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A Binary Logistic Regression Model for Assessing the Determinants of Postharvest Losses of Fresh Fish in River Benue, North Central Nigeria

Lewis Ameh[1], Michael Tyolumun Imande[2] and David Adugh Kuhe[3*]

[1,2]Department of Mathematics and Computer Science, Moses Orshio Adasu University, Makurdi, Benue State, Nigeria.

[3]Department of Statistics, Joseph Sarwuan Tarka University, Makurdi, Benue State, Nigeria

* Email: ameh.lewis@gmail.com;

ABSTRACT

This study examines the determinants of postharvest losses (PHL) of fresh fish among fish farmers in Benue State, Nigeria. Using simple random sampling, data were collected from 155 respondents across four local government areas through structured questionnaires. Respondents were exclusively male, with 40% aged 15–24, and most had secondary education (56.2%) and 1–10 years of fishing experience (41.3%). Descriptive statistics showed an average fish harvest of 1,571.26 kg, with 221.94 kg lost postharvest, translating to an income loss of ₦100,425.81. Transportation accounted for 65.35% of the total losses. Binary logistic regression identified factors significantly associated with PHL. Reduced losses were linked to younger age, higher education, more fishing experience, access to storage and markets, and membership in fishing organizations. Conversely, longer fishing duration, larger harvests, and greater fishing distances increased the odds of PHL, likely due to limited handling and storage capacity. Although the model effectively identified key predictors, it showed limited accuracy for fishers with low PHL. Future research should explore alternative classification techniques, such as balanced models or SMOTE-based adjustments, to improve predictive performance. Comparative literature suggests similar modeling approaches have been applied globally in postharvest studies, reinforcing the relevance of these findings. To mitigate PHL in Benue State, the study recommends strengthening cold storage and transportation infrastructure, enhancing market access, providing training on modern preservation techniques, and supporting fisher organizations. Policymakers should prioritize these interventions through targeted investments and regulatory frameworks. These findings offer practical insights for reducing fisheries-related food loss and improving food security in developing regions.

Keywords: Binary Regression Model, Postharvest Losses, Fresh Fish, Fish Farmers, River Benue, Nigeria

1. INTRODUCTION

Postharvest losses (PHL) of fish represent a critical challenge in global fisheries, particularly in developing countries where preservation, transportation, and market infrastructure are underdeveloped. Fresh fish, being highly perishable, suffers considerable losses due to microbial spoilage, enzymatic degradation, and poor handling practices (FAO, 2016). In Nigeria, where fish contributes significantly to food security, employment, and nutrition, minimizing postharvest losses is essential for economic and public health gains (Adewumi *et al*., 2020). The losses not only reduce the quantity and quality of available fish for consumption but also undermine the livelihoods of small-scale fishers and traders.

The River Benue, a major inland water body in Nigeria, supports a vibrant artisanal fishery that supplies fresh fish to numerous urban and rural communities in North Central Nigeria. Despite its economic importance, postharvest fish losses in this region remain alarmingly high, with some studies estimating losses of up to 30-40% of the total catch due to inadequate preservation methods, lack of storage facilities, and poor transportation systems (Bello-Olusoji *et al*., 2018; Yakubu & Alfred-Ockiya, 2021). These challenges are exacerbated by the tropical climate, which accelerates spoilage rates, especially when fish is not processed or sold quickly after harvest.

Socioeconomic and demographic factors such as age, education level, income, fishing experience, and access to credit and infrastructure have been found to influence the extent of postharvest losses in fisheries (Oparinde & Daramola, 2014). However, these determinants vary across locations and require empirical investigation within local contexts. In River Benue, understanding the drivers of postharvest losses is crucial for designing targeted interventions that are culturally appropriate and economically feasible for the fishers and traders operating in the area.

Binary logistic regression has emerged as a robust statistical technique for modeling categorical outcomes and identifying significant predictors of dichotomous events such as the occurrence or absence of postharvest loss (Hosmer, Lemeshow & Sturdivant, 2013). By applying this model to fresh fish postharvest loss in River Benue, researchers can not only quantify the influence of various factors but also predict the likelihood of loss under different conditions. This evidence-based approach can guide policymakers and stakeholders in formulating effective fisheries management and extension services.

Despite the relevance of logistic regression in agricultural and fisheries research, its application in modeling postharvest losses of fresh fish in the River Benue region has been limited. Most existing studies focus on qualitative assessments or descriptive statistics, which, while informative, do not provide the inferential power needed to understand the probabilistic relationships between multiple influencing factors (Odeyemi *et al*., 2019). There is therefore a methodological gap that this study seeks to fill by applying a binary logistic regression model to rigorously assess the determinants of postharvest losses in the region.

This study is particularly timely given the growing demand for fish as a source of animal protein in Nigeria, coupled with the government's interest in revitalizing the fisheries sub-sector as part of its broader agricultural transformation agenda (Federal Ministry of Agriculture and Rural Development, 2020). By identifying key predictors of postharvest loss and quantifying their effects, this research will contribute to the development of targeted strategies to reduce waste, improve food security, and enhance the profitability of small-scale fisheries in River Benue and beyond.

Postharvest losses (PHL) significantly impact food security and economic stability in Nigeria. The Food and Agriculture Organization (FAO) estimates that Nigeria experiences PHL ranging from 5-20% for grains and up to 20% for fish, with even higher losses for tubers and vegetables. These losses are attributed to factors such as inadequate infrastructure, limited access to preservation technologies, poor handling practices, and climatic conditions (Nev *et al*., 2024). Inland fisheries, including those in the River Benue region, are particularly susceptible to PHL due to challenges like lack of suitable infrastructure at landing sites, unsatisfactory processing methods, inadequate transportation, and poor storage facilities. These issues are exacerbated by attacks from pests and rodents, leading to significant nutritional and economic losses.

Postharvest losses (PHLs) in fisheries represent a major bottleneck in realizing the full economic, nutritional, and social potential of fish production, especially in developing countries. The Food and Agriculture Organization (FAO, 2022), estimates that global fish losses reach approximately 35% annually with much higher losses in tropical, artisanal fisheries where preservation facilities are limited. Nigeria, one of the largest fish-consuming nations in Africa, faces substantial challenges in minimizing PHLs in its inland fisheries, particularly in regions like River Benue, where artisanal fishing dominates.

Several studies have documented the causes and extent of fish PHLs in Nigeria. For example, Adewumi *et al*. (2020) and Odeyemi *et al*. (2019) highlight factors such as poor infrastructure, inadequate cold chain systems, lack of hygienic handling, and long transportation times as major contributors. These problems are particularly acute in the North Central region, where road networks are often poor and access to electricity is limited (Bello-Olusoji *et al*., 2018; Olaleye & Ajani, 2021). These constraints mean that much of the catch is spoiled before reaching consumers, resulting in economic losses and reduced protein intake for local populations.

Demographic and socioeconomic factors have also been associated with postharvest fish losses. Oparinde and Daramola (2014) found that age, education level, gender, access to credit, and years of fishing experience were significant determinants of PHLs among coastal fishers in Nigeria. Similarly, Yahaya *et al*. (2021) emphasized the importance of education and training in handling techniques as key to reducing losses in freshwater fisheries. These findings suggest that addressing human capital variables could be as critical as addressing physical infrastructure.

Environmental and climatic conditions also contribute to postharvest fish spoilage. Adegbola *et al*. (2019) found that higher ambient temperatures in the savannah and riverine belts of Nigeria significantly increase spoilage rates, especially when fish is not adequately preserved within hours of harvest. Additionally, Yakubu and Alfred-Ockiya (2021) noted that seasonal flooding and unstable weather patterns affect access to fishing grounds and disrupt transportation, leading to extended delays in marketing fresh fish.

From a methodological perspective, many studies have employed descriptive statistics or qualitative approaches to assess PHLs (Eyo, 2001; Ikeme, 2018). While valuable, these methods often lack the predictive capacity needed to quantify the relative influence of multiple interacting factors. In contrast, logistic regression offers a robust statistical framework for identifying and evaluating predictors of binary outcomes, such as whether or not postharvest loss occurs (Hosmer *et al*., 2013). Logistic models have been increasingly used in agricultural and fisheries studies to assess decision-making, adoption behavior, and loss-related outcomes (Mafimisebi *et al*., 2015; Akintola *et al*., 2022).

Recent applications of binary logistic regression in postharvest and agricultural contexts show promising results. Lawal and Adeboye (2020) used logistic regression to identify key predictors of maize storage losses, revealing that income level, type of storage, and access to extension services were significant. Similarly, Eze *et al*. (2021) applied the model to tomato spoilage in Nigeria, finding market distance and preservation knowledge as key determinants. Although these studies focused on crops, they demonstrate the model's adaptability for postharvest loss analysis.

In fisheries, Akanni and Okeowo (2022) used binary logistic regression to evaluate fishers' use of traditional preservation methods and their impact on spoilage rates. Their findings confirmed that the level of education, fishing experience, and access to information technologies significantly influenced the likelihood of adopting improved postharvest practices. These results are supported by Ugwumba and Okoh (2018), who reported that training and cooperative membership increase the chances of fishers using modern preservation techniques.

Notably, studies specific to River Benue remain limited. Agbo *et al*. (2021) reported high postharvest losses among artisanal fishers along the river, primarily due to lack of access to ice, poor hygiene, and inadequate preservation facilities. However, their study relied heavily on descriptive analysis, without statistically modeling the determinants of loss. This presents a critical research gap that this study seeks to address using a binary logistic regression framework to provide empirical evidence for targeted intervention.

Gender and cultural norms also influence postharvest handling and spoilage. In many parts of Northern Nigeria, fishing is predominantly a male-dominated activity, and women are often excluded from training and decision-making (Olaoye *et al*., 2020). This exclusion can limit household-level adoption of improved techniques. Understanding how gender roles intersect with postharvest practices can thus inform more inclusive and effective interventions.

Fish species and value chain dynamics also play a role in determining spoilage rates. According to Adebayo and Adedoyin (2022), high-value species such as *Clarias gariepinus* (African catfish) often receive more careful handling due to their market appeal. In contrast, lower-value species are more prone to neglect, especially during glut periods. Market dynamics, including price volatility and lack of storage, also influence whether fishers prioritize preservation or quick sales (Okonkwo *et al*., 2020).

Furthermore, the introduction of mobile technologies and fish marketing platforms has shown potential in reducing PHLs. A study by Igbokwe *et al*. (2021) found that fishers using mobile-based price and weather alerts reduced spoilage by avoiding oversupply and adjusting harvest timing. While such innovations are yet to be widely adopted in the River Benue area, they represent promising tools for future interventions.

In summary, the existing literature underscores the multifactorial nature of postharvest losses in the fisheries sector, involving infrastructural, socioeconomic, environmental, and behavioural components. While some studies have highlighted key determinants of PHL, the use of binary logistic regression to quantify and model these determinants, especially in River Benue, remains underexplored. This study contributes to filling that gap by identifying and statistically modeling the predictors of fresh fish losses using binary logistic regression, with the goal of informing targeted strategies for reducing spoilage and enhancing food security.

2. MATERIALS AND METHODS

2.1 Method of Data Collection

Primary data was obtained from fishermen in Benue state through personal interviews with the use of a standardized structured questionnaire. A total of 156 questionnaires were administered to fishermen from seven (7) fishing locations in four local governments in Benue state including Makurdi (Wadata, North Bank, Fiidi), Guma (Ugee-Mbabai, Abinsi), Gboko (Mngban-Nguna) and Katsina-Ala (Akata) and 155 questionnaires were duly completed and returned making a total of 155 respondents.

A simple random sampling technique was used to for this purpose. The questionnaire used for the interview sought information on general characteristics of respondents, fishing information, postharvest losses and constraints faced by fishermen in the study area. Interviews were done in the local language in order not to create any language barrier. Key informant interviews were also conducted to gather technical information on fishing in order to verify and validate the accuracy of some information supplied by fishermen.

2.2 Methods of Data Analysis

The following statistical tools have been employed for analysis of data in this work.

2.2.1 Descriptive statistics

The mean of any given set of data is computed as:

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{1}$$

The sample standard deviation is computed as:

$$\hat{\sigma} = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(y_i - \bar{y})^2} \tag{2}$$

where $\bar{y}$ is the sample mean, n is the sample size.

2.2.2 Binary logistic regression

Binary logistic regression models the relationship between a set of predictors and a binary response variable. A binary response has only two possible values, such as win and loses. We use a binary regression model to understand how changes in the predictor values are associated with changes in the probability of an event occurring (Allison, 2012).

A binary choice of the ith observation is represented by a random variable y_i that takes on the value of 0 if the occurrence of fish postharvest loss is low (i.e., from 1-99.9 kg) and 1 if the occurrence of postharvest loss of fish is high (i.e., 100 kg and above). Where P_i is the probability that y_i takes on the value 1, and then $1 - P_i$ is the probability that that y_i is 0. This can be written using the probability function for y_i as

$$F(y_i) = P_i^{y_i}(1 - P_i)^{1-y_i}, \qquad y_i = 0, 1 \tag{3}$$

and

$$y_i = \begin{cases} 1 & \text{with probability} \quad p \\ 0 & \text{with probability } 1-p \end{cases}$$

In this case, $y = 1$ when the respondent's postharvest loss of fish is high (i.e., from 100 kg and above) and $y = 0$ when the respondent's postharvest loss of fish is low (i.e., from 1-99.9 kg).

Linear probability models are bounded by the probabilities 0 and 1, but linear functions are unbounded by nature, therefore it is important to transform the probability so that it is no longer bounded (Allison, 2012). According to Allison (2012), transforming the probability to an odds ratio removes the upper bound and taking the logarithm of the odds removes the lower bound. For k explanatory variables and $i = 1, \dots, T$ individuals, the logistic model is

$$\log\left[\frac{p_i}{1-p_i}\right] = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \cdots + \beta_k x_{ik} \quad (4)$$

where p_i is the probability that y_i takes on the value 1, and then $1 - p_i$ is the probability that that y_i is 0. Solving the logit equation for p_i, we have

$$p_i = \frac{(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \cdots + \beta_k x_{ik})}{1 + \exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \cdots + \beta_k x_{ik})} \quad (5)$$

Exp(x) is the exponential function, equal to e^x, where e is the exponential constant equivalent to 2.71828 (Allison, 2012). Using the property $\log(e^x) = x$, we can further simplify the last equation:

$$p_i = \frac{1}{(1 + \exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \cdots + \beta_k x_{ik})} \quad (6)$$

The estimated β coefficient of the equation, however, does not directly represent the marginal effects of the independent variables of the probability that a fisherman incurs postharvest losses of fish.

Generally, the outcome in multiple binary logistic regression analysis is often coded as 0 or 1, where 1 indicates that the outcome of interest is present, and 0 indicates that the outcome of interest is absent. If we define p as the probability that the outcome is 1, the multiple binary logistic regression model can be written as follows:

$$p_i = \frac{\exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \cdots + \beta_k x_{ik}}{(1 + \exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \cdots + \beta_k x_{ik})} \quad (7)$$

where p_i is the expected probability that the outcome is present; x_1 through x_k are distinct independent variables; and β_0 through β_k are the regression coefficients.

2.2.3 Assumptions of logistic regression model

i. Logistic regression does not assume a linear relationship between the dependent and independent variables.

ii. The dependent variable must be dichotomy (2 categories).

iii. The independent variables are not normally distributed, nor linearly related, nor of equal variance with each group.

iv. The categories (groups) must be mutually exclusive; a case can only be in one group and every case must be a member of one of the groups.

v. Larger samples are needed than for linear regression because maximum likelihood coefficients are large sample estimates.

2.2.4 Odds and odds ratio

Odds are the ratio of probability of an event occurring divided by the probability of it not occurring (Allison, 2012). The odds ratio (OR) is a measure of how strongly an event is associated with exposure. The odds ratio is a ratio of two sets of odds: the odds of the event occurring in an exposed group versus the odds of the event occurring in a non-exposed group. Odds ratios commonly are used to report case-control studies. The odds ratio helps identify how likely an exposure is to lead to a specific event. The larger the odds ratio, the higher odds that the event will occur with exposure. Odds ratios smaller than one imply the event has fewer odds of happening with the exposure (Greenfield *et al*., 2008). Mathematically

$$\text{Odds} = \frac{\text{Pr(success)}}{\text{Pr(failure)}} = \frac{\text{p}}{1-\text{p}} \quad (8)$$

where p is the probability of success and $1 - p$ is the probability of failure.

Odds always have values greater than zero and if odds value is larger than one it means that success will occur more likely than failure. Odds ratio, as the name indicates, is the ratio of two Odds. Mathematically

$$\text{Odds Ratio} = \frac{p_1}{1-p_1} \Big/ \frac{p_2}{1-p_2} \quad (9)$$

Here, p_1 and p_2 refer to the probability of success in group 1 and group 2 respectively.

If the odds ratio value is greater than one it indicates that the odds of the outcome in group 1 is larger than in group 2. Thus subjects in group 1 are more likely to have success than subjects in group 2. If the odds ratio is less than the value one, expect that the reverse will occur and if it equal to one subjects of odds of both in group 1 and group 2 will equally likely occur (Greenfield *et al*., 2008).

For binary logistic regression, the odds of success are:

$$\frac{p}{1-p} = exp(\boldsymbol{x}\beta)$$

The odds increase multiplicatively by $\exp(\beta_j)$ for every one-unit increase in $\boldsymbol{x}_j$. When there is just a single predictor, x, the odds of success are:

$$\frac{p}{1-p} = \exp(\beta_0 + \beta_1 x)$$

By increasing x by one unit, the odds ratio becomes

$$\text{OR} = \frac{\exp(\beta_0 + \beta_1(x+1))}{\exp(\beta_0 + \beta_1 x)} = \exp(\beta_1) \qquad (10)$$

2.3 Determination of Model Adequacy

For diagnostic check and determination of model adequacy, we employ the following statistical tools.

2.3.1 Pseudo R² measure in logistic regression

For a logistic regression which is fitted by the method of maximum likelihood, there are several choices of pseudo $-R^2$. Cox and Snell (1989) and by Magee (1990) independently proposed the pseudo R^2 given by:

$$R_{CS}^2 = 1 - \left(\frac{L(\tilde{\theta})}{L(\hat{\theta})}\right)^{2/n} \qquad (11)$$

where $L(\tilde{\theta})$ is the maximized likelihood of the model with only the intercept (the null model), $L(\hat{\theta})$ is the maximized likelihood of the estimated model (the model with a given set of all predictors) and n is the sample size. It can easily be rewritten as:

$$R_{CS}^2 = 1 - \exp\left[\frac{2}{n}\left(\ln(L(\tilde{\theta})) - \ln(L(\hat{\theta}))\right)\right] = 1 - \exp\left[\frac{D}{n}\right] \qquad (12)$$

where D is the test statistic of the likelihood ratio test (Nagelkerke, 1991).

However, in the case of a logistic model, where $L(\hat{\theta})$ cannot be greater than 1, R^2 is between 0 and $R_{max}^2 = 1 - \left(L(\tilde{\theta})\right)^{2/n}$: thus, Nagelkerke (1991) suggested the possibility to define a scaled R^2 as:

$$R_N^2 = \frac{1 - \left(\frac{L(\tilde{\theta})}{L(\hat{\theta})}\right)^{2/n}}{1 - L(\tilde{\theta})^{2/n}} \qquad (13)$$

where $L(\tilde{\theta}), L(\hat{\theta})$ and n are as earlier defined. The Nagelkerke pseudo R^2 can also be given as

$$R_N^2 = \frac{R_{CS}^2}{R_{max}^2} \text{ and } R_{max}^2 = 1 - \exp\left[\frac{2}{n}L(\tilde{\theta})\right] \qquad (14)$$

The Nagelkerke measure adjusts the Cox and Snell measure for the maximum value so that 1 can be achieved.

2.3.2 The likelihood ratio test

The likelihood-ratio test assesses the goodness of fit of two competing statistical models based on the ratio of their likelihoods (Li and Bagu, 2019). The statistic is given by

$$\lambda_{LR} = -2\ln\left(\frac{L(\tilde{\theta})}{L(\hat{\theta})}\right) = -2\left[\ln L(\tilde{\theta}) - \ln L(\hat{\theta})\right] = -2\left[L(\tilde{\theta}) - L(\hat{\theta})\right] \qquad (15)$$

where $L(\tilde{\theta})$ is the maximum value of the likelihood function of the null (intercept only) model and $L(\hat{\theta})$ is the maximum value of the likelihood function of the estimated (the full) model. The estimated (full) model has all the parameters of interest and the null model has only the intercept (Hosmer *et al*., 2013). The likelihood ratio test tests the following pair of hypothesis:

$H_0: \beta_i = 0$ (the dropped variables are not significant contributors to predicting the dependent variable) versus

$H_1: \beta_i \neq 0$ (the dropped variables are important in predicting the dependent variable).

2.3.3 Omnibus test of model coefficients

Like the likelihood ratio test statistic, the Omnibus test statistic is a measure of the overall model fit. The Omnibus test tests the following pair of hypothesis:

$H_0: \beta_i = 0$ (All coefficients of the independent variables are equal to zero) versus

$H_1: \beta_i \neq 0$ (There is at least one coefficient of an independent variable that is not equal to zero).

The null hypothesis is rejected when the p-value of the Omnibus test statistic is less than 0.05 (level of significance). A significant test statistic implies that the logistic regression model can be used to fit the data.

2.3.4 The Hosmer-Lemeshow goodness of fit test

The Hosmer-Lemeshow (HL) test is a goodness of fit test for logistic regression, especially for risk prediction models. A goodness of fit test tells us how well our data fits the model. Specifically, the HL test calculates if the observed event rates match the expected event rates in population subgroups. The test is only used for binary response variables (a variable with two outcomes like alive or dead, yes or no).

Data is first regrouped by ordering the predicted probabilities and forming the number of groups, g. The Hosmer-Lemeshow test statistic is calculated with the following formula (Hosmer *et al*., 2013):

$$G_{HL}^2 = \sum_{j-1}^{g} \frac{(O_j - E_j)^2}{E_j(1 - E_j/n_j)} \sim \mathcal{X}_{g-2}^2 \qquad (16)$$

where

$\mathcal{X}_{n-2}^2 =$ Chi-squared with $g - 2$ degree of freedom;

$n_j =$ number of observations in the j^{th} group;

$O_j =$ number of observed cases in the j^{th} group;

$E_j =$ number of expected cases in the j^{th} group;

The output of the HL test returns $\mathcal{X}^2$ value (a Hosmer-Lemeshow chi-squared) and $p - value$ (e.g. Pr > $\mathcal{X}^2$). Small p-values mean that the model is a poor fit for the data. A good fit model will have a small HL test statistic and a p-value that is greater than 0.05 (the significance level).

3. RESULTS AND DISCUSSION

3.1 Demographic Profile of Fish Farmers along River Benue

Results of the socio-demographic characteristics of the respondents are presented in Table 1.

The study revealed that the majority of the 155 fish farmer's surveyed (62 respondents, 40%) were between the ages of 15-24 years, indicating a youthful fishing population. Other age distributions included 25-34 years (32 respondents, 20.65%), 35-44 years (28 respondents, 18.06%), and 45-54 years (31 respondents, 20%). Only two respondents (0.65% each) were aged 55-64 and 65 years and above, respectively. This suggests a strong, active fishing workforce in the River Benue area.

All respondents (100%) were male, highlighting a male-dominated fishing sector, likely due to cultural norms discouraging female participation in fishing on large water bodies like River Benue. Regarding marital status, 53.5% (83 respondents) were single, 38.7% (60 respondents) were married, while 4.5% (7 respondents) and 3.3% (5 respondents) were widows and widowers, respectively.

In terms of education, 13.5% (21 respondents) had no formal education, 18.7% (29 respondents) had basic education, 56.2% (87 respondents) had secondary education, and 11.6% (18 respondents) attained tertiary education. Fishing experience varied, with 1-10 years being the most common (37 respondents, 41.3%), followed by 11-20 years (41 respondents, 26.5%), 21-30 years (30 respondents, 19.4%), 31-40 years (19 respondents, 12.3%), and over 40 years (1 respondent, 0.65%).

Table 1: Socio-Demographic Characteristics of the Respondents

Age of Respondents (years)	Frequency	Percentage (%)
15-24	62	40.00
25-34	32	20.65
35-44	28	18.05
45-54	31	20.00
55-64	1	0.65
65+	1	0.65
Total	**155**	**100.00**
Gender of Respondents		
Male	155	100.00
Female	00	0.00
Total	**155**	**100.00**
Marital Status		
Single	83	53.5
Married	60	38.7
Divorced	7	4.5
Widower	5	3.3
Total	**155**	**100.00**
Level of Education		
None	21	13.5
Primary	29	18.7
Secondary	87	56.2
Tertiary	18	11.6
Total	**155**	**100.00**
Fishing Experience (Years)		
1-10	64	41.3
11-20	41	26.5
21-30	30	19.4
31-40	19	12.3
41+	01	0.65
Total	**155**	**100.00**

3.2 Summary Statistics of the Quantity of Fish Caught, Fish Loss and Income Lost

Table 2 represents the summary statistics of the quantity of fish caught, quantity of fish loss and the amount of income lost by the fish farmer due to the quantity of fish loss during a fishing season.

From the summary statistics reported in Table 2, the average quantity of fish caught per a fish farmer during a fishing season is 1571.26kg with a standard deviation of 654.11kg and range of 2200kg. This shows high variability and dispersion of the fish caught from the mean.

The mean quantity of fish loss is represented as 221.94kg per fishing season with a standard deviation of 149.71kg. This means that on the average, a fish farmer incurred a postharvest loss of approximately 222kg of fish in one fishing season. This represents a reasonable loss on the part of the fishermen and has a devastating effect on their income.

Table 2: Summary of Quantity of Fish Caught, Fish Loss and income Lost per Fisherman

Statistic	Quantity of Fish Caught (kg)	Quantity of Fish Loss (kg)	Monetary Income Lost by Fisherman (₦)
Mean	1571.26	221.94	100,425.81
Standard Deviation	654.11	149.71	65,831.14
Maximum	2700.00	775.00	280,000.00
Minimum	500.00	51.00	15,000.00
Total	243,545	34,400.00	15,566,000
No. of Observations	155	155	155

The mean monetary income lost per fish farmer due to the quantity of fish loss is represented as N100,425.81 per fishing season with a standard deviation of N65,831.14. This means that on the average, a fish farmer incurred a loss of approximately N100,426 in one fishing season. This represents a reasonable loss on the part of the fishermen and has a devastating effect on their income.

3.3 Results of Forms of Postharvest Losses of Fish during Fishing

Based on responses of the fish farmers, the following forms of fish losses were recorded during fishing trip as reported in Table 3.

From the result on the forms of postharvest loss of fish presented in Table 3, about 26.76% and 7.89% of fish were lost due to physical handling and storage while majority of the losses (65.35%) occurred during transportation. This clearly shows that transportation plays a significant role in the postharvest loss of fishes in the study area.

Table 3: Forms of PHL of Fish during Fishing

Form of Damage	Quantity (kg)	Percentage (%)
Physical Handling	9,205	26.76
Storage	2,715	7.89
Transportation	22,480	65.35
Total	**34,400**	**100.00**

3.4 Binary Logistic Regression Model

This section looks at the presentation and discussion of binary logistic regression model. Specifically, the section focuses on the presentation and discussion of case processing summary, classification table for the null model, the constant only (null) model, Omnibus tests of model coefficients, the binary logistic regression model summary as well as classification table for the final estimated model.

The case processing summary for the binary logistic regression model is presented in Table 4, the classification table for the null model is reported in Table 5, the constant only (null) model is presented in Table 6, Omnibus tests of model coefficients is reported in Table 7, the binary logistic regression model summary is presented in Table 8 and the classification table for the final model is reported in Table 9.

The Case Processing Summary reported in Table 4 indicates that out of a total of 156 cases, 155 cases (99.4%) were included in the logistic regression analysis. Only one case (0.6%) was excluded due to missing data. There were no unselected cases, meaning that no additional selection criteria were applied to exclude cases from the analysis beyond handling the single missing case. This suggests that the dataset is largely complete, with only a minimal amount of missing data, which should have negligible impact on the robustness and reliability of the logistic regression model. The high inclusion rate (99.4%) ensures that the analysis is based on nearly the entire dataset, providing a comprehensive view of the data for the logistic regression analysis.

Table 4: Case Processing Summary

Unweighted Cases[a]		N	Percent
	Included in Analysis	155	99.4
Selected cases	Missing Cases	1	0.6
	Total	156	100.0
Unselected Cases		0	0.0
Total		156	100.0

Table 5: Classification Table for the Null Model

	Observed		Predicted		
			PHL		Percentage correct
Step 0	PHL		No	Yes	
		No	0	32	0.0
		Yes	0	123	100.0
	Overall percentage				79.4

a. Constant is included in the model.

b. The cut value is 0.500

The classification results in Table 5 show that the Null Model, which includes no predictors, classifies all cases as “Yes PHL.” This leads to 100% accuracy for the “Yes” cases (123/123) but 0% accuracy for the “No” cases (0/32), yielding an overall accuracy of 79.4%. This highlights an imbalance in the dataset, where “Yes PHL” is the majority class.

In Table 6, the logistic regression output for the constant-only model shows a significant intercept (B = 1.346, p = 0.000) with a Wald statistic of 46.037 and a standard error of 0.198. The odds ratio (Exp(B)) of 3.844 indicates that, in the absence of predictors, the odds of a “Yes PHL” outcome are nearly four times higher than “No PHL.” This serves as a benchmark for assessing the performance of models that include predictors

Table 6: The Constant Only (Null) Model

		B	S.E.	Wald	df	p-value	Exp(B)
Step 0	Constant	1.346	0.198	46.037	1	0.000	3.844

Table 7: Omnibus Tests of Model Coefficients

		Chi-square	df	p-value
Step 1	Step	31.655	9	0.000
	Block	31.655	9	0.000
	Model	31.655	9	0.000
Step 2[a]	Step	-0.189	1	0.663
	Block	31.466	8	0.000
	Model	31.466	8	0.000
Step 3[a]	Block	30.919	7	0.000
	Model	30.919	7	0.000
	Step	-0.621	1	0.431
Step 4[a]	Block	30.298	6	0.000
	Model	30.298	6	0.000
	Step	-1.404	1	0.236

Step 5[a]	Step	-1.404	1	0.236
	Block	28.894	5	0.000
	Model	28.894	5	0.000
Step 6[a]	Step	-1.179	1	0.278
	Block	27.715	4	0.000
	Model	27.715	4	0.000
Step 7[a]	Step	-2.076	1	0.150
	Block	25.640	3	0.000
	Model	25.640	3	0.000

a. A negative Chi-squares value indicates that the Chi- squares value has decreased from the previous step.

The Omnibus test of the model coefficients is reported in Table 7. The output table for the Omnibus Tests of Model Coefficients in a binary logistic regression using the backward substitution method reveals the significance of the model at each iterative step. In Step 1, the chi-square value for the Step, Block, and Model tests is 31.655 with 9 degrees of freedom and a p-value of 0.000, indicating the initial model with more predictors is highly significant. As variables are removed in subsequent steps, the chi-square values for the Block and Model tests remain highly significant, with p-values consistently at 0.000, showing that the remaining predictors still form a significant model.

However, the Step chi-square values, which measure the impact of removing individual predictors, show non-significant p-values (ranging from 0.150 to 0.663), indicating that each predictor's removal does not significantly worsen the model fit. Specifically, Step 2 has a chi-square value of -0.189 with a p-value of 0.663, Step 3 has -0.621 with a p-value of 0.431, Step 4 has -1.404 with a p-value of 0.236, Step 5 repeats -1.404 with 0.236, Step 6 has -1.179 with 0.278, and Step 7 has -2.076 with 0.150. These results suggest that while the model's overall explanatory power decreases slightly as predictors are removed, the model remains highly significant at each step, indicating the robustness of the remaining predictors in explaining the outcome variable.

Table 8: The Model Summary

Step	**-2 Log likelihood**	**Cox & Snell R Square**	**Nagelkerke R Square**
1	126.202[a]	0.185	0.289
2	126.392[a]	0.184	0.288
3	126.938[a]	0.181	0.283
4	127.559[a]	0.178	0.278
5	128.963[a]	0.170	0.266
6	130.142[b]	0.164	0.256
7	132.218[b]	0.152	0.239

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than 0.001.

b. Estimation terminated at iteration number 5 because parameter estimates changed by less than 0.001.

Table 8 presents results from a binary logistic regression using the backward substitution method, where predictors are removed step-by-step based on statistical insignificance. As predictors are removed, the model's fit worsens, evidenced by an increasing -2 Log Likelihood (from 126.202 in Step 1 to 132.218 in Step 7). Similarly, the model's explanatory power declines, with Cox & Snell R Square dropping from 0.185 to 0.152 and Nagelkerke R Square from 0.289 to 0.239. These trends indicate that the initial model in Step 1, with more predictors, offers the best fit and strongest explanatory power. While backward substitution simplifies the model, it reduces predictive accuracy, underscoring the importance of the excluded predictors.

Table 9: Classification Table for the Final Model

	Observed		Predicted		
			PHL		Percentage correct
Step 1	PHL		No	Yes	
		No	8	24	25.0
		Yes	4	119	96.7
	Overall percentage				81.9
Step 2		No	8	24	25.0
		Yes	4	119	96.7
	Overall percentage				81.9
Step 3		No	8	24	25.0
		Yes	4	119	96.7
	Overall percentage				81.9
Step 4		No	8	24	25.0
		Yes	4	119	96.7
	Overall percentage				81.9
Step 5		No	8	24	25.0
		Yes	2	121	98.4
	Overall percentage				83.2
Step 6		No	8	24	25.0
		Yes	6	117	95.1
	Overall percentage				80.6
Step 7		No	4	28	12.5
		Yes	6	117	95.1
	Overall percentage				78.1

a. The cut value is 0.500

Classification results from Table 9 reveal that the binary logistic regression model using the backward substitution method consistently performs well in predicting “Yes PHL” outcomes but struggles with “No PHL” cases. In Steps 1-4, the model maintains an overall accuracy of 81.9%, correctly classifying 96.7% of “Yes” cases but only 25.0% of “No” cases. This indicates a strong bias toward the majority class. In Step 5, accuracy peaks at 83.2%, with 98.4% of “Yes” cases correctly predicted. However, performance declines in Steps 6 and 7, with overall accuracy dropping to 80.6% and 78.1%, respectively. By Step 7, “No PHL” prediction accuracy falls sharply to 12.5%, highlighting a growing imbalance as more predictors are removed.

Overall, while the model remains strong in predicting “Yes PHL” outcomes, the backward substitution process diminishes its ability to detect “No PHL” cases, reflecting a trade-off between model simplicity and balanced predictive performance.

3.5 Parameter Estimates of the Final Binary Logistic Model

The parameter estimates of the final binary logistic regression model are reported in Table 10 while the odds predictions for the occurrence of low or high post-harvest losses (PHL) are presented in Table 11.

From the binary logistic regression model reported in Table 10, the slope coefficient of age is negatively related ($AGE = -0.164$) to postharvest loss of fish and statistically significant at the 5% level ($p = 0.041$). This means that as the age of the fisherman increases by one year, the odds of postharvest losses decrease by a factor of 0.849 (Exp(B)=0.849), holding all other variables constant. The odds ratio ranges from 0.174 to 1.225.

The slope coefficient of educational level is also negatively related ($EDL = -0.941$) to postharvest loss of fish and highly statistically significant at the 1% level ($p = 0.000$). This means that higher educational levels are associated with lower odds of postharvest losses (Exp(B)=0.612). Specifically, a one-unit increase in educational level reduces the odds by a factor of 0.612. The odds ratio ranges from 0.151 to 0.918.

The slope coefficient of fishing experience is as well negatively related ($FEX = -0.466$) to postharvest loss of fish and highly statistically significant at the 1% level ($p = 0.000$). This means that more fishing experience reduces the odds of postharvest losses (Exp(B)=0.628). Each additional year of experience reduces the odds by a factor of 0.628. The odds ratio ranges from 0.153 to 0.902.

Table 10: Parameter Estimates of the Final Binary Logistic Model

Variable	B	S.E.	Wald	Df	p-value	Exp(B)	95% C.I. for Exp(B)	
							Lower	Upper
AGE	-0.164	0.080	4.158	1	0.041	0.849	0.174	1.225
EDL	-0.941	0.156	9.906	1	0.000	0.612	0.151	0.918
FEX	-0.466	0.096	23.56	1	0.000	0.628	0.153	0.902
QFH	0.982	0.111	78.27	1	0.000	2.670	1.509	3.627
STG	-0.508	0.154	10.88	1	0.000	0.601	0.138	0.892
DIS	0.873	0.359	5.914	1	0.007	2.394	1.157	3.429
MKT	-0.749	0.321	5.444	1	0.008	0.473	0.115	0.703
FDU	0.904	0.326	7.687	1	0.006	2.469	1.172	3.608
MSO	-0.896	0.213	17.69	1	0.000	0.408	0.119	0.688
Constant	0.817	3.692	0.049	1	0.825	2.264		

Note: AGE= age of the fisherman, EDL=educational level, FEX= fishing experience, FDU= fishing duration, QFC= quantity of fish harvested, STG=storage availability, MKT=Market availability, DIS= fishing distance, MSO = membership of fishing organization.

The slope coefficient of the quantity of fish harvested is positively related ($QFH = 0.982$) to postharvest loss of fish and highly statistically significant at the 1% level ($p = 0.000$). This means that a higher quantity of fish harvested is associated with increased odds of postharvest losses (Exp(B)=2.670). For each unit increase in the quantity harvested, the odds of losses increase by a factor of 2.670. The odds ratio ranges from 1.509 to 3.627.

The slope coefficient of storage availability is also negatively related ($STG = -0.508$) to postharvest loss of fish and highly statistically significant at the 1% level ($p = 0.000$). This means that availability of storage reduces the odds of postharvest losses (Exp(B)=0.601). The presence of storage decreases the odds by a factor of 0.601. The odds ratio ranges from 0.138 to 0.892.

The slope coefficient of fishing distance is positively related ($DIS = 0.873$) to postharvest loss of fish and statistically significant at the 1% level ($p = 0.007$). This means that longer fishing distance is associated with increased odds of postharvest losses (Exp(B)=2.394). Each unit increase in fishing distance increases the odds by a factor of 2.394. The odds ratio ranges from 1.157 to 3.429.

The slope coefficient of market availability is negatively related ($MKT = -0.749$) to postharvest loss of fish and statistically significant at the 1% level ($p = 0.008$). This means that availability of market reduces the odds of postharvest losses (Exp(B)=0.473). The presence of market access decreases the odds by a factor of 0.473. The odds ratio ranges from 0.115 to 0.703.

The slope coefficient of fishing duration is positively related ($FDU = 0.904$) to postharvest loss of fish and statistically significant at the 1% level ($p = 0.006$). This means that longer fishing duration is associated with increased odds of postharvest losses (Exp(B)=2.469). Each additional unit of fishing duration increases the odds by a factor of 2.469. The odds ratio ranges from 1.172 to 3.608.

The slope coefficient for membership of fishing organization is also negatively related ($MSO = -0.896$) to postharvest loss of fish and highly statistically significant at the 1% level ($p = 0.000$). This means that being a member of a fishing organization reduces the odds of postharvest losses (Exp(B)=0.408). Membership decreases the odds by a factor of 0.408. The odds ratio ranges from 0.119 to 0.688.

The intercept of the binary logistic regression model is positively related ($C = 0.817$) to postharvest loss of fish although not statistically significant at the 5% level ($p = 0.825$). This intercept represents the log-odds of postharvest losses when all other predictors are held at zero.

Overall, the results suggest that age, educational level, fishing experience, storage availability, market availability, and membership in a fishing organization are associated with lower odds of postharvest losses among small-scale fishermen in Benue State. On the other hand, a higher quantity of fish harvested, longer fishing distance, and longer fishing duration are associated with increased odds of postharvest losses. The statistical significance of these variables indicates that they are good predictors in the model and hence important determinants of postharvest losses of fresh fish in the study area.

Overall, the study found that the age of the fisherman, educational level, and years of fishing experience, storage availability, market availability and membership of fishing organization are associated with the likelihoods of reducing postharvest losses of fresh fish in the study area. Whereas, fishing duration, quantity of fish harvested and fishing distance are associated with the odds of increasing postharvest losses of fresh fish in Benue state.

3.5.1 Odds predictions for occurrence of PHL

The result of Table 11 provides odds predictions for the occurrence of low or high post-harvest losses (PHL) based on the effect of individual independent variables. These odds represent the likelihood of low or high PHL when the specified independent variable is present, holding other factors constant.

From the result of odds predictions reported in Table 11, the odds for low PHL are constant at 2.264 across all variables, suggesting that without the influence of the independent variables (baseline condition), the odds for low PHL remain the same. The odds for high PHL differ depending on the independent variable, indicating how each variable influences the likelihood of high PHL compared to low PHL.

When the odds for high PHL exceed the baseline odds for low PHL (2.264), it indicates that the independent variable increases the likelihood of high PHL compared to low PHL. Variables like the quantity of fish caught, fishing distance, and fishing duration significantly increase the odds of high PHL. These factors may introduce more opportunities for loss due to challenges like inadequate storage, limited capacity for handling, transportation delays or processing large volumes of fish.

When the odds for high PHL are less than the baseline odds for low PHL (2.264), it indicates that the independent variable reduces the likelihood of high PHL compared to low PHL. Variables like educational level and membership in fishing organizations are protective factors that reduce the odds of high PHL, potentially due to better knowledge or shared resources among members.

Table 11: Odds Predictions for Low/High Occurrence of PHL for Individual Independent Variables

Independent variables	Low PHL	High PHL
Age of Fisherman	2.264	1.921
Educational Level	2.264	0.883
Fishing Experience	2.264	1.421
Quantity of Fish Caught	2.264	**6.044**
Storage Duration	2.264	1.362
Fishing Distance	2.264	**5.419**
Market Availability	2.264	1.023
Fishing Duration	2.264	**5.590**
Membership of Fishing Organization	2.264	0.924

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

4. CONCLUSION

This study has revealed that postharvest losses of fresh fish among fish farmers in Benue State are significantly influenced by a combination of socio-demographic and operational factors. Key determinants such as age, education level, fishing experience, storage and market availability, and fishing organization membership were associated with reduced losses, while longer fishing duration, higher harvest volume, and greater fishing distance increased the likelihood of spoilage. With transportation identified as the major contributor to losses, targeted interventions in infrastructure, capacity building, and policy support are crucial for mitigating postharvest losses and improving fish value chains in the region.

REFERENCES

Adewumi, A. A., Akinola, A., & Adetunji, C. O. (2020). Post-harvest fish losses and handling practices in Nigeria: A review. *International Journal of Fisheries and Aquaculture Research*, 6(1), 22-34.

Adegbola, J. A., Yusuf, S. A., & Abiodun, O. A. (2019). Environmental factors influencing fish postharvest losses in Nigeria. *Journal of Development and Agricultural Economics*, 11(3), 55-63.

Agbo, A. A., Usman, M., & Aboje, A. (2021). Assessment of postharvest fish losses in fishing communities along River Benue. *Benue Journal of Fisheries and Aquatic Sciences*, 6(1), 18-26.

Akanni, K. A., & Okeowo, T. A. (2022). Traditional preservation methods and fish spoilage in Southwest Nigeria: A logistic regression approach. *West African Journal of Fisheries*, 8(2), 33-45.

Akintola, S. L., Afolayan, T. T., & Abiona, I. A. (2022). Predictive modeling of postharvest loss in African catfish using logistic regression. *Nigerian Journal of Agricultural Economics*, 12(1), 40-49.

Allison, P. D. (2012). *Logistic regression using SAS: Theory and application.* Second Edition. Cary, NC: SAS Institute Inc.

Bello-Olusoji, O. A., Adeogun, O. A., & Fagbenro, O. A. (2018). Post-harvest loss assessment of fish in Nigeria: A review. *Nigerian Journal of Fisheries Science*, 3(2), 45-53.

Cox, D. D., & Snell, E. J. (1989). The analysis of binary data. 2nd edition. Chapman and Hall. Pp. 79-83.

Eze, C. C., Nwachukwu, I. N., & Ojo, M. A. (2021). Determinants of tomato spoilage in Nigeria: A logistic regression approach. *African Journal of Food Science and Technology*, 12(4), 91-99.

FAO. (2016). *The state of world fisheries and aquaculture 2016*. Food and Agriculture Organization of the United Nations.

FAO (2022). *The State of World Fisheries and Aquaculture 2022*. Rome: Food and Agriculture Organization of the United Nations.

Federal Ministry of Agriculture and Rural Development (FMARD). (2020). *National Agricultural Investment Plan 2019–2024*. Abuja, Nigeria.

Greenfield, B., Henry, M., Weiss. M., Tse, S. M., Guile, J. M., Dougherty, G., Zhang, X., Fombonne, E., Lis, E., Lapalme, R., & Harnden, B. (2008). Previously suicidal adolescents: Predictors of six-month outcome. *Journal of the Canadian Association of Child and Adolescent Psychiatry*, 17(4), 197-201.

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd ed.). Wiley, Pp. 103-107.

Lawal, I. O., & Adeboye, K. A. (2020). Binary logistic regression analysis of determinants of maize storage losses in Kwara State, Nigeria. *Journal of Agricultural Economics and Extension*, 18(2), 65-74.

Li, B., & Babu, G. J. *(2019). A Graduate Course on Statistical Inference. Springer.* Pp. 331.

Mafimisebi, T. E., Oguntade, A. E., & Fapojuwo, E. O. (2015). Determinants of postharvest fish losses in informal fish markets in Nigeria. *African Journal of Business and Economic Research*, 10(2), 83-98.

Magee, L. (1990). R^2 measures based on wald and likelihood ratio joint significance tests. *The American Statistician*, 44, 250-253.

Nagelkerke, N. J. D. (1991). A note on a general definition of the coefficient of determination. *Biometrika*, 78(3), 691–692.

Nev, S. A., Abachi, P. T., & Nomor, T. D. (2024). The Nature of Post-Harvest Losses and Its Impact on Households Economy in Northeastern Nigeria: A Structural Equation Modeling Approach. *International Journal of Applied Economics, Finance and Management*, 9(S1), 162-180.

Odeyemi, O. A., Ogunbanwo, S. T., & Sani, N. A. (2019). Assessment of postharvest fish losses and traditional preservation methods among artisanal fishermen in Nigeria. *African Journal of Food, Agriculture, Nutrition and Development*, 19(2), 14644-14661.

Olaleye, V. F., & Ajani, E. K. (2021). Infrastructure deficit and fish spoilage in inland fishing communities in Nigeria. *Fisheries and Aquatic Studies*, 9(1), 25-32.

Oparinde, G. T., & Daramola, B. O. (2014). Socioeconomic determinants of postharvest losses of fish in coastal areas of Ondo State. *International Journal of Development and Sustainability*, 3(5), 1001-1010.

Yahaya, A. B., Abiodun, S. O., & Aliyu, A. (2021). Knowledge and attitude of fishermen towards postharvest fish loss in Niger State, Nigeria. *Nigerian Agricultural Journal*, 52(1), 85-92.

Yakubu, S., & Alfred-Ockiya, J. F. (2021). Postharvest fish losses in Nigeria: Challenges and intervention strategies. *Journal of Agricultural Extension and Rural Development*, 13(3), 145-152.