic regression model with treatment for predicting depression.

## 2.0 LITERATURE REVIEW

This section reviews earlier work that bears on the present study. It is organised around four questions: what is known about the burden of depression and its occurrence in Kenya; what evidence links the individual symptoms used as predictors in this study to depression; how treatment has been shown to change symptoms and outcomes; and how depression has been represented in mathematical and statistical models. For each body of work, the review notes its strengths, its limitations, its relevance to the current study and what it contributes. Two general observations frame the discussion. First, much of the clinical literature is descriptive, so it establishes that a symptom or risk factor matters but does not supply a model that turns symptoms into probabilities. Second, the modelling literature rarely targets a specific occupational group, and it seldom examines how treatment changes the contribution of individual symptoms. The studies reviewed mostly concern the general population, of which police officers are a part, and this gap motivates the present work.

### Burden and Prevalence of Depression, and the Kenyan Context

The World Health Organisation identifies depression as one of the leading contributors to the global disease burden, a point already noted in the Introduction. Lim et al. (2018) pooled community prevalence estimates from 30 countries between 1994 and 2014. The strength of this work is its breadth, since it allows comparison across regions and shows that depression is common in many societies. Its limitation, shared by most pooled estimates, is that the contributing surveys use different instruments and populations, and the results are not specific to any occupation. For the present study, the review is relevant because it establishes the scale of the problem; it does not, however, say anything about who is at greatest risk within a given workforce.

Studies in Kenya provide the local picture. Nyongesa et al. (2019) examined the prevalence and correlates of depressive symptoms among adults living with HIV in rural Kilifi; Musyimi et al. (2017) examined depression among patients under the care of traditional health practitioners, and Kumar et al. (2024) used the Global Burden of Disease Study 2019 to describe mental and substance use disorders among Kenyan adolescents and young adults. Marangu et al. (2021) surveyed the mental health literacy of primary health care workers, which is relevant to the access barriers discussed in the Introduction. Kuria et al. (2012) examined the association between alcohol dependence and depression before and after treatment for alcohol dependence, which links one of the risk factors named in the Introduction to treatment. These studies are grounded in Kenyan settings and show that depression is widespread and often accompanies other conditions. Their limitations are that each addresses a particular clinical or demographic group, that most are prevalence or correlation studies rather than predictive models, and that none concerns police officers. They are relevant because they justify the national context and the choice of treatment as a variable; the present study contributes by building a predictive model for an occupational group that these studies do not cover.

Research on police personnel is more directly relevant to the study population. Ceschi et al. (2022) profiled the psychological characteristics, emotion regulation and aggression of police applicants in a Swiss cross-sectional study. The study is valuable because it focuses on policing and treats psychological vulnerability

as measurable. It is limited by its cross-sectional design, by its focus on applicants who have not yet served, and by its setting, which differs from the Kenyan police service. It shows that police recruits can be studied as a distinct group, but it does not follow officers through states of depression over time, which the present model does.

## **Depression Symptoms Used as Predictors**

The logistic component of the model uses observable symptoms as predictors of the latent depression state. The evidence for each symptom is reviewed below.

- **Insomnia**

The strongest quantitative evidence comes from the meta-analysis of Baglioni et al. (2011), which pooled longitudinal epidemiological studies and reported an overall odds ratio of 2.60 (95% confidence interval 1.98 to 3.42) for insomnia predicting later depression. Its strengths are the longitudinal designs, which support a temporal ordering, and the precision of the pooled estimate. Its limitations are that the definitions of depression and insomnia varied between studies, that the subgroup analysis was restricted mainly to age groups, and that a pooled odds ratio describes a population-level association rather than an individual's probability of moving into a depressed state. Geoffroy et al. (2018) examined insomnia and hypersomnia in major depressive episodes in a population-based sample, and Batterham et al. (2012) followed a cohort prospectively to study sleep disturbance, personality and the onset of depression and anxiety. Together, these studies support the inclusion of insomnia as a predictor. The present study builds on them by converting the association into a transition probability that can be computed for each officer.

- **Guilt**

Tilghman-Osborne et al. (2010) reviewed how guilt is defined and measured and found little theoretical discussion of what makes guilt excessive or inappropriate, with definitions varying across studies. The strength of the review is that it exposes this conceptual weakness; its limitation is that it offers no predictive model. Alexander et al. (1999) studied shame and guilt in a depressed sample, which is useful for separating guilt from related emotions, although the sample was clinical and the study did not model transitions between states.

These works are relevant because they warn that guilt must be measured with care, and the present study handles this by recording guilt on a graded severity scale.

- **Suicidal Ideation, Stress and Resilience**

Yip et al. (2014) represented suicide risk in a population as a dynamic system using a Markov chain, and Goldstein et al. (2021) examined whether states with greater mental health treatment capacity had lower youth suicide rates. The first is a useful precedent for applying Markov models to suicide dynamics, but it works at the population level and does not use individual symptom profiles. The second links treatment capacity to outcomes, but it is ecological and concerns adolescents and young adults, not working adults in a high-stress occupation. Rutter (1985) described protective factors and resilience in the face of adversity, which helps to explain why people exposed to the same stressors differ in outcome. Resilience is difficult to measure from routine clinical data and is not included among the predictors here, which is a limitation the present study shares with most symptom-based models.

- **Psychomotor Retardation**

Sobin and Sackeim (1997) reviewed psychomotor symptoms of depression, and Dantchev and Widlöcher (1998) discussed how retardation is measured. Wüthrich et al. (2022) synthesised actigraphic studies of psychomotor slowing in depression in a systematic review and meta-analysis. The strength of this group of studies is that retardation is established as a core clinical feature and can be measured both by clinical rating and objectively. Their limitation is that they are descriptive and measurement-oriented; they do not estimate how retardation contributes to the probability of depression alongside other symptoms. This is the contribution the logistic model makes.

- **Anxiety**

Thase (2011) reviewed treatment-resistant depression, and Ionescu et al. (2013) reviewed the neurobiology of anxious depression. Both stress that anxiety and depression frequently occur together and that this comorbidity complicates treatment. Their strength is clinical depth, but they concentrate on treatment-resistant or clinical samples, so their findings may not carry over to officers who have not yet sought care. Their relevance is that they support including anxiety as a predictor and anticipating that its relationship with treatment may be complex, which the treatment-by-symptom interaction terms in this study are designed to examine.

## **Treatment and Its Effect on Symptoms**

Evidence on treatment is usually reported as average symptom change or response rates. Edinger et al. (2023) studied objective sleep duration and response to combined pharmacotherapy and cognitive behavioural therapy for insomnia in patients with both depression and insomnia, and Kuria et al. (2012) reported depression before and after treatment for alcohol dependence in a Kenyan sample. Demic and Cheng (2014) modelled the dynamics of disease states in depression and used the model to compare treatment approaches. These studies are strong in that they follow patients through treatment and, in the latter case, connect treatment to a formal model. Their limitations are that treatment is usually modelled as a single effect, that samples come from particular clinical populations, and that none estimates how treatment changes the effect of each separate symptom on the probability of depression. This is the point at which the current study contributes: it introduces a treatment indicator and its interactions with individual symptoms, so that the model can show whether treatment reduces the influence of a particular symptom as well as the overall probability.

## **Mathematical and Statistical Modelling of Depression**

Ali et al. (2024) formulated a compartmental model of social media addiction and depression and analysed its equilibrium points, reproduction number, bifurcation behaviour and sensitivity. Nivetha et al. (2025) developed a model with optimal control of depression dynamics influenced by saboteurs, and Best et al. (2010) built a mathematical model of serotonin synthesis, release and reuptake. These models are analytically rigorous and allow control strategies and long-term behaviour to be studied. Their limitations are that they work with aggregate compartments or biochemical pathways, depend on parameters that are hard to estimate from individual-level data, and are not specific to an occupational group. They are relevant as a contrast: the present study models individual symptom profiles and estimates its parameters from data. Oskooyee et al. (2011) used a Markov chain to predict the severity of major depression, Yip et al. (2014) used one for suicide dynamics, and Long and Meadows (2018) reviewed simulation modelling in mental health.

Brailsford et al. (2009) analysed the academic literature on simulation and modelling in health care. The main strengths of Markov models are their simplicity and the direct interpretation of transition probabilities. Their main weakness, noted in the Introduction, is the assumption that the person's state of mind is observed without error, which seldom holds for a condition that is diagnosed from symptoms and is often hidden. Two-state formulations also give limited insight into long-term behaviour. These models are the direct basis of the present work, and the hidden Markov formulation used here relaxes the assumption of an observable state. Cramer et al. (2016) treated major depression as a complex dynamic system of interacting symptoms, and Guloksuz et al. (2017) discussed the pitfalls and promise of network methods in mental disorders. Van Loo et al. (2012) reviewed data-driven subtypes of major depressive disorder. These approaches are strong in capturing the heterogeneity of depression and the way symptoms reinforce each other. They are less suited to prediction for a specific group, and network estimates are sensitive to modelling choices, as Guloksuz et al. (2017) discuss. Bzdok and Meyer-Lindenberg (2018) described the opportunities and challenges of machine learning for precision psychiatry.

Such methods can improve prediction, but a logistic model keeps coefficients that a clinician can interpret directly, which matters when the model is intended to support a doctor's judgement. Gamerman and Lopes (2006) present Markov chain Monte Carlo methods for Bayesian inference. Their strength is that posterior distributions can be approximated even when they cannot be written in closed form, which is the situation for the logistic model with treatment interactions. The cost is computational effort and the need to check convergence. This literature is relevant because it underpins the Gibbs sampling procedure used to estimate the model parameters.

## Research Gap and Contribution of the Current Study

The review shows that depression is well described clinically and that each symptom used here has an established association with it. It also shows that Markov and other dynamic models have been applied to depression and suicide. Three gaps remain. First, existing models rarely use observable symptoms to predict a hidden depression state while allowing for the fact that this state is not directly observed. Second, little work has modelled how treatment changes the effect of individual symptoms on the probability of depression. Third, almost no work has targeted police officers, particularly in Kenya, where stigma and limited access to care delay diagnosis. The present study responds to these gaps by developing a Bayesian logistic model for the observable symptoms within a hidden Markov framework, by adding a treatment indicator and treatment-by-symptom interactions, and by estimating the parameters through Gibbs sampling on a simulated population of police officers. Because the reviewed literature concerns the general population, the model is also expected to be applicable to other occupational groups.

## 3.0 METHODOLOGY

### 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  $\text{dom}(X) = \{x_1, x_2, \dots, x_k\}$ , such that  $x \in \text{dom}(X)$  each is called a latent (or hidden) state. The latent state comprises of the mental state of depression (D) or Normal (N). We denote  $Y_1, Y_2, \dots, Y_m$  as the set of observable variables, such that the  $i^{\text{th}}$  observation  $Y_i$  takes values on some set

$\text{dom}(Y_i)$ . 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  $\{0, 1, \dots, T\}$ , 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. The depression state is declared when the patient has a value of the symptom greater than or equal to one, while the normal state is said to be there when all the symptoms have zero score.

## Markov Chain Monte Carlo sampling (MCMC)

Markov Chain Monte Carlo (MCMC) is an increasingly popular method for characterising distributions, especially for estimating posterior distributions in Bayesian inference. MCMC is a computer-driven sampling method (Kumar et al., 2012). It lets you characterise a distribution without knowing all its mathematical properties by randomly sampling values from it. 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 a distribution's properties by examining random samples from it. For instance, instead of finding the mean of a normal distribution by calculating it directly from the distribution's equations, a Monte Carlo approach would be to draw a large number of random samples from the distribution and calculate their sample mean. 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 means the random samples are generated by a sequential process. MCMC is particularly useful in Bayesian inference because it focuses on posterior distributions, which are often difficult to analyse analytically. In these cases, MCMC lets users approximate aspects of posterior distributions that cannot be calculated directly. This study will employ the Gibbs sampling algorithm. In statistics, Gibbs sampling is a Markov chain Monte Carlo (MCMC) algorithm that generates a sequence of observations drawn 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 randomised algorithm and is an alternative to deterministic algorithms for statistical inference such as the expectation-maximisation algorithm (EM). As with other MCMC algorithms, Gibbs sampling generates a Markov chain of samples, each of which is correlated with nearby samples.

## 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.

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

$u_j$  is assumed to be normally distributed. In either case, we estimate the coefficients  $\beta_1, \beta_2, \dots, \beta_k$  where  $I$  is the number of possible outcomes.

The independent variables  $x_{1j}, x_{2j}, \dots, x_{kj}$  are the observable depression symptoms which includes;  $x_{1j}$  = Anxiety,  $x_{2j}$  = Retardation,  $x_{3j}$  = Insomnia,  $x_{4j}$  = Suicidal, and  $x_{5j}$  = Guilt  $x_{6j}$  = fatigue. The model will comprise of the following observable variables

$$P(\text{Outcome}_{i=i}) = P(k_{i=1} < \beta_1 x_{1j} + \beta_2 x_{2j} + \beta_3 x_{3j} + \beta_4 x_{4j} + \beta_5 x_{5j} + \beta_6 x_{6j} + \mu_i)$$

## 4.0 FINDINGS AND DISCUSSION

### The Statistical Model to Predict Depression with Treatment

The main purpose of treatment is to completely eradicate the disease. This can only be achieved if the patient receives treatment over time. The efficiency 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 psychiatrist 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 is an indicator variable with values of 0 and 1. Then, this indicator variable follows a Bernoulli distribution and can be presented as follows;

Each symptom was measured at four levels. The treatment-symptom combination can be presented as follows;

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

Each symptom was measured as four level  $(0 = \text{notpresent}, 1 = \text{mild}, 2 = \text{moderate}, \text{and } 3 = \text{severe})$ .

The treatment, symptom combination can be presented as follows;

**Table 1: Treatment Symptoms Combination**

|         |            | 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)     |

The table gives the treatment-symptom combination at different levels of symptom. From the table, the combination implies that the patient had no symptoms and did not receive treatment. The combination implies that the patient had a mild symptom and did not receive treatment. The combination implies that the patient had severe symptoms and also received treatment. This was extended to all the symptoms when treatment was given to the patient, and hence the transition probability computed as presented in the next section.

## Model with Treatment

We define the transitional probability  $\pi_{iND}(x_1, x_2, \dots, x_6)$  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;

$$\pi_{iND}^T(x_1, x_2, \dots, x_6, T, Tx_i)$$

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 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.

$$\pi_{iND}^T(x_1, x_2, \dots, x_6, T, Tx_i, Tx_k)$$

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  $(x_1, x_2, \dots, x_6)$  and treatment  $T$ . Thus equation (3.9) become;

$$\pi_{iND}^T(x_1, x_2, \dots, x_6, T, Tx_1, Tx_2, \dots, Tx_6)$$

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.

## Posterior with Treatment Model

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

$$\text{pr}(Y_1, Y_2, \dots, Y_n | x_1, x_2, \dots, x_6, T, Tx_1) = \pi_{iND}^T(y_i)(1 - \pi_{iND}^T(.))^{1-y_i}$$

For  $n$  police officers (3.12) becomes

$$\begin{aligned} \prod_{j=1}^n \text{pr}(Y_1, Y_2, \dots, Y_n | x_1, x_2, \dots, x_6, T, Tx_1) &= \prod_{j=1}^n \pi_{iND}^T(y_i)(1 - \pi_{iND}^T(.))^{1-y_i} \\ \prod_{j=1}^n \text{pr}(Y_1, Y_2, \dots, Y_n | x_1, x_2, \dots, x_6, T, Tx_1) &= \pi_{iND}^T(\sum_{i=1}^n y_i)(1 - \pi_{iND}^T(.))^{n - \sum_{i=1}^n y_i} \end{aligned}$$

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;

$$f(\beta|X_1, X_2, \dots, X_6, T, TX_i) \propto \pi_{iND}^T \prod_{j=1}^6 \frac{1}{\sigma_j \sqrt{2\pi}} \exp\left(\frac{-(\beta_j - \mu_0)^2}{2\sigma_j^2}\right)$$

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;

$$\begin{aligned} & f(\beta|X_1, X_2, \dots, X_6, T, TX_i, TX_k) \\ & \propto \pi_{iND}^T \prod_{j=1}^6 \frac{1}{\sigma_j \sqrt{2\pi}} \exp\left(\frac{-(\beta_j - \mu_0)^2}{2\sigma_j^2}\right) \end{aligned}$$

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

$$\begin{aligned} & \prod_{j=1}^n \text{pr}(Y_1, Y_2, \dots, Y_n | x_1, x_2, \dots, x_6, T, TX_1, TX_2) \\ & = \prod_{j=1}^n \pi_{iND}^T \prod_{j=1}^6 \frac{1}{\sigma_j \sqrt{2\pi}} \exp\left(\frac{-(\beta_j - \mu_0)^2}{2\sigma_j^2}\right) \\ & \prod_{j=1}^n \text{pr}(Y_1, Y_2, \dots, Y_n | x_1, x_2, \dots, x_6, T, TX_1, TX_2) = \\ & \pi_{iND}^T \prod_{j=1}^6 \frac{1}{\sigma_j \sqrt{2\pi}} \exp\left(\frac{-(\beta_j - \mu_0)^2}{2\sigma_j^2}\right) \end{aligned}$$

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;

$$f(\beta|X_1, X_2, \dots, X_6, T, TX_1, TX_2, \dots, TX_6) \propto \pi_{iND}^T \prod_{j=1}^6 \frac{1}{\sigma_j \sqrt{2\pi}} \exp\left(\frac{-(\beta_j - \mu_0)^2}{2\sigma_j^2}\right)$$

## Metropolis Gibbs Sampling

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

- set the initial values of the parameter

$$\beta^{(0)} = (\beta_0^{(0)} = 1, \beta_0^{(1)} = 1, \dots, \beta_0^{(13)} = 1)$$

- b. Set the number of desired iterations L
- c. At the iterations s the values if  $\beta_j; j = 1, 2, \dots, 13$  is updated as follows
- d. sample  $\beta_0^{(s)} \sim f(\beta_0 | \beta_1^{(s-1)}, \beta_2^{(s-1)}, \dots, \beta_{13}^{(s-1)})$
- e. sample  $\beta_1^{(s)} \sim f(\beta_1 | \beta_0^{(s-1)}, \beta_2^{(s-1)}, \dots, \beta_{13}^{(s-1)})$
- f. sample  $\beta_{13}^{(s)} \sim f(\beta_{13} | \beta_0^{(s-1)}, \beta_1^{(s-1)}, \dots, \beta_{12}^{(s-1)})$

## 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.

*Parameter of one symptom treatment model*

**Table 2: Parameter of the Model**

| 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  |

From the results in table (2), it can be observed that the average value of the coefficient of  $\beta_1$  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  $\beta_2$  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  $\beta_3$  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  $\beta_4$  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  $\beta_5$  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  $\beta_7$  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.

## Transitional Probability for Treatment Model with One Symptom Interaction

From the table, it can be observed that the coefficient of the treatment T was negative. This implies that treatment reduces 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 reduces the probability of transition.

**Table 3: Transition Probability of Treatment Model**

| Y | insomnia | guilt | suicidal | retardation | anxiety | fatigue | T | T*insomnia | $\pi^T_{table}$ |
|---|----------|-------|----------|-------------|---------|---------|---|------------|-----------------|
| 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     |

## The Parameter Estimation for Treatment Model with two Symptoms Under Treatment

The table gives the results of the coefficients of the treatment model. Table 4 shows the mean estimate of the coefficient, the standard deviation, and the naive error.

**Table 4: Parameter for Two-Treatment Model**

| 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  |

From the results in table 5, it can be observed that the average value of the coefficient of  $\beta_1$  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  $\beta_2$  was positive 0.001173. This means that the symptom guilt in a patient positively influences the probability of depression among the patients. The results of the study also indicate that the average coefficient of  $\beta_3$  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  $\beta_4$  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  $\beta_5$  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  $\beta_6$  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  $\beta_7$  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 guilt does not decreases the probability on depression among the patients.

## Transitional Probability for Treatment Model With Two Symptom Interaction

From the table, it can be observed that the coefficient of the treatment T was negative. This implies that treatment reduces 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 the probability of transition. Finally, the results indicate

that the coefficient of interaction between treatment and suicidal was positive. This means that the interaction between treatment and suicidal does not reduce the probability of the depression state.

**Table 5: Transitional Probability for two Symptom Treatment Model**

| y | insomni<br>a | guil<br>t | suicida<br>l | retardatio<br>n | anxiet<br>y | fatigu<br>e | T | T*insomni<br>a | T*guil<br>t | $\pi_{IND}^T$   |
|---|--------------|-----------|--------------|-----------------|-------------|-------------|---|----------------|-------------|-----------------|
| 1 | 3            | 1         | 3            | 2               | 0           | 3           | 1 | 3              | 1           | 0.50450352<br>3 |
| 1 | 2            | 3         | 3            | 3               | 2           | 0           | 1 | 2              | 3           | 0.50448319      |
| 1 | 0            | 3         | 2            | 1               | 3           | 3           | 1 | 1              | 3           | 0.50414626<br>5 |
| 1 | 0            | 0         | 0            | 1               | 3           | 2           | 0 | 0              | 0           | 0.50195664      |
| 1 | 3            | 2         | 0            | 2               | 0           | 0           | 1 | 3              | 2           | 0.50299717<br>9 |
| 0 | 0            | 0         | 0            | 0               | 0           | 0           | 0 | 0              | 0           | 0.5001489       |
| 1 | 1            | 3         | 2            | 0               | 2           | 1           | 1 | 1              | 3           | 0.50297405      |
| 1 | 0            | 1         | 0            | 1               | 3           | 1           | 1 | 1              | 1           | 0.50233520<br>3 |
| 1 | 0            | 2         | 0            | 0               | 3           | 3           | 0 | 0              | 0           | 0.50254887<br>8 |
| 1 | 0            | 3         | 1            | 3               | 2           | 3           | 1 | 1              | 3           | 0.50413426<br>6 |

## The Parameter Estimation for Treatment Model with All Symptoms Under Treatment

**Table 6: Parameters for Treatment Model for All Symptoms Treatment Combination**

| 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  |

From the results in table 6, it can be observed that the average value of the coefficient of  $\beta_1$  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  $\beta_2$  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  $\beta_3$  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  $\beta_4$  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  $\beta_5$  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  $\beta_6$  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  $\beta_7$  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  $\beta_8$  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  $\beta_9$  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  $\beta_{10}$  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  $\beta_{11}$  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  $\beta_{13}$  was equal to -0.0012155. This implies that the interaction between the medical intervention and fatigue decreases the probability on depression among the patients.

### **Transitional Probability for Treatment Model with All Symptom Interaction**

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

**Table 7: Transition Probability of Treatment Model with All Treatment Symptoms Combination**

| Y | insomnia | guilt | Suicidal | retardation | anxiety | fatigue | T | Interaction   | $\pi_{IND}^T$ |
|---|----------|-------|----------|-------------|---------|---------|---|---------------|---------------|
| 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   |

## 5.0 CONCLUSION

**Conclusion:** The study had the following assumptions. Symptoms are observable and measurable. The six symptoms—insomnia, guilt, suicidal ideation, psychomotor retardation, anxiety, and fatigue can be observed or assessed reliably for each police officer by a qualified mental-health professional or a validated screening instrument. Symptoms are measured on an ordinal severity scale. Each symptom is recorded on a common four-level scale: 0 = no symptom, 1 = mild symptom, 2 = moderate symptom, 3 = severe symptom. This assumes that a higher score represents greater symptom severity. Presence of one or more symptoms indicates depression risk. An officer with all symptom scores equal to zero is classified as being in the normal state N. If at least one symptom score is above zero, the officer is regarded as having depressive symptoms and is classified as being at risk of, or in, the depression state D. From the results, the study concludes that treatment has a negative influence on the probability of depression among the police patients.

The study also concludes that the interaction between the treatment and the symptom influences the probability of depression among the patients. From the results, the study concludes that the treatment model that has only one symptom interaction between treatment and symptom insomnia influences the probability of depression among the patients. Further, the study concludes that the interaction of treatment and guilt and insomnia influences the probability of depression. Finally, from the results, the study concluded that the treatment model with interaction between the treatment and all the symptoms influences the probability of depression among the patients. The study also concludes that a medical doctor can use the predictive model to predict patients' depression status, given the observable symptoms. This can be evaluated further if real data is applied to the model.

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