FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 9 No. 12, December (Special Issue), 2025, pp 22 – 28
DOI: https://doi.org/10.33003/fjs-2025-0912-4147

A BINARY LOGISTIC REGRESSION MODEL FOR ASSESSING THE PREDISPOSING FACTORS OF MALARIA FEVER AMONG FARMERS IN BENUE STATE, NIGERIA

*[1]Joseph Sunday Idikwu, [2]David Adugh Kuhe and [2]Jacob Aondongu Nyitar

[1]Center for Food Technology and Research, Rev. Fr. Moses Orshio Adasu University, Makurdi, Benue State, Nigeria.
[2]Department of Statistics, Joseph Sarwuan Tarka University, Makurdi, Benue State, Nigeria.

*Corresponding authors' email: josephinnocent99@gmail.com

ABSTRACT

Despite sustained control efforts, the burden of malaria fever persists due to socio-demographic, environmental, and behavioural factors. This study employed a binary logistic regression model to assess the predisposing factors of malaria fever among farmers in Benue State, Nigeria. A cross-sectional survey was conducted among 750 respondents, predominantly farmers, selected from malaria-endemic communities in Ado, Katsina-Ala, Logo, Makurdi, and Ukum LGAs. Data were collected using structured questionnaires covering socio-demographic characteristics, environmental conditions, and malaria prevention practices, with malaria status as the binary dependent variable. The analysis revealed a malaria prevalence of 77.1%, indicating a high disease burden. The full model was statistically significant (Omnibus test $\chi^2 = 33.749$, $p = 0.009$) with strong explanatory power (Nagelkerke $R^2 = 0.747$) and acceptable goodness-of-fit (Hosmer and Lemeshow $\chi^2 = 8.142$, $p = 0.420$). Key predictors increasing malaria risk included occupation (OR = 2.066), previous household malaria (OR = 2.199), poor housing (OR = 2.713), residence near stagnant water (OR = 2.968), and travel to endemic areas (OR = 2.921), all significant at $p < 0.001$. Conversely, higher education (OR = 0.438), use of treated nets/insecticides (OR = 0.760), timely treatment (OR = 0.585), malaria prevention training (OR = 0.720), community programmes (OR = 0.737), and access to healthcare (OR = 0.863) significantly reduced infection odds. The study recommends that policymakers and public health stakeholders implement community-specific interventions prioritizing vulnerable groups, expanding healthcare access, promoting behavioural change, and addressing structural inequalities to reduce malaria burden in Benue State, Nigeria.

Keywords: Predisposing Factors, Malaria Fever, Farmers, Benue State

INTRODUCTION

Malaria is a significant world's health hazard, predominantly in tropical and subtropical regions where the climatic conditions encourage the breeding and transmission of the disease-causing parasites. The disease is caused by Plasmodium-genus protozoan parasites, which people contract through the bite of female Anopheles mosquitoes carrying the parasite (Bamikole, 2024). Plasmodium falciparum is the cause of most malaria-related illness and death in sub-Saharan Africa, including Nigeria. (World Health Organization [WHO], 2020).

Nigeria bears an excessively high burden of malaria, amounting to a significant percentage of global cases and mortalities. The country's climatic conditions, including high temperatures, humidity, and abundant breeding spots for mosquitoes, contribute to the widespread transmission of malaria. According to WHO (2023), the total malaria deaths recorded in Nigeria alone in 2022 was 26.8% of all malaria deaths worldwide, with children below five years as the most susceptible.

Malaria imposes a substantial economic and social burden on affected populations, particularly in rural agricultural communities where subsistence farming is a predominant source of livelihood. Farmers are especially vulnerable to malaria due to their prolonged exposure to mosquito-infested environments, such as farmlands, forests, and stagnant water bodies that serve as mosquito breeding sites (Asenso-Okyere et al., 2011). The seasonal nature of agricultural activities often coincides with peak malaria transmission periods, increasing farmers' risk of infection.

Empirical studies across Nigeria and other malaria-endemic regions have consistently shown that malaria prevalence is influenced by a combination of socioeconomic, environmental, climatic, and behavioural factors, aligning with this study on. Socioeconomic studies such as those by Oyibo et al. (2020) and Eboh and Adebayo (2023) revealed that proximity to stagnant water, low income, poor housing, and distance to health centres significantly predict malaria incidence among farming communities. Similarly, Braimah et al. (2024) found that rural residence, inadequate sanitation, and low insecticide-treated net (ITN) usage increased infection risks despite high malaria awareness, highlighting the gap between knowledge and preventive practices. The influence of occupational exposure was further underscored by Onyango *et al.* (2016), who reported that farmers' prolonged outdoor activities during early mornings and evenings heightened their susceptibility to mosquito bites. These findings reinforce the relevance of including environmental and behavioural predictors in logistic regression models to statistically estimate farmers' malaria risk in Benue State.

Climatic and biological factors also play critical roles in malaria transmission, as shown by Segun *et al.* (2020), Agyekum et al. (2022), Nyawanda *et al.* (2024), and Ibrahim et al. (2021), who found that rainfall, humidity, and temperature fluctuations strongly correlate with malaria incidence, particularly during the wet season when mosquito breeding intensifies. Kripa *et al.* (2024) demonstrated that optimal temperatures (20-30°C) accelerate *Plasmodium falciparum* development within mosquitoes, thus increasing transmission rates in agricultural regions. Additionally, Ugwu and Zewotir (2020) and Oladipo et al. (2022) emphasized that climate change and environmental degradation expand malaria-prone zones, while Okumu et al. (2017) cautioned that pesticide misuse in agriculture fosters vector resistance, weakening control measures. Biological studies such as Ndila *et al.* (2018) and Beeson *et al.* (2019) further revealed that genetic factors like the sickle cell trait and immune adaptation influence susceptibility levels, whereas vulnerable groups especially pregnant women (Poespoprodjo et al., 2018; Okwa & Oloruntoba, 2019) experience higher malaria morbidity. Together, these empirical findings provide a strong evidence base for this study's use of binary logistic regression to statistically identify and quantify the relative contributions of socioeconomic, environmental, climatic, and genetic factors that predispose farmers in Benue State to malaria fever. This is with the view to offer evidence-based suggestions for enhancing malaria prevention and control tactics in agricultural communities in Benue State (Isiko et al., 2024; Mohammed et al., 2025).

The organization of the remaining sections of the paper is as follows; section 2 discusses the materials and methodology employed, section 3 results obtained and section 4 the conclusion and recommendations for tailored interventions.

MATERIALS AND METHODS

Research Design and Sample Size Determination

A cross-sectional survey design was employed, allowing simultaneous assessment of various predisposing factors among farming communities in Benue State. A multistage sampling procedure was used for the study. In the first stage, five out of the twenty-three Local Government Areas (LGA) in Benue State; Ado, Katsina-Ala, Logo, Makurdi and Ukum were purposively selected due to their closeness to the river. Furthermore, Simple random sampling technique was used to select farmers from each Local Government Area.

Methods of Data Collection and Variable Description

A questionnaire containing both open and closed-ended questions was administered to farmers in the study area. To ensure efficient completion, respondents were guided on how to answer the questionnaire in the case of personal disability or language barrier.

The outcome variable of this study is farmers' Malaria status. Questions on whether the farmer has Malaria fever or does not have Malaria fever, with responses 1= Yes (Malaria fever) or 0=No (No Malaria fever) represents the dependent variable in the dataset. The explanatory (independent) variables included in this study are: Age, Gender, Marital Status, Years of Formal Education, Household size, Access to Health Campaign, Use of Mosquito Net, Closeness to bush and dumps, Closeness to Stagnant Water, Distance to Hospital, Farm Income, Farming Experience, Number of times Malaria was treated per year.

Method of Data Analysis

The raw data collected from the field was coded and analyzed using Statistical Package for Social Sciences (SPSS) version 21. Descriptive statistics such as frequencies, means, percentages and cross-tabulation statistics was used to assess the sociodemographic characteristics of the respondents while a Binary logistic Regression model was designed to assess the predisposing factors of Malaria fever among farmers in the study area.

The binary logistic regression model is used when the dependent variable is binary (0 or 1). Therefore, it modelled the probability that a farmer has malaria fever (Y = 1) or does not have malaria fever (Y = 0) based on the explanatory variables as:

Assuming there are, k explanatory variable $X_{1,}X_{2,}X_{3,}\dots X_{k,}$. The response variables y is a binary variable indicating whether the farmer has Malaria fever $(Y = 1)$ or does not have Malaria fever$(Y = 0)$. If P_i is the probability that a farmer has malaria fever given the explanatory variables, then, $P_i = P\left(Y = 1|X_{1,}, \dots, X_{k,}\right)$ and $1 - P_i = P\left(Y = 0|X_{1,}, \dots, X_{1,}\right)$ are probabilities of having and not having malaria respectively. Then, the binary logistic regression models are given by:

$$P_i = \frac{exp\{\sum_{j=0}^{k}\beta_j X_{j,}\}}{1+exp\left\{\sum_{j=0}^{k}\beta_j X_{j,}\right\}}, \quad (1)$$

and

$$1 - P_i = \frac{1}{1+\left\{\sum_{j=0}^{k}\beta_j X_{j,}\right\}} \quad (2)$$

where β_0 is the intercept, $\beta_1, \dots \beta_k$ are the regression coefficient. Equation (1) models a farmer has malaria while (2) models a farmer does not have malaria. These models ensures that P_i always lies between 0 and 1.

To allow the relationship between the predictors and the response variable to be modeled linearly, the logit transform of Equation (1) and (2) in terms of P_i, was taken. Furthermore, the odds ratio (OR) to measures how a one-unit change in an explanatory variable affects the odds of having malaria fever for a variable $X_{j,}$ was considered as follows: If $OR_j > 1$, an increase in $X_{j,}$ increases the odds of malaria fever, If $OR_j < 1$, an increase in $X_{j,}$decreases the odds of malaria fever, If $OR_j = 1$, $X_{j,}$has no effect on malaria fever. For example, if the use of mosquito nets $(X_{1,})$ has $OR_j = exp^{\beta_1} = 0.5$, it means that farmers using mosquito nets are 50% less likely to have malaria than those who do not. Also, to estimate the coefficient $\left(\beta_j^{\prime s}\right)$ that is $\beta_0, \beta_1, \dots \beta_k$of the explanatory variables, the Maximum Likelihood Estimation (MLE) method was applied. Furthermore, to test the adequacy of the logistic regression model, the Wald test, Hosmer-Lemeshow goodness of fit test, and Cook's influence plots was used.

RESULTS AND DISCUSSION

Socio-Demographic Characteristics of the Respondents

Figure 1 presents the socio-demographic characteristics of the 750 respondents surveyed in the study. The data shows that 55.9% of the respondents were male, while 44.1% were female, indicating a male-dominated farming population in the study area. The mean age of respondents was 40.63±14.77 years, with the largest age group being 25-34 years (26.1%), followed by 35-44 years (20.7%), suggesting that most respondents were in their economically active years. Regarding educational attainment, 33.6% of respondents has secondary education, 26.5% tertiary education, while 15.6% has no formal education, implying a moderate literacy level that could influence awareness and preventive behaviour toward malaria control. Occupationally, a majority (63.2%) were farmers, confirming that the study population was primarily engaged in agricultural activities, an occupation that increases exposure to mosquito bites due to frequent outdoor work.

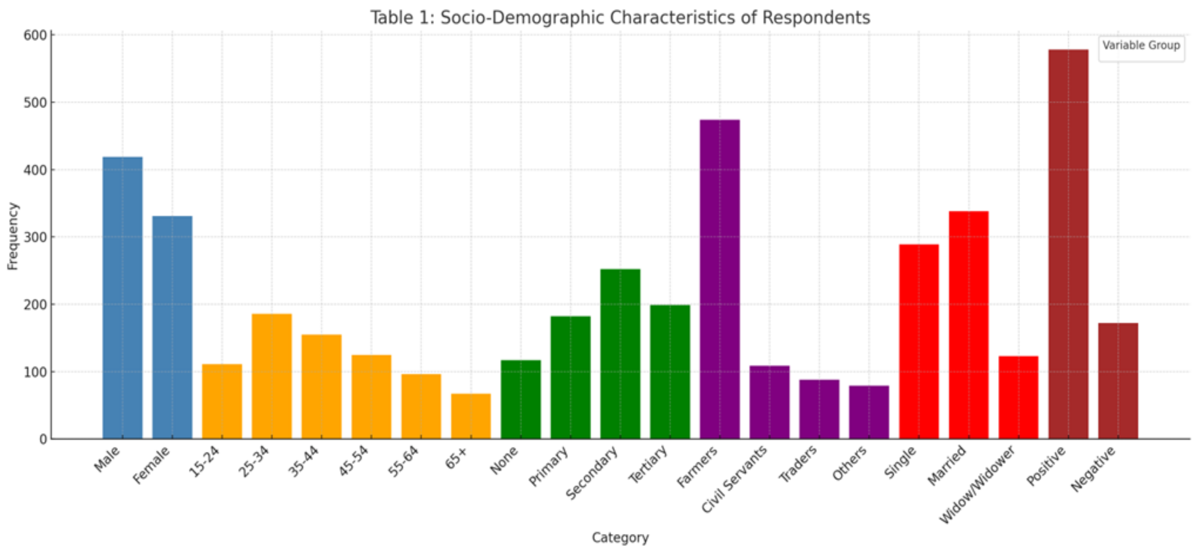

Figure 1: Socio-Demographic Characteristics of the Respondents

Importantly, 77.1% tested positive for malaria, while only 22.9% were negative, indicating a high malaria burden among the population. Overall, these results reflect a predominantly middle-aged, male, and farming population with moderate education levels and a high prevalence of malaria infection.

Binary Logistic Regression Model Results

Table 1 presents the classification results for the full binary logistic regression. The table compares the observed malaria status of respondents with the model's predicted classifications to evaluate how accurately the model differentiates between malaria-positive and malaria-negative individuals. The results show that all 578 malaria-positive cases (100%) were correctly classified as positive, while all 172 malaria-negative cases (0%) were misclassified as positive.

Table 1: Classification Table for the Full Model

Observed			Predicted		
			Malaria Status		Percentage Correct
			Negative	Positive	
Step 1	Malaria Status	Negative	0	172	0.00
		Positive	0	578	100
	Overall Percentage				77.1

a. Constant is included in the model
b. The cut value is 0.500

This gives an overall classification accuracy of 77.1%, which matches the proportion of malaria-positive respondents in the sample. This outcome indicates that although the model performs well in identifying malaria-positive individuals, it fails to correctly classify non-infected (negative) cases, likely due to the high prevalence of malaria (77.1%) among the respondents. In practical terms, the model's predictive strength is heavily skewed toward the majority class (malaria-positive cases), showing that it correctly predicts infection but lacks sensitivity in detecting those not infected. This imbalance may suggest that additional or refined predictor variables could improve the model's discrimination ability between positive and negative malaria cases. Nonetheless, the model's overall classification rate confirms that malaria remains widespread among the farming population in Benue State.

The Constant Only (Null) Model

Table 2 presents the results of the constant-only (null) model from the binary logistic regression analysis, which predicts malaria infection among farmers in Benue State without including any independent variables. The constant (B = 1.212) represents the log odds of a respondent being malaria-positive when no predictors are involved in the model. The standard error (S.E.) of 0.087 indicates a relatively small variability in this estimate, suggesting the coefficient is stable. The Wald statistic (194.741), with 1 degree of freedom and a p-value of 0.000, shows that the constant is highly significant, meaning the probability of malaria infection in the sample is significantly different from zero. The Exp(B) value of 3.360 represents the odds ratio, indicating that, in the absence of any predictors, the odds of a respondent being malaria-positive are approximately 3.36 times higher than the odds of being malaria-negative. This finding aligns with the high malaria prevalence (77.1%) observed among the respondents and confirms that malaria infection is widespread within the population. However, since the model does not include explanatory variables, it lacks predictive power regarding the factors influencing malaria infection. Therefore, the null model establishes a baseline.

Table 2: The Constant Only (Null) Model

		B	S.E.	Wald	Df	p-value	Exp(B)
Step 0	Constant	1.212	0.087	194.741	1	0.000	3.360

Omnibus Tests of Model Coefficients

Table 3 presents the Omnibus Tests of Model Coefficients, which assess whether the inclusion of predictor variables in the binary logistic regression model significantly improves its ability to predict malaria infection among farmers in Benue State compared to the null (constant-only) model. The results show a Chi-square value of 33.749, with 15 degrees of freedom (df) and a p-value of 0.009, indicating that the model with predictors provides a statistically significant improvement over the null model at the 1% level of significance. In practical terms, this means that adding the explanatory variables such as occupation, housing condition, proximity to stagnant water, travel history, and malaria prevention practices significantly enhances the model's predictive accuracy for determining the likelihood of malaria infection. The significance of the Chi-square test ($p < 0.05$) confirms that at least one of the predictors contributes meaningfully to explaining variations in malaria status among the respondents. Therefore, the overall regression model is statistically valid and provides a better fit to the data than the model without predictors.

Table 3: Omnibus Tests of Model Coefficients

		Chi-square	df	p-value
	Step	33.749	15	0.009
Step 1	Block	33.749	15	0.009
	Model	33.749	15	0.009

The Full Model Summary

Table 4 presents the summary statistics for the full binary logistic regression model, which includes all the predictor variables influencing malaria infection among farmers in Benue State. The -2 Log Likelihood (−2LL) value of 783.956 measures how well the model fits the data—the smaller this value, the better the model's fit. Since the −2LL has decreased compared to the null model, it indicates that the inclusion of explanatory variables improved the model's performance in predicting malaria infection. The Cox and Snell R^2 (0.731) and Nagelkerke R^2 (0.747) are pseudo R-squared statistics that explain the proportion of variance in malaria infection accounted for by the predictors in the model. Specifically, the Cox and Snell R^2 suggests that approximately 73.1% of the variation in malaria infection is explained by the model, while the Nagelkerke R^2 (an adjusted version that can reach a maximum of 1) indicates a slightly higher explanatory power of 74.7%. These values demonstrate that the model has a strong explanatory ability, meaning that the socio-demographic, environmental, and behavioural variables included effectively predict malaria infection among the respondents. The note that estimation terminated at iteration 4 signifies that the model achieved convergence, confirming that the results are stable and reliable.

Table 4: The Full Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	783.956[a]	0.731	0.747

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than 0.001

Hosmer and Lemeshow Test for the Full Model

Table 5 presents the Hosmer and Lemes how Goodness-of-Fit Test, which assesses how well the predicted probabilities from the binary logistic regression model match the actual observed outcomes of malaria infection among farmers in Benue State. The test result shows a Chi-square value of 8.142, with 8 degrees of freedom and a p-value of 0.420. Since the p-value (0.420) is greater than 0.05, the result is not statistically significant, indicating that there is no meaningful difference between the predicted and observed values. In other words, the model's predictions fit the observed data well. This implies that the logistic regression model provides an adequate and reliable representation of the factors influencing malaria infection among the respondents. A good model fit such as this suggests that the included variables such as occupation, housing quality, proximity to stagnant water, education, and preventive practices appropriately explain variations in malaria status without over- or under-estimating outcomes. Therefore, the model is considered statistically sound and suitable for interpreting the predictors of malaria infection in the study area.

Table 5: Hosmer and Lemeshow Test for the Full Model

Step	Chi-Square	Df	P-value
1	8.142	8	0.420

Estimates of the Full Binary Logistic Model

Table 6 presents the parameter estimates (B coefficients), odds ratios [Exp(B)], and significance levels (p-values) for variables predicting malaria infection among farmers in Benue State. These results show which factors significantly increase or decrease the likelihood of malaria occurrence. Significant predictors ($p < 0.05$): Occupation, educational level, community participation in malaria sensitization (CPMS), type of house, living near stagnant water (LNSW), travel to areas with malaria prevalence (TAWMP), use of insecticide-treated nets (TMNI), receiving malaria prevention training (MPT), community involvement in malaria prevention (CIPMT), and healthcare access (HcareAcces). Occupation (B = 0.723, Exp(B) = 2.066): Farmers' occupation doubles their odds of contracting malaria, likely due to outdoor exposure. Community participation in malaria sensitization (CPMS, Exp(B) = 2.199): Higher participation is associated with increased malaria awareness, but in this model, it coincides with higher reported cases, possibly due to increased detection. Poor housing type (Exp(B) = 2.713), proximity to stagnant water (Exp(B) = 2.968), and travel to malaria-prone areas (Exp(B) = 2.921) significantly increase malaria risk. Educational level (Exp(B) = 0.438): Higher education reduces malaria risk, likely through better awareness and preventive behaviour. Use of treated nets (TMNI, Exp(B) = 0.760), receiving malaria prevention training (MPT, Exp(B) = 0.720), community involvement in prevention (CIPMT, Exp(B) = 0.737), and healthcare access (Exp(B) = 0.863) significantly lower malaria odds. Non-significant predictors ($p > 0.05$): Sex, age, and marital status were not statistically significant, indicating they do not independently predict malaria infection in this population.

Odds Predictions for Negative/Positive Outcome of Malaria

Table 7 presents the predicted odds of testing positive or negative for malaria when each independent variable moves from a low to a high level, holding other variables constant. The odds were calculated using the logistic regression equation Odds $= e^{(\beta_0+\beta_i x_i)}$.

Table 6: Parameter Estimates of the Full Binary Logistic Model

Variable	B	S.E.	Wald	Df	p-value	Exp(B)	95% CI for Exp(B)	
							Lower	Upper
Sex	0.049	0.179	0.076	1	0.783	1.051	0.739	1.493
Age	-0.006	0.006	0.880	1	0.348	0.994	0.982	1.007
Occup	0.723	0.086	70.68	1	0.000	2.066	0.927	3.156
Maritastatus	-0.060	0.090	0.446	1	0.504	0.941	0.788	1.124
EduLevel	-0.826	0.089	86.14	1	0.000	0.438	0.218	1.161
CPMS	0.788	0.184	18.34	1	0.000	2.199	0.973	3.972
TMNI	-0.275	0.089	9.547	1	0.003	0.760	0.525	1.099
Housetype	0.998	0.130	58.94	1	0.000	2.713	1.372	4.157
LNSW	1.088	0.182	35.74	1	0.000	2.968	1.741	4.508
TAWMP	1.072	0.186	33.22	1	0.000	2.921	1.546	4.248
MDT	-0.356	0.185	3.690	1	0.045	1.427	0.993	2.051
RMST	-0.536	0.190	7.958	1	0.005	0.585	0.265	1.599
MPT	-0.329	0.128	6.606	1	0.007	0.720	0.476	1.497
CIPMT	-0.305	0.083	13.50	1	0.000	0.737	0.515	1.054
HcareAcces	-0.148	0.048	9.507	1	0.003	0.863	0.601	1.239
Constant	0.268	0.075	12.77	1	0.000	1.307		

a. Variable(s) entered on step 1: Sex, Age, Occup = Occupation, Maritalstatus = Marital status, Edulevel = Educational level, CPMS = You or your family member's Current or previous malaria status, TMNI= Use of treated bed nets or insecticides, Housetype = House type, LNSW = Living or working in swampy areas or areas with stagnant water, TAWMP = Travelling to areas where Malaria is prevalent, MDT = Having malaria diagnostic test before, RMST = Recognizing malaria symptoms and seeking treatment promptly, MPT = Having information or training on Malaria prevention, CIPMT = Having local community initiatives or programs aimed at reducing Malaria transmission, HcareAccess = Access to Healthcare

The constant (baseline odds) is 1.3073, meaning that when all predictors are at their reference (low) levels, the odds of being malaria positive are 1.3073 to 1. Variables Increasing Odds of Malaria (High > Low). These variables raise the likelihood of being malaria positive: Occupation (Low = 1.3073 → High = 2.6939): Occupation strongly increases malaria risk, indicating that certain jobs—especially outdoor ones like farming—expose individuals to mosquito bites. Community Participation in Malaria Sensitization (CPMS: 1.3073 → 2.8748): Higher community involvement corresponds with increased malaria detection, possibly due to better screening and reporting. Housing Type (1.3073 → 3.5466): Poor-quality housing greatly raises malaria risk, likely because of open eaves and lack of mosquito protection. Living Near Stagnant Water (LNSW: 1.3073 → 3.8806): The strongest predictor of malaria infection, as stagnant water serves as mosquito breeding sites. Travel to Areas with Malaria Prevalence (TAWMP: 1.3073 → 3.8190): Travel to endemic regions significantly increases exposure risk. Healthcare Access (1.3073 → 1.1275): Slight increase suggests that individuals in malaria-prone areas may have more frequent contact with health facilities due to infection risk; Variables Decreasing Odds of Malaria (High < Low): These variables reduce the likelihood of being malaria positive. Education Level (1.3073 → 0.5724): Higher education reduces malaria odds substantially, likely through better knowledge of prevention methods. Use of Treated Mosquito Nets (TMNI: 1.3073 → 0.9930): Slightly lowers malaria odds, reflecting moderate protection effectiveness. Receiving Malaria Drugs/Treatment (MDT: 1.3073 → 0.9158): Indicates that timely treatment reduces infection risk. Regular Mosquito Spraying in the House (RMST: 1.3073 → 0.7649): Spraying significantly reduces malaria odds by minimizing mosquito presence. Malaria Prevention Training (MPT: 1.3073 → 0.9408): Training reduces odds by improving preventive practices. Community Involvement in Malaria Prevention (CIPMT: 1.3073 → 0.9637): Slightly lowers malaria odds by promoting community-based interventions. Variables with Minimal Effect Sex (1.3073 → 1.3730) and Marital Status (1.3073 → 1.2312) show minor effects on malaria odds, suggesting limited gender or marital-related differences in infection. Age (1.3073 → 1.2995) also has negligible influence, implying that malaria affects individuals across all age groups similarly.

Table 7: Odds Predictions for Negative/Positive Outcome of Malaria for Individual Predictors

Independent variables	Low	High
Sex	1.3073	1.373003
Age	1.3073	1.299527
Occup	1.3073	**2.693927**
Maritastatus	1.3073	1.231213
EduLevel	1.3073	0.572353
CPMS	1.3073	**2.874849**
TMNI	1.3073	0.993024
Housetype	1.3073	**3.546638**
LNSW	1.3073	**3.880640**
TAWMP	1.3073	**3.819044**
MDT	1.3073	0.915761
RMST	1.3073	0.764908
MPT	1.3073	0.940823
CIPMT	1.3073	0.963676
HcareAccess	1.3073	1.127497

Note: $\text{Odds} = e^{\beta_0+\beta_i x_{i,\ i=0,1}}$.

Discussions

The findings from Figure 1 and Tables 1 to 7 of this study align strongly with previous empirical research, confirming that malaria prevalence among farmers in Benue State is shaped by a combination of socioeconomic, environmental, and behavioral factors. The high infection rate (77.1%) observed in Figure 1 corroborates reports by Oyibo et al. (2020) and Eboh and Adebayo (2023), who identified poor housing, low education, and proximity to stagnant water as significant predictors of malaria incidence in rural Nigeria. The binary logistic regression results (Tables 1, 3-6) further revealed that occupation, housing type, closeness to stagnant water, and travel to malaria-endemic areas significantly increased the likelihood of infection consistent with Braimah et al. (2024), who emphasized the occupational exposure of farmers and limited access to healthcare as critical drivers of malaria risk. Conversely, higher education, use of insecticide-treated nets, mosquito spraying, and malaria prevention training were found to reduce infection odds.

Furthermore, the model's strong predictive accuracy (Tables 1, 4-7) complements climatic and biological studies that highlight the broader ecological context of malaria transmission. Research by Segun et al. (2020), Agyekum et al. (2022), and Nyawanda et al. (2024) linked malaria surges to rainfall and temperature fluctuations, which align with the environmental risk factors captured in this model. Similarly, Ugwu and Zewotir (2020) and Oladipo et al. (2022) observed that climate change and environmental degradation exacerbate vector breeding in agricultural zones such as Benue. The protective role of behavioral and educational factors identified in this study also resonates with findings from Ndila et al. (2018) and Beeson et al. (2019), who underscored how genetic and adaptive immunity moderate susceptibility among exposed populations. Collectively, the results affirm that malaria risk in Benue State is multifactorial driven by environmental exposure, occupational hazards, and limited preventive practices thus supporting the use of binary logistic regression as a robust tool for modelling and addressing malaria determinants in endemic farming communities.

CONCLUSION

This study modelled a binary logistic regression to investigate the predisposing factors of malaria fever among farmers in Benue State, Nigeria, revealing a high malaria prevalence of 77.1% among respondents. Significant predictors of malaria infection included occupation, poor housing, proximity to stagnant water, travel to malaria-endemic areas, and household malaria history, while higher education, use of insecticide-treated nets and insecticides, timely treatment, malaria prevention training, community participation, and better healthcare access reduced infection risk, necessitating an integrated control strategy that combines environmental management, health education, improved housing, vector control, and strengthened healthcare systems.

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