ASSESSING THE ROLE OF SOCIOECONOMIC FACTORS ON WILLINGNESS-TO-PAY FOR MALARIA INSURANCE WITH OUTDOOR MOSQUITOES COMMUNITY FUMIGATION IN KWARA STATE, NIGERIA

TAOHEED Rahmat Bolanle
and ADAM Shehu Usman

Department of Economics and Development Studies

Kwara State University, Malete, Nigeria

Abstract

Malaria remains a significant public health challenge around the world, especially in sub-Saharan African countries. The high transmission rates of this disease contribute to a substantial economic burden in the form of out-of-pocket expenditure and health issues, which can lead to death, especially among children under five years old and pregnant women. Several methods have been employed to eradicate malaria and prevent mosquitoes; however, the eradication of mosquito breeding sources has not yet been explored. This study assesses the role of socioeconomic factors on willingness to pay (WTP) for malaria health insurance with outdoor mosquitoes' community fumigation (MHI-OMCF) in Kwara state, Nigeria. Data was collected from one local government with the highest prevalence of malaria incidences in Kwara state. Random utility theory with expected utility theory was used to elicit 450 households' WTP for MHI-OMCF. Subsequently, probit regression was used to analyse the level of education, level of income, type of employment, age, premium amount, marital status, gender and residential area on WTP for MHI-OMCF. All the socioeconomic factors have a significant effect on WTP for MHI-OMCF except gender. The study recommended that the Nigerian government and private parastatals should improve and facilitate the establishment of MHI-OMCF with proper inclusion in the national malaria elimination program.

Keywords: Contingent valuation, fumigation, health insurance, malaria, mosquitoes and willingness to pay

Jel Classification Code: D12, I13, I18, Q51, Q57

1. Introduction

Malaria parasite infection is one of the leading causes of death in Nigeria. According to the 2022 World Malaria Report, Nigeria alone accounted for 27 per cent of malaria cases globally and 23 per cent of deaths from the disease. In addition, 30 per cent of admissions to Nigeria's hospitals are because of malaria (Shekarau et al., 2024). The World Malaria 2022 report also notes that half the world still lives at risk of malaria disease, which costs a child's life every two minutes. Thus, reducing the burden of malaria in Nigeria will contribute to the economic well-being of communities. Mosquito infection can take a significant toll on human health. Fortunately, evolving treatments and innovations could alleviate the consequences of mosquito infection (Kelly, 2023).

Although it is difficult to precisely define the economic burden of malaria, the expenses imposed on households paying for unplanned incidence of malaria are undeniably huge, which is, without doubt, enormous in Nigeria. Civil society organisations and private individuals have often provided support and care for malaria prevention and treatment for local communities in Nigeria. Such support includes Roll Back Malaria, initiated in 1998, which developed as a social movement, Nigeria Malaria Operational Plans established by the government from 2014 to 2020 and Malaria Consortium, established in 2008, operating under the Ministry of Health. Several private health maintenance organisations have recently sprung up to cater for citizens affected by malaria. Some of these organisations are AXA Mansard Hygeia and Wellahealth. They share malaria relief materials yearly and introduce several malaria plans (insurance policy) to reduce or eliminate unplanned out-of-pocket (OOP) health expenditures.

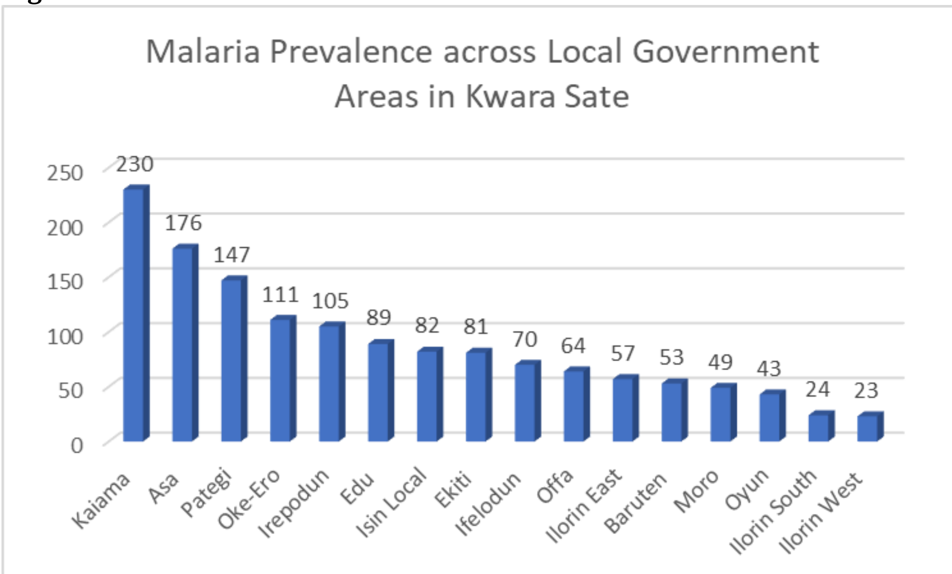
Taking into consideration all the 61 health maintenance organisations currently operating in Nigeria (NHIA, 2025), none of these insurance companies offer preventive outdoor mosquitoes' communal fumigation against malaria diseases in their insurance policy cover. This indicates that individuals with insurance policy cover still incur OOP payments for prevention of mosquitoes, such as buying insecticide-treated mosquito nets, mosquito repellent body spray and purchase of various brands of indoor insecticide sprays. These OOP expenditure practices are largely dominant among both the rich and poor households with or without health insurance cover in Nigeria. Outdoor mosquitoes' communal fumigation is a vector control strategy aimed at reducing the populations of disease-carrying insects, such as mosquitoes, to prevent the transmission of vector-borne diseases like dengue, malaria, and others. WHO (2022) emphasises that the goal of vector control is to prevent the transmission of such diseases. Most developed countries have integrated vector management strategies that combine chemical methods with community engagement and environmental management to enhance effectiveness and minimise potential risks from outdoor communal fumigation practices.

In a bid to eradicate malaria in Europe and the United States, social changes like improvement in the housing system with robust primary healthcare that is readily available and accessible were implemented. Also, environmental engineering pertaining to sanitary management was embarked on, which created a hostile environment for malaria parasite breeding and transmission. Piperaki and Daikos (2016) noted that the implementation of national elimination programs, which consisted of environmental engineering, supplemented by drug therapy and community insecticide spraying, further reduced malaria prevalence, which later led to the eventual elimination of malaria in Europe and the United States. Therefore, the community insecticide spraying (fumigation), which, among others, accounted for the success of mosquito elimination in Europe and the United States, could be the strategy that is yet to be adopted by low-income countries, including Nigeria.

Meanwhile, most literature reviewed has only assessed WTP for insecticide-treated nets (ITNs), which, according to WHO (2022), is not sufficient to prevent malaria and completely eradicate the breeding sources of mosquitoes. This necessitates the need to explore other alternative measures of malaria prevention and control, such as malaria health insurance with outdoor mosquitoes' community fumigation (MHI-OMCF). Unfortunately, this control measure is yet to be applied in Nigeria, which means its effectiveness has not been tested and therefore unknown. In addition, there exists a dearth of knowledge on factors that determine households' WTP for MHI-OMCF in Kwara State, Nigeria.

Figure 1 was obtained from the Kwara State Ministry of Health district health information system database 2024. It shows the rate of malaria incidence yearly, which indicates the total number of malaria incidences per one thousand individuals across each local government in Kwara State, Nigeria. The figure shows that Kaiama has the highest incidence rate, while Ilorin-West has the lowest rate of malaria incidence as of 2024 database compilations from DHIS.

Figure 1: Malaria Incidence as of 2024



Sources: Kwara District Health Information System (DHIS) 2024.

This study focuses on malaria endemic communities in Kwara State, which assesses the role of socioeconomic factors on willingness-to-pay for malaria insurance with outdoor mosquitoes' community fumigation in Kwara State, Nigeria. This provides an insight into people's health-seeking behaviour, community preferences and socioeconomic factors that affect the uptake of the malaria intervention program. Likewise, the analysis of a specific disease in this study should improve the quality of data related to factors that determine households' ability to value the benefits of a malaria health insurance with outdoor mosquitoes' community fumigation. Furthermore, the study focuses on disease prevention (mosquito vector control) and financial protection (malaria insurance) to eradicate the breeding sources of mosquitoes and provide financial security to reduce out-of-pocket expenditure on health.

The paper is organised into five sections. Following the introductory part in Section 1, Section 2 examines relevant articles on knowledge, attitudes and perception of households towards MHI-OMCF. The methodology adopted in the study is explained in Section 3, while Section 4 presents the results and discusses the findings. Lastly, Section 5 highlights conclusions based on the findings and offers recommendations for policy purposes.

2. Literature Review

Namuhani et al. (2024) examined WTP for the National Health Insurance Scheme (NHIS) among informal sector workers in Iganga and Mayuge districts, Uganda. Employing a contingent valuation method with a bidding game approach, the researchers surveyed 853 informal workers using multistage sampling, focusing on their socioeconomic characteristics. It was revealed that household income, prior awareness of NHIS, recent illness episodes, participation in savings, gender, employment status, and absence of disability were significantly associated with higher WTP. The study found that 81.5% of respondents were willing to pay UGX 25,000, which is equivalent to ₦10,700 of Nigerian currency as of 2024. While the findings reflect strong latent demand for health prepayment-based schemes among informal workers, the reliance on selfreported bidding responses may introduce hypothetical bias, meaning actual payment behaviour could differ from stated intentions.

Topan et al. (2024) examine the determinants of households' WTP for health insurance in Burkina Faso, using the Contingent Valuation Method (CVM) coupled with a Tobit regression model. Based on a cross-sectional dataset collected from 211 households. The study found household income, educational attainment, insurance reimbursement rate and occupation of the head of household as major determinants of WTP. It also revealed that WTP was approximately 7,644 FCFA per year per household, equivalent to ₦21,000 Nigerian currency. Though limited by sample size and reliance on direct CVM responses, this research provides timely and policy-relevant insights for financing inclusive health insurance systems in low- and middle-income countries.

Also, Abebe and Fanuel (2023) investigate community-based health insurance (CBHI) enrollment and associated factors among households in Southern Ethiopia. The study adopted a quantitative cross-sectional research design and employed the contingent valuation method with regression analysis to explore the socioeconomic factors that determine WTP for community-based health insurance. It was revealed that wealth status, education level, family size, and the presence of chronic illness in the household have a significant effect on the WTP for CBHI in the study area. The study was geographically restricted, potentially limiting generalizability to other parts of Ethiopia with different cultural or economic profiles.

Azuonwu and Smart (2023) investigate the socio-demographic determinants and utilisation of social health insurance services among civil servants in Bayelsa State, Nigeria. The study engaged 491 completed questionnaires for data analysis within the study period, which was analysed using mean, standard deviation, and point biserial correlation. It was revealed that household size, place of residence, educational status, employment status, income status, and availability of healthcare services played a significant role in determining subscription to and utilisation of social health insurance services among civil servants. One major limitation of the study is that the researcher did not involve standard methodology like CVM to back the analysis in the study; this could be because of reasons best known to the researcher.

Elegbede et al. (2022) investigated WTP for CBHI among artisans in Ekiti State, Nigeria. A total of 416 artisans were interviewed, with a focus on assessing both their interest in enrolment and financial commitment. The findings revealed that approximately 86.3% of respondents were willing to pay ₦1,000 and ₦5,000 per year for CBHI, suggesting relatively modest affordability thresholds. Key determinants of WTP included older age, female gender, tertiary education, having fewer children, and higher monthly income.

Akwaowo et al. (2021) conducted a contingent valuation study to assess the WTP for a contributory social health insurance scheme among rural residents in Akwa Ibom State, Nigeria. The findings revealed that income and household size have a significant impact on WTP. Also, approximately 82% of respondents expressed WTP for health insurance coverage, with a maximum WTP of ₦11,142 per household annually. However, the limited sample size and geographic focus on rural areas may constrain the generalizability of its findings. Likewise, it does not account for ability to pay, nor does it examine how proposed premium levels compare with other household budgets.

Esan et al. (2020) analysed the willingness of people to participate and pay for a community-based health insurance in a rural community in Osun State, Nigeria. The study collected its data from the community through a structured questionnaire within the period of study, by assessing the respondents' socio-demographic profile, health status, socio-economic status, the level of trust, and reciprocity in the community. The study shows that most of the respondents were willing to participate in the CBHIS. The modal amount respondents were willing to pay was ₦6,000, which is equivalent to $16.7 annually. Regarding the result from this study, it is limited by the small sample sizes adopted in the study, which cannot effectively represent the entire rural community in the state.

A similar study in Ghana by Adu et al. (2018) examined households' willingness to pay for private malaria insurance. An interview was conducted across various urban and rural areas to gather data on households' characteristics during the period of study. The researchers utilised a contingent valuation method involving a step-by-step hypothetical bidding game scenario to measure households' WTP. Followed by the specification of a double-bounded dichotomous choice format to estimate the actual WTP. The result of their findings revealed that despite price sensitivity, overall support for malaria insurance was robust, which implies that malaria disease was perceived as a burden and the insurance scheme was valued as important and necessary to reduce out-of-pocket expenditure on health. The only limitation observed in this research is that a lot of people might have overstated their WTP amount, which will not actually represent real market behaviour for the services.

More so, Alesane and Anang (2018) explore the factors that determine the uptake of health insurance by the rural poor in Ghana. The study makes use of 178 questionnaires retrieved from the respondents as data that was analysed using the logit model. Age, sex, literacy level and household size were indicated as major factors that determine households' subscription to the health insurance scheme. The result also indicated that health insurance uptake is higher among younger people; likewise, older women are, however, more likely to take up health insurance compared to older men. In addition, the study reveals that insurance uptake increases with the level of education. The study is subject to limitations due to the small sample sizes adopted in the study, which cannot effectively represent the entire poor rural areas in the country.

Onwujekwe et al. (2009) examined socio-economic status and geographic differences in the willingness of respondents to pay for community-based health insurance in Nigeria. The result from the analysis indicated that 40% of the people are willing to pay for the CBHI in the urban areas, while this percentage is lower for the people in the rural community. The study concluded that economic status and place of residence, amongst other factors, play a significant role in people's WTP for CBHI in Nigeria. The study, in its efforts, fails to create proper awareness for people in the community to introduce and educate them about the importance of the CBHI to ensure that more people subscribe to the scheme.

Asgary et al. (2004) examined WTP for health insurance among rural households in Iran using the CVM. Employing an iterative bidding game format. Based on data from 2,139, the average WTP was 22,044 Iranian rials (approximately US$2.77/month). Their regression analysis showed that education, age of household head, satisfaction with local health services, and proximity to urban health infrastructure were positively associated with WTP, while access to utilities such as piped water and telephone, which are proxies for more developed areas, had a negative effect. Despite its strengths in sample design and analytical depth, the study's limitations include its reliance on hypothetical WTP, which is subject to hypothetical bias.

Asafu-Adjaye and Dzator (2003) assess households' willingness to pay for a specific insurance scheme in Ghana using the contingent valuation method. The findings revealed strong support for malaria insurance, with household income, education level, occupation, and number of children significantly influencing the amount respondents were willing to pay. The study was conducted in specific rural and urban areas in Ghana, which would not fully represent the entire country's diversity; thus, the findings may have limited generalizability to other regions within Ghana and other countries.

In a study by Asenso-Okyere et al. (1997), WTP for a national health insurance scheme was studied among informal sector workers in Ghana. The study employed the contingent valuation method (CVM) analysis. The results revealed that over 90% of respondents expressed interest in participating in the proposed health insurance scheme, while 63.6% of the respondents were willing to pay 5,000 Ghanaian cedis, equivalent to US$3.03 per month for a five-person household. It was also revealed that the level of education, income level, lower dependency ratios, prior healthcare expenditures, and previous experience with cost-related treatment denial all have a significant effect on WTP for health insurance. However, the key limitation of the study is the hypothetical nature of CVM, which might overstate the actual WTP adopted in the study.

3. Methodology

This research adopts the microeconomics theory of Random Utility theory by McFadden (1974) and Expected Utility Theory EUT by Von Neumann & Morgenstern (1944). The theories assume that individuals make decisions to maximise utility under budget constraints. When assessing the value of non-market goods such as malaria health insurance with outdoor mosquitoes' community fumigation (MHI-OMCF), households' decisions are often constrained by limited financial resources. The RUT and EUT theories are consistent with the contingent valuation method (CVM) to elicit households' WTP for MHI-OMCF in Kwara State. The model was conceptualised by Hanemann (1984) and further elaborated by Mitchell and Carson (2013). The Function is stated as follows:

$$U_i = U(WTP_i, X_i) \dots\dots\dots\dots\dots\dots\dots\dots (1)$$

Where:

U_i= Utility function for the individual

WTP_i= willingness to pay for the good

X_i households' characteristics such as age, income, marital status, level of education, gender, residential area and type of employment.

The unobservable factors affecting individual choices will be evaluated through contingent valuation methods (CVM) for eliciting households' WTP for malarial health insurance with outdoor mosquitoes' communal fumigation in Kwara State. Therefore, a single bounded dichotomous choice CVM with an open-ended question will be specified for analysis. Hoehn and Randall (1987) explained that dichotomous choice CVM, also known as the referendum format, presents respondents with a hypothetical scenario. This is to ensure that the strategic changes in respondents' behaviour when the initial bid is presented are avoided and well taken care of to avoid both starting point bias and interval range bias. Carson et al. (1997) stated that the dichotomous choice CVM has become a recommended guideline since its adoption for the National Oceanic and Atmospheric Administration (NOAA). To prevent hypothetical bias, a hypothetical market scenario will be introduced to the respondents detailing the reasons for introduction, cost and benefit of malaria health insurance with outdoor mosquitoes' communal fumigation.

The Single Bounded Dichotomous Choice Model

In the single bound model, the interval is bound by the bid and the limit of the WTP distribution (the upper limit if the answer was positive, the lower limit otherwise) (Hanemann, 1984; Calia & Strazzera, 1999). Closed-ended questions for the single-bound dichotomous choice were presented on the WTP bid for malaria health insurance, with outdoor mosquitoes' communal fumigation thereafter presented. A minimum bid of ₦7,000 and a maximum bid of ₦27,000 were obtained from the pretest questionnaire during our in-depth interview survey. The maximum and the minimum values were then divided into five versions of bid vector methods to properly mimic how product bargaining takes place in the market, which also allows for a larger sample size to be adopted in the study. Carson et al. (1997) recommend that higher bid vectors in CVM tend to improve the reliability of WTP values by presenting different bid amounts and structures to different groups of respondents. In this study, households are presented with a binary decision whether to pay a specified amount for MHI-OMCF or not. This aligns with Hanemann's (1984) single-bound utility preference model, where the probability of accepting the bid depends on the difference in deterministic utilities between two states (with and without the intervention), which is adjusted for random errors. If the respondent answers "Yes" or "No", the probability of the response, as explained in Hanemann (1984), is represented as follows:

If the respondent says "No" to the initial Bid Value (BV): $\pi^n(BV_I) = 0$, which implies the $Pr\{BV_I > maximum\, WTP\}$

If the respondent says "Yes" to the initial Bid Value: $\pi^y(BV_I) = \infty$ =, which implies the $Pr\{BV_I \leq maximum\, WTP\}$.

To model the above responses, the binary probit regression model will be adopted, which is assumed to be appropriate for analysing CVM data with dichotomous choice formats. The dependent variable represents a binary response, 1 = willing to pay and 0 = not willing to pay. This modelling approach is grounded in Random Utility Theory (RUT), which assumes that individuals choose the alternative that maximises their utility, and that utility comprises both observed and unobserved components (Hanemann, 1984; Louviere et al., 2007). The probit model specifically assumes that the error terms in the utility difference are normally distributed, making it suitable when the decision to accept or reject a proposed bid is influenced by underlying latent preferences and normally distributed stochastic variation.

Probit regression estimates the cumulative normal probability of this utility difference being positive and therefore enables estimation of mean and median WTP (Cameron & James, 1987). Compared to linear probability models, probit regression ensures that the estimated probabilities lie strictly within the range of 0 and 1, addressing heteroskedasticity and non-linearity issues (Wooldridge, 2010). Additionally, probit models perform well in small and moderate sample sizes and are commonly used in health economics and environmental valuation studies due to their theoretical consistency and ease of interpretation (Haab & McConnell, 2002).

Therefore, the use of binary probit regression in this study is methodologically justified as it aligns with the decision and theoretical foundation of CVM to accommodate the dichotomous nature of the WTP responses and provides statistically valid parameter estimates to compute mean WTP.

The probit representation of the probability for a 'Yes" response = 1 is stated as:

$$P(YES = 1) = P_i^y = \frac{1}{1+ e^{-(\alpha + \beta B7_I)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Further expanding the equation to include sociodemographic variables gives us:

$$P_i^y = \frac{1}{1+ e^{-(\alpha + \beta B7_I + \varphi X_i)}}$$

Where:

P_i^y = Probability of Yes, which equals 1

BV_I = bid value (price)

α = Intercept term while

β and φ = parameters to be estimated

X_i = Household characteristics that capture attitudes, subjective norms and perceived behavioural control, which include (Age, income, Marital status, level of education, Gender, Residential area, Type of employment).

Taking the log-odds transformation for a binary probit regression model, we get:

$$\log(oddsP_i^y) = \propto_0 + \beta_I BV_I + \varphi_1 MIDDLEAGE_i + \varphi_2 AINCOME_i + \varphi_3 MRT_i + \varphi_4 EDUC_i + \varphi_5 GEN_i + \varphi_6 RESIDENCE_i + \varphi_7 OCCUP_i + \varepsilon_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

This presents a probit regression that models the log odds of the outcome as a linear function of the independent variables.

ε_i = Error term

After the probit regression has been established, the mean WTP will be calculated with the formula stated below:

$$Mean\,WTP = -\frac{\beta_0}{\beta_1}$$

Where:

$Mean\,WTP$ = maximum amount households are willing to pay

β_0 = estimated constant

β_1 = coefficient on the bid variable.

About the *a priori*, we expected all parameters to satisfy the following sign restrictions: $\beta_I < 0$ *and* $\varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5, \varphi_6$ and $\varphi_7 > 0$.

Bid Value is postulated to have a negative effect on WTP in CVM as the relationship reflects basic economic theory of demand that as the price of a good increases, quantity demanded decreases (Varian, 2010). Hanemann (1984) explains that a higher bid amount limits positive response WTP. *Income level* is included to capture how different income households respond to WTP. Based on the consumer theory of goods and services, WTP is expected to increase as income rises, as described by the income elasticity of demand, where richer households derive greater utility from the same good and are more likely to afford and pay for it. Hanemann (1984) reported a positive correlation between income and WTP in several CVM models.

The inclusion of *education* is because increasing awareness and understanding of the program will have a positive effect on WTP. Educated individuals often exhibit greater WTP, reflecting better risk perception. Asenso-Okyere et al. (1997) found that education level significantly increases WTP for health insurance in Ghana. *Marital status* often makes individuals more risk-averse, which means they are more likely to invest in preventive measures against diseases related to health. Adu et al. (2018) reported that married respondents were more likely to pay for malaria insurance. Age is an important sociodemographic factor which is often expected to have a positive effect on WTP.

Gender inclusion as a variable is used to ascertain the impact of intra-household decision-making roles among men and women in the family. Gender often influences household decision-making roles, especially in health-related expenditures, where male equals 1 and female equals zero. It is expected to have a positive effect on MHI-OMCF. *Type of employment* often correlates with income stability, which influences the ability to afford health insurance and participate in community healthcare programs. Topan et al. (2024) found that both formal and informal sector workers have a significant impact on WTP for health insurance.

3.1 Data Collection Procedure

The questionnaire initially developed for the study was subjected to pretest through a pilot study, to justify the correctness and applicability of its content to the target population. Following the pilot study's results, some questions were revised to improve respondents' comprehension and understanding of certain concepts after the initial questionnaire was evaluated by experts in the field.

The Kobotoolbox was used to administer the questionnaire in the selected local government, this is to ensure the correctness and accuracy of the data to prevent missing data or incomplete data. The format adopted in the questionnaire was to ensure all the biases relating to primary data analysis were potentially addressed, and proper precautions were taken to prevent any of these biases. Considering the range of values presented can affect respondents’ answers, with narrower ranges leading to higher valuations. To address range bias, an interview was conducted among a few respondents during the pretest stage to have a view of the minimum and maximum amount households are willing to pay. Likewise, a literature review on health insurance companies suggested that some bid ranges starting point was later adopted in the study. To guard against sequence bias, the study adopts the sequence and structure of the CVM questionnaire as suggested by Bateman et al. (2002).

a. Content and Construct Validity of the Questionnaire: The content validity was explored in a way that items in the questionnaire broadly cover all variables in the theoretical framework, Random Utility Theory and Expected Utility Theory. It also describes the payment vehicle, which is the annual premium, and lastly, a hypothetical market scenario was presented with follow-up questions, which fully capture WTP for malaria health insurance with outdoor mosquitoes’ community fumigation. The structures and the scale rank measurement values of the questions were adapted from previous studies that successfully measured selected variables in similar contexts, which is also is in line with total design methods explained by Mitchell and Carson (2013) and Bateman et al. (2002). Some of the items included were adapted from Ataguba et al. (2008) questionnaire which serves as empirical grounding from literature that were reviewed. Finally, economists’ experts inform the supervisory committee to help to refine the questionnaire.

b. Implementation Methods: The interview was conducted in three different languages (English, Yoruba, and Barkobaru) because of language differences in the local government selected. Before the start of the interviews, the participants were introduced to the scheme using the videotape designed to provide detailed information about MHI-OMCF. Permission was sought from the respondents before the interview commenced. The trained researchers were those who understood the language of the prospective interviewees, which made it easier to communicate to get the desired outcome from the interview section.

Afterwards, Microsoft Excel was used to clean and code the data and create initial visualisations of the data downloaded from KoboToolbox. SPSS was used to carry out descriptive analysis, while Stata was used to test econometric models adopted in the study.

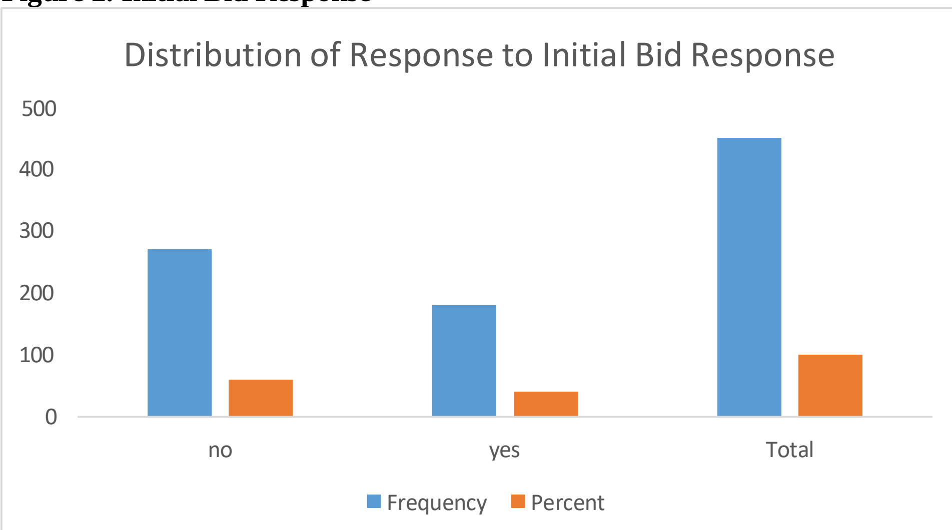
4. Results

The results of the study's analyses are presented and discussed in this section. The analyses include descriptive statistics, probit regression and WTP estimate.

4.1 Descriptive Statistics

This presents simple descriptive information about the variables adopted in the model, which shows the distribution of the variables. This will include measures such as means, medians, and frequencies for variables such as age, gender, income, education, initial bid response, and health status.

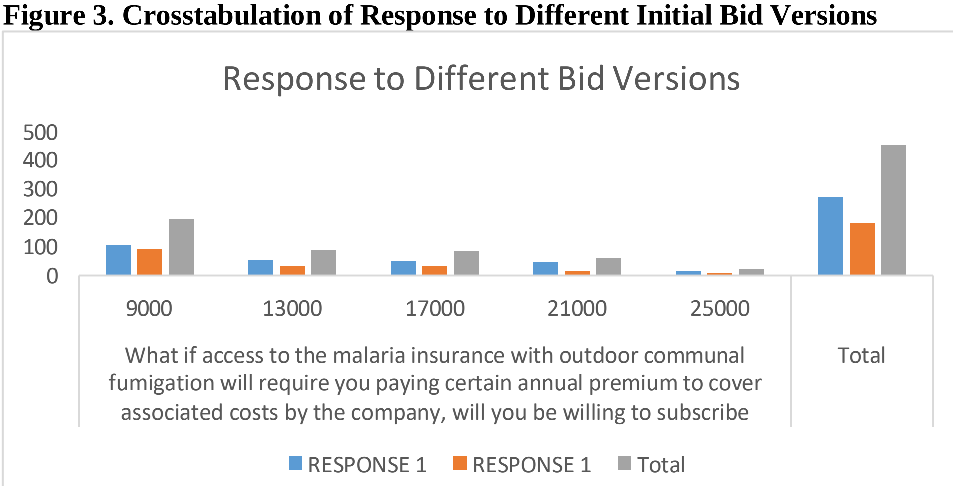
Figure 2. Initial Bid Response



Source: Authors' computation 2025

The chart shows that out of 450 respondents, 270 (60.0%) answered "no", indicating that the majority of the respondents did not want to pay the specific amount stipulated. 180 (40.0%) of the respondents answered "yes", this is suggestive of limited agreement regarding the premium amount of MHI-OMCF.

Figure 3. Crosstabulation of Response to Different Initial Bid Versions



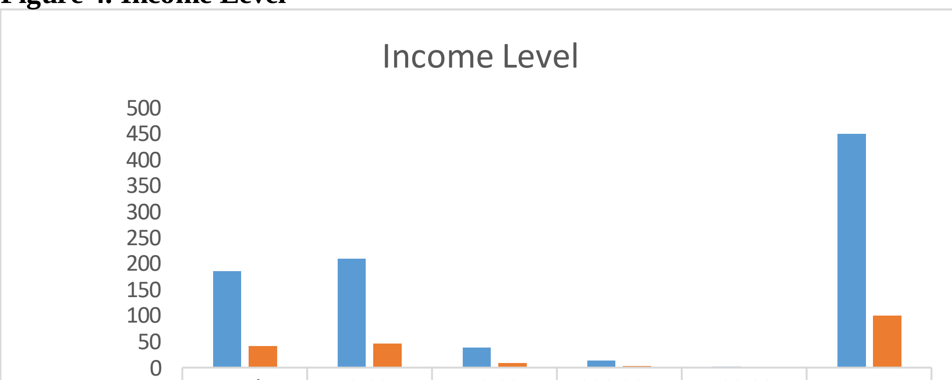
Source: Authors' computation 2025.

The chart in Figure 3 shows the distribution of willingness to subscribe to MHI-OMCF at different annual premiums (bid) amounts. It can be observed from the chart that as the premium increases, the number of people willing to subscribe decreases. This is consistent with the law of demand for a normal good, which states that higher prices reduce the likelihood of subscribers to services in the case of a normal good. As the premium increased from ₦9,000 to ₦ 25,000, the number of "yes" responses declined, reflecting a typical inverse relationship between price and WTP.

Going further, only 32 respondents were willing to pay ₦13,000, while 33 respondents were willing to pay ₦17,000, 15 respondents were willing to pay ₦21,000, and 9 respondents were willing to pay the highest premium of ₦25,000. In summary, 180 respondents (40%) were willing to subscribe at different given prices, while 270 (60%) were not. This trend suggests a clear sensitivity to the price of MHI-OMCF.

Figure 4 shows that 186 respondents (41.3%) earn less than ₦70,000 per month, indicating a relatively low-income population in the study area. 210 (46.7%) of the respondents fall within ₦70,001 to ₦150,000 income, indicating the second-largest income group, indicating that most respondents earn below ₦150,000 monthly.

Figure 4. Income Level

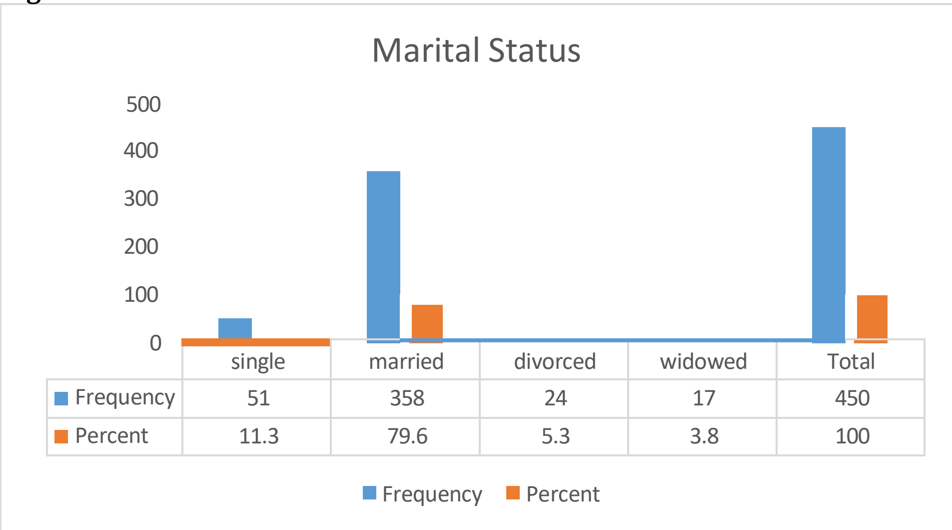


	Less than 70,000	70,001-150,000	150,001-300,000	300,001-500,000	500,001 above	Total
Frequency	186	210	39	13	2	450
Percent	41.3	46.7	8.7	2.9	0.4	100

Source: Authors' computation 2025.

Also, 39 (8.7%) of respondents earn within the middle-income bracket of ₦150,001 to ₦300,000, while 13(2.9%) respondents earn ₦300,001 to ₦500,000, which is the upper-middle range income level and only 2 (0.4%) respondents fall in the high-income category of ₦500,001 above. This income profile implies that the price of the premium and affordability will be a major factor in the WTP for MHI-OMCF.

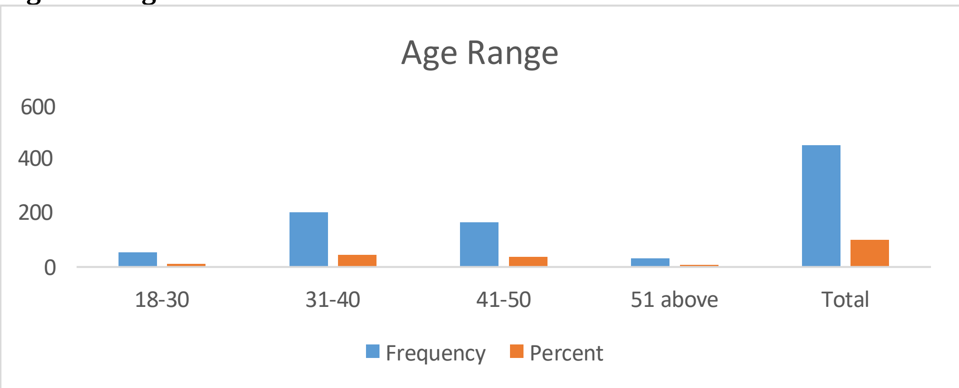
Figure 5. Marital Status



Source: Authors' computation 2025.

Figure 5 indicates that 358 (79.6%) respondents are married, making them the dominant group in the study. 51 (11.3%) respondents are single, while 24 (5.3%) of the respondents fall into the divorced category. 17 (3.8%) of the respondents are widowed, representing the smallest group. This chart sums up different households with distinct economic challenges and financial priorities that affect their WTP for MHI-OMCF.

Figure 6. Age Distribution

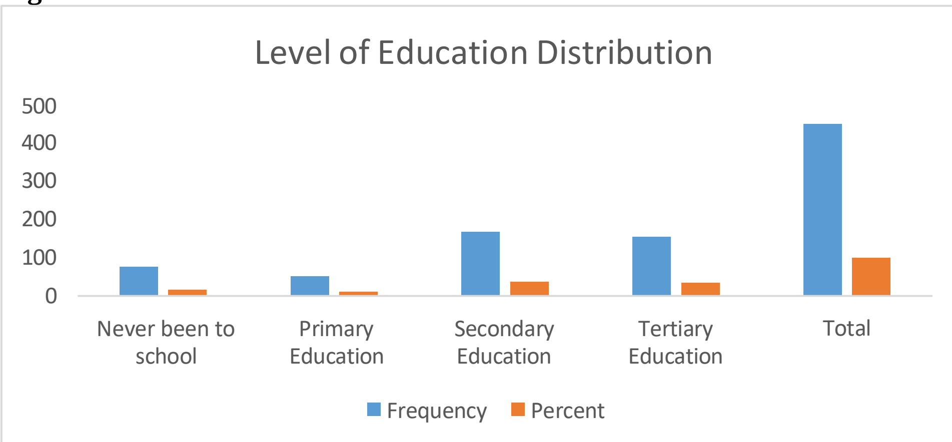


Source: Authors' computation 2025.

The distribution of respondents by age reveals that 18–30 make up 53 (11.8%) of the sample, indicating young adults. While the majority are middle-aged adults, who represent 201 (44.7%) aged 31–40 and 164 (36.4%) aged 41–50. Lastly, only 32 (7.1%) are aged 51 and above. This indicates that the sample size is largely composed of individuals in their economically active and family-supporting years.

Figure 7 indicates that 76 (16.9%) respondents have never been to school, while 52 (11.6%) have a primary school education. Secondary school education is the largest group with 168 (37.3%) respondents, followed by tertiary education with 154 (34.2%) respondents.

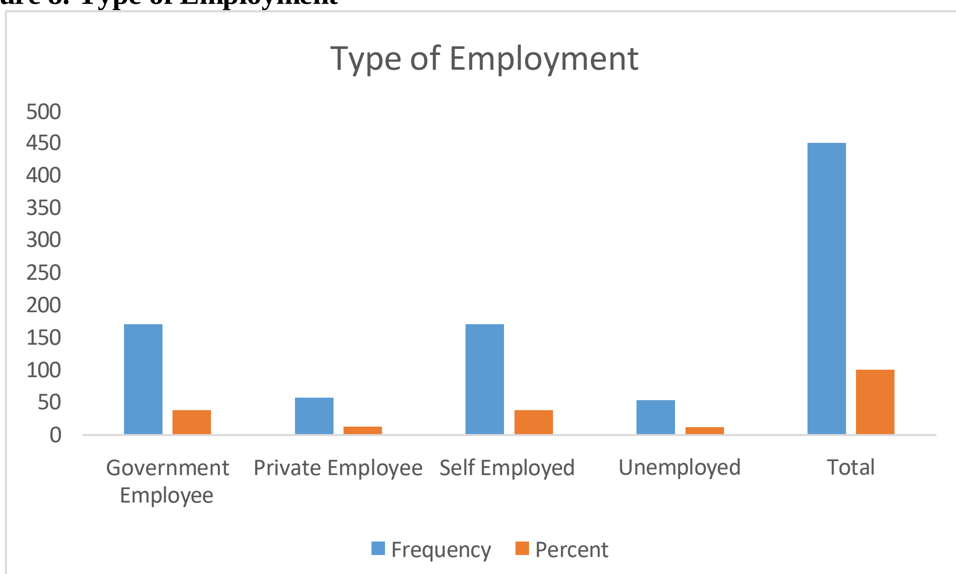
Figure 7. Level of Education



Source: Authors' computation 2025.

This sample suggests a relatively high level of education in the sample, with over 70% of the respondents having at least secondary education.

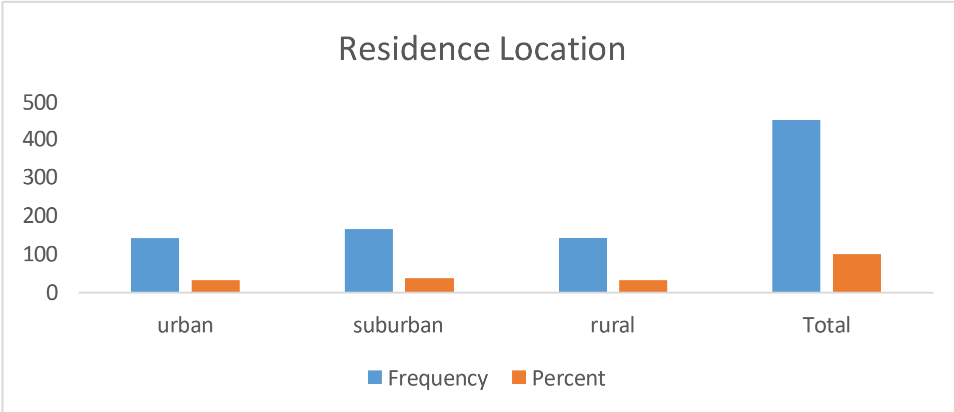
Figure 8. Type of Employment



Source: Authors' computation 2025.

The chart in Figure 8 shows that both government employees and self-employed dominate the sample, with 170 each making up 240 (75.6%) of respondents. 57 (12.7%) Private employees are 57 (12.7%) and 53 (11.8%) of unemployed respondents. The Private employee with an unemployment rate is relatively low compared to government and self-employment.

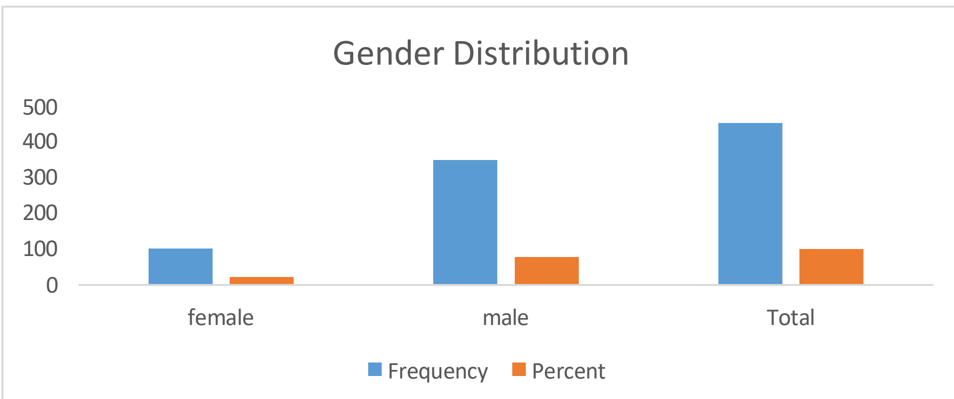
Figure 9. Residential Location



Source: Authors' computation 2025.

Figure 9 indicates that 142 (31.6%) of the respondents reside in the urban areas in the study area. Suburban has 165 (36.7%) while respondents' rural area has 143 (31.8%). Although suburban areas have the highest population (36.7%), the distribution is relatively balanced across all three categories.

Figure 10. Gender Distribution



Source: Authors' computation 2025.

The chart in Figure 10 shows that male respondents are 348, which is 77.3% of the total respondents, while female respondents are 102 (22.7%). This result aligns with expected norms in African family settings where men are usually the head of households. In this regard, men are primary decision-makers and thus more likely to participate in this study.

4.2 Probit Regression Results

This section presents the analysis and results of the probit regression stipulated in section three above.

Table 4.1 The Probit Regression Result

Variables	Coefficient	Std. Error	Z-statistics	P-value
IBID	-0.0000184	0.00000447	-4.12	0.000
AINCOME	0.00000143	0.000000295	4.85	0.000
MRT	-0.0963512	0.0402006	-2.40	0.017
EDUC	-0.1401073	0.0493075	-2.84	0.004
MIDDLEAGE	0.1687715	0.0605583	2.79	0.005
OCCUP	-0.1454824	0.0438184	-3.32	0.001
GEN	-0.0476554	0.0552459	-0.86	0.388
RESIDENCE	0.1126660	0.0260239	4.33	0.000
R-squared	0.1002			
Log likelihood	-272.51226			
No of Observations	450			
Mean VIF	1.13			

Explanatory note: The dependent variable is the probability of WTP for MHI-OMCF (RI = 1). A coefficient is statistically significant if the associated P-value is less than 0.05.
Source: Authors' computation 2025.

The study carried out a multicollinearity test using the Variance Inflation Factor (VIF) test, which shows no evidence of high multicollinearity as the VIF of each explanatory variable is less than 5. Therefore, we failed to reject the null hypothesis of the absence of multicollinearity in the model. The linktest was used to test for misspecification error, which produced a p-value of 0.511, which is greater than the chosen significance level of 0.05 and following the decision rule, we failed to reject the null hypothesis of constant variance and concluded that there was no evidence of misspecification error in the model. The R-squared of 0.1002 is within an acceptable rate for a social science study according to McFadden (McFadden, 1974), which indicates that the explanatory variables explain about 10% of the variation in the WTP for MHI-OMCF. There is statistically significant evidence of heteroskedasticity in the model at 0.05, which was corrected after robust standard errors were calculated to adjust the coefficients of the standard errors without changing the point estimate in the model.

Having assessed the diagnostic statistics of the equation, we now proceeded to evaluate the performance of each of the explanatory variables. The coefficient for the bid amount (IBID) is -0.0000184 with a p-value of 0.000, indicating a negative effect on WTP for MHI-OMCF, which conforms to our negative *a priori* expectation and is statistically significant. This means that an increase in the bid amount decreases the probability of willingness to pay for MHI-OMCF. Specifically, a ₦1 increase in the bid amount reduces the likelihood of WTP by approximately 0.0000184%. This finding is consistent with the basic law of demand in microeconomics, which postulates that a price increase generally decreases quantity demanded. Also, consistent with the contingent valuation study of Hanemann (1984), this negative effect indicates that households are sensitive to the premium amount. Therefore, this study concludes that there exists a negative effect of IBID on WTP for MHI-OMCF in Kwara State.

The coefficient of household income (AINCOME) is 0.00000143 with a p-value of 0.000 exhibiting a positive and highly statistically significant which conforms to the positive *a priori* expectation and is supported by existing literature, such as Onwujekwe et al. (2009) report a positive association between income and WTP. This result indicates that higher-income 8households are more willing to pay for MHI-OMCF. Indicating that as income increases by ₦1, the probability of WTP for MHI-OMCF also increases by 0.000143%, albeit by a small percentage per naira. This could be since higher-income households have greater financial flexibility and are better able to afford risk-mitigating measures like MHI-OMCF.

Concerning the negative coefficient of marital status (MRT), which is -0.0963512 with a p-value of 0.017. This means that respondents within the married category are 9.63% less likely to subscribe to MHI-OMCF in Kwara State. The coefficient is negative and statistically significant, which is not in conformity with the positive *a priori* expectation posited and with existing literature such as Adu et al. (2018). The discrepancy may be context-specific, such as additional financial responsibilities that often come with marriage, like caring for children or supporting dependents, which might reduce available funds for families. Furthermore, decision-making in married households may be more complex, which sometimes requires consensus between partners, which can sometimes delay decision-making. The study concludes that MRT shows a negative effect on WTP for MHI-OMCF.

As regards the negative coefficient of secondary and tertiary education (EDUC), which is -0.1401073 with a p-value of 0.004, which shows that the negative coefficient is statistically significant, which is not in line with the positive a priori expectation. However, this is not in line with previous studies such as Giedion & Uribe (2009), where a positive coefficient was detected. This might be due to harbouring misconceptions about the effectiveness or trustworthiness of MHI-OMCF. Furthermore, they may be more sceptical about paying for preventive services or less confident in the formal health system. Educational attainment affects how individuals interpret health information and evaluate risk. Results highlight the need for awareness campaigns that are specifically designed to reach and educate every member of the community.

The coefficient of age (MIDDLEAGE) is 0.00000143 with a p-value of 0.005, exhibits a positive and highly statistically significant which conforms to the positive a priori expectation and with existing literature such as Esan et al. (2020) and Onwujekwe et al. (2009), who reported a positive association between age and WTP. The coefficient implies that with each additional year in age, the likelihood of a household WTP for MHI-OMCF increases by 0.00000143. This implies middle-aged individuals are often more risk-averse and focus more on family welfare, thereby increasing their WTP for MHI-OMCF. This age group (31 to 50 years) typically falls within the most economically productive and health-conscious stage of life. They are often the heads of households, responsible for the well-being of spouses and children, and thus may prioritise preventive healthcare measures such as this program.

Concerning the negative coefficient of type of occupation, self-employed (OCCUP), which is -0.1454824 with a p-value of 0.001, which indicates that the coefficient is negative and statistically significant, which is not in conformity with the positive *a priori* expectation posited and supported with existing literature, such as Topan et al. (2024). Being self-employed is negatively associated with WTP for MHI-OMCF. This implies that as the level of self-employment increases by 1% the likelihood of a self-employed individual WTP for MHI-OMCF decreases by 0.145%. This may be due to irregular income streams and financial uncertainty that sometimes limit the ability to commit to the services. The result suggests that financial stability is beyond just income, which in most cases is critical for WTP for MHI-OMCF.

Gender (GEN) coefficient -0.0476554 with p-value 0.388 is negative and statistically not significant in this model. The negative sign suggests that females may be less likely to pay for insurance than males, but the result is not robust enough to support this claim confidently. Also, the lack of significance may be due to cultural dynamics not captured in the model. The insignificant result did not match Esan et al. (2020), whose results report gender to be statistically significant in their study.

The coefficient of urban residence (RESIDENCE) is 0.1126660 with a p-value of 0.000, exhibiting a positive and highly statistically significant which conforms to the positive a priori expectation and is consistent with Adu et al. (2018), urban dwellers displayed higher WTP, likely due to exposure, access, and trust in the insurance provider. Rural residents may require more targeted awareness and trust-building interventions to bridge information gaps. This study concludes, therefore, that there is a positive effect of place of residence on willingness to pay for malaria health insurance with outdoor mosquitoes' community fumigation in Kwara State.

Table 4.2 Willingness to Pay Results

Variables	**Coeff.**	**Z-statistic**	**P-value**	**95% Conf. Interval**
WTP	8317.138	4.79	0.000	4910.907 11723.37
No of Observation	450			

Explanatory note: A Nonlinear combination of the estimator command in Stata was used to compute the mean Willingness to Pay (WTP) for MHI-OMCF in Kwara State.
Source: Authors' computation 2025.

The result of the mean WTP for MHI-OMCF in Kwara State indicates that, on average, respondents are willing to pay ₦8,317 (which is equivalent to $5.5 current US dollars) for MHI-OMCF in Kwara State. The P-value is 0.000, which indicates that the WTP amount is significant. The WTP amount is in line with the amount (Esan et al., 2020; Namuhani et al., 2024), recommend in their study. The interval value gives the range within which the true mean WTP is expected to fall at 95% of the time. The researcher is confident that the population's average WTP lies between ₦4,911 and ₦11,723 in this study.

5. Conclusion and Recommendations

This study examines the effect of some sociodemographic factors on willingness to pay for WTP for MHI-OMCF. It establishes that income level, middle-aged individuals and urban residence have a positive and significant effect. In contrast, premium amount, marital status, level of education and type of employment have a negative and significant effect on WTP for MHI-OMCF in Kwara State, Nigeria. Lastly, the mean WTP was estimated to amount to ₦8,317/$5.5 for MHI-OMCF in Kwara State, Nigeria.

In light of the above findings that households are sensitive to premium amount and income is a major determinant, it is suggested that the government impose a price ceiling of ₦8,317/$5.5, which was informed by this study to ensure affordability and encourage broader participation. The urban residence shows more WTP for MHI-OMCF; awareness programs on MHI-OMCF should be prioritised in the rural areas, as this will significantly enhance uptake and long-term sustainability of MHI-OMCF in Kwara State, Nigeria.

Although this study has added to the body of knowledge through the adoption of CVM to test the WTP for malaria health insurance with outdoor mosquitoes community fumigation in Kwara State which differs from other WTP studies that concentrate majorly on WTP insecticides treated net and health insurance, this study is limited to only cross-sectional data, which captures WTP at one point in time. Therefore, Future research should use longitudinal designs to track changes in WTP over time, especially before and after actual exposure to MHI-OMCF. This would enable stronger causal inference and a deeper understanding of how trust and the usage of MHI-OMCF influence household behaviour over time.

References

Abebe, Y., & Fanuel, B. (2023). Determinants of willingness to pay for a community-based health insurance scheme among households in the rural community of southern Ethiopia. *BMC Health Services Research*, *23*(1). https://doi.org/10.1186/s12913-023-10406-w

Adu, D. T., Adom, P. K., & Gyimah-Brempong, K. (2018). Willingness to pay for private malaria insurance in Ghana. *Health Economics Review*, *8*(1), 1–14.

Akwaowo, C. D., Umoh, I., Motilewa, O., Akpan, B., Umoh, E., Frank, E., Nna, E., Okeke, U., & Onwujekwe, O. E. (2021). Willingness to Pay for a Contributory Social Health Insurance Scheme: A Survey of Rural Residents in Akwa Ibom State, Nigeria. *Frontiers in Public Health*, *9*. https://doi.org/10.3389/fpubh.2021.654362

Alesane, A., & Anang, B. T. (2018). Uptake of health insurance by the rural poor in Ghana: determinants and implications for policy. *The Pan African Medical Journal*, *31*, 124. https://doi.org/10.11604/pamj.2018.31.124.16265

Asafu-Adjaye, J., & Dzator, J. (2003). Willingness to Pay for Malaria Insurance: A Case Study of Households in Ghana Using the Contingent Valuation Method. *Economic Analysis and Policy*, *33*(1), 31–47. https://doi.org/10.1016/s0313-5926(03)50003-0

Asenso-Okyere, W. Kwadwo., Osei-Akoto, I., Anum, A., & Appiah, E. N. (1997). Willingness to pay for health insurance in a developing economy. A pilot study of the informal sector of Ghana using contingent valuation. *Health Policy*, *42*(3), 223–237. https://doi.org/10.1016/s0168-8510(97)00069-9

Asgary, A., Willis, K., Taghvaei, A. A., & Rafeian, M. (2004). Estimating rural households? Willingness to pay for health insurance. *The European Journal of Health Economics, Formerly: HEPAC*, *5*(3), 209–215. https://doi.org/10.1007/s10198-004-0233-6

Ataguba, J., Ichoku, E. H., & Fonta, W. (2008). Estimating the Willingness to Pay for Community Healthcare Insurance in Rural Nigeria. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1266163

Azuonwu, G., & Smart, U. O. (2023). Socio-Demographic Determinants and Utilisation of Social Health Insurance Services among Civil Servants in Bayelsa State. *Nursing & Healthcare International Journal*, *7*(5). https://doi.org/10.23880/nhij-16000297

Calia, P., & Strazzera, E. (1999). Bias and Efficiency of Single vs Double Bound Models for Contingent Valuation Studies: a Monte Carlo Analysis. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.158412

Carson, R. T., Hanemann, W. M., Kopp, R. J., Krosnick, J. A., Mitchell, R. C., Presser, S., Ruud, P. A., & Smith, V. K. K. (1997). Was the NOAA Panel Correct about Contingent Valuation? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.31992

Elegbede, O. E., Durowade, K. A., Sanni, T. A., Ipinnimo, T. M., & Alabi, A. K. (2022). Assessment of Willingness to pay for Community-Based Health Insurance among Artisans in a selected Community of Ekiti State, Southwest Nigeria. *Ibom Medical Journal*, *15*(2), 148–158. https://doi.org/10.61386/imj.v15i2.253

Esan, O. T., Opeloye, R. O., Oyeniyi, T. W., Joseph, A. O., Oluwalana, I. B., Babalola, S. B., & Adeniji, I. O. (2020). Willingness to Participate and Pay into a Community-Based Health Insurance Scheme in Imesi-Ile, a Rural Community in Osun State, Nigeria. *Asian Journal of Medicine and Health*, 73–84. https://doi.org/10.9734/ajmah/2020/v18i1030255

Giedion, U., & Uribe, M. V. (2009). Colombia's Universal Health Insurance System. *Health Affairs*, *28*(3), 853–863. https://doi.org/10.1377/hlthaff.28.3.853

Haab, T. C., & McConnell, K. E. (2002). *Valuing Environmental and Natural Resources*. Edward Elgar Publishing.

Hanemann, W. M. (1984). Valuing the Environment Through Contingent Valuation. *Journal of Economic Perspectives*, *8*(4), 19–43. https://doi.org/10.1257/jep.8.4.19

Hoehn, J. P., & Randall, A. (1987). A satisfactory benefit-cost indicator from contingent valuation. *Journal of Environmental Economics and Management*, *14*(3), 226–247. https://doi.org/10.1016/0095-0696(87)90018-0

Kelly. (2023, May 23). 6 Mosquito Diseases That Can Be Deadly. *Centres for Disease Control and Prevention*. https://www.pfizer.com/news/articles/6_mosquito_diseases_that_can_be_deadly

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2007). *Stated choice methods: analysis and applications*. Cambridge University Press.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, *3*(4), 303–328. https://doi.org/10.1016/0047-2727(74)90003-6

Mcffaden, D. (1974). *Frontiers in Econometrics*. New York: Academic Press.

Mitchell, R. C., & Carson, R. T. (2013). *Using surveys to value public goods: the contingent valuation method*. Rff press.

Namuhani, N., Kisakye, A., & Kiwanuka, S. N. (2024). Willingness and Perceived ability to pay for Uganda's Proposed National Health Insurance Scheme among Informal Sector workers in Iganga and Mayuge districts, Uganda: A Contingent Valuation Method. *MedRxiv (Cold Spring Harbour Laboratory)*. https://doi.org/10.1101/2024.07.24.24310952

Onwujekwe, O., Okereke, E., Onoka, C., Uzochukwu, B., Kirigia, J., & Petu, A. (2009). Willingness to pay for community-based health insurance in Nigeria: do economic status and place of residence matter? *Health Policy and Planning*, *25*(2), 155–161. https://doi.org/10.1093/heapol/czp046

Piperaki, E. T., & Daikos, G. L. (2016). Malaria in Europe: emerging threat or minor nuisance? *Clinical Microbiology and Infection*, *22*(6), 487–493. https://doi.org/10.1016/j.cmi.2016.04.023

Shekarau, E., Uzoanya, M., Nnenna, O., Godwin, N., Simon, N., Ijezie, M., Ihuoma, U., Seye, B., Chizoba, F., Eze, N., Lekia, N., Olugbenga, M., Uchenna, N., Iniabasi, N., Ishola-Gbenla, O., Methodius, O., Motunrayo, F., Olusola, O., Getachew, D., …Erinle, V. (2024). Severe malaria intervention status in Nigeria: workshop meeting report. *Malaria Journal*, *23*(1). https://doi.org/10.1186/s12936-024-05001-1

Topan, G. J., Thiombiano, N., & Sarambe, I. (2024). Determinants of households' willingness to pay for health insurance in Burkina Faso. *Health Economics Review*, *14*(1). https://doi.org/10.1186/s13561-024-00576-6

Varian, H. R. (2010). Clinical Trials in Economics. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1889372

von Neumann, J., & Morgenstern, O. (1944). Theory of Games and Economic Behaviour. *Journal of the Royal Statistical Society*, *107*(3/4), 293. https://doi.org/10.2307/2981222

WHO. (2022, December 8). World Malaria Report. *Racking Progress and Gaps in the Global Response to Malaria*. https://www.who.int/teams/global-malaria-programme/reports/world-malaria-report-2022