INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

Determinants of Post-Harvest Efficiency and Losses among Smallholder Lakatan Banana Farmers in Bukidnon, Philippines: Evidence from Fractional Logit and Two-Part Econometric Models

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DOI: https://dx.doi.org/10.47772/IJRISS.2026.100600272

Received: 27 May 2026; Accepted: 01 June 2026; Published: 22 June 2026

ABSTRACT

Post-harvest losses remain a major constraint to agricultural productivity, farm profitability, and food system efficiency, particularly in developing countries where inadequate post-harvest management and limited access to technologies contribute to substantial product deterioration. Despite the economic importance of Lakatan banana production in the Philippines, empirical evidence on the determinants of post-harvest efficiency and loss dynamics at the farm level remains limited. This study examined post-harvest efficiency and the determinants of post-harvest losses among Lakatan banana farmers in Valencia City and Impasug-ong, Bukidnon. Using cross-sectional data from 205 randomly selected farmers, the study employed a fractional logit model to analyze post-harvest efficiency and a two-part econometric framework consisting of a logistic regression model and a Gamma generalized linear model (GLM) to separately examine the occurrence and magnitude of post-harvest losses. Results showed that average post-harvest losses amounted to 148.45 kg per harvest, representing approximately 12.5% of total production, while mean post-harvest efficiency reached 87.49%. Fractional logit estimates revealed that gender, fertilizer application, and source of planting materials significantly influenced post-harvest efficiency. Female farmers exhibited higher efficiency levels, whereas excessive fertilizer application reduced efficiency. Farmers obtaining planting materials from external sources achieved significantly higher efficiency than those relying on self-sourced suckers. Logistic regression results indicated that gender, educational attainment, farm location, farming system, and fertilizer application significantly affected the probability of experiencing post-harvest losses. Conditional on positive losses, the Gamma GLM revealed that gender, farm size, farm location, fertilizer application, and farmgate price significantly influenced loss magnitude. Farmers located in Impasug-ong incurred substantially greater losses, while higher farmgate prices were associated with lower loss severity. The findings highlight the importance of farmer characteristics, input management, market incentives, and location-specific conditions in shaping post-harvest outcomes and underscore the need for targeted interventions to improve post-harvest management and reduce losses among smallholder Lakatan banana farmers.

Keywords: Lakatan banana; post-harvest efficiency; post-harvest losses; fractional logit model; two-part models

INTRODUCTION

Post-harvest losses remain a significant challenge to global food systems because they reduce food availability, diminish farm incomes, and lower the efficiency of agricultural resource utilization. The problem is particularly acute in developing countries, where inadequate infrastructure, limited access to post-harvest technologies, and inefficient handling practices constrain agricultural productivity and value-chain performance. Among horticultural commodities, bananas are especially vulnerable due to their highly perishable nature and susceptibility to mechanical damage, rapid ripening, and physiological deterioration after

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

harvest (Mohapatra et al., 2011; Murmu & Mishra, 2018; Abraham et al., 2022). Previous studies have documented substantial losses throughout banana supply chains, identifying harvesting, transportation, storage, and marketing as critical points of inefficiency (Davara & Patel, 2009; Nayak et al., 2018; Saha et al., 2021; Gemechu et al., 2021; Nkwain et al., 2022). Beyond reducing the quantity and quality of marketable produce, these losses undermine the profitability, efficiency, and sustainability of agricultural production systems.

In the Philippines, bananas are among the most important agricultural commodities in terms of production volume, harvested area, employment generation, and export earnings (PSA, 2025). The industry recently strengthened its position in the global market as the country regained its status as the world's second-largest banana exporter (Manila Bulletin, 2026). Despite this achievement, domestic production systems continue to face significant challenges, including productivity constraints, pest and disease pressures, climate-related risks, and persistent post-harvest inefficiencies that affect smallholder producers and domestic supply chains (Business Mirror, 2024). These challenges are particularly relevant for Lakatan banana, one of the country's most valuable dessert banana varieties due to its strong consumer preference, premium market price, and widespread cultivation among smallholder farmers. In major producing areas such as Bukidnon, Lakatan banana farming serves as an important source of livelihood and contributes substantially to local economic development. However, the profitability of Lakatan production is frequently undermined by losses that reduce both the quantity and quality of marketable output.

Within the Philippine context, existing research has largely focused on post-harvest handling practices, value-chain interventions, and quality preservation strategies for bananas (Laborte, 2016; Quevedo et al., 2017). While these studies provide valuable insights into the technical dimensions of post-harvest management, relatively little empirical evidence exists regarding the socioeconomic, farm-specific, and managerial factors that influence post-harvest efficiency and loss dynamics among smallholder Lakatan banana producers. More importantly, the literature has generally treated post-harvest losses as a single outcome, emphasizing loss quantification and technological solutions while overlooking the possibility that the factors influencing the occurrence of losses may differ from those affecting their magnitude once they occur. Farmers who successfully avoid losses altogether may face different incentives, constraints, and management conditions than those who experience losses of varying severity. Ignoring this distinction may obscure important behavioral and production mechanisms and ultimately limit the effectiveness of policy interventions.

From an agricultural economics perspective, post-harvest outcomes reflect not only technical handling practices but also broader resource allocation and farm management decisions. Farm households allocate harvested output among market sales, household consumption, and unavoidable losses while simultaneously making decisions regarding labor use, input application, technology adoption, and market participation. Consequently, post-harvest efficiency provides a meaningful indicator of how effectively farmers transform production into economic value. Understanding the determinants of both post-harvest efficiency and post-harvest losses is therefore essential for identifying interventions that improve profitability, enhance resource-use efficiency, and strengthen agricultural value chains.

This study addresses these gaps by examining post-harvest efficiency, production allocation behavior, and post-harvest losses among Lakatan banana farmers in Valencia City and Impasug-ong, Bukidnon. Specifically, the study estimates post-harvest efficiency levels, analyzes the allocation of harvested output among marketed surplus, household consumption, and losses, and identifies the determinants of post-harvest efficiency and post-harvest losses. To achieve these objectives, the study employs a fractional logit model to analyze post-harvest efficiency and a two-part econometric framework consisting of a logistic regression model and a Gamma generalized linear model to separately investigate the occurrence and magnitude of post-harvest losses. By distinguishing between loss incidence and loss severity while simultaneously examining efficiency outcomes, the study contributes to the literature on post-harvest management, agricultural efficiency, and food loss reduction. The findings provide evidence-based insights for policymakers, extension agencies, and development practitioners seeking to enhance the productivity, profitability, and sustainability of smallholder banana production systems in the Philippines

Theoretical Framework

This study is anchored on the Post-Harvest System Theory, Agricultural Household Production Theory, and Technology Adoption Theory to explain the factors influencing post-harvest efficiency and post-harvest losses among Lakatan banana farmers in Bukidnon. These theories collectively provide a comprehensive framework for understanding how farmer characteristics, production practices, resource utilization, and production allocation decisions affect post-harvest outcomes.

Post-Harvest System Theory

The primary theoretical foundation of this study is the Post-Harvest System Theory, which conceptualizes post-harvest activities as an integrated system consisting of harvesting, handling, sorting, storage, transportation, processing, and marketing operations. The theory posits that inefficiencies occurring at any stage of the post-harvest chain contribute to quantitative and qualitative losses, thereby reducing the proportion of harvested produce that reaches consumers in acceptable condition. According to Hodges et al. (2014), post-harvest losses arise from technical, managerial, infrastructural, and institutional constraints that diminish the value and usability of agricultural products.

In banana production systems, post-harvest losses are often attributed to improper harvesting techniques, mechanical damage during handling, inadequate packaging, poor transportation conditions, delayed marketing, and insufficient storage facilities. Empirical studies have consistently demonstrated that post-harvest inefficiencies substantially reduce farmer income and marketable output in banana value chains (Davara & Patel, 2009; Gemechu et al., 2021; Nkwain et al., 2022; Saha et al., 2021). Furthermore, improvements in post-harvest technologies, packaging systems, grading methods, and storage practices have been shown to reduce losses and improve product quality and profitability (Guo et al., 2020; Mohapatra et al., 2011; Ruiz Medina & Ruales, 2024).

Within the context of this study, post-harvest efficiency is defined as the ability of farmers to maximize the proportion of harvested Lakatan bananas that are successfully utilized through marketing or household consumption while minimizing losses. Thus, post-harvest efficiency serves as an indicator of the effectiveness of post-harvest management practices employed by farmers.

Agricultural Household Production Theory

The Agricultural Household Production Theory provides the second theoretical pillar of the study. The theory views farm households as both production and consumption units that simultaneously make decisions regarding resource allocation, production, consumption, and market participation. According to this framework, farm households allocate agricultural output among competing uses, including household consumption, market sales, and unavoidable losses.

This theory directly supports the inclusion of the Marketed Surplus Ratio (MSR), Subsistence Ratio (SR), and Loss Rate (LR) in the analytical framework. Following the household production perspective, total agricultural output may be allocated to:

1. Products sold in the market (Marketed Surplus Ratio);

2. Products retained for household consumption (Subsistence Ratio); and

3. Products lost due to post-harvest inefficiencies (Loss Rate).

The allocation of production among these competing uses reflects household objectives, market incentives, production constraints, and post-harvest management practices. Farmers with stronger market orientation are generally expected to invest more resources in preserving product quality and reducing losses because a greater proportion of production is intended for commercial sale. Conversely, higher post-harvest losses represent inefficiencies that reduce both household welfare and marketable surplus.

The Agricultural Household Production Theory therefore provides the conceptual basis for analyzing production allocation behavior and its relationship with post-harvest efficiency among Lakatan banana farmers.

Technology Adoption Theory

The Technology Adoption Theory further explains how farmer characteristics and production practices influence post-harvest outcomes. The theory posits that the adoption of improved technologies depends on factors such as education, farming experience, access to information, resource availability, and expected economic benefits. Farmers who possess greater knowledge, experience, and access to productive resources are generally more likely to adopt innovations that improve production and post-harvest performance.

In the context of banana production, technologies such as improved planting materials, appropriate fertilizer and pesticide application, better harvesting equipment, modern packaging systems, grading technologies, ripening management techniques, and improved storage facilities contribute significantly to reducing post-harvest losses and enhancing product quality (Bantayehu & Alemayehu, 2020; Abraham et al., 2022; Arunima et al., 2024). Studies have shown that adoption of improved agricultural and post-harvest technologies increases efficiency, extends shelf life, and enhances market competitiveness.

This theory supports the inclusion of farmer-specific and farm-specific variables such as age, educational attainment, farming experience, years engaged in Lakatan banana production, labor utilization, source of planting materials, fertilizer application, pesticide use, farm size, and farming system. These factors influence farmers' capacity and willingness to adopt improved production and post-harvest management practices, which ultimately affect both the occurrence and magnitude of post-harvest losses as well as overall post-harvest efficiency.

The three theories collectively explain the determinants of post-harvest efficiency among Lakatan banana farmers. The Post-Harvest System Theory emphasizes the role of post-harvest operations in minimizing losses and preserving product quality. The Agricultural Household Production Theory explains how farmers allocate production among market sales, household consumption, and losses. The Technology Adoption Theory explains how farmer characteristics and production practices influence the adoption of technologies and management strategies that improve post-harvest performance.

Guided by these theoretical perspectives, the study hypothesizes that farmer socio-demographic characteristics, farm attributes, production inputs, market conditions, and production allocation behavior significantly influence post-harvest losses and post-harvest efficiency. Consequently, these factors are incorporated into the empirical framework to estimate farm-level post-harvest efficiency and identify the determinants of post-harvest losses and efficiency among Lakatan banana farmers in Bukidnon.

Conceptual Framework

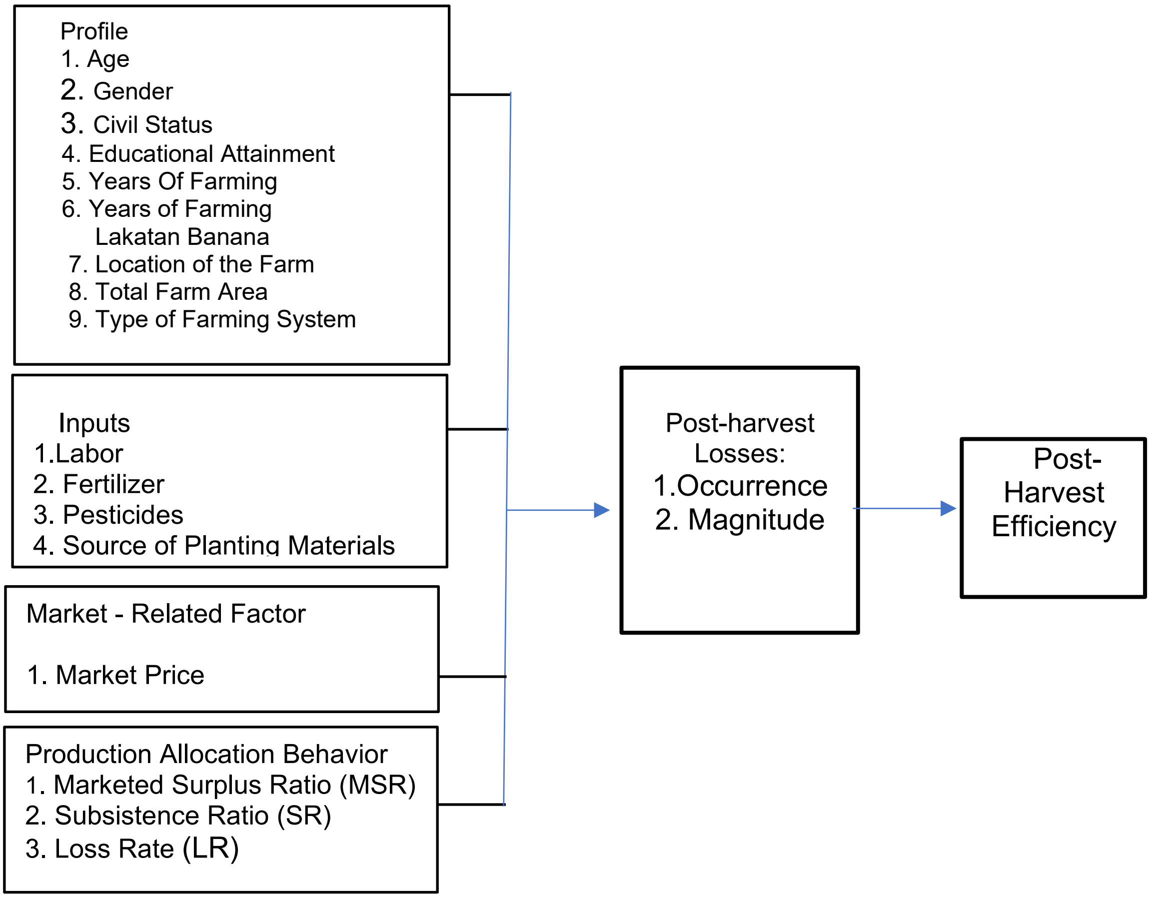
This study conceptualizes post-harvest efficiency in Lakatan banana production as the outcome of a multifactor production, allocation, and post-harvest management process in which farmer characteristics, production input utilization, and market incentives jointly influence post-harvest losses and post-harvest efficiency. Anchored in the analytical structure of Kikulwe et al. (2018), the framework treats post-harvest efficiency as a value-retention process that reflects producers' ability to maximize the proportion of harvested output that is successfully marketed or consumed while minimizing physical and quality losses. This perspective is consistent with the Post-Harvest System Theory, which views post-harvest performance as the cumulative result of decisions and practices occurring throughout the production and handling process.

As illustrated in Figure 3, the framework is organized into three major categories of explanatory variables: farmer profile and farm characteristics, production inputs and resource utilization, and market-related factors. These factors are hypothesized to influence post-harvest losses and post-harvest efficiency. Production allocation behavior, measured through the Marketed Surplus Ratio (MSR), Subsistence Ratio (SR), and Loss

Rate (LR), is analyzed descriptively to characterize the distribution of harvested output among market sales, household consumption, and losses.

Figure 3

The schematic diagram of the study of Post-harvest Efficiency in Lakatan Banana Production



Farmer characteristics such as age, educational attainment, farming experience, and years engaged in banana production influence managerial capacity, technology adoption, and post-harvest decision-making. Previous studies have shown that farmer knowledge, experience, and management practices significantly affect post-harvest handling efficiency and loss reduction strategies (Ansah & Tetteh, 2016; Ngowi & Selejio, 2019; Midamba & Kizito, 2022). Farm characteristics including location, farm size, and farming systems may also influence production performance and exposure to post-harvest risks through differences in production conditions and access to resources (Anzures et al., 2022; Ambuko et al., 2006).

Production inputs and resource utilization constitute the second component of the framework. Labor availability, fertilizer application, pesticide use, and the quality of planting materials directly affect crop productivity, fruit quality, resistance to pests and diseases, and ultimately post-harvest outcomes. Studies on banana production have demonstrated that improved agronomic practices and input utilization contribute to higher-quality produce and lower post-harvest losses (Bantayehu & Alemayehu, 2020; Abraham et al., 2022; Ruiz Medina & Ruales, 2024). Similarly, advances in post-harvest technologies and quality assessment systems have been shown to improve handling efficiency and reduce deterioration in banana supply chains (Guo et al., 2020; Arunima et al., 2024).

Market-related factors, represented by farmgate prices, are expected to influence farmer incentives regarding harvesting, grading, handling, and marketing decisions. Economic theory suggests that higher expected returns encourage producers to allocate greater effort and resources toward preserving product quality and reducing losses. Studies on post-harvest management have likewise reported that market incentives and commercialization orientation significantly affect the adoption of loss-reduction practices and post-harvest investments (Nayak et al., 2018; Nkwain et al., 2022).

The framework further incorporates production allocation behavior through the Marketed Surplus Ratio (MSR), Subsistence Ratio (SR), and Loss Rate (LR). Consistent with the Agricultural Household Production Theory, farm households allocate harvested output among market sales, household consumption, and losses. These allocation decisions reflect household objectives, resource constraints, and market opportunities and are expected to influence overall post-harvest efficiency. Farmers with greater market orientation are generally expected to have stronger incentives to preserve product quality and minimize losses, whereas higher loss rates directly reduce the efficiency with which harvested output is transformed into economic value (Allen, 2014; Habib et al., 2023).

The framework assumes that variations in socioeconomic characteristics, farm attributes, production practices, resource utilization, and market incentives generate differences in the occurrence and magnitude of post-harvest losses, which ultimately determine overall post-harvest efficiency. Production allocation indicators (MSR, SR, and LR) are included to describe how harvested output is distributed among market sales, household consumption, and losses and to provide additional context for interpreting post-harvest performance. Consistent with this conceptualization, post-harvest losses are analyzed using a two-part modeling framework that separately estimates loss occurrence and loss magnitude, while post-harvest efficiency is estimated using a fractional regression model appropriate for bounded efficiency measures (Debebe, 2022; Koufie & Darfor, 2026; Ramalho et al., 2010).

Transportation costs, storage facilities, and ripening technologies were excluded from the empirical framework because Lakatan bananas in the study area are predominantly sold directly at the farm gate. Consequently, downstream storage, distribution, and retail decisions are largely undertaken by traders rather than producers. This production and marketing arrangement is consistent with observations from Philippine banana marketing systems, where farmers frequently transfer ownership immediately after harvest, thereby limiting their involvement in subsequent post-harvest activities (Laborte, 2016; Quevedo et al., 2017). Accordingly, the framework focuses on determinants operating at the farm level, where farmers exercise direct control over production, handling, and allocation decisions.

Objectives of the Study

The general objective of the study is to analyze the selected areas of Bukidnon Lakatan production and determine its post-harvest efficiency.

Specifically, the study aims to:

1. To describe the socio-demographic characteristics, farm attributes, and production input utilization of Lakatan banana farmers, including age, gender, civil status, educational attainment, farming experience, years of experience in Lakatan banana production, farm location, total farm area, type of farming system, labor use, fertilizer and pesticide application, sources of planting materials, and market price.

2. To estimate farm-level post-harvest efficiency, post-harvest losses, and production allocation behavior among Lakatan banana farmers.

3. To identify the determinants of post-harvest efficiency, the probability of experiencing post-harvest losses, and the magnitude of post-harvest losses among Lakatan banana farmers using a fractional logit model and a two-part econometric framework.

Scope and Limitations of the Study

This research focused on assessing the post-harvest efficiency of Lakatan banana production at the farm level in the municipalities of Valencia City and Impasug-ong, Bukidnon. The study examined the socio-demographic characteristics of farmers, including age, gender, educational attainment, years of farming experience, years of experience in Lakatan banana production, farm location, total farm area, and farming system. It also assessed production inputs such as labor utilization, fertilizer application, pesticide use, source of planting materials, farmgate price, and yield obtained. It aimed to identify key factors influencing production efficiency and to estimate post-harvest losses occurring immediately after harvest on the farm premises.

Quantitative analysis was conducted using descriptive statistics, a fractional logit model, and a two-part econometric framework consisting of a binary logistic regression model and a Gamma generalized linear model (GLM). These methods were employed to estimate post-harvest efficiency, the probability of experiencing post-harvest losses, and the magnitude of post-harvest losses among Lakatan banana farmers.

Participating farmers must meet specific criteria to ensure the relevance and reliability of the data. Respondents must: (1) be currently cultivating Lakatan banana as a primary or one of their main crops; (2) reside and operate within Valencia City or Impasug-ong; (3) be actively farming during the data collection period; (4) be directly involved in on-farm post-harvest activities such as harvesting, sorting, cleaning, or packing; (5) be willing and able to participate in interviews or focus group discussions; and preferably (6) have at two years of experience in Lakatan banana farming. The exact number of respondents in the study was 205.

Limitations of the study include its reliance on self-reported data, which may be subject to recall bias and estimation errors. The findings were also limited to a specific harvest period and may not capture seasonal variations in post- harvest losses. Additionally, due to geographic and logistical constraints, only farmers who meet the outlined criteria and are available during the data collection period were interviewed. Lastly, the study employs a cross-sectional design, which limits the ability to infer causality between variables.

METHODOLOGY

Research Design

This study employed a descriptive–correlational cross-sectional quantitative research design to examine the determinants of post-harvest efficiency and post-harvest losses among Lakatan banana farmers in Bukidnon, Philippines. The analytical framework integrates descriptive statistics and econometric modeling to investigate how farmer characteristics, farm attributes, production inputs, and commercialization behavior influence post-harvest outcomes. The study is anchored on Post-Harvest Systems Theory, which conceptualizes post-harvest performance as the outcome of interconnected production, handling, storage, and marketing processes (Hodges et al., 2011). Given that post-harvest losses are characterized by non-negative values, substantial right-skewness, and the presence of zero observations, conventional Ordinary Least Squares (OLS) regression may produce biased and inefficient estimates due to violations of normality and homoscedasticity assumptions (Manning & Mullahy, 2001). Consequently, this study employs a Two-Part Model (TPM) combined with a Gamma Generalized Linear Model (GLM), which is widely recommended for non-negative and highly skewed economic outcomes (Belotti et al., 2015).

Research Locale

The study was conducted in Valencia City and the Municipality of Impasug-ong, Bukidnon Province, Northern Mindanao, Philippines. These municipalities were purposively selected because they are among the major Lakatan banana-producing areas in the province and represent contrasting production environments. Valencia City is characterized by relatively larger and more commercialized farming operations, stronger market integration, and improved transportation infrastructure. In contrast, Impasug-ong is dominated by smallholder farming systems operating under more heterogeneous agroecological and topographical conditions. The inclusion of these two municipalities allows the study to capture variations in production scale, market participation, production systems, and post-harvest management practices that may influence post-harvest efficiency and losses.

Population, Sampling Procedure, and Sample Size Determination

Bukidnon, namely Valencia City and the Municipality of Impasug-ong. The sampling frame was constructed using official records obtained from the City Agriculture Office and Municipal Agriculture Office, which contained the list of registered Lakatan banana farmers in the study area. Stratification was adopted to improve the representativeness of the sample and reduce sampling variability by ensuring proportional representation of farmers across municipalities (Cochran, 1977).

The required sample size was determined using Cochran's (1977) formula for proportions:

$$n_0 = Z^2 . \frac{p(1-p)}{e^2}$$

where n_0 denotes the initial sample size, Z is the standard normal variate corresponding to the desired confidence level, p is the estimated population proportion, and e is the margin of error. Assuming a 95% confidence level (Z = 1.96), a population proportion of 0.50, and a margin of error of 5 percent, the initial sample size was computed as follows:

$$n_0 = \frac{(1.96)^2(0.50)(0.50)}{(0.50)^2}$$

$$= \frac{3.8416 \times 0.25}{0.0025}$$

$$= 384.16$$

Because the target population of Lakatan banana farmers was finite (N = 470), the initial sample size was adjusted using the Finite Population Correction (FPC):

$$n = \frac{n_0}{1 + \frac{n_{0-1}}{N}}$$

where $N = 470$ is the total population of the two municipalities. Applying the correction:

$$n = \frac{384.16}{1 + \frac{384.16}{470}} = \frac{384.16}{1 + 0.8152} = \frac{384.16}{1.8152} = 211.63 \approx 212$$

Although the final analytical sample consisted of 205 respondents after data cleaning and validation, the sample remained adequate for econometric estimation and exceeded the minimum observations required for logistic and fractional regression analyses. The final sample size of 205 remained adequate for the estimation of logistic regression and Gamma generalized linear models, as previous methodological studies have shown that reliable parameter estimation can be achieved when sufficient observations are available relative to the number of explanatory variables and outcome events included in the model (Hosmer et al., 2013; Peduzzi et al., 1996).

Stratification

Following the determination of the required sample size, the population of Lakatan banana farmers was stratified by municipality to ensure proportional representation of respondents from the two major production areas of Bukidnon. Stratification was employed to improve the precision of the estimates and reduce sampling variability by ensuring that farmers from each municipality were adequately represented in the sample (Cochran, 1977).

The total population consisted of 470 registered Lakatan banana farmers, of which 199 were located in Valencia City and 271 were located in Impasug-ong. The required sample was allocated proportionately across municipalities using the proportional allocation formula:

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

$$n_h = \frac{N_h}{N} \times n$$

Where:

n_h = sample size allocated to municipality *h*

N_h = population of municipality *h*

N = total population

n = total sample size

Final Sample Size Allocation

$$n_{valecia} = \frac{199}{470} \times 205 = 86.86 \approx 87$$

$$n_{impasug-ong} = \frac{271}{470} \times 205 = 118.14 \approx 118$$

Accordingly, 87 respondents were allocated to Valencia City and 118 respondents were allocated to Impasug-ong. Within each municipality, respondents were selected using simple random sampling to ensure that every eligible Lakatan banana farmer had an equal probability of selection. Table 1 presents the distribution of the population and sample across the two municipalities.

Table 1. Distribution of Respondents and Sample Size by Municipality

MUNICIPALITY	POPULATION	SAMPLE SIZE
Valencia City	199	87
Impasug-ong	271	118
Total	470	205

The use of proportional allocation ensured that the sample reflected the actual distribution of Lakatan banana farmers across the study area, thereby enhancing the representativeness and external validity of the study findings.

Data Collection Procedures

Primary data were collected through face-to-face interviews using a structured questionnaire administered during the peak harvesting period. Prior to full deployment, the questionnaire underwent expert validation by agricultural economists, extension specialists, and crop production experts to ensure content validity and relevance to the study objectives. A pilot survey was subsequently conducted among non-sample Lakatan banana farmers to assess clarity, reliability, and contextual appropriateness. Necessary revisions were incorporated before final administration.

The survey collected information on socio-demographic characteristics, farm structure, production inputs, production allocation behavior, post-harvest handling practices, quantities harvested, quantities sold, household consumption, and post-harvest losses. Secondary information was obtained from the Philippine Statistics Authority (PSA), Department of Agriculture (DA), Food and Agriculture Organization (FAO), and relevant peer-reviewed literature.

Methods of Analysis

To address the objectives of this study, various statistical and econometric analyses were employed to generate meaningful insights into the postharvest losses of Lakatan banana production in Bukidnon. The analysis focused on the relationships among farmer profiles, input types, market prices, and their influence on postharvest losses across different stages of the value chain.

For objective number one, to describe the socio-demographic characteristics, farm attributes, and production input utilization of Lakatan banana farmers, the study employs descriptive statistics, including frequency counts and percentage distributions. All variables are categorized to ensure uniformity in presentation and facilitate interpretation. Socio-demographic and farm-related variables—including age, gender, civil status, educational attainment, farming experience, years of experience in Lakatan banana production, farm location, total farm area, and type of farming system—are grouped into meaningful classes and summarized by frequency and percentage. This provides a clear profile of the respondents in terms of human capital and farm structure. Similarly, production input variables—such as type of labor employed (family, hired, or mixed), fertilizer application, pesticide use, and sources of planting materials—are analyzed using frequency counts and percentage distributions to identify prevailing input utilization patterns among farmers.

For objective number two, which is to estimate farm-level post-harvest efficiency and examine production allocation and commercialization behavior, the analysis proceeds through a structured empirical framework. Following agricultural value-chain accounting approaches (Kikulwe et al., 2018), production allocation was validated using the production identity:

$$Production_i = Sold_i + Loss_i$$

A residual term is computed as:

$$\varepsilon_i = (Sold_i + Consumption_i + Loss_i)$$

Observations with substantial deviations from this identity are excluded to ensure internal consistency. Negative values of post-harvest losses, interpreted as measurement errors, are treated as missing.

Second, normalized indicators are constructed to quantify production allocation, market participation, and post-harvest inefficiency. Specifically, the normalized indicators are defined and interpreted as follows:

Marketed Surplus Ratio (MSR)

$$MSR_i = \frac{Sold_i}{Production_i}$$

The marketed surplus ratio measures the proportion of total output that is sold in the market, thereby capturing the degree of market participation. Higher MSR values indicate a stronger orientation toward commercialization, while lower values suggest limited engagement with output markets.

Subsistence Ratio (SR)

$$SR_i = \frac{Consumption_i}{Production_i}$$

The subsistence ratio reflects the share of production retained for household consumption. This indicator captures the extent to which farming activity serves subsistence needs, with higher values indicating a greater reliance on own-produced output for household use.

Loss Rate (LR)

$$LR_i = \frac{Loss_{Unsold\ Produced}}{Production_i}$$

The loss rate represents the proportion of total production lost due to spoilage, mechanical damage, rejected produce, handling losses, storage losses, and unsold bananas that became unmarketable due to deterioration. Losses due to theft and intentional giveaways were excluded because they do not reflect post-harvest inefficiency or measurable quality and quantity reduction in the product (FAO, 2020).

Taken together, these indicators provide a scale-neutral decomposition of output allocation, enabling consistent comparison across farms with heterogeneous production levels and offering a coherent framework for analyzing commercialization behavior and post-harvest efficiency within smallholder production systems.

To achieve Objective 3, the study employed a combination of fractional response and two-part econometric models to identify the factors influencing post-harvest efficiency and post-harvest losses among Lakatan banana farmers. The use of multiple econometric approaches was necessary because post-harvest efficiency and post-harvest losses exhibit different statistical properties and therefore require different estimation procedures.

Post-harvest efficiency was measured as:

$$PHE_i\ (\%) = \left(\frac{Total\ Production_i - Post - Harvest\ Losses_i}{Total\ Production_i}\right) x\ 100$$

where PHE_i represents the percentage of total production successfully retained after accounting for post-harvest losses. Because post-harvest efficiency is a bounded proportion ranging from 0 to 100 percent, conventional Ordinary Least Squares (OLS) regression may generate predicted values outside the feasible range and violate assumptions of homoscedasticity. Following the fractional regression framework proposed by Papke and Wooldridge (1996), post-harvest efficiency was analyzed using a Fractional Logit Model. This approach is particularly appropriate because post-harvest efficiency is measured as a proportion bounded between 0 and 100 percent and, after transformation, lies within the unit interval ([0,1]). Conventional linear regression models are not well suited for such data because they may generate predicted values outside the admissible range and often fail to account for the heteroskedasticity commonly associated with fractional outcomes. Fractional logit models directly accommodate bounded dependent variables and provide consistent estimates of conditional mean responses without imposing restrictive distributional assumptions (Papke & Wooldridge, 1996; Ramalho et al., 2010).

$$PHE_i^* = \frac{PHE_i}{100}$$

The fractional logit model is specified as:

$$E(PHE_i^* | X_i) = G(X_i \beta)$$

where G(.) denotes the logistic cumulative distribution function, X_i is the vector of explanatory variables, and β is the vector of parameters to be estimated. The application of fractional logit models has become increasingly common in agricultural and resource economics when the dependent variable represents proportions, shares, rates, or efficiency scores. Misango et al. (2022) employed a fractional logit approach to analyze the intensity of integrated pest management adoption among farmers in Rwanda, demonstrating its suitability for bounded agricultural outcomes. Similarly, Allen (2014) applied fractional multinomial logit models to examine land allocation decisions among agricultural households, while Habib et al. (2023) used fractional multinomial logit estimation to investigate livelihood diversification strategies among rural households. In efficiency analysis, Ramalho et al. (2010) specifically recommended fractional regression models for second-stage efficiency estimation because efficiency measures are naturally bounded and often exhibit nonlinear relationships with explanatory variables. These methodological advantages make the fractional logit specification particularly suitable for modeling post-harvest efficiency among Lakatan banana farmers.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

To examine post-harvest losses, the study employed a Two-Part Model (TPM). This approach is appropriate because post-harvest loss data are characterized by a substantial proportion of zero observations and a highly right-skewed distribution among positive losses. Conventional OLS regression assumes a continuous and normally distributed dependent variable and is therefore unsuitable for modeling agricultural loss data. Likewise, Tobit regression assumes that zero observations arise from censoring of an underlying latent variable, an assumption that may not hold when farmers genuinely experience no post-harvest losses (Manning & Mullahy, 2001). The TPM overcomes this limitation by separately estimating the probability of loss occurrence and the magnitude of losses once they occur.

In the first stage, the probability that a farmer experiences post-harvest loss is estimated using a binary logistic regression model. A dichotomous dependent variable is defined as:

$D_i = 1$, if post-harvest loss > 0

$D_i = 0$, if post-harvest loss = 0

The logistic regression model is specified as:

$Pr(D_i = 1 \mid X_i) = \exp(X_i\beta) / [1 + \exp(X_i\beta)]$

where D_i denotes the occurrence of post-harvest loss, X_i represents a vector of explanatory variables, and β is the vector of parameters to be estimated. Marginal effects were subsequently computed to facilitate interpretation of the estimated probabilities.

where:

$X_i = \beta_0 + \beta_1 AGE_i + \beta_2 GENDER_i + \beta_3 CIVSTAT_i + \beta_4 EDUC_i + \beta_5 FARMEXP_i + \beta_6 LAKATEXP_i + \beta_7 FARMSIZE_i + \beta_8 LOCATION_i + \beta_9 FARMSYS_i + \beta_{10} LABOR_i + \beta_{11} FERTILIZER_i + \beta_{12} PESTICIDE_i + \beta_{13} PLANTMAT_i + \beta_{14} PRICE_i + \varepsilon_i$

where:

AGE = age of farmer (years)

GENDER = gender of farmer

CIVSTAT = civil status

EDUC = educational attainment

FARMEXP = years of farming experience

LAKATEXP = years engaged in Lakatan banana production

FARMSIZE = total farm area (hectares)

LOCATION = municipality of farm

FARMSYS = farming system

LABOR = type of labor employed

FERTILIZER = fertilizer application

PESTICIDE = pesticide application

PLANTMAT = source of planting materials

PRICE = average farmgate price

ε_i = stochastic error term

Marginal effects were estimated to facilitate interpretation of the probability of experiencing post-harvest losses.

The use of logistic regression is well established in agricultural and post-harvest research for analyzing binary outcomes related to technology adoption, training access, market participation, and post-harvest management decisions. For example, Midamba and Kizito (2022) employed a binary logistic regression model to examine factors influencing farmers' access to post-harvest loss management training among maize producers in Uganda. Similarly, Mark et al. (2025) utilized binary logistic regression to assess factors associated with crop post-harvest losses under farmers-herders conflict conditions in Benue State, demonstrating the suitability of the approach for identifying determinants of post-harvest outcomes. In post-harvest quality studies, Tolesa et al. (2018) applied logistic regression to evaluate the marketability of tomato fruits under different storage and handling conditions, further illustrating the usefulness of binary response models in post-harvest research.

The explanatory variables included age, gender, civil status, educational attainment, farming experience, years engaged in Lakatan banana production, farm size, farm location, farming system, labor type, fertilizer application, pesticide use, source of planting materials, and average farmgate price. These variables were selected based on empirical evidence suggesting that farmer socioeconomic characteristics, production practices, resource endowments, and market conditions influence post-harvest management decisions and the likelihood of incurring losses. Human capital variables such as education, farming experience, and age may affect managerial ability and adoption of improved post-harvest practices. Farm-level characteristics including farm size, location, labor arrangements, and production systems may influence harvesting efficiency, handling practices, transportation conditions, and storage management. Input use and planting material quality may affect crop quality and resistance to physical damage, while market-related factors such as farmgate prices can alter incentives for harvesting, grading, and post-harvest handling.

To facilitate interpretation of the estimated coefficients, marginal effects were computed following model estimation. Because logistic regression coefficients are expressed in log-odds units and are not directly interpretable in probability terms, marginal effects provide a more meaningful measure by quantifying the change in the probability of experiencing post-harvest losses associated with a one-unit change in a continuous explanatory variable or a change in category for a discrete variable, holding other factors constant. The use of marginal effects is widely recommended in applied logistic regression analysis because it enables direct interpretation of the practical significance of explanatory variables on outcome probabilities.

Conditional on positive losses, the second stage estimates the magnitude of post-harvest losses using a Gamma Generalized Linear Model (GLM) with a log-link function:

$$E(Loss_i \mid Loss_i > 0, X_i) = \exp(Z_i)$$

where $Loss_i$ represents the quantity of post-harvest losses incurred by farmer i. The Gamma GLM was selected because post-harvest loss data are continuous, strictly positive, and typically exhibit right-skewed distributions characterized by heteroskedasticity, where the variance increases with the mean. Traditional Ordinary Least Squares (OLS) regression assumes normally distributed errors and constant variance, assumptions that are often violated in agricultural loss data. The Gamma distribution provides a more appropriate framework for modeling such outcomes because it accommodates positive-valued dependent variables and allows the variance to increase proportionally with the conditional mean (McCullagh & Nelder, 1989; Ahlawat, 2025).

The use of a log-link function further enhances the suitability of the model by ensuring that predicted values remain strictly positive and by allowing the effects of explanatory variables to be interpreted in multiplicative rather than additive terms. Under this specification, estimated coefficients represent proportional changes in expected post-harvest losses associated with changes in explanatory variables, thereby facilitating economically meaningful interpretations of the results (Salinas Ruíz et al., 2023). Similar applications of

Gamma GLMs have been widely employed in agricultural and environmental studies involving non-negative and skewed outcome variables, demonstrating their effectiveness in modeling heterogeneous response data characterized by increasing variance structures (Guo et al., 2015).

The adoption of a two-part modeling framework recognizes that the determinants influencing the occurrence of post-harvest losses may differ from those affecting the magnitude of losses once they occur. In the first stage, a binary logistic regression model estimates the probability that a farmer experiences any post-harvest loss. In the second stage, the Gamma GLM estimates the extent of losses among farmers who reported positive losses. This approach allows separate identification of factors influencing loss incidence and loss severity, thereby providing a more comprehensive understanding of post-harvest inefficiencies than a single-equation model. Two-part models are particularly appropriate when the dependent variable contains a substantial proportion of zero observations alongside continuous positive values, as they avoid potential biases arising from imposing a common data-generating process on both outcomes.

The explanatory variables included age, gender, civil status, educational attainment, farming experience, years engaged in Lakatan banana production, farm size, farm location, farming system, labor type, fertilizer application, pesticide use, source of planting materials, and average farmgate price. These variables were selected based on theoretical and empirical evidence from the agricultural economics, farm management, and post-harvest literature, which suggests that farmer characteristics, production practices, resource endowments, and market conditions influence both the likelihood and severity of post-harvest losses. Human capital variables such as age, education, and farming experience may affect managerial capacity and adoption of improved post-harvest practices, while farm-specific factors such as farm size, location, production system, labor arrangements, and input use may influence harvesting efficiency, handling practices, and exposure to physical and quality deterioration. Market-related factors, including farmgate prices, may also affect harvesting decisions, product handling, and incentives for loss reduction. Collectively, these variables capture the socioeconomic, technical, and institutional conditions that shape post-harvest performance among Lakatan banana farmers.

To assess model validity and robustness, multicollinearity among explanatory variables was examined using Variance Inflation Factors (VIF), with values below 10 indicating acceptable levels of collinearity (Gujarati & Porter, 2009). Model adequacy was evaluated using Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), deviance statistics, and Pearson goodness-of-fit measures. Robust (Huber–White) standard errors were also estimated to account for potential heteroskedasticity and improve the reliability of statistical inference.

Research Instrument

The primary research instrument used in this study was a structured questionnaire designed to collect quantitative data from Lakatan banana farmers in Valencia City and Impasug-ong, Bukidnon. The questionnaire was developed based on the study objectives, theoretical framework, and relevant literature on post-harvest management, agricultural efficiency, and farm-level production systems. Prior to data collection, the instrument underwent content validation by experts in agricultural economics, crop production, and agricultural extension to ensure relevance, clarity, and alignment with the study objectives. A pilot test was subsequently conducted among non-sample Lakatan banana farmers to evaluate the comprehensibility, reliability, and contextual appropriateness of the questionnaire. Necessary revisions were incorporated before final administration.

The questionnaire consisted of three major sections. The first section gathered information on the socio-demographic characteristics of respondents, including age, gender, civil status, educational attainment, years of farming experience, and years engaged in Lakatan banana production. The second section collected farm-level information, including farm size, farm location, farming system, labor utilization, fertilizer application, pesticide use, source of planting materials, and average farmgate price. The third section focused on production and post-harvest information, including total production, quantity sold, household consumption, post-harvest losses, and post-harvest handling practices. These data were used to estimate post-harvest efficiency, production allocation behavior, marketed surplus ratio, subsistence ratio, loss rate, and the

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

determinants of post-harvest efficiency and post-harvest losses.

The questionnaire was administered through face-to-face interviews to ensure data accuracy, completeness, and consistency. Responses were encoded, validated, and subjected to consistency checks before statistical and econometric analyses were conducted.

RESULTS AND DISCUSSION

Socio-Demographic Characteristics and Farm Attributes of Lakatan Banana Farmers

Table 1 presents the socio-demographic characteristics and farm attributes of the 205 Lakatan banana farmers included in the study.

Table 1. *Socio-Demographic Characteristics and Farm Attributes of Lakatan Banana Farmers (n = 205)*

Variable	Category	Frequency	Percentage (%)
Age	20–25 years	2	0.99
	26–35 years	10	4.95
	36–45 years	54	26.73
	46–55 years	60	29.70
	56–65 years	49	24.26
	Above 65 years	30	14.63
	Total	**205**	**100.00**
Sex	Male	175	85.37
	Female	30	14.63
	Total	**205**	**100.00**
Civil Status	Single	25	12.20
	Married	176	85.85
	Widowed	4	1.95
	Total	**205**	**100.00**
Educational Attainment	Elementary Level	92	44.88
	High School Level	58	28.29
	College Level	51	24.88
	College Graduate	4	1.95
	Total	**205**	**100.00**
Farming Experience	2–5 years	6	2.93

	6–10 years	28	13.66
	11–15 years	28	13.66
	16–20 years	35	17.07
	21–29 years	56	27.32
	30 years and above	52	25.37
	Total	**205**	**100.00**
Farm Size	1–4 hectares	120	58.54
	5 hectares and above	85	41.46
	Total	**205**	**100.00**
Farm Location	Valencia City	87	42.44
	Impasug-ong	118	57.56
	Total	**205**	**100.00**
Labor Type	Family Labor	184	89.76
	Hired Labor	21	10.24
	Total	**205**	**100.00**
Sucker Source	Own Farm Source	135	65.85
	Other Sources	70	34.15
	Total	**205**	**100.00**

Source: Survey data, 2025.

The results indicate that Lakatan banana production in the study area is largely undertaken by middle-aged and older farmers. The largest proportion of respondents (29.70%) belonged to the 46–55 years age group, followed by those aged 36–45 years (26.73%) and 56–65 years (24.26%). Only 5.94% of respondents were below 35 years old. These findings suggest that Lakatan banana farming is predominantly managed by mature and experienced individuals who have accumulated substantial farming knowledge and production skills over time. Similar age distributions have been reported in banana-producing communities where agricultural production is dominated by older household heads with extensive farming experience (Ansah & Tetteh, 2016; Anzures et al., 2022). The aging structure of the farming population may provide valuable production experience but may also limit the adoption of innovative technologies and modern post-harvest management practices.

The sample was overwhelmingly male-dominated, with male farmers accounting for 85.37% of respondents and female farmers comprising only 14.63%. This pattern reflects the labor-intensive nature of banana production and the traditional gender division of labor commonly observed in agricultural communities. Similar findings have been documented in studies of banana production systems in developing countries where men are often responsible for farm management and marketing decisions while women participate primarily in supporting farm activities (Nkwain et al., 2022). The predominance of male respondents suggests that production and post-harvest management decisions are largely influenced by male household heads.

With respect to civil status, the majority of respondents were married (85.85%), while only 12.20% were single and 1.95% were widowed. The high proportion of married farmers may indicate greater household labor availability and stronger family participation in farm operations. Family labor is particularly important in smallholder banana production because harvesting, sorting, hauling, and other post-harvest activities often require coordinated household involvement. Married households may therefore possess advantages in managing labor-intensive post-harvest operations and reducing losses.

Educational attainment results reveal that most farmers had relatively low levels of formal education. Nearly half of the respondents (44.88%) attained only elementary-level education, while 28.29% reached high school level and 24.88% attended college. Only 1.95% were college graduates. These findings suggest that although most farmers possess basic literacy and numeracy skills, relatively few have advanced formal education. Education is often associated with improved managerial capacity, access to information, and technology adoption, all of which influence production efficiency and post-harvest management practices (Midamba & Kizito, 2022). Consequently, educational attainment may play an important role in explaining variations in post-harvest efficiency among farmers.

The respondents exhibited extensive farming experience. More than half of the farmers (52.69%) reported at least 21 years of farming experience, while only 2.93% had less than five years of experience. The large proportion of highly experienced farmers suggests that banana production in the study area is characterized by substantial accumulated technical knowledge and familiarity with local production conditions. Previous studies have reported that farming experience contributes positively to production management and post-harvest handling efficiency because experienced farmers are more capable of identifying potential sources of losses and implementing appropriate mitigation strategies (Ansah & Tetteh, 2016; Ngowi & Selejio, 2019).

Farm size distribution indicates that the majority of respondents (58.54%) cultivated between one and four hectares, while 41.46% operated farms larger than five hectares. This finding suggests that Lakatan banana production in the study area is dominated by small- to medium-scale producers. Farm size may influence post-harvest outcomes through economies of scale, labor allocation, and investment capacity. Larger farms generally possess greater opportunities to invest in improved production practices and post-harvest technologies, although they may also face greater challenges in managing larger production volumes.

In terms of geographic distribution, 57.56% of respondents were located in Impasug-ong, while 42.44% were from Valencia City. The inclusion of farmers from both municipalities provides variation in production environments and market conditions, allowing the study to examine whether location-specific factors contribute to differences in post-harvest performance. Geographic location has been identified as an important determinant of agricultural productivity and post-harvest losses due to differences in infrastructure, accessibility, environmental conditions, and market linkages (Qange et al., 2024).

Labor utilization patterns show that family labor remains the dominant source of labor in Lakatan banana production. Approximately 89.76% of respondents relied primarily on family labor, whereas only 10.24% employed hired labor. This finding is consistent with the characteristics of smallholder farming systems in developing countries, where family labor serves as the primary source of labor for production and post-harvest activities. The reliance on family labor may reduce production costs but could also constrain the timely completion of labor-intensive post-harvest operations during peak harvest periods.

Finally, the results indicate that a majority of farmers (65.85%) obtained planting materials from their own farms, while 34.15% sourced planting materials from external suppliers. The continued reliance on self-propagated suckers suggests that many farmers depend on traditional propagation practices because of their low cost and immediate availability. However, the substantial proportion of farmers acquiring planting materials from external sources indicates a growing recognition of the benefits associated with improved or certified planting stocks. Access to high-quality, disease-free planting materials can enhance productivity, improve fruit quality, and reduce susceptibility to pests and diseases, thereby contributing to better post-harvest outcomes. Previous studies have shown that the quality of planting materials plays a critical role in crop performance, disease incidence, and post-harvest quality characteristics in banana production systems (Bantayehu & Alemayehu, 2020; Abraham et al., 2022). The presence of both sourcing strategies among

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

farmers suggests variation in technology adoption and production management practices, which may contribute to differences in post-harvest efficiency and loss outcomes.

The results portray Lakatan banana farmers in Bukidnon as predominantly male, married, and highly experienced producers operating small- to medium-scale farms. Production relies heavily on family labor and self-sourced planting materials, while educational attainment remains relatively modest. These socioeconomic and farm characteristics provide important context for understanding variations in post-harvest losses and post-harvest efficiency examined in the succeeding sections of the study.

Farm-Level Post-Harvest Efficiency, Production Allocation, And Commercialization Behavior Of Banana Farmers

Table 2 presents the descriptive statistics of banana production, output allocation, and post-harvest performance among Lakatan banana farmers in Bukidnon. Average production was 1,187.56 kg per harvest with substantial variability (SD = 791.29 kg), indicating considerable differences in farm scale and production capacity among respondents. The wide production range of 120 to 6,000 kg further confirms the presence of both smallholder and relatively large-scale producers within the sample.

Table 2. *Descriptive Statistics of Banana Production, Output Allocation, and Post-Harvest Loss*

VARIABLE	MEAN	STD. DEV.	MIN	MAX
Production (kg)	1,187.56	711.28	120.00	6,000
Sold (kg)	1,023.70	678.28	50.00	6,000
Farm Price per kg	23.48	4.01	15	30
Household Consumption (kg)	10.04	20.64	0	100
Post-Harvest Loss (kg)	148.45	216.14	0.00	1,068.75
Post-Harvest Efficiency	87.49	18.21	0	100
Marketed Surplus Ratio (MSR)	0.864	0.183	0.100	1.000
Subsistence Ratio (SR)	0.011	0.040	0.000	0.500
Loss Rate (LR)	0.125	0.182	0.000	0.890

Note. MSR = sold ÷ production; SR = household consumption ÷ production; LR = post-harvest loss ÷ production. All ratio variables are expressed as proportions. Values exceeding 1 (e.g., MSR > 1) may reflect reporting inconsistencies, resale activities, or timing differences between production and sales. Descriptive statistics are based on cleaned data after applying consistency checks on the production identity. *Source: Author's computations using* Stata 19.5

The average quantity sold was 1,023.70 kg per harvest, corresponding to a mean marketed surplus ratio (MSR) of 0.864. This indicates that approximately 86.4% of total production was marketed, demonstrating the highly commercialized nature of Lakatan banana farming in the study area. The maximum MSR value of 1.00 further suggests that some farmers sold their entire harvest, while the relatively low subsistence ratio (SR = 0.011) indicates that only about 1.1% of production was retained for household consumption. These findings confirm that Lakatan banana production functions primarily as a market-oriented enterprise rather than a subsistence activity.

The average farmgate price was ₱23.48 per kilogram, with prices ranging from ₱15.00 to ₱30.00 per kilogram.

The moderate variation in prices received by farmers may reflect differences in fruit quality, buyer arrangements, market accessibility, and prevailing market conditions during the harvest period. Overall, the results suggest a relatively stable pricing environment, although some farmers obtained substantially higher prices than others.

Average post-harvest losses amounted to 148.45 kg per harvest, while the mean loss rate (LR) was 0.125, indicating that approximately 12.5% of total production was lost after harvest. The large standard deviation relative to the mean and the maximum loss rate of 0.89 suggest substantial heterogeneity in post-harvest performance across farmers. While many farmers reported minimal or no losses, others experienced considerable losses, likely reflecting differences in harvesting practices, handling methods, storage conditions, transportation facilities, and market access.

The mean post-harvest efficiency of 87.49% indicates that, on average, farmers successfully retained a large proportion of harvested output for productive use. However, the relatively high standard deviation (18.21%) and the wide range of efficiency values (0% to 100%) reveal substantial variation in post-harvest management performance among producers. Although many farmers achieved high efficiency levels, some experienced significant inefficiencies that reduced the proportion of output ultimately available for sale or consumption.

The analysis thus suggests a commercial but operationally disparate production system, in which gains in post-harvest efficiency could be significantly increased by focusing on improved post-harvest management practices, thereby improving true output, stabilizing incomes, and promoting resource efficiency.

The Determinants of Production Efficiency of Lakatan Banana

Table 3 presents the results of the fractional logit model estimating the determinants of post-harvest efficiency among Lakatan banana farmers in Bukidnon. The model was statistically significant overall, as indicated by the Wald χ^2 statistic of 668.29 ($p < 0.001$), demonstrating that the explanatory variables jointly contributed to explaining variations in post-harvest efficiency. The estimated pseudo R^2 of 0.0891 suggests modest explanatory power, which is common in cross-sectional agricultural studies where production outcomes are influenced by numerous observed and unobserved socioeconomic, environmental, and managerial factors (Misango et al., 2022; Habib et al., 2023). The log pseudolikelihood value of −29.917, together with the Akaike Information Criterion (AIC = 95.834) and Bayesian Information Criterion (BIC = 155.648), indicates satisfactory model fit. Furthermore, all predicted values remained within the theoretical interval of 0 and 1, confirming the suitability of the fractional response framework for modeling proportion-valued efficiency measures bounded within the unit interval. This characteristic represents a major advantage of fractional regression models compared with conventional linear regression approaches when analyzing efficiency scores and other fractional outcomes (Ramalho et al., 2010). The mean predicted efficiency was 0.8749, with predicted values ranging from 0.7347 to 1.0000. Notably, 103 farmers, representing 50.24% of the sample, achieved perfect post-harvest efficiency, indicating that a substantial proportion of Lakatan banana farmers were able to minimize or entirely avoid post-harvest losses.

Table 3

Fractional Logit Estimates and Diagnostic Statistics for Post-Harvest Efficiency among Lakatan Banana Farmers

Variable	**Average Marginal Effect (AME)**	**Robust Std. Error**	**z-value**	**p-value**
Age	0.000998	0.000685	1.46	0.145
Gender (Ref. Male)				
Female	-0.033474	0.018102	-1.85	0.064*
Civil Status (Ref. Single)				

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

Married	-0.002279	0.028430	-0.08	0.936
Widowed	0.011885	0.031614	0.38	0.707
Educational Attainment (Ref. Elementary School)				
High School	-0.014031	0.007928	-1.77	0.077*
College Level	0.003669	0.017810	0.21	0.837
College Graduate	-0.010883	0.020731	-0.52	0.600
Experience in Lakatan Farming	-0.001108	0.000680	-1.63	0.103
Years in Farming	-0.001447	0.001289	-1.12	0.261
Farm Area	0.0000004	0.0000009	0.48	0.633
Farm Location (Ref. Valencia City)				
Impasug-ong Area	-0.037924	0.034062	-1.11	0.266
Farming System (Ref. Monocrop)				
Others	0.005099	0.015984	0.32	0.750
Labor Type (Ref. Family Labor)				
Hired Labor	0.005787	0.016023	0.36	0.718
Fertilizer Application	-0.000008	0.000003	-2.38	0.017**
Pesticide Application	-0.000001	0.000007	-0.20	0.843
Planting/Sucker Source (Ref. Owned)				
Others	0.037975	0.004134	9.19	0.000***
Farmgate Price	0.004067	0.004382	0.93	0.353
Number of Observations		205		
Wald χ^2 (17)		668.29		
Prob > χ^2		0.0000		
Log Pseudolikelihood		−29.917		
Pseudo R^2		0.0891		
Akaike Information Criterion (AIC)		95.834		
Bayesian Information Criterion (BIC)		155.648		
Mean Predicted Efficiency		0.8749		

Minimum Predicted Efficiency	0.7347		
Maximum Predicted Efficiency	1.0000		
Observations with Efficiency = 100%	103		
Percentage with Efficiency = 100%	50.24%		

Notes. Dependent variable = Post-Harvest Efficiency (proportion). Estimates are average marginal effects from a fractional logit model. Robust standard errors were used to account for heteroskedasticity. Reference categories for factor variables are omitted. Predicted values remained within the admissible interval [0,1], satisfying the assumptions of the fractional response model. *p < 0.10, **p < 0.05, ***p < 0.01.

Among the explanatory variables, gender exhibited a negative association with post-harvest efficiency and was statistically significant at the 10% level (AME = -0.0335, p = 0.064). The estimated average marginal effect indicates that female farmers achieved post-harvest efficiency levels approximately 3.35 percentage points lower than their male counterparts, holding other factors constant. This finding suggests that gender-related differences may influence post-harvest outcomes through variations in access to productive resources, labor allocation, extension services, technical knowledge, and participation in post-harvest operations. While the present study does not directly identify the specific mechanisms underlying this relationship, previous research has emphasized that effective harvesting, handling, sorting, grading, and transportation practices are critical in minimizing post-harvest losses and preserving product quality (Laborte, 2016; Quevedo et al., 2017). Similarly, access to post-harvest training and technical assistance has been shown to strengthen farmers' capacity to adopt improved management practices and reduce losses (Midamba & Kizito, 2022). From the perspective of Technology Adoption Theory, differences in access to information, skills, and productive resources may contribute to variations in the adoption of post-harvest management practices, which in turn influence efficiency outcomes. Consequently, the observed gender differential highlights the importance of ensuring that extension programs and capacity-building initiatives are accessible and responsive to the needs of both male and female farmers.

Farmers with a high school education exhibited lower post-harvest efficiency than those with elementary education and were marginally significant at the 10% level (AME = -0.0140, p = 0.077). The estimated marginal effect indicates that farmers with a high school education achieved post-harvest efficiency levels approximately 1.40 percentage points lower than those in the reference category, holding other factors constant. Although education is generally expected to enhance managerial capacity, information processing, and technology adoption, the results suggest that formal schooling alone does not necessarily translate into improved post-harvest performance. In smallholder banana production systems, practical farming experience, hands-on technical knowledge, and direct exposure to post-harvest management practices may be more important determinants of efficiency than years of formal education (Davara & Patel, 2009; Nayak et al., 2018). Notably, the coefficients for college-level education (AME = 0.0037, p = 0.837) and college graduates (AME = -0.0109, p = 0.600) were not statistically significant, indicating the absence of a clear monotonic relationship between educational attainment and post-harvest efficiency. This pattern suggests that factors beyond formal education may influence post-harvest outcomes. One possible explanation is that more educated individuals often engage in off-farm employment, business activities, or other income-generating opportunities that reduce their direct involvement in day-to-day farm management and post-harvest operations. Consequently, higher educational attainment may not necessarily result in greater attention to harvesting, sorting, grading, and handling practices that directly affect post-harvest efficiency. Similar studies have reported that the adoption of improved post-harvest technologies and management practices depends more heavily on access to extension services, technical training, and practical experience than on educational attainment alone (Ngowi & Selejio, 2019; Midamba & Kizito, 2022). From the perspective of Technology Adoption Theory, education may facilitate the acquisition of information, but the effective adoption and implementation of improved post-harvest practices ultimately depend on access to extension support, training opportunities, resource availability, and farmer engagement. Therefore, the findings imply that strengthening farmer training programs and extension services may be more effective in improving post-harvest efficiency than relying solely on increases in formal educational attainment.

Fertilizer application was negatively associated with post-harvest efficiency and was statistically significant at the 5% level (AME = -0.000008, p = 0.017). The estimated average marginal effect indicates that a one-unit increase in fertilizer application reduces post-harvest efficiency by approximately 0.0008 percentage points, holding all other factors constant. Although the relationship is statistically significant, the magnitude of the effect is extremely small, suggesting that its practical or economic significance may be limited under typical farming conditions. For instance, a substantial increase in fertilizer application would be required to produce a meaningful change in post-harvest efficiency. This finding indicates that fertilizer management, while important, is unlikely to be a major determinant of efficiency relative to other factors such as planting material quality, post-harvest handling practices, and market-related conditions. Nevertheless, the negative coefficient suggests that excessive or imbalanced nutrient application may adversely affect fruit quality and increase susceptibility to post-harvest deterioration. Previous studies have demonstrated that pre-harvest production practices significantly influence fruit firmness, ripening behavior, shelf life, and susceptibility to mechanical damage during handling and transportation (Mohapatra et al., 2011; Bantayehu & Alemayehu, 2020; Abraham et al., 2022). Murmu and Mishra (2018) further noted that physiological deterioration and quality degradation often originate from pre-harvest management decisions that affect fruit structure and storage potential. Similarly, Ambuko et al. (2006) emphasized that nutrient management influences fruit quality attributes that subsequently affect storage performance and marketability. Therefore, while the estimated effect is modest in magnitude, inappropriate fertilizer management may indirectly contribute to post-harvest losses through its influence on fruit quality and post-harvest behavior.

The source of planting materials emerged as the most influential determinant of post-harvest efficiency in the model. Farmers obtaining planting materials from sources other than their own farms achieved significantly higher post-harvest efficiency than those relying on self-sourced planting materials (AME = 0.0380, p < 0.001). The estimated average marginal effect indicates that these farmers achieved efficiency levels approximately 3.80 percentage points higher than those in the reference category, all else being equal. This finding suggests that externally sourced planting materials may possess superior genetic quality, greater vigor, better disease resistance, and more uniform growth characteristics. Such attributes can improve fruit quality and reduce susceptibility to damage throughout the post-harvest chain. Research has shown that cultivar characteristics and production conditions substantially affect banana quality, shelf life, and post-harvest performance (Ambuko et al., 2006). Similarly, studies in the Philippine banana industry have identified planting material quality as a critical production constraint influencing productivity and marketability (Anzures et al., 2022). High-quality planting materials are more likely to produce fruits with desirable physical attributes that can better withstand handling, storage, and transport, thereby reducing losses and improving post-harvest efficiency (Ruiz Medina & Ruales, 2024). This finding is consistent with Technology Adoption Theory, which posits that the adoption of improved production inputs enhances farm performance and production outcomes. Farmers who obtain planting materials from external or certified sources are more likely to benefit from superior genetic quality, disease resistance, and uniform plant growth, thereby improving fruit quality and reducing susceptibility to post-harvest damage. The significant positive effect of planting material source on post-harvest efficiency therefore suggests that input quality is an important pathway through which technology adoption contributes to improved post-harvest performance.

The results indicate that post-harvest efficiency among Lakatan banana farmers is driven primarily by management-related factors rather than demographic or structural farm characteristics. The significant negative effect of fertilizer application and the strong positive effect of sourcing planting materials from external sources highlight the importance of input management and production quality in determining post-harvest outcomes. These findings are consistent with the broader post-harvest literature, which emphasizes that losses are often the cumulative result of decisions made throughout the production and handling process rather than solely during storage and marketing stages (Mohapatra et al., 2011; Guo et al., 2020; Nkwain et al., 2022). Moreover, the findings provide empirical support for the theoretical framework underpinning this study. Consistent with Technology Adoption Theory, the quality of planting materials emerged as a key determinant of post-harvest efficiency, highlighting the importance of improved inputs in enhancing production performance and reducing post-harvest losses. The negative effect of fertilizer application further suggests that the benefits of technology adoption depend not only on input use but also on the appropriate management and

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

application of those inputs. Likewise, the significant influence of farm location on both the occurrence and magnitude of post-harvest losses supports Post-Harvest System Theory, which emphasizes the critical role of infrastructure, transportation conditions, and market accessibility in shaping post-harvest performance. Furthermore, the negative association between farmgate prices and loss severity is consistent with Agricultural Household Production Theory, which predicts that stronger market incentives encourage farm households to allocate resources more efficiently and adopt practices that preserve product quality and minimize losses. Collectively, these findings demonstrate that post-harvest outcomes are shaped not only by technical handling practices but also by broader production, market, and institutional conditions that influence farmer decision-making. Therefore, interventions aimed at improving nutrient management, strengthening access to certified planting materials, enhancing post-harvest infrastructure, improving market access, and expanding farmer training on post-harvest handling practices may substantially enhance post-harvest efficiency and profitability among Lakatan banana producers in Bukidnon.

Determinants of Post-Harvest Loss Occurrence among Lakatan Banana Farmers

Table 4 presents the results of the first-stage logistic regression model estimating the factors associated with the occurrence of post-harvest losses among Lakatan banana farmers. The model was statistically significant overall (Wald $\chi^2 = 46.57$, $p < 0.001$), indicating that the explanatory variables jointly contributed to distinguishing farmers who experienced post-harvest losses from those who did not. The model exhibited satisfactory explanatory power, with a pseudo R^2 of 0.2390, suggesting that approximately 23.90% of the variation in loss occurrence was explained by the included socioeconomic, farm-specific, and management-related variables. The log pseudolikelihood value of -106.009 and the information criteria values (AIC = 246.018; BIC = 302.175) further indicate an acceptable model fit. Classification diagnostics demonstrated strong predictive performance, with an overall classification accuracy of 70.65%, sensitivity of 72.55%, and specificity of 68.69%. Moreover, the receiver operating characteristic area under the curve (ROC-AUC) was 0.8106, indicating excellent discriminatory ability and confirming that the model effectively differentiated between farmers who experienced losses and those who did not. It is important to note that the planting source variable was excluded from the logistic regression model due to perfect prediction and collinearity. The exclusion occurred because the source of planting materials perfectly predicted post-harvest loss outcomes among the sampled farmers. In particular, farmers who obtained planting materials from external sources exhibited either no post-harvest losses or highly homogeneous loss outcomes, resulting in insufficient variation for reliable parameter estimation. Consequently, the variable was automatically omitted during model estimation to avoid statistical instability. While this omission was necessary from an econometric perspective, the result itself is informative and suggests that access to improved or externally sourced planting materials may serve as a strong protective factor against the occurrence of post-harvest losses. This finding is consistent with Technology Adoption Theory, which emphasizes the role of improved inputs and technology adoption in enhancing production performance and reducing inefficiencies. Multicollinearity was not a concern, as evidenced by the mean variance inflation factor (VIF) of 2.90, which was well below commonly accepted thresholds. Collectively, these diagnostic statistics suggest that the model provides a reliable framework for identifying the determinants of post-harvest loss occurrence among Lakatan banana farmers.

Table 4 *Determinants of Post-Harvest Loss Occurrence among Lakatan Banana Farmers: Logistic Regression Results and Model Diagnostics*

Variable	Coefficient	Robust SE	z-value	p-value	AME
Age	-0.0025	0.0283	-0.09	0.930	-0.0004
Gender (Ref. Male)					
Female	1.2176	0.6440	1.89	0.059*	0.2159
Civil Status (Ref. Single)					

Married	0.0738	1.1976	0.06	0.951	0.0131
Widowed	-0.0977	1.2972	-0.08	0.940	-0.0172
Education Attainment (Ref. Elementary School)					
High School	0.8919	0.4478	1.99	0.046**	0.1610
College Level	0.2759	0.5291	0.52	0.602	0.0488
College Graduate	1.3243	1.5563	0.85	0.395	0.2382
Experience in Lakatan Farming	0.0261	0.0302	0.86	0.387	0.0046
Years in Farming	0.0589	0.0596	0.99	0.323	0.0104
Farm Area	-0.000017	0.000024	-0.69	0.488	-0.000003
Farm Location (Ref. Valencia City)					
Impasug-ong	1.5367	0.8432	1.82	0.068*	0.2988
Farming System (Ref. Monocropping)					
Others	-1.3221	0.7173	-1.84	0.065*	-0.2271
Labor Type (Ref. Family Labor)					
Hired Labor	-0.3585	0.6384	-0.56	0.574	-0.0637
Fertilizer Application	0.000582	0.000211	2.75	0.006***	0.000103
Farmgate Price	-0.0617	0.0860	-0.72	0.473	-0.0109
Constant	-2.2910	2.6545	-0.86	0.388	—
Model Diagnostics		**Value**			
Number of Observations (N)		201			
Wald χ^2 (16)		46.57			
Prob > χ^2		0.0001			
Log Pseudolikelihood		-106.009			
Pseudo R^2		0.2390			
AIC		246.018			
BIC		302.175			
Sensitivity		72.55%			
Specificity		68.69%			

Correctly Classified	70.65%			
ROC-AUC	0.8106			
Mean VIF	2.90			

Notes. Dependent variable = 1 if post-harvest loss > 0 and 0 otherwise. Robust standard errors were estimated using the Huber–White sandwich estimator. Average Marginal Effects (AMEs) are reported to facilitate interpretation. Reference categories are omitted for factor variables. Planting source was omitted because it perfectly predicted post-harvest loss outcomes and was therefore collinear with the dependent variable, preventing reliable parameter estimation. VIF values below 10 indicate the absence of serious multicollinearity. ROC-AUC values above 0.80 indicate excellent discriminatory ability. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Among the explanatory variables, gender was positively associated with the probability of experiencing post-harvest losses and was statistically significant at the 10% level ($\beta = 1.2176$, $p = 0.059$). The estimated average marginal effect (AME = 0.2159) indicates that female farmers were approximately 21.59 percentage points more likely to experience post-harvest losses than male farmers, holding all other factors constant. This result suggests that gender-related differences in access to production resources, labor availability, farm management responsibilities, and post-harvest handling practices may influence the likelihood of loss occurrence. In many smallholder farming systems, women often face constraints in accessing extension services, technical information, mechanization, and financial resources, factors that can affect the effectiveness of post-harvest operations and increase vulnerability to losses. Previous studies have similarly highlighted the importance of human capital, training, and access to agricultural support services in reducing post-harvest losses and improving farm-level performance (Midamba & Kizito, 2022; Nkwain et al., 2022).

Educational attainment also emerged as a significant determinant of post-harvest loss occurrence. Farmers with a high school education were more likely to experience post-harvest losses than those with elementary education ($\beta = 0.8919$, $p = 0.046$). The corresponding average marginal effect indicates that belonging to this educational category increased the probability of incurring post-harvest losses by approximately 16.10 percentage points, ceteris paribus. Although education is generally associated with improved managerial capability and technology adoption, the positive relationship observed in this study suggests that formal schooling alone may not necessarily translate into effective post-harvest management. It is possible that differences in commercialization behavior, production intensity, or market orientation expose more educated farmers to greater post-harvest risks. The result reinforces the argument that practical training, technical assistance, and experience-based knowledge may be more important than formal educational attainment in improving post-harvest outcomes (Davara & Patel, 2009; Nayak et al., 2018).

Farm location was positively associated with post-harvest loss occurrence and was marginally significant at the 10% level ($\beta = 1.5367$, $p = 0.068$). The estimated average marginal effect (AME = 0.2988) indicates that farmers located in Impasug-ong were approximately 29.88 percentage points more likely to experience post-harvest losses than those located in Valencia City. This finding underscores the importance of spatial and infrastructural factors in shaping post-harvest performance. Differences in transportation networks, road quality, market accessibility, distance to trading centers, and the availability of post-harvest facilities may substantially influence the ability of farmers to preserve product quality after harvest. Similar observations have been reported in agricultural value-chain studies where geographic isolation and limited market access increase handling time, transportation damage, and spoilage risks, ultimately leading to higher post-harvest losses (Saha et al., 2021; Gemechu et al., 2021). The finding is consistent with Post-Harvest System Theory, which views post-harvest performance as the cumulative outcome of interconnected production, handling, transportation, and marketing processes. According to the theory, deficiencies in infrastructure and market access create bottlenecks within the post-harvest system that increase product deterioration and losses. The significantly higher probability and magnitude of losses observed among farmers in Impasug-ong therefore reinforce the importance of transportation networks, road quality, and market accessibility as critical components of an efficient post-harvest system.

The farming system variable exhibited a negative and marginally significant effect (β = -1.3221, p = 0.065). The corresponding average marginal effect (AME = -0.2271) indicates that farmers operating under alternative farming systems were approximately 22.71 percentage points less likely to experience post-harvest losses than those practicing monocropping. This result suggests that diversified or integrated farming systems may provide management advantages that reduce post-harvest risks. Such systems often promote better resource utilization, improved labor scheduling, and greater flexibility in harvesting and marketing decisions. In addition, diversified production environments may encourage closer crop monitoring and more efficient allocation of labor during critical post-harvest periods, thereby reducing the likelihood of quality deterioration and physical damage.

Fertilizer application emerged as the most statistically robust determinant of post-harvest loss occurrence (β = 0.000582, p = 0.006). Although the estimated average marginal effect was numerically small (AME = 0.000103), the positive coefficient indicates that increased fertilizer application was associated with a higher probability of experiencing post-harvest losses. This finding may reflect the indirect effects of intensive nutrient application on fruit characteristics and post-harvest behavior. Excessive fertilizer use can promote rapid vegetative and fruit growth, potentially increasing fruit susceptibility to bruising, physiological disorders, and handling damage if post-harvest management practices are not adjusted accordingly. Previous studies have emphasized that pre-harvest production decisions play a crucial role in determining fruit quality, shelf life, and resistance to post-harvest deterioration (Mohapatra et al., 2011; Abraham et al., 2022; Murmu & Mishra, 2018). Consequently, improving nutrient management practices may be an important strategy for reducing loss occurrence while maintaining productivity.

The remaining explanatory variables, including age, civil status, years engaged in Lakatan banana production, total farming experience, farm area, labor type, pesticide application, and farmgate price, did not exert statistically significant effects on the probability of post-harvest loss occurrence. Their lack of significance suggests that post-harvest losses among Lakatan banana farmers are influenced more strongly by management-related decisions, production practices, and locational factors than by demographic characteristics or farm structural attributes. Overall, the results highlight the importance of strengthening post-harvest management capacities, improving access to technical support, promoting balanced input use, and addressing location-specific constraints as key strategies for reducing post-harvest losses among Lakatan banana producers.

Determinants of the Magnitude of Post-Harvest Losses among Lakatan Banana Farmers

Table 5 presents the second-stage results of the two-part model, which examine the factors influencing the magnitude of post-harvest losses among Lakatan banana farmers who reported positive losses. A Gamma Generalized Linear Model (GLM) with a log-link function was employed because post-harvest losses are continuous, strictly positive, and highly right-skewed, making the Gamma specification particularly suitable for modeling agricultural loss data. The estimation was based on 102 observations representing farmers who incurred positive post-harvest losses, while the remaining 103 farmers who reported zero losses were excluded because the Gamma distribution is defined only for positive values. Consequently, the model explains the severity of losses conditional on their occurrence rather than the probability of experiencing losses. The overall model was highly significant (Wald $\chi^2 = 68.76$, $p < 0.001$), indicating that the explanatory variables jointly explain variations in the magnitude of post-harvest losses among affected farmers. The log pseudolikelihood value of −509.694 confirms successful model convergence, while the Akaike Information Criterion (AIC = 1053.388) and Bayesian Information Criterion (BIC = 1098.012) indicate a reasonable balance between model fit and model parsimony. Diagnostic statistics further support the adequacy of the model specification. The Pearson chi-square statistic was 48.600 and the deviance statistic was 44.241, producing Pearson and deviance ratios of 0.572 and 0.520, respectively. Ratios below one suggest that the Gamma variance function adequately captured the dispersion in the data and that there is no evidence of substantial overdispersion. These diagnostic indicators confirm that the Gamma GLM with a log-link function provides a statistically appropriate and robust framework for analyzing the determinants of post-harvest loss severity among Lakatan banana farmers. Consequently, the estimated standard errors and statistical tests can be considered reliable. Furthermore, the model generated a mean predicted loss of 53.82 kilograms, indicating good predictive performance for the observed distribution of positive losses. These diagnostic indicators confirm that the Gamma GLM with a log-link function provides a statistically appropriate and robust framework for analyzing the determinants of post-

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

harvest loss severity among Lakatan banana farmers. The results, therefore, strengthen the empirical validity of the second-stage estimates and support the suitability of the two-part modeling approach for examining post-harvest loss dynamics in smallholder banana production systems (Salinas Ruíz et al., 2023; Guo et al., 2015; Ahlawat, 2025).

Table 5 *Determinants of the Magnitude of Post-Harvest Losses among Lakatan Banana Farmers: Gamma Generalized Linear Model (Log-Link)*

Variable	Coefficient	Robust SE	z-value	p-value	Marginal Effect (dy/dx)
Age	-0.0086	0.0090	-0.95	0.344	-0.5511
Gender (Ref. Male)					
Female	0.7034	0.2455	2.87	0.004***	45.2907
Civil Status (Ref. Single)					
Married	0.1529	0.3239	0.47	0.637	9.8475
Widowed	-0.1600	0.3887	-0.41	0.681	-10.3034
Education Attainment (Ref. Elementary)					
High School	0.2202	0.2131	1.03	0.301	14.1800
College Level	0.1905	0.2946	0.65	0.518	12.2678
College Graduate	0.5584	0.4330	1.29	0.197	35.9552
Experience in Lakatan Farming	0.0019	0.0089	0.21	0.832	0.1208
Years in Farming	0.0109	0.0234	0.47	0.641	0.7018
Farm Area	0.0000465	0.0000187	2.49	0.013**	0.0030
Farm Location (Ref. Valencia City)					
Impasug-ong	1.5675	0.3623	4.33	0.001***	100.9282
Farming System (Ref. Monocropping)					
Others	-0.0708	0.3622	-0.20	0.845	-4.5584
Labor Type (Ref. Family Labor)					
Hired Labor	-0.0544	0.4739	-0.11	0.909	-3.5032
Fertilizer Application	0.0001422	0.0000430	3.31	0.001***	0.0092
Pesticide Application	0.0000490	0.0001226	0.40	0.689	0.0032
Planting Source	Omitted	Collinear	—	—	—
Farmgate Price	-0.0758	0.0394	-1.92	0.055*	-4.8800

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

Constant	2.9238	1.0362	2.82	0.005***	—
Model Statistics and Diagnostics			**Value**		
Number of Observations (Positive Losses Only)			102		
Wald χ^2 (16)			68.76		
Prob > χ^2			0.0000		
Log Pseudolikelihood			-509.694		
AIC			1053.388		
BIC			1098.012		
Pearson χ^2			48.600		
Pearson χ^2 / df			0.572		
Deviance			44.241		
Deviance / df			0.520		
Mean Predicted Loss (kg)			53.820		

Notes: Dependent variable = Magnitude of post-harvest loss (kg). Estimates were obtained using a Gamma Generalized Linear Model (GLM) with a log-link function and robust standard errors. Marginal effects (dy/dx) represent the average change in expected post-harvest losses associated with a one-unit change in the explanatory variable, holding all other variables constant. Reference categories are omitted for categorical variables. The planting source variable was omitted from the estimation because it perfectly predicted post-harvest loss outcomes, resulting in perfect collinearity and preventing reliable parameter estimation. This outcome suggests that access to externally sourced planting materials may be a strong protective factor against post-harvest losses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The planting source variable was also omitted from the Gamma GLM estimation due to perfect prediction and collinearity. Farmers who obtained planting materials from external sources exhibited either no post-harvest losses or highly homogeneous loss outcomes, preventing reliable estimation of the variable's independent effect on loss severity. As a result, the variable was automatically excluded from the model. Although direct estimation was not possible, this outcome is itself informative and suggests that access to improved or externally sourced planting materials may play an important role in reducing post-harvest losses. The finding supports Technology Adoption Theory, which posits that the adoption of higher-quality production inputs contributes to improved production efficiency, product quality, and post-harvest performance.

Among the explanatory variables, gender was positively and statistically significantly associated with the magnitude of post-harvest losses ($\beta = 0.7034$, $p = 0.004$). The estimated marginal effect indicates that female farmers experienced, on average, approximately 45.29 kilograms higher post-harvest losses than male farmers, holding all other variables constant. This finding suggests that gender-related differences in farm management responsibilities, labor allocation, access to post-harvest technologies, and technical knowledge may influence the severity of losses once they occur. Previous studies have emphasized that access to post-harvest training, extension services, and technical support plays an important role in reducing losses and improving post-harvest performance among agricultural producers (Midamba & Kizito, 2022). Likewise, research on banana value chains has demonstrated that deficiencies in harvesting, sorting, grading, packaging, and transportation practices can substantially increase post-harvest losses and reduce farmer profitability (Laborte, 2016; Nkwain et al., 2022).

Farm area emerged as a significant determinant of post-harvest loss magnitude ($\beta = 0.0000465$, $p = 0.013$). The positive coefficient indicates that larger farms tend to experience greater post-harvest losses. The estimated marginal effect suggests that an increase in farm area is associated with an average increase of approximately 0.003 kilograms of post-harvest losses, ceteris paribus. Although numerically small, this effect likely reflects the greater production volumes handled by larger farms, which increase exposure to harvesting, transportation, storage, and handling losses. Similar findings have been reported in studies showing that larger-scale operations often face greater logistical and management challenges that contribute to post-harvest losses when adequate handling and storage systems are lacking (Ansah & Tetteh, 2016; Debebe, 2022). For perishable commodities such as bananas, increases in production scale can intensify pressures on labor, transportation, and marketing systems, thereby increasing loss severity (Davara & Patel, 2009; Nayak et al., 2018).

Farm location emerged as the strongest predictor of post-harvest loss magnitude in the model ($\beta = 1.5675$, $p < 0.001$). The estimated marginal effect indicates that farmers located in Impasug-ong incurred, on average, approximately 100.93 kilograms more post-harvest losses than farmers in Valencia City, holding all other factors constant. This substantial difference highlights the importance of geographic and infrastructural conditions in shaping post-harvest outcomes. Variations in road quality, transportation efficiency, market accessibility, distance to trading centers, and the availability of post-harvest facilities may contribute to the higher losses observed among farmers in Impasug-ong. Similar observations have been reported in studies of banana supply chains in Bangladesh, Ethiopia, and Cameroon, where inadequate transportation systems, poor infrastructure, and limited market access significantly increased post-harvest losses and product deterioration (Saha et al., 2021; Gemechu et al., 2021; Nkwain et al., 2022). Furthermore, Quevedo et al. (2017) noted that upland production areas often encounter logistical constraints that complicate post-harvest handling and marketing, thereby increasing loss risks.

Fertilizer application was positively associated with post-harvest loss magnitude and was statistically significant at the 1% level ($\beta = 0.0001422$, $p = 0.001$). The marginal effect indicates that a one-unit increase in fertilizer application increases expected post-harvest losses by approximately 0.009 kilograms, holding all other factors constant. Although fertilizer application is intended to increase productivity, excessive or imbalanced nutrient use may alter fruit characteristics and increase susceptibility to bruising, physiological disorders, and quality deterioration during harvesting and transportation. Previous studies have demonstrated that pre-harvest management practices significantly influence fruit quality, ripening behavior, shelf life, and resistance to post-harvest deterioration (Mohapatra et al., 2011; Bantayehu & Alemayehu, 2020; Abraham et al., 2022). Similarly, Ambuko et al. (2006) reported that production conditions and management practices substantially affect post-harvest quality attributes and storage performance in bananas. These findings suggest that productivity-enhancing inputs should be accompanied by appropriate post-harvest handling and balanced nutrient management to prevent increases in loss severity.

Farmgate price exhibited a negative relationship with post-harvest loss magnitude and was marginally significant at the 10% level ($\beta = -0.0758$, $p = 0.055$). The estimated marginal effect indicates that a one-peso increase in farmgate price is associated with an average reduction of approximately 4.88 kilograms of post-harvest losses. This finding suggests that stronger market incentives encourage farmers to adopt better harvesting, handling, sorting, grading, and marketing practices to preserve product quality and maximize returns. Higher output prices increase the opportunity cost of losses, thereby motivating producers to reduce waste and improve post-harvest management. Similar relationships between market incentives and post-harvest management behavior have been observed in studies examining commercialization, market participation, and loss reduction among agricultural producers (Ngowi & Selejio, 2019; Qange et al., 2024). This result is consistent with Agricultural Household Production Theory, which posits that farm households allocate resources and production outputs in response to economic incentives. Higher farmgate prices increase the expected returns from preserving product quality and minimizing losses, thereby encouraging farmers to invest greater effort in harvesting, sorting, handling, and marketing activities. The negative relationship between farmgate price and post-harvest loss magnitude therefore supports the theoretical prediction that stronger market incentives improve resource allocation decisions and promote more efficient post-harvest management.

The remaining explanatory variables, including age, civil status, educational attainment, years engaged in Lakatan banana production, overall farming experience, farming system, labor type, and pesticide application, were not statistically significant determinants of post-harvest loss magnitude. The absence of significant effects suggests that demographic characteristics alone are insufficient to explain variations in post-harvest losses among Lakatan banana farmers. Instead, structural and management-related factors—particularly farm location, farm size, fertilizer management, market incentives, and gender-related differences in post-harvest practices—appear to exert a more substantial influence on loss severity. Overall, the findings are consistent with the broader post-harvest literature, which emphasizes that losses are the cumulative outcome of production decisions, handling practices, infrastructure quality, transportation conditions, and market-related constraints throughout the agricultural value chain (Mohapatra et al., 2011; Guo et al., 2020; Ruiz Medina & Ruales, 2024). These results underscore the need for integrated interventions that combine improved farm management, balanced input use, enhanced post-harvest infrastructure, targeted extension services, and stronger market linkages to reduce losses and improve the profitability of Lakatan banana production systems.

CONCLUSION

This study analyzed the post-harvest efficiency of Lakatan banana production in selected municipalities of Bukidnon and examined the factors influencing post-harvest performance and losses among farmers. The findings provide important insights into the socio-demographic characteristics of producers, the level of post-harvest efficiency and commercialization, and the determinants of both post-harvest efficiency and loss magnitude.

With respect to the first objective, the results revealed that Lakatan banana production in Bukidnon is predominantly undertaken by middle-aged and older farmers, with males comprising the majority of producers. Most respondents were married and possessed elementary to high school educational attainment. Farmers generally had extensive farming experience, reflecting a long-standing engagement in agricultural production and the continuation of farming traditions across generations. The majority of respondents operated relatively small to medium-sized farms, utilized family and hired labor, and relied on varying levels of fertilizer and pesticide application. These characteristics indicate that Lakatan banana production in the study area remains largely smallholder-based but commercially oriented.

Regarding the second objective, the study found that Lakatan banana production is highly commercialized, with farmers marketing almost all of their harvested output and allocating only a minimal proportion for household consumption. The average post-harvest efficiency was estimated at 96.20%, indicating that most farmers retained a high proportion of marketable production. Nevertheless, the existence of substantial losses among some farmers demonstrates that inefficiencies persist within the post-harvest segment of the value chain. The average post-harvest loss amounted to 42.48 kilograms per harvest, representing approximately 3.1% of total production. Although the overall loss rate appears relatively low, the large variation observed among respondents suggests that some producers continue to face significant challenges related to harvesting, handling, transportation, storage, and market access.

In relation to the third objective, the empirical results identified several factors that significantly influence post-harvest efficiency and post-harvest losses. The fractional logit model showed that fertilizer application negatively affected post-harvest efficiency, while the use of improved planting materials significantly enhanced efficiency levels. These findings highlight the importance of balanced input management and the adoption of high-quality planting materials in improving post-harvest outcomes. The two-part modeling framework further revealed that gender, educational attainment, farm location, farming system, and fertilizer application significantly influenced the probability of experiencing post-harvest losses. Among farmers who incurred losses, the Gamma generalized linear model indicated that gender, farm area, farm location, fertilizer application, and farmgate price significantly affected the magnitude of losses. Farm location emerged as the strongest determinant of loss magnitude, suggesting that geographic conditions, infrastructure quality, transportation efficiency, and market accessibility play critical roles in shaping post-harvest outcomes.

The results further revealed that gender-related differences influenced both the probability and severity of post-harvest losses, while higher farmgate prices were associated with lower loss magnitudes. These findings suggest that both household-level characteristics and market incentives play important roles in shaping post-harvest outcomes among Lakatan banana farmers. The findings also provide empirical support for the theoretical framework of the study. Consistent with Technology Adoption Theory, the use of improved planting materials was associated with higher post-harvest efficiency, highlighting the importance of input quality in improving farm performance. The significant effects of farm location support Post-Harvest System Theory, which emphasizes the role of infrastructure and market accessibility in shaping post-harvest outcomes. Likewise, the negative relationship between farmgate prices and loss severity is consistent with Agricultural Household Production Theory, which predicts that stronger market incentives encourage farmers to allocate resources more efficiently and adopt loss-reducing practices.

These findings demonstrate that post-harvest performance in Lakatan banana production is influenced by a combination of farmer characteristics, production practices, planting material quality, market incentives, and location-specific conditions. While the sector exhibits a high degree of commercialization and relatively high average efficiency, opportunities remain to further reduce post-harvest losses and improve value-chain performance. Strengthening farmer training programs, promoting the use of improved planting materials, encouraging balanced fertilizer management, expanding access to post-harvest technologies, and improving rural infrastructure and market connectivity are likely to enhance post-harvest efficiency and reduce losses. Such interventions would contribute to higher farmer incomes, improved resource utilization, greater market competitiveness, and the long-term sustainability of the Lakatan banana industry in Bukidnon.

Several limitations should be acknowledged when interpreting the findings of this study. First, the cross-sectional nature of the data limits the ability to establish causal relationships among variables; consequently, the estimated associations should be interpreted as correlational rather than causal effects. Second, the analysis relied on self-reported information provided by farmers, which may be subject to recall bias and measurement error, particularly in the estimation of post-harvest loss quantities and production allocation. Third, the study focused exclusively on losses occurring at the farm level and did not track losses throughout the broader banana value chain, including transportation, wholesale, and retail stages. Fourth, although the exclusion of storage and transportation variables was justified by the predominance of farm-gate sales in the study area, the absence of these variables implies that the estimated losses likely underestimate total post-harvest losses occurring beyond the farm. Finally, while the sample is representative of Lakatan banana farmers in Valencia City and Impasug-ong, the findings may not be directly generalizable to other banana-producing regions in the Philippines that differ in production systems, banana varieties, market structures, infrastructure conditions, and post-harvest practices. Future studies may benefit from longitudinal or panel data approaches and value-chain analyses that capture losses across multiple marketing stages to provide a more comprehensive understanding of post-harvest inefficiencies.

RECOMMENDATIONS

Based on the empirical findings, the following policy, programmatic, and institutional interventions are recommended to improve post-harvest efficiency and reduce post-harvest losses among Lakatan banana farmers in Valencia City and Impasug-ong, Bukidnon. The recommendations are directly derived from the significant determinants identified in the fractional logit, logistic regression, and Gamma generalized linear models.

First, the Municipal Agriculture Offices (MAOs) of Valencia City and Impasug-ong, in partnership with the Provincial Agriculture Office and the Department of Agriculture, should intensify extension programs focusing on post-harvest management and nutrient management. The results revealed that fertilizer application significantly reduced post-harvest efficiency and increased both the probability and magnitude of post-harvest losses. This suggests that productivity-enhancing inputs alone do not guarantee improved post-harvest outcomes. Farmers should therefore be trained on balanced and site-specific fertilizer application, proper harvest scheduling, and integrated crop management practices that optimize both yield and fruit quality. Regular soil testing and nutrient management planning should also be promoted to avoid excessive fertilizer use that may increase fruit susceptibility to bruising, physiological disorders, and post-harvest deterioration.

Second, local government units should prioritize the promotion and distribution of high-quality planting materials through accredited nurseries, farmer cooperatives, and government-supported propagation programs. The study identified planting material source as the most important determinant of post-harvest efficiency. Access to certified, disease-free, and genetically superior planting materials can improve fruit uniformity, reduce susceptibility to pests and diseases, and enhance resistance to handling damage. Establishing community-based nurseries and strengthening linkages with accredited suppliers would help ensure a sustainable supply of quality planting materials for Lakatan banana farmers throughout Bukidnon.

Third, targeted infrastructure investments should be prioritized in Impasug-ong, where farmers were found to experience significantly higher post-harvest losses than those in Valencia City. The results indicate that location was the strongest determinant of post-harvest loss magnitude, with farmers in Impasug-ong incurring substantially greater losses. This highlights the need for improved farm-to-market roads, transportation networks, loading facilities, and post-harvest handling centers in upland production areas. The establishment of strategically located consolidation, packing, and temporary storage facilities would reduce handling damage, shorten marketing delays, and improve product quality during transport to major trading centers in Valencia City and other markets.

Fourth, post-harvest technology interventions should be expanded, particularly for smallholder farmers. Local government units, farmer organizations, and development agencies should promote the adoption of appropriate harvesting tools, plastic crates, packing materials, and hauling equipment designed to reduce mechanical damage during harvesting and transport. Given the highly commercialized nature of Lakatan banana production in the study area, investments in low-cost post-harvest technologies can generate substantial returns through reductions in physical losses and improvements in product quality.

Fifth, programs aimed at strengthening market access and improving farmgate prices should be supported. The study found that higher farmgate prices were associated with lower post-harvest losses, suggesting that stronger market incentives encourage farmers to adopt better quality management and handling practices. Strengthening market information systems, facilitating direct linkages between farmers and institutional buyers, and promoting contract-growing arrangements may improve price stability and encourage investments in post-harvest management. Local government units and agricultural agencies should also support the development of value-chain partnerships that reward quality production and reduced losses.

Sixth, farmer cooperatives and producer organizations should be strengthened to improve collective marketing, transportation, and input procurement. Since Lakatan banana production in the study area is highly commercialized, collective action can help farmers reduce transportation costs, improve bargaining power, access post-harvest facilities, and coordinate product delivery schedules. Cooperative-based transport and marketing systems may be particularly beneficial for producers in geographically isolated areas of Impasug-ong where transportation costs and handling risks are relatively high.

Seventh, gender-sensitive agricultural extension programs should be implemented to address the significant relationship between gender and post-harvest outcomes. Training programs should ensure equitable participation of both male and female farmers in post-harvest management, financial literacy, value-chain development, and enterprise management. Strengthening the participation of women in farmer organizations and local decision-making processes may further enhance household-level management and improve overall post-harvest performance.

Collectively, these recommendations address the key determinants of post-harvest efficiency and loss severity identified in the study, namely input quality, nutrient management, market incentives, infrastructure conditions, and farmer characteristics. Their implementation would contribute to reducing post-harvest losses, improving farm profitability, strengthening market competitiveness, and enhancing the overall sustainability of Lakatan banana production in Bukidnon.

Finally, future research should investigate post-harvest losses at specific stages of the Lakatan banana value chain, including harvesting, sorting, transportation, storage, wholesaling, and retail distribution. Additional studies employing longitudinal or panel data would provide deeper insights into seasonal patterns of loss occurrence and the long-term effects of infrastructure improvements, technology adoption, and market interventions on post-harvest efficiency. Economic evaluations of specific post-harvest technologies and infrastructure investments would also help guide evidence-based policymaking and resource allocation for the sustainable development of the Lakatan banana industry in Bukidnon.

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