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Master Thesis
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Abstract

Malaria is a life threatening disease that has adverse effects on child development. The effects include absenteeism from school and pains associated with malaria. This paper investigates risk factors associated with malaria in children using logistic regression and generalized linear mixed effect model(GLMM).The study used secondary data derived from Kenya Malaria Indicator Survey (KMIS) conducted in 2015. Based on Akaike information criterion (AIC), GLMM model results to a better fit compared to logistic regression. The study revealed that age, place of residence, level of anemia, wealth quintile, availability of electricity and cluster altitude were significant predictors of malaria.In addition, the findings revealed that access to radio and television by households result to reduction in malaria prevalence.

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Declaration and Approval

I the undersigned declare that this dissertation is my original work and to the best of my knowledge, it has not been submitted in support of an award of a degree in any other university or institution of learning.

Signature   Date

ABUGA JAMES GEKARA
Reg No. I56/82459/2015

In my capacity as a supervisor of the candidate's dissertation, I certify that this dissertation has my approval for submission.

Signature   Date

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Dedication

This research paper is dedicated to my family.

Contents

Acknowledgments

Glory to the Almighty God for seeing me through my post graduate studies. My profound gratitude goes to Kenya National Bureau of Statistics for financing my post graduate studies. I would also, with deep appreciation thank the Kenya National Bureau of Statistics for providing me the data for this research.

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Abuga James Gekara

Nairobi, 2017.

1 Introduction

1.1 Background of the study

Malaria is a parasitic disease caused by a protozoan of the genus Plasmodium. The disease is caused by Plasmodium vivax, Plasmodium Ovale, Plasmodium malariae and Plasmodium falciparum in humans. Plasmodium falciparum is the common species in Africa. Malaria parasite require a human host to complete its life cycle. Bites of infected mosquito are the means of transmission of the parasite between two hosts. Persons residing in areas experiencing high cases of malaria are more likely to be infected by the disease.

The occurrence of malaria has a substantial effect at the national and individual level. There is strong correlation between malaria and poverty. Countries experiencing high cases of malaria are generally characterized with low economic growths compared that are malaria free. Research by Malaney et al 2004 observed that countries having high malaria prevalence recorded lower economic growths compared to their counterparts having few cases. In high endemic countries, malaria is attributed to a reduction in economic growth by more than one percentage point per year. Countries experiencing high cases of malaria will in the long run lag behind in economic development relative to malaria free countries. Research by Gallup and Sach 2001 revealed that a 10% reduction in occurrence of malaria was associated with 0.3 per cent increase in economic growth. At the individual level, Chuma et al 2006 showed that mean the direct costs of malaria accounted for 7.1% and 5.9% of total household expenditure during wet and dry season respectively. The expenditure was high during the wet season mainly due to provision of favorable condition for the spread of the parasite.

Globally, 212 million new cases of malaria were reported in 2015. In the same year 429,000 lives were lost mainly young children from Africa. The disease results to death of a child every 2 minutes. World Health Organization estimates that 90% of malaria cases and 92% of death associated with malaria were reported in Africa. In Sub Saharan Africa, it is estimated that 114 million people are infected with the disease. The highest proportion being children aged 2-10 years. Malaria is associated with malnutrition in children which eventually lead to about 50% of deaths among children among children aged below 5 years. (WHO 2016).

In Kenya, 75% of the population is at risk of malaria. The population at risk of contracting the disease comprise of young children, pregnant mothers and chronically ill persons. The

Kenya Malaria Indicator Survey (KMIS) conducted in 2015 revealed that children aged 5-14 years have higher chances of contracting malaria. Results of malaria rapid diagnostic test revealed that the prevalence of malaria was high among children aged between 5-9 years while the finding of the microscopy test indicated that prevalence was high in children aged 10-14 years. The results of the survey revealed that the burden of malaria is shifting from children aged less than 5 years to those aged above 5years. It further demonstrated that the interventions that have been undertaken by the government and donors mainly targeting children aged below 5 years are paying off. Children aged 5 years and above act as a reservoir for the transmission of the parasite. This is partly attributed to irregular use of bed nets by children aged 5-14 years.

Kenya is categorized into 4 malaria zones namely: Lake Victoria and the coast region; arid and semi-arid areas; western highlands and low risk malaria areas. Favorable climatic conditions in the Lake Victoria and coast regions make the spread of the parasite fast. Arid and semi-arid parts of the country experience hot temperatures. The main economic activity of communities in this region is rearing cattle. During the dry season, the animals leave depressions on the ground which acts as breeding sites for the malaria vector when the rainy season begins. In the highlands of western Kenya, the spread of malaria is experienced when the average temperature is around 180c. Increase in minimum temperature during long rains favors the vector breeding. In the minimal risk areas, increase in temperature result to conducive condition for the vector to breed.

The burden associated with malaria is reduced by using antimalarial drugs and protection from mosquito bite. Control initiatives have received greater attention due to increased funding from development partners. The main intervention used at the community level is vector control. The two major types of malaria control strategies are the use of treated nets and indoor residual spraying (IRS). The preferred treated nets are the long lasting insecticide nets (LLINs). The World Health Organization recommends that all persons at risk of contracting malaria should be targeted by malaria control initiatives. The population at risk can be covered by providing insecticide treated nets at no cost so that everyone sleeps under a net each night. Indoor residual spraying is an effective method of reducing the transmission of malaria substantially. The intervention is effective when 80% of the targeted area is sprayed. The other control measures include; use of mosquito coils and repellants, and intermittent preventive treatment (IPT). Intermittent preventive treatment reduces maternal malaria incidences and neonatal mortality.

1.2 Statement of problem

Malaria control interventions have been implemented to attain United Nations and roll back malaria targets. Despite the various efforts that have been put in place, the burden of the disease is still being felt among children. Past studies on prevalence of malaria in Kenya among children link socioeconomic, socio-demographic and environmental factors as well as awareness of malaria with occurrence of the disease. Previous studies on the prevalence of malaria have mainly utilized logistic regression model ignoring the effect of correlation of observations. To determine the likelihood of contracting malaria from predictors containing observations that are correlated; estimates derived from generalized linear mixed effect model (GLMM) are better than those derived from logistic regression model. Therefore, this study examines the socioeconomic, demographic and environmental factors associated with prevalence of malaria in children using logistic regression and GLMM.

1.3 Objectives

1.3.1 General Objective

The main objective is to determine risk factors associated with occurrence of malaria among children in Kenya.

1.3.2 Specific Objectives

- To determine the socioeconomic factors associated with occurrence of malaria among children.
- To determine the demographic factors associated with occurrence of malaria among children.
- To determine the environmental factors associated with occurrence of malaria among children.
- To compare logistic regression and generalized linear mixed model

1.4 Significance of the study

Prevalence of malaria is high among children aged 5-14 years relative to those aged less than 5 years. The study is designed to understand factors that increase the prevalence of the disease. Analysis from the study will provide information that will be useful to policy makers and household's heads to determine the best intervention to use to reduce the burden of the disease. This study will focus on children aged between 6 months and 14 years to determine the factors associated with malaria prevalence using logistic regression and GLMM. The study will provide insight regarding the appropriate model to use when handling data with correlated observation. The study will also add to the existing literature on malaria control in Kenya.

1.5 Limitation of the study

The dataset had gaps in some important variables such as level of education of the mother and number of bed nets. The variables were not included in the analysis despite being significant in determining the prevalence of malaria in children.

2 Literature Review

2.1 Introduction

Malaria is a major cause of death in children. The disease can be linked to a dynamic interaction of socioeconomic, demographic, environmental and sociocultural risk factors with other health determinants. This chapter explores the health seeking behavior and risk factors associated with the disease.

2.2 Health seeking behaviour

2.2.1 Prevention

Several interventions have been initiated in malaria prone areas to reduce morbidity and mortality of the disease. The interventions have led to substantial reduction of malaria cases. There is strong evidence that regular use of treated nets lowers the risk of malaria at the individual level. In their study on the net benefit, lim et al 2011 found out that the use of ITN's resulted in significant reduction in child mortality. The findings also revealed that increasing the coverage of ITN in several countries led to decrease in child mortality. Research by Atieli et al 2011 showed that the usage of ITN was low among school age children exposing them to higher risk of contracting malaria. In a similar study, Walldorf et al 2015 found that children attending school used bed nets less often compared to other age groups. The less usage of mosquito nets by this category leaves them exposed to higher risk of mosquito bites. Research by Ncogo et al 2015 revealed that children who do not use bed nets were 2 times more likely to contract malaria compared to their counterparts using bed nets.

Indoor residual spaying implemented at the community level result in significant reduction of malaria risk. A study by Zhou et al 2010 revealed that cases of malaria among school age children reduced by 64.4% and 46.3% in the intervention valley and uphill area, respectively. This resulted in overall reduction of malaria prevalence by 50%.

2.2.2 Treatment

A study by M Nyamongo and Nyamongo IK 2006 revealed that mothers classify illnesses into 4 categories. The categories are; not serious, serious but not life threatening, sudden and serious and chronic. The classification of illness enables the mother to take the necessary remedial action. The study further indicated that private health facilities were more compared to public health facilities. This was partly attributed to the perception that the facilities offer better health services. In a similar study, Deressa et al 2008 observed that people prefer private clinics though they charge prohibitive cost mainly due to perceived high quality of services they offer. However, research by Munguti 1998 showed that patients prefer public health facilities when seeking treatment mainly due to low cost charged at the facilities. In cases where the disease persisted, the patients sought treatment in private health facilities or used medicinal plants. Research by Nyamongo IK 2002 revealed that patients begin with self-treatment to minimize expenses on the treatment of the disease. In addition, the findings showed that expenses on fever episodes consume between 9% and 15% of available resources in young children.

In their study on malaria related belief and behavior in Southern Ghana, Ahorlu et al 1997 found out that home treatment of malaria using herbs, over the counter drugs and wrong dosage of chloroquine was widespread in the region. Majority of the caretakers of children aged 1-9 year were female and their illiteracy level was high. Some people consider malaria to be an ordinary disease. Complications associated with malaria were treated by traditional healers. The research further revealed that the choice of drugs was based on past prescription of the disease and advice from family members. Fathers had a considerable influence on where their children sought treatment compared to mothers (Falade et al, 2006). Tolhurst and Nyonator (2006) observed that women who didn't receive economic support from their husbands or male relatives faced challenges in accessing health care for their children.

Research by Amin et al 2003 showed that 2655 fevers were observed among 6287 children sampled from four districts in Kenya. There was a considerable number of fevers that were not treated (28.1%) across all the four selected districts. The finding revealed that the median delay in accessing treatment was 2 days. A paltry 2.3% of the fever was treated within 24 hours of the onset of the fever with the recommended drug for uncomplicated malaria. In a similar study by Mota et al 2009, the findings revealed that informal sector services result to cost savings though it is associated with health risk of inadequate prescription to young children. Research by Lindelow 2005 on the utilization of health care in Mozambique revealed that utilization differed considerably across social economic groups. The analysis indicated that income was not a significant factor for determining the preference of health facility. On the contrary, the findings pointed out that education and physical access were significant factors for health care selection.

2.3 Socioeconomic factors

Yadav et al 2014 revealed that lower income, house type, distance to health Centre, awareness of malaria and use of mosquito nets were correlated with occurrence of malaria. The study further observed that improving the economic status and increasing awareness about malaria prevention measures would decrease the occurrence of malaria. However, the study indicated that there was no significant association between education level and malaria occurrence.

Roberts and Mathews 2016 carried out a study using generalized linear mixed model to establish factors associated with malaria in children. The analysis revealed that main construction material of the floor and wall and access to electricity were the socioeconomic factors closely related to risk of malaria. The findings further revealed that that older children were more probable to contract malaria though their risk decreased with increase in altitude and mother's education level.

Research carried out by Ayele et al 2012 using generalized linear models indicated that source of water, type of toilet facility, number of sleeping rooms, construction material of wall an roof material construction material of the wall and roof were significant predictors of malaria occurrence. Household having access to clean water reported low cases of malaria. Children residing in houses having hatch roof and earth floor had higher risk of suffering from malaria. The findings of the study indicated that source of drinking water and housing condition had a two-way interaction effects.

Malaria is associated with poverty and poor living condition. Research by Odaga J 2004 to investigate health inequality in Uganda revealed that children from rich families were less likely to suffer from malaria. The researcher showed that household in the poorest wealth quintile were 2.4 times more likely to suffer ill health compared to their counterparts in the richest quintile. Children from wealthy backgrounds access better health care services and own mosquito nets. Poor households live in dwellings that can hardly protect them from mosquito bites and seldom acquire insecticide treated nets.

2.4 Demographic factors

In their study on prescription patterns of antimalarial drugs in children below five years, Etuk et al 2008 found out that malaria cases were more in males compared to female. This was partly attributed to males being biological more likely to contract infectious diseases relative to females. Occupation of household members have an influence on malaria prevalence. Research by Incordona et al. 2007 in Cambodia revealed that male involved in forest activities are exposed to considerable risk of contracting malaria. Children residing in forest areas are more likely to contract malaria.

Research by Pinchoff et al 2016 showed that malaria prevalence was high among children aged 5-15 years. The high prevalence in this age category was attributed to discrimination in the distribution of mosquito net in favor of pregnant women and young children. As children become older, the usage of bed net decreases. The results of a study by Walldorf et al 2015 revealed that children aged between aged 6-15 years were 4.8 times more likely to suffer from malaria relative to those aged less than 5 years. A study by Noor et al 2009 revealed that school age children were less likely to sleep under a net. They represented the highest proportion of between 38% and 42% of those at risk of being bitten by mosquitoes.

2.5 Environmental

The environment plays a pivotal role in the health of a community. However, in some countries the environment has received less emphasis. Environmental factors that increase the prevalence of malaria are temperature, rainfall, humidity, poor water and sanitation infrastructure. In tropical areas, cases of malaria increase during rainy season due to favorable condition for breeding of the parasite. Mosquitoes require long time for them to complete their life cycle. Environmental factors that hamper the life cycle of the parasite affect the prevalence of malaria. Temperature affects the rate of multiplication of mosquitoes. As a result, this affects the rate at which salivary secretion is infected and eventually the probability of successful transmission to another host (Reiter 2001). Marquins et al 2015 carried out a study to investigate the relationship between rainfall and temperature on malaria or anemia mortality in western Kenya among children aged less than five years. Findings of the study confirmed that malaria mortality was associated with changes in temperature and rainfall. Asiedu and Okwabi 2014 found out that place of residence was a significant predictor of childhood malaria prevalence.

In Equatorial Guinea, prevalence of malaria was higher in rural areas compared to urban setting (Ncogo et al 2015). Children living in rural areas are exposed to high risk of contracting malaria. Rural areas are associated with open fields, stagnant water pools and green vegetation which provide favorable breeding site for mosquitoes especially during the raining season. Children are exposed to mosquito bites during the day as they accompany their parents to the farms. On the other hand, urban dwellers create favorable condition for the spread of the parasite by poor waste disposal and not taking care of bushes around the residual areas.

2.6 Sociocultural

Sociocultural factors affect the uptake and treatment of malaria in some communities. The people who are mainly affected are those occupying the low socioeconomic stratum. Households in the low socioeconomic stratum adhere to their customs at the expense of their health. This was confirmed by a study conducted by Yadav et al 2007 which indicated that a third of the respondents had neither taken treatment for malaria nor participated in the vector control programs. This was mainly due to their perception that malaria bites are harmless and regarded the disease as mild. The other factors that contributed to the increase in prevalence of the disease in the area included; outdoor sleeping habits, sharing beds with children and a feeling of suffocation while using mosquito nets.

3 Methodology

3.1 Introduction

This chapter highlights an overview of logistic regression and generalized linear mixed effect model. GLMM handles observations that are correlated by incorporating the random effect in the model. The chapter also highlights the approximation techniques used in estimating GLMM model

3.2 Data collection

The study utilized secondary data derived from Kenya Malaria Indicator Survey (KMIS). The sample for the survey was drawn from the four epidemiological zones of the country (highland epidemic, endemic, semi-arid and low risk malaria areas). The sampling frame for the study was the fifth National Sample Survey and Evaluation Programme (NASSEP V). The frame is created and maintained by KNBS.The frame is divided into four sub samples. KMIS sample was drawn from one of the sub samples.

Data was collected using a two-stage cluster stratified sampling design. In the first stage, 246 clusters were selected with equal probability from NASSEP V comprising of 131 rural and 115 urban clusters. In the second stage, 30 households were selected using systematic sampling from each of the selected clusters. Data was collected using questionnaires which were programmed into the computer to ease data collection and expedite data analysis. The survey used three types of questionnaires namely; household questionnaire, a woman questionnaire and a biomarker questionnaire. The household questionnaire was used to select women of reproductive age to participate in the individual interviews and children aged between 6 months and 14 years to undergo malaria and anemia test. The woman questionnaire was used to collect information on background characteristics of the household, reproductive history for the last 6 years, antenatal care and preventive malaria treatment for the most recent birth, fever prevalence and treatment among children under age 5, and knowledge and attitudes regarding malaria treatment and prevention. The biomarker questionnaire was utilized to record level of hemoglobin and results of malaria test among children. Blood samples were taken from children eligible for malaria and anemia test.

3.3 Data analysis

3.3.1 Logistic regression model

Logistic regression is a special type of generalized linear model (GLM). The model is used to analyze binary and categorical dependent variables. It accommodates continuous and/or categorical independent variables. Systematic component comprise of X's which are linear in the parameters. The link function is the logit which models the log odds of the mean. Binary logistic regression model is appropriate when the response variable takes one of the two possible outcomes. The log odds of malaria prevalence in children is given by

$$log\pi_i = \frac{\pi_i}{1-\pi_i} \tag{1}$$

Parameter estimation

The objective of logistic regression is to find the unknown parameters. Maximum likelihood estimation is used to derive a set of parameters having high probability of observed data. They are derived from the probability distribution of the dependent variable. Maximum likelihood estimator maximizes the likelihood function. The estimates are obtained by taking the first and second derivative of the likelihood function.

Model selection

Logistic regression model is derived by including all variables and excluding insignificant variables one at a time. The procedure continues until the model consist of significant variables only. Akaike information criterion (AIC) is used to measure the goodness of fit test. AIC adjusts the likelihood ratio statistic. It is adjusted because the likelihood ratio statistics decreases as a new independent variable is included in the logistic regression model whether it is significant or insignificant. Akaike information criterion is expressed as

$$AIC = -2logL + 2p \tag{2}$$

In equation 2, p is the number of parameters and -2logL the likelihood ratio statistic.

Overall goodness of fit

Hypothesis
Ho: Reduced model is better than the saturated model
H1: Saturated model is better than the reduced model
In the null hypothesis, the model omits some of the predictor variables which are insignificant while in the alternate hypothesis all the predictor variables are included in the model. The likelihood ratio statistics is given by:

$$\triangle G^2 = -(2logL\,reducedmodel) - (-2logL\,saturatedmodel) \tag{3}$$

In equation 3, -2 log L is the deviance statistics. The number of degrees of freedom is equivalent to the number of coefficients in the model. High values of likelihood ratio statistics lead to small p value, providing evidence against reduced model in favor of the saturated model.

Hosmer Lemeshow Statistics

The test is Pearson like chi-square calculated after the data has been grouped with similar predicted probabilities. The null hypothesis for the test is that the model fits well while the alternate is that the model does not fit well. Results derived from the model are dependent on how the variables are grouped. For the test to assess the model adequately, the number of groups should be more than 5.

3.3.2 Generalized Linear Mixed Effect Model

GLMM is an extension of generalized linear model (GLM). The model include random effect in addition to fixed effect. Fixed effects are the same as the explanatory variables of the linear regression model. Random effects are the observational blocks. When observations are collected in clusters, there will be variation within cluster and between clusters. Observations that come from the same cluster are correlated whereas the ones from different clusters are uncorrelated. Random effects are included in the model to correct statistical tests when the observations are correlated. The model is given by

$$\mathbf{y_j} = \mathbf{X_j}\beta + \mathbf{Z_j}\mathbf{u_j} + \varepsilon_\mathbf{j} \tag{4}$$

where
$\mathbf{y_j}$ is a vector of response variable
$\mathbf{X_j}$ is a matrix for the predictors in cluster j
$\beta_\mathbf{j}$ is a vector of fixed regression coefficients
$\mathbf{Z_j}$ is matrix for the random effects of cluster j
$\mathbf{u_j}$ is a vector of random effects of cluster j
$\varepsilon_\mathbf{j}$ is a matrix of residuals for cluster j

The equation of GLMM can be generalized through a linear link function that relates the linear predictor to the mean of the response variable. The function is expressed as

$$E(\mathbf{y_j}|\mathbf{X_j},\mathbf{u_j}) = \mu_\mathbf{j} = g^{-1}(\mathbf{X_j}\beta_\mathbf{j} + \mathbf{Z_j}\mathbf{u_j}) \tag{5}$$

When the response variable is a binary outcome, the link function g(.)is logit. The probability of success is expressed as

$$p[y_i j = 1|\mathbf{X_j},\mathbf{u_j}] = \frac{exp(\mathbf{X_j}\beta + \mathbf{Z_j}\mathbf{u_j})}{1 + exp(\mathbf{X_j}\beta + \mathbf{Z_j}\mathbf{u_j})} \tag{6}$$

In mixed effect models, the mean of outcome $\mathbf{y_i j}$ is conditional on the predictors included in the model and the random effect estimates. Responses from different clusters are assumed to be independent after conditioning on the random effects.The random effects are not observed as a result inference for the fixed effect coefficients and variance of random effects are derived by integrating over the random effect $\mathbf{u_j}$. The result of the integration is the marginal likelihood function shown below

$$L(\beta, \mathbf{G} = \prod \int f(\mathbf{y_j}|\mathbf{u_j};\beta) f(\mathbf{u_j};\mathbf{G}) \mathrm{d}x \tag{7}$$

In equation above, $f(\mathbf{u_j};\mathbf{G})$ is the probability density of $\mathbf{u_j}$ follows a multivariate normal distribution with mean 0 and variance $\mathbf{G}$. Addition of multiple random effects increase the computation burden of the model. Estimating GLMM using maximum likelihood involve integrating over the random effect. The estimates of the model are derived by approximation because the marginal likelihood function doesn't have a closed form solution. The three approximation techniques are Gauss quadrature, Laplace approximation and penalized quasi likelihood method

Gauss Hermite Quadrature (GHQ)

Gaussian Hermite Quadrature approximation technique uses multiple points to integrate the marginal likelihood. The estimates derived using this method are accurate when more quadrature points are selected because the likelihood function is divided into smaller pieces. The number of quadrature points determine the computation burden of the model. Researchers using the technique need to make a tradeoff between accuracy and the number of quadrature points. Laplace approximation is derived by utilizing 1 quadrature point. The approximate marginal likelihood is computed by

$$L(\beta, \mathbf{G}) = \prod \sum f(\mathbf{y_t}|\mathbf{u_j} = v_t) w_t \tag{8}$$

Where, v_t is the evaluation point and w_t is the weight of the evaluation point. The approximation improves as the number of quadrature points increases. The strengths of Gaussian quadrature are that it leads to accurate approximation of marginal likelihood as well as calculation of deviance statistics which is used to assess the goodness of the GLMM fit. The main shortcoming of the method is computation burden because the number of computations increases exponentially with the number of random effects. In addition, the computation burden adversely affects the convergence of the model when there are many random effects. When many quadrature points are selected with multiple random effects, the model will take several hours to converge. On the other hand, too few quadrature points result to inaccuracy approximation.

Laplace Approximation method

The aim of Laplace approximation is to derive an approximation of marginal likelihood so that integration can be carried out. Laplace approximation uses Taylor series expansion as opposed to numerical method that is utilized by Gauss Hermite quadrature so that the resulting integral is closed form solution. The major drawback of the approximation is that it is a slow and less flexible method of approximating the marginal likelihood. Marginal likelihood function can be written as

$$L(\beta, \mathbf{G}) = (2\pi)^{\frac{-k}{2}} |\mathbf{G}| exp \int \mathbf{h}(\mathbf{u_j}) \mathrm{d}\mathbf{u_j} \tag{9}$$

where

$$\mathbf{h}(\mathbf{u_j}) = logf(\mathbf{y_j}|\mathbf{u_j},\beta - \frac{1}{2}(\mathbf{u_j^T}\mathbf{G^{-1}}\mathbf{u_j}) \tag{10}$$

The second order Taylor expansion is applied to the above equation and taking the exponent about the mode of $\mathbf{u_j}$uj. The resultant equation is

$$exp[\mathbf{h}(\mathbf{u_j})] = exp[\mathbf{h}(\tilde{\mathbf{u}}_\mathbf{j} + \frac{1}{2}(\mathbf{u}-\mathbf{u_j})^T * \frac{\delta^2}{\delta\mathbf{u_j}\delta\mathbf{u_j^T}}(\mathbf{u_j}-\tilde{\mathbf{u}}_\mathbf{j}) + D_j] \tag{11}$$

The resulting integrand has a closed form and evaluation of the integral can be carried out. This is equivalent to using adaptive Gaussian quadrature with only one point. D is the residual and it is neglected because it approaches zero as the sample size increases. Laplace approximation can replicate comparable results as those obtained from Gaussian Quadrature in a shorter time when the number of random effects are many. Unlike gaussian quadrature which does not handle crossed random effects, Laplace approximation accommodates crossed random effects.

Penalized Quasi Likelihood (PQL

This approximation technique approximates the model by linearizing the nonlinear components of the model to obtain random and fixed effect coefficients. Variance components are estimated on condition of random and fixed effect coefficients. Once the variance components have been estimated, the fixed and random effects are updated and the procedure is repeated until the difference between iterations is very small.
The marginal likelihood function is obtained by integrating out the random effect $\mathbf{u_j}$ from the joint distribution of $\mathbf{y_j}$ and $\mathbf{u_j}$. Taking the exponent of each component of the joint distribution, the integrand of the likelihood function is an exponential function of $\mathbf{u_j}$. Second order Taylor series expansion is used to approximate the function at around a point $\tilde{\mathbf{u}}$ at which the first order term is equal to zero $\tilde{\mathbf{u}}_\mathbf{j} = E(\mathbf{u_j}|\mathbf{y_j})$. The resulting approximating function is an exponential with quadratic exponent in $(\mathbf{u}-\tilde{\mathbf{u}})$ and its form is a constant multiple of multivariate normal density. Thus, the integral is a closed form and approximation for the integral of the marginal likelihood function is treated as a likelihood and maximized with respect to β and $\sum$. The integral approximation gives a function of the form

$$q(\beta,\mathbf{y_j}) - \frac{1}{2}\tilde{u_j^T}\sum\tilde{u_j} \tag{12}$$

In equation 12, $q(\beta, \mathbf{y_j}$ resembles the quasi likelihood function for the condition $\mathbf{u} - \tilde{\mathbf{u}}$. The approximation result to a penalty for the quasi log likelihood function which increases as the elements of u increases. Penalized quasi likelihood does not require numerical integration hence it is easy to compute compared to maximum likelihood methods. The estimates obtained from quasi likelihood are poor when the distribution of the outcome variable is not normal. When variance components are large, penalized quasi likelihood produce variance components that have negative bias.

4 Results and Discussion

4.1 Introduction

The chapter presents the descriptive and confirmatory tests conducted on the data. In addition, the chapter highlights the interpretation of the model parameters derived from logistic regression and GLMM.

4.2 Descriptive Statistics

Table 1. Relationship between age category and results of malaria test

Result	0-4	5-9	10-14
Negative	3094	3135	2491
Positive	315	543	421

Test on the hypothesis that;
H_0: Result of malaria test is independent on the age of the child
H_1: Result of malaria test is dependent on the age of the child
Pearson's Chi-square independent test statistic was 58.607 with 2 degrees of freedom and a p value of 0.000. This implies that the statistic was highly significant with 95% confidence and we reject the null hypothesis. Thus, we conclude that the result of malaria test is dependent on age of the child. 42.5% of the children who tested positive were aged 5-9 years compared to 32.9% and 24.6% in children aged 10-14 and under 5 years, respectively. children aged 5-14 years registered more cases of malaria relative to those aged less than 5 years.

Table 2. Relationship between gender and results of malaria test

Result	Male	Female
Negative	4388	4332
Positive	673	606

Test on the hypothesis that;
H_0: Result of malaria test is independent on the gender of the child
H_1: Result of malaria test is dependent on the gender of the child
Pearson's Chi-square independent test statistic was 2.357 with 1 degree of freedom and a p value of 0.125. This implies that the statistic was not significant with 95% confidence

and we fail to reject the null hypothesis. Thus we conclude that the result of malaria test is independent on gender of the child.

Table 3. Relationship between gender of the household head and results of malaria test

Result	Male	Female
Negative	5734	2986
Positive	877	402

Test on the hypothesis that;
H_0: Result of malaria test is independent on the gender of the household head
H_1: Result of malaria test is dependent on the gender of the household head
Pearson's Chi-square independent test statistic was 3.938 with 1 degree of freedom and a p value of 0.047. The statistic was significant with 95% confidence and we reject the null hypothesis. Thus, we conclude that the result of malaria test is dependent on gender of head of the household.15.29% of children in households headed by male tested positive for malaria as relative to 13.46% in their female counterparts.

Table 4. Relationship between type of residence and results of malaria test

Result	Urban	Rural
Negative	3447	5273
Positive	246	1033

Test on the hypothesis that;
H_0: Result of malaria test is independent on the type of residence
H_1: Result of malaria test is dependent on the type of residence
Pearson's Chi-square independent test statistic was 197.257 with 1 degree of freedom and a p value of 0.000. This indicates that the statistic was highly significant at 5% level of significance thus we reject the null hypothesis. The result of malaria test was dependent on the type of residence. A higher proportion of children from rural areas tested positive for the malaria test compared to their counterparts in urban areas.

Table 5. Relationship between wealth index and results of malaria test

Result	Poorest	Poorer	Middle	Richer	Richest
Negative	2633	1684	1644	1495	1264
Positive	378	460	281	132	28

Test on the hypothesis that;
H_0: Result of malaria test is independent on wealth index

H_1: Result of malaria test is dependent on wealth index
Pearson's Chi-square independent test statistic was 312.703 with 4 degree of freedom and a p value of 0.000. This implies that the statistic was highly significant with 95% confidence and we reject the null hypothesis. Thus we conclude that the result of malaria test is dependent on wealth index of the household. The highest number of cases of malaria were reported in low social economic stratum. The results indicate that children from household in the poor wealth quintile category were more likely to test positive for malaria test. The findings reveal that with increase in wealth index children are less likely to suffer from malaria.

Table 6. Relationship between Education level of the household head and results of malaria test

Result	Primary	Post Primary	Secondary	College	University
Negative	3942	135	1925	566	190
Positive	783	20	185	19	10

Test on the hypothesis that;
H0: Result of malaria test is independent on the education level of the head of household
H1: Result of malaria test is dependent on the education level of the head of household
Pearson's Chi-square independent test statistic was 54.616 with 4 degrees of freedom and a p value of 0.000. This implies that the statistic was highly significant with 95% confidence and we reject the null hypothesis. Thus we conclude that the result of malaria test is dependent on level of education of the head of the household. In households whose head possess higher level of education the chances of a child testing positive were low

Table 7. Relationship between anemic level of and results of malaria test

Result	Severe	Moderate	Mild	Not anemic
Negative	29	592	890	7200
Positive	21	227	241	783

Test on the hypothesis that;
H_0: Result of malaria test is independent on anemia level of child
H_1: Result of malaria rapid diagnostic test is dependent on anemia level of child
Pearson's Chi-square independent test statistic was 340.129 with 3 degree of freedom and a p value of 0.000. This implies that the statistic was highly significant with 95% confidence and we reject the null hypothesis. Thus we conclude that the result of malaria test is dependent on anemic level of the child. The finding reveals that the more severe the anemic level of the child the higher the probability that child is suffering from malaria.

Test on the hypothesis that;
H_0: Result of malaria test is independent on number of persons who slept under the net

Table 8. Number of persons who slept under a net and results of malaria test

Result	1	2	3	4
Negative	557	1653	1461	655
Positive	75	271	254	203

H_1: Result of malaria test is dependent on number of persons who slept under the net Pearson's Chi-square independent test statistic was 53.017 with 3 degree of freedom and a p value of 0.000. This implies that the statistic was highly significant with 95% confidence and we reject the null hypothesis. Thus we conclude that the result of malaria test is dependent on the number of persons who slept under the net. The results reveal that the more the number of persons who share the net the more likely they are to suffer from malaria.

Table 9. Malaria Endemicity and results of malaria test

Result	Highland	Lake	Coast	Semi arid	Low risk
Negative	2421	1311	1109	2210	1669
Positive	131	911	210	20	7

Test on the hypothesis that;
H_0: Result of malaria rapid diagnostic test is independent on malaria endemicity
H_1: Result of malaria rapid diagnostic test is dependent on endemicity
Pearson's Chi-square independent test statistic was 2243.536 with 4 degree of freedom and a p value of 0.000. This implies that the statistic was highly significant with 95% confidence and we reject the null hypothesis. Thus we conclude that the result of malaria test is dependent on malaria endemicity. Seventy per cent of those who tested positive were from the lake endemic followed by the coastal endemic.

4.3 Interpretation of Logistic regression model

Statistical analysis were performed using R software. Akaike information criteria for the model was 6,127.5.The analysis revealed that place of residence, cluster altitude,availability of electricity, main material of wall, main material of roof, wealth index, level of anemia and age of a child were significant predictors of malaria prevalence. Children residing in urban areas were 39% less likely to contract malaria compared to their counterparts in rural areas. Households connected with electricity were 40% less probable to contract malaria compared to those residing in rural areas. Households having access to a radio were 5% less likely to have malaria relative to the ones with no radio. Households listening to the radio and watching television were less likely to contract malaria.
Households residing in houses having mud walls were 15% more likely to have malaria

relative to bamboo with mud.However, household whose main wall material of wall was brick, cement, cement blocks, iron sheets and wood planks were less likely to suffer from malaria than those in bamboo with mud walls. Households in the poorer wealth quintile were 1.35 times more likely to have malaria compared to those in middle quintile.In addition, children from richer and richest wealth quintiles were 30% and 40%, respectively less probable to contract malaria relative to those in middle quintile
Households headed by males are 16% more probable to suffer from malaria compared to female headed households. Male are more vulnerable to malaria compared to their female counterparts. They are 8% more likely to contract the disease compared to their female counterparts. Children aged 10-14 years are 3.78 times more likely to suffer from malaria compared to those aged less than 5 years. On the hand, those aged between 5 and 9 years are 3.14 times more likely to test positive for malaria relative to children aged less than 5 years.

4.4 Interpretation of GLMM model

Statistical analyses were performed using R software. In the analysis, penalized quasi likelihood was not used in approximating because the estimates derived by the method are biased when the data is binary. Cluster number was treated as a random effect in the model. The estimates were derived using the adaptive Gaussian quadrature estimation mainly because the estimates are accurate as opposed to those derived from Laplace approximation. The akaike information criteria (AIC) for the model was 4,345.7. Generalized linear mixed effect model was developed to determine the risk factors of malaria. The analysis indicated that place of residence, availability of electricity in the household, gender of the household head, anemic level and age of the child were found to be significant predictors of malaria using adaptive gaussian quadrature approximation techniques.
Age of the child was a significant determinant of malaria. Children aged 10-14 years were 3.90 times more likely to suffer from malaria compared to those aged less than 5 years. On the other hand, children aged 5-9 years were 3.39 times more probable to contract malaria relative to those aged less than 5 years.The findings of the study revealed that the prevalence of malaria increases with increase in age. This is paltry attributed to non-usage of mosquito bed nets in those age categories as more efforts are directed to the young children and pregnant women. Male children were 7% more likely to suffer from malaria compared to females. This is consistent with similar studies that have observed that males are biologically more susceptible to malaria compared to females. Prevalence of malaria was more pronounced in households whose head was a man. Children who were reported to be suffering from severe and moderate anemic were 4.81 and 1.67 times, respectively more likely to contract malaria compared to their counterparts who had mild anemia. However, children who were not anemic had low chances of suffering from malaria.This implies that level of area is correlated with occurrence of malaria in children. Children residing in urban areas were 74.15% less likely to have malaria compared to their counterparts from rural areas. This was mainly due to lack of health care infrastructure in

rural areas.
Prevalence of malaria was high in poor households. Children from poor households are vulnerable to malaria as their households cannot afford to cater for expenses to take preventive measures such as purchasing a mosquito net. On the other hand, children from wealthy households access better health services and have adequate resources at their disposal to take appropriate preventive measures. Households residing in houses whose main material of floor was cement, dung, earthen and wood planks were more probable to suffer from malaria relative to those residing in houses whose main material of floor was carpet. Prevalence of malaria was high in households whose roofing materials were dung, iron sheets, no roof, others and thatched compared to asbestos sheets. The media plays a pivotal role in the reduction of malaria prevalence. Various initiatives geared towards reducing the burden of the disease are communicated via the radio and television. Prevalence of malaria was low in household owning a television and radio. This demonstrates that the mass media can be an effective tool to reduce the burden of malaria.

Discussion

The study investigated the risk factors of malaria using logistic regression and generalized linear mixed effect model (GLMM). The findings revealed that GLMM had a lower value of AIC compared to logistic regression model. This indicates that GLMM gives better estimates when the observation are correlated.The study revealed that malaria was more pronounced in children aged above 5 years relative to those less less than 5 years. This clearly demonstrates that the intervention by the government and development partners targeting children aged less than 5 years are paying off. The findings of the study is consistent with results from another research which indicated that prevalence was high in children aged 5-15 years [35].Male children were more likely to have malaria. The finding is similar to previous study which pointed out that biological, males were more likely to have malaria relative to females [9].
Socioeconomic status of the household was a significant predictor of malaria prevalence. Children from rich households were less likely to have malaria. The findings are similar to a study in Uganda that observed that high cases of malaria were registered in poor households [28]. households in the poor wealth quintile are financial disadvantaged making it difficult to acquire mosquito nets. similar to earlier study, the study found out that the prevalence of malaria was high in rural areas relative to urban areas. This was mainly attributed favorable breeding sites in rural areas especially open fields and stagnant water [24]. households living in poor houses were more likely to contract malaria. The analysis is to an earlier study that revealed that children residing in houses with hatch roof and mud floor were more probable to have malaria [5]. prevalence of malaria was

low in households having access to radio and television. This implies that the media plays a pivotal role in malaria prevention in kenya.

Table 10. Results of Logistic Regression Model

Variable	Estimate	Std. Error	Z value	pr(>|z|)
Intercept	-3.62	1.13	-3.9	0.00
Altitude	0.00	0.00	-12.40	0.00
Residence:Urban	-0.49	0.09	-5.54	0.00
Electricity:Yes	-0.50	0.17	-3.03	0.00
Radio:Yes	-0.05	0.08	-0.69	0.49
TV:Yes	0.00	0.16	0.00	0.99
Floor:Cement	0.02	0.37	0.05	0.96
Floor:Ceramic tiles	-0.22	0.64	-0.34	0.73
Floor:Dung	0.38	0.38	1.00	0.32
Wall:Bricks	-2.04	0.39	-5.21	0.00
Wall:Cement blocks	-1.88	0.51	-3.71	0.00
Wall:Dung	0.14	0.18	0.77	0.44
Wall:Iron sheets	-1.16	0.32	-3.69	0.00
Roof:Concrete	1.57	1.28	1.23	0.22
Roof:Dung	2.96	1.05	2.82	0.00
Roof:Iron sheets	2.73	1.02	2.68	0.01
Roof:Grass	2.62	1.02	2.56	0.01
Roof:Tiles	2.56	1.46	1.76	0.08
Hgender:Male	0.12	0.07	1.57	0.12
Wealth:Poor	0.30	0.09	3.17	0.00
Wealth:Richer	-0.21	0.15	-1.44	0.15
Wealth:Richest	-0.52	0.27	-1.92	0.05
Gender:Male	0.07	0.07	1.08	0.28
Education:Post Primary	0.60	0.36	1.66	0.10
Education:Primary	0.52	0.24	2.19	0.03
Education:Secondary	0.27	0.28	1.12	0.26
Education:University	0.23	0.41	0.36	0.58
Anemia:Moderate	0.50	0.12	4.13	0.00
Anemia:Not anemic	-1.21	0.10	-12.63	0.00
Anemia:Severe	1.27	0.34	3.74	0.00
Age:5-9	1.14	0.09	12.13	0.00
Age:10-14	1.33	0.10	13.11	0.00

Table 11. Results of GLMM

Variable	Estimate	Std. Error	Z value	pr(>|z|)
Intercept	-4.91	1.91	-2.57	0.01
Altitude	0.00	0.00	-1.67	0.09
Residence:Urban	-1.25	0.52	-2.58	0.01
Electricity:Yes	-0.50	0.24	-2.10	0.04
Radio:Yes	-0.11	0.11	-1.05	0.29
TV:Yes	-0.05	0.19	-0.23	0.82
Floor:Cement	0.17	0.47	0.37	0.72
Floor:Ceramic tiles	-0.21	0.76	-0.28	0.78
Floor:Dung	0.46	0.49	0.94	0.35
Wall:Bricks	-0.94	0.54	-1.74	0.08
Wall:Cement blocks	-1.00	0.64	-1.58	0.12
Wall:Dung	0.09	0.31	0.28	0.78
Wall:Iron sheets	0.16	0.49	0.32	0.75
Roof:Concrete	1.87	2.05	0.91	0.36
Roof:Dung	1.24	1.75	0.71	0.48
Roof:Iron sheets	0.42	1.71	0.24	0.81
Roof:Grass	0.31	1.71	0.18	0.86
Roof:Tiles	0.97	2.11	0.46	0.65
Hgender:Male	0.24	0.10	2.42	0.02
Wealth:Poor	0.29	0.12	2.32	0.02
Wealth:Richer	-0.10	0.18	-0.53	0.59
Wealth:Richest	-0.57	0.34	-1.66	0.10
Gender:Male	0.07	0.08	0.86	0.39
Education:Post Primary	0.51	0.46	1.12	0.26
Education:Primary	0.18	0.30	0.61	0.55
Education:Secondary	-0.10	0.30	-0.33	0.74
Education:University	0.10	0.48	0.22	0.83
Anemia:Moderate	0.51	0.16	3.26	0.00
Anemia:Not anemic	-1.02	0.12	-8.36	0.00
Anemia:Severe	1.57	0.52	3.05	0.00
Age:5-9	1.22	0.12	10.54	0.00
Age:10-14	1.36	0.12	10.98	0.00

5 Conclusion and Recommendation

5.1 Introduction

The aim of this chapter is to highlight conclusion and give recommendations to health practitioners from the findings of the study.

5.2 Conclusion

This study set out to establish the association between risk of malaria in children using logistic regression and generalized linear mixed effect model. The results revealed that the generalized linear mixed effect resulted to a better fit compared to logistic logistic regression model. The understanding of factors associated with malaria prevalence become handy in the formulation of policies aimed at reducing prevalence of the disease. In the present study, the burden of the disease is high in children aged 10-14 years and 5-9 years compared to their counterparts aged less than 5 years. The findings of the study revealed that mass media like television and radio are important channels that health practitioners can use to communicate malaria prevention messages.The analysis further revealed that children residing n rural are highly exposed to malaria. The other factors that were significant include; cluster altitude, wealth quintile and availability of electricity.

5.3 Recommendation

The study recommends that all children be included in malaria control intervention by the Ministry of Health to achieve World Health Recommendation of universal coverage of all persons at risk of malaria. From the findings, the study suggests the government include both the radio and television to communicate malaria messages.

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