# ADOPTION OF FARM BIOSECURITY MEASURES AND THE EFFECTS ON COST EFFICIENCY OF POULTRY FARMERS IN NYANZA, KENYA

**WYCLIFFE AWINO OTIENO**

**A56/38923/2020**

**A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF SCIENCE IN AGRICULTURAL AND APPLIED ECONOMICS**

**DEPARTMENT OF AGRICULTURAL ECONOMICS**

**FACULTY OF AGRICULTURE**

**UNIVERSITY OF NAIROBI**

**2023**

## DECLARATION

This thesis is my original work and has not been submitted for the award of a degree in any other University.

**Wycliffe Awino Otieno** Signature............................................Date July 28, 2023

(Name of Candidate)

This thesis has been submitted with our approval as university supervisors.

[Signature] .............................................................. Date July 28, 2023..................

**Prof. Rose Nyikal**

Department of Agricultural Economics

University of Nairobi

[Signature]........................................... Date July 28, 2023......................

**Prof. Stephen G. Mbogoh**

Department of Agricultural Economics

University of Nairobi

[Signature]....................................... Date July 28, 2023...............................

**Dr. James Rao**

Senior Scientist

International Livestock Research Institute (ILRI)

## DEDICATION

*To God and my dear mother, Mary Anyango Achieng, who has sacrificed everything to see me this far.*

## ACKNOWLEDGEMENTS

God has kept me safe and given me a sound mind throughout my study. I am grateful to Him for the Grace that made it possible to complete this thesis.

I would like to extend sincere gratitude to my supervisors: Prof. Rose A. Nyikal, Prof. Stephen G. Mbogoh, and Dr. James Rao. Prof. Nyikal agreed to supervise my thesis at a time when she had many administrative responsibilities. Amidst all this, Prof. gave me all the necessary support I needed to conduct my research and write the thesis. I have benefitted immensely from the experience of Prof. Mbogoh: Prof. has been very patient guiding me to improve my writing skills. I was also privileged to learn from Dr. Rao, a kind-hearted individual whose professional path I desire to emulate.

I acknowledge the support I received from my peers from the University of Nairobi and the International Livestock Research Institute (ILRI). To one Samuel Jeff Otieno, with whom our paths seem intertwined, I have benefitted immensely from your support.

I would like to extend my sincerest appreciation to USAID for their unwavering support and funding of the USAID-TRANSFORM Project. I would also like to acknowledge the invaluable contributions of the USAID-TRANSFORM Project’s implementing partners, including Cargill Inc., Heifer International, Ausvet, and International Poultry Council. I am also grateful for the support received from the University of Nairobi, the African Economic Research Consortium (AERC), and ILRI (PILs Program and the Capacity Development). Thank you, Agrippina, Joseph Auma, Joyce Wanderi, Ken Gichuki, Stephen Oloo, Ruth Kundu, and all who impacted me in one way or the other.

## LIST OF ABBREVIATIONS AND ACRONYMS

| | |
|---|---|
| AE | Allocative Efficiency |
| AgGDP | Agricultural Gross Domestic Product |
| AIC | Akaike Information Criterion |
| AMR | Antimicrobial Resistance |
| ANOVA | Analysis of Variance |
| ASC | Alternative-specific Constant |
| BIC | Bayesian Information Criterion |
| CE | Cost Efficiency |
| CIDPs | County Integrated Development Plans |
| COLS | Corrected Ordinary Least Squares |
| DEA | Data Envelopment Analysis |
| FAO | Food and Agriculture Organization of the United Nations |
| GHSA | Global Health Security Agenda |
| GIT | Gastro-intestinal track |
| GLR | Generalized Likelihood Ratio |
| HH | Household Head |
| HPAI | Highly Pathogenic Avian Influenza |
| HPI-K | Heifer Project International - Kenya |
| Ibid | In the Same Source |
| IIA | Independence from Irrelevant Attributes |
| ILRI | International Livestock Research Institute |
| IPC | The International Poultry Council |

| | |
|---|---|
| KMO-MSA | Kaiser-Meyer-Olkin Measure of Sampling Adequacy |
| KShs | Kenya Shillings |
| LC | Latent Class |
| LCA | Latent Class Analysis |
| LR | Likelihood Ratio |
| MLE | Maximum Likelihood Estimation |
| MLM | Mixed Logit Model |
| MLogit | Multinomial Logistic Regression |
| MOLS | Modified Ordinary Least Squares |
| MVP | Multivariate Probit |
| OLS | Ordinary Least Squares |
| PCA | Principal Component Analysis |
| POs | Producer Organizations |
| RPL | Random Parameter Logit |
| RUM | Random Utility Model |
| SDG | Sustainable Development Goals |
| SFA | Stochastic Frontier Analysis |
| SSA | Sub-Saharan Africa |
| TADs | Transboundary Animal Diseases |
| TE | Technical Efficiency |
| TRANSFORM | Transformational Strategies for Farm Output Risk Mitigation |
| USAID | United States Agency for International Development |

## ABSTRACT

Antimicrobial resistance (AMR) –resistance to antibiotics– is among the leading causes of death globally. The rise in AMR is largely attributed to the interaction with livestock and/or consumption of their products. The high incidences of AMR in livestock stem from farmers' attempts to combat diseases, which are among the causes of low poultry productivity. Besides poor poultry health outcomes, this strategy has also accelerated the challenge of drug resistance. This study was motivated by the need to find sustainable ways of dealing with diseases and AMR in poultry production. Existing literature suggests that preventive livestock health management practices, otherwise known as biosecurity, can be effective in tackling AMR. However, evidence on the uptake of such practices is scanty among poultry farmers in Sub-Saharan Africa, including Kenya. Further, no study has shown the impact of adopting such practices on poultry farmers' cost performance. This study bridges the gap by exploring the uptake of biosecurity and the corresponding effect on the cost efficiency of poultry farmers. The study follows a three-step estimation procedure; first, constructing latent classes that describe adoption patterns, then, evaluating the determinants of adoption through a multinomial logistic regression (MLogit), and finally, estimating a stochastic cost frontier to assess the cost performance of farmers. The findings of this study demonstrate that poultry farmers belong to three classes of biosecurity with 'low', 'moderate', and 'high' adoption behaviors. A correlation analysis between the classes and key animal health indicators suggests that farmers practicing more biosecurity measures have better poultry health outcomes. The outcome of the multinomial logistic regression shows that information access and the perceived benefits of biosecurity measures are the greatest drivers of adoption. For instance, farmers who accessed information on biosecurity measures were 25.3% more likely to belong to the 'high adopters' category and 20.8% less likely to be in the 'moderate adopters' class. As such, the study recommends enhanced information dissemination to improve the uptake of biosecurity measures. The output of stochastic cost frontier analysis shows that poultry farmers in Nyanza are largely cost-efficient. The study also notes a pattern indicating that increased use of biosecurity practices enhances farmers' cost efficiency. In this regard, the study recommends enhanced efforts to promote the uptake of biosecurity measures for increased poultry productivity.

***Keywords:*** Antimicrobial resistance, poultry biosecurity, latent class analysis, stochastic cost frontier analysis

## TABLE OF CONTENTS

## LIST OF TABLES

# CHAPTER ONE: INTRODUCTION

## 1.1. Background

Livestock-sourced foods represent 13% of global calories and 28% of proteins consumed (Kleyn & Ciacciariello, 2021). These figures will rise further, with the global population expected to hit 9.8 billion by 2050. ILRI (2021) and Alexandratos and Bruinsma (2012), independently, project the demand for livestock products to increase by 70% in the same period, owing to increased purchasing power and urbanization, especially in Sub-Saharan Africa (SSA). Notably, poultry is one of the major livestock sub-sectors among smallholders (Kleyn & Ciacciariello, 2021): in SSA, up to 85% of rural households keep poultry and rely on them for household food security and livelihood. According to Kleyn and Ciacciariello (2021) the demand for eggs and poultry meat is projected to increase by 65% and 121%, respectively by 2050. The rise will be driven largely by increased consumption in Africa, among other places. While the demand for poultry products in SSA continue to rise, the production has largely remained stagnant (Erdaw & Beyene, 2022).

The disparities in demand and the local production of poultry are attributed to a combination of institutional, policy, and natural constraints. Key among these challenges is livestock diseases and the associated costs (Byaruhanga et al., 2017). Diseases reduce productivity and result in losses at the farm level and in industry. Some economic burdens of diseases include a reduction in eggs, low poultry meat productivity, increased costs of production due to clinical treatments, and increased mortality, setting the stage for reduced stock sizes in smallholdings. Furthermore, farmers' attempts to address diseases through clinical treatments often encourage excessive use of antimicrobials which has led to the growing concern of antimicrobial resistance (AMR) (Laanen et al., 2014): this is beside the respective costs. Moreover, common knowledge of growth-enhancing properties of antimicrobials results in misuse, thus exacerbating AMR challenge.

AMR has overtaken many causes of death to become one of the top killers globally. World Bank (2017) estimates that more than 700,000 people die annually due to AMR. It is projected that the number will rise to over 10 million annually by 2050, causing a decline of 3.8 percent in global annual GDP if no action is taken. Murray et al. (2022) agree with these projections, estimating the number of deaths associated with AMR in 2019 alone at 4.95 million. The SSA region is the most affected, with Western Sahara recording up to 27.3 deaths per 100,000 attributable to bacterial AMR (*Ibid*). Like in other countries, AMR is already prevalent in Kenya, mostly driven by misuse or over-use of antimicrobials in both humans and animals (Prestinaci et al., 2015; Taitt et al., 2017).

Witte (2000) argues that the use of antibiotics as growth promoters in livestock feeds creates a large reservoir of transferable antibiotic resistance in the ecosystem. The study further demonstrates that the use of such antibiotics as oxytetracycline and streptothricin transfer significant resistance to human bacterial pathogens. Dadgostar (2019) also finds that AMR in livestock production results from the misuse of drugs. Another study by Menz et al. (2019) postulated that antibiotic residues reach the environment through land application of livestock manure, and this facilitates AMR. The residues impact the functionality and structure of microbial communities, promoting the spread of antibiotic-resistant bacteria and genes. Unfortunately, developing countries, including Kenya have not formulated policies to regulate feed antimicrobials. Besides AMR, antibiotic residues in livestock products can have potential carcinogenic or mutagenic effects (Vass et al., 2008).

Another challenge of livestock diseases is their transboundary nature. According to Torres-Velez et al. (2019), transboundary animal diseases (TADs) are those that spread through animal populations, having negative societal and economic impacts. They cause high stock mortalities in low-income areas and spread faster, complicating control measures. Léger et al. (2017) argue that increased cases of TADs can be explained by poor on-farm biosecurity measures. Consumers of livestock products are not spared either as both AMR and many TADs are zoonotic, passing from animals to humans through the consumption of their products. FAO (2017) estimates that 75 percent of emerging human infectious diseases are zoonotic.

AMR, TADs, and Zoonoses are major constraints in the production and sustainability of the poultry sector. The diseases not only decrease productivity but also compromise human health. Smallholder poultry farmers are at higher risk because of limited access to veterinary and extension services. Consequently, farmers resort to self-diagnosis and presumptive administration of antimicrobials and other drugs. These farmers unknowingly increase the resistance of animals to antimicrobials.

Biosecurity measures are crucial alternatives to conventional control measures, such as clinical treatment through antibiotics, as they focus on preventing the spread of diseases in the first place. Antibiotic treatment can be effective in certain cases, but overuse has led to antibiotic resistance, making the treatment of infections more difficult. Biosecurity measures, on the other hand, reduce the risk of disease introduction and spread, thereby reducing the need for clinical treatment (Mutua et al., 2022; Merrill et al., 2019); . These measures can range from simple practices like hand hygiene to more complex measures like quarantining infected animals or implementing strict sanitation protocols. The adoption of biosecurity measures not only helps in controlling the spread of diseases but also ensures that animals are kept in a healthy and safe environment (Kompas et al., 2015).

Given the challenges of livestock diseases, biosecurity measures offer a sustainable alternative to maintaining the overall health of animals and humans. Against this backdrop, Cargill Inc. in partnership with Heifer Project International (HPI), Ausvet, and the International Poultry Council intend to implement a project dubbed "Transformational strategies for farm output risk mitigation in Kenya" (TRANSFORM-Kenya). The project is funded by the USAID and aims to sustainably strengthen animal source food systems to prevent emerging zoonoses, TADs, and AMR. This will be achieved by promotion of practices that embed preventive healthcare, thus reducing use of antimicrobials while optimizing feed resources to enhance productivity and therefore increase income from livestock enterprises in the intermediate term. The broader project targets both dairy and poultry farmers in Nyanza and North Rift. The choice of the two regions for the implementation of the project was reached following the relative importance of dairy and poultry in the smallholder households. Further, the four counties of Nyanza –Migori, Homabay, Kisumu, and Siaya– are some of the major producers of poultry in Kenya (Omiti, 2016). However, my thesis only concentrates on poultry in Nyanza, but the results can be adapted to other regions and livestock sub-sectors.

## 1.2. Statement of the problem

Empirical evidence has demonstrated that the implementation of biosecurity practices can effectively lower the risk of antimicrobial resistance (AMR), prevent transboundary animal diseases (TADs), and decrease the incidence of zoonoses (Brennan & Christley, 2013; Ingvartsen & Moyes, 2013; Sordillo, 2016). Despite these benefits, there is limited information available on the uptake of biosecurity practices among poultry farmers in SSA, including Kenya. Previous studies, including Nyokabi (2015), Nantima et al. (2016) and Nyokabi et al. (2018) have shown low awareness of biosecurity measures among poultry farmers, which may suggests poor adoption of such practices. However, the situation of adoption of biosecurity measures among poultry farmers in Kenya is not known. Further, the relationship between biosecurity adoption and poultry health outcomes is not known, and neither is the effect of biosecurity adoption on poultry productivity. It is also not clear what factors influence the uptake of biosecurity measures among smallholder poultry farmers.

## 1.3. The objectives of the study

The overall goal of this study is to evaluate the adoption of farm biosecurity measures and the effect on the cost efficiency of poultry farmers in Nyanza, Kenya.

The specific objectives of the study are to:

i. Evaluate adoption of farm biosecurity measures among smallholder poultry farmers in Nyanza, Kenya.

ii. Assess the effect of farm biosecurity adoption on the cost efficiency of smallholder poultry farmers in Nyanza, Kenya

## 1.4. Research hypotheses

i. Access to information and the perceived benefits do not influence adoption patterns for farm biosecurity measures among smallholder poultry farmers in Nyanza, Kenya.

ii. Adoption of farm biosecurity measures do not influence smallholder cost efficiency among poultry farmers in Nyanza, Kenya.

## 1.5. Justifications of the study

Preventive flock health management practices have the potential to enhance the productivity and health of chicken, thus eliminating the need to use antimicrobials. In line with this understanding, Cargill Inc. in partnership with HPI, Ausvet, and the IPC intend to implement the USAID-TRANSFORM Project. The project is in line with the Global Health Security Agenda (GHSA) that aims to sustainably strengthen animal-sourced food systems, address the emerging zoonoses and AMR. This will be achieved by promoting practices that embed preventive healthcare, thus reducing use of antimicrobials while optimizing feed resources to enhance productivity. This study is part of the TRANSFORM Project and provides useful information on the uptake of biosecurity practices among poultry farmers.

The project is being implemented in the regions of Kenya where county governments have identified livestock as an important subsector in their County Integrated Development Plans (CIDPs). The four counties of Nyanza; Migori, Homabay, Kisumu, and Siaya emphasize poultry production as an enabler in development among the smallholders. This study illustrates the importance of biosecurity measures in improving poultry productivity, lowering the cases of stock mortality, and strengthening animal-sourced foods. Further, the study identifies variables that could be amenable to policies that promote the uptake of biosecurity practices. Besides the CIDPs, the study is also in line with Kenya's development goals, including the "Big 4 Agenda" and Kenya's Vision 2030. Agricultural productivity and food security are key pillars in both plans, with a focus on food safety and sustainability. The focus on alternatives to antibiotics provides useful information for realizing the food safety components of these development goals.

The United Nations' Sustainable Development Goals 1, 2, and 3 seek to end poverty, achieve zero hunger, and attain good health and well-being of people. SDG 1 targets to help developing countries implement policies and programs to end poverty. Similarly, SDG 2 aims at doubling the agricultural productivity and incomes of small-scale food producers, especially women, through among other factors, the provision of knowledge. By providing information on determinants of adoption, the study recommends policies to enhance the uptake of risk-mitigating, cost-reducing, and productivity-enhancing practices. The recommendation could see the realization of the goals in less expensive and more sustainable ways.

Among other things, this study provides information on farmers' perception of biosecurity practices, which as underscored by Fatch et al. (2021), is critical to explaining hindrances in the uptake of good practices.  To address the low uptake of preventive flock health practices, one must evaluate farmers' perceptions, and whether they consider such measures useful in enhancing health and productivity. Lastly, the study contributes to the literature on the adoption of biosecurity practices among poultry farmers in the SSA and the corresponding effect on cost efficiency. Such knowledge is scanty in the existing literature.

## 1.6. Organization of the thesis

This thesis is written in the paper format. Chapter 2 covers the general literature review, including on transboundary animal diseases, antimicrobial resistance, zoonoses, and disease management strategies. Chapter 3 is based on objective 1 and features an abstract, a brief introduction, the methodology, results and discussions, and specific conclusion. Chapter 4 is based on the second objective and features an abstract, introduction, methodology, results and discussions, and specific conclusion. Chapter 5 covers general conclusions and recommendations. The last section provides a list of references and the appendices.

# CHAPTER TWO: LITERATURE REVIEW

## 2.1. Poultry disease management strategies

Livestock diseases are among the greatest barriers to sustainable poultry production. Kompas et al. (2015) highlight TADs as key threats limiting the meaningful contribution of livestock to food security and smallholders' livelihoods. TADs also disrupt global and regional trade, create food supply shortages, increase the costs of control measures, reduce flock size, and force a decline in consumption (Clemmons et al., 2021). The emergence of Bird flu "*avian influenza*", for instance, has spurred import bans and caused a serious stock decline in South Africa (Uwishema et al., 2021). The disease, as noted by Roy Chowdhury et al. (2019), poses serious economic losses due to high mortality and morbidity risks. TADs and zoonoses are not only devastating but also endemic in developing countries, including Kenya. While these studies provide useful information on the burden of TADs, most of them are based on reviews and none explores alternative disease management strategies and their consequences.

In tackling TADs and emerging/re-emerging infections, Windsor et al. (2020) argue that smallholder farmers' limited understanding of disease risk mitigation and focus on clinical treatment heightens the threat of antimicrobial resistance. Clinical treatment also poses negative socioeconomic impacts. Indeed, Prestinaci et al. (2015) and Taitt et al. (2017) establish that AMR is already apparent among humans and livestock in developing countries. A study by Ngai et al. (2021) analyzing AMR on poultry feed remains in the Ruiru sub-county found 41 percent and 62 percent *E. coli* and *Salmonella sp.* isolates resistant to ampicillin, respectively. Dadgostar (2019) highlights the misuse of antibiotics as the greatest driver of AMR. Using antibiotics as growth promoters have been shown to create a reservoir of transferable AMR (Witte, 2000). Antimicrobial residues find their way through land application of livestock manure, altering the functionality and structure of microbial communities, and making them resistant to antibiotics (Menz et al., 2019). The residues also pose a risk of spreading potential mutagens and carcinogens (Vass et al., 2008). Further, Prestinaci et al. (2015) and Garcia-Migura et al. (2014) argue that AMR is zoonotic, passing from animals to humans through consumption of livestock products. All these studies agree that AMR is increasingly becoming a risk to the sustainable production of livestock, especially chicken. This study explores alternative, and potentially more sustainable strategies for managing livestock diseases.

Biosecurity –measures taken to reduce the risk of introduction and spread of infectious agents– has been shown to have reduced disease treatment incidences (Laanen et al., 2014; Kompas et al., 2015). Further, Yun et al. (2021) find that enhanced biosecurity can lead to a reduction in antibiotic use which could potentially decrease the cases of AMR. Davies and Wales (2019) also make similar conclusions, arguing that there exists an interrelationship between biosecurity (farm hygiene) and drug use. While making such assertions, these studies do not report to extent of farmers' uptake of such practices, and neither do they make empirical conclusions. This study differs in that it evaluates the extent of biosecurity adoption and the impact it has on farmers' costs and animal health outcomes.

One aspect of biosecurity involves feeding holistic nutrition which plays an equally important role in tackling diseases. Sharma et al. (2018) argue that feed additives such as enzymes act as stimulators that promote livestock health and immunity. The enzymes enhance digestion and nutrient availability within an animal’s gastro-intestinal track (GIT). The study concludes that feed enzymes and other additives play a major role in reducing AMR in livestock. Swaggerty et al.

(2019) argue that incorporating nutrition programs that boost chicken immune response can improve health and reduce the need for antibiotics. Targeted dietary supplementation and/or the use of feed additives like organic acid supplements have been shown to have beneficial effects on chicken (Khan & Iqbal, 2016). They improve nutrient digestibility, consequently lowering subclinical infection and enhancing immunity. Despite the importance of nutrition in preventive medicine, most studies that tackle biosecurity often exclude it. This study integrates holistic nutrition practices among other biosecurity measures.

Despite evidence supporting the effectiveness of preventive flock health management practices in dealing with livestock diseases, reducing AMR, and enhancing productivity, the literature points to low awareness which signals poor adoption. Nyokabi et al. (2018) argue that knowledge of zoonotic diseases and biosecurity practices is marginal or non-existent among informal value chain actors in Kenya. Another study by Nantima et al. (2016) also finds low awareness of biosecurity practices which limits adoption. Notably, none of these studies explore adoption patterns for biosecurity practices in Kenya or anywhere in SSA. Sidinei et al. (2021) are among the few studies that assess the level of biosecurity in broiler farms in Brazil. However, the study relies upon data from merely 70 farms and explores only a few biosecurity measures. Moreover, the authors use a scoring system to classify farmers, which limits further empirical analysis. The current study differs to the extent that it considers more biosecurity practices and a larger sample size.

### 2.2.Theoretical background

Farmers’ choice of biosecurity practices to adopt can be analyzed through several theories, including the attribution theory, theory of utility maximization, and the random utility theory. Attribution theory posits that individuals make decisions based on their perception of the causes of events and their apparent control over them (Heider, 1944; Kelley, 1967; Weiner & Kukla, 1970). The theory suggests that the choice of biosecurity practices would be influenced by farmers' perception of the cause of a disease outbreak and the degree to which they believe they have control over it.

In contrast, the theory of utility maximization assumes that individuals make rational choices to maximize their benefit, or utility (Pareto, 1906). In the context of biosecurity, this theory would suggest that farmers choose the practices that provide the greatest benefit in terms of reduced risk of disease transmission and increased productivity. While this theory is useful in understanding the dual challenge of poultry production within the SSA, it limits the inclusion of other factors that could explain the sources of deviation.

The random utility theory, on the other hand, acknowledges that the choice of biosecurity practices is not solely based on the expected utility of each practice, but also includes random components, such as the influence of social networks, and the availability of resources (McFadden, 1974). The theory allows for the consideration of multiple factors that influence the choice of biosecurity practices, including economic, social, and psychological factors. Given the multidimensional and complementary nature of biosecurity practices, the random utility theory appears to be the most appropriate for analyzing the choice of biosecurity practices. It considers the fact that farmers may adopt different combinations of practices, depending on their specific circumstances, and that their decision may not be based solely on maximizing the expected utility. This nuanced approach is more in line with the reality of the complex decision-making processes of farmers. Notably, the cost component of this study is a consequence of the set of biosecurity practices that a farmer chooses to implement. The random utility theory can thus be extended to capture the cost of biosecurity practices.

While analyzing the technical and economic biosecurity scores of dairy farms in Turkey, Can and Altuğ (2014) develop a technical scoring system that allocates each biosecurity practice a value of 1 if the farmer follows it, and 0 otherwise. The scores are then aggregated to obtain a farmer's biosecurity score, with a maximum of 19 for those who follow all the practices. While this approach may be simple, Watto and Mugera (2014) argue that such scores lack statistical properties, which makes it difficult to conduct any further analysis. This study finds the approach insufficient because it limits statistical inference.

The choice of biosecurity practices is driven by unobserved quantities known as latent variables. These quantities are multidimensional constructs measured on many variables. Laanen et al. (2014) argue that the complexity presented by such constructs can be handled using a latent variable model, where multiple unobserved characteristics are explained by observed variables. Choosing an appropriate latent variable model depends on the structure of the observed indicator. Where the indicators are continuous and map onto continuous latent variables, factor or covariance structure analysis is considered appropriate (De Roover et al., 2017). It is also possible to map discrete observed variables on continuous latent variables using latent trait analysis (Laanen et al., 2014). The opposite is also possible, where continuous observed variables map onto discrete latent variables using latent profile analysis. Lastly, latent class analysis (LCA) can be used to model relationships where discrete observed variables map onto discrete latent variables. This study uses the LCA framework which sufficiently addresses the scenario presented by the adoption of biosecurity practices.

Oyinbo et al. (2019) applied a latent class analysis as part of a choice experiment evaluating farmers' preference for site-specific agricultural extension services. The study argues that the population of farmers belongs to discrete latent classes, with a positive probability of fitting into a particular class. Preferences are homogenous for members of the same latent class and heterogenous across groups. The probability of a particular farmer choosing a given alternative in the choice set is conditioned on membership to a particular latent class. Once latent classes are constructed, an appropriate structural model can be applied to observed socio-economic, institutional, and farm-specific factors to predict the probability of individuals belonging to a particular class. The approach allows for the computation of measurement errors and subsequent predictions. Charlier et al. (2021) applied a similar strategy, using latent class analysis to categorize households as either fuel-sufficient or fuel-poor. The study used three observable objective characteristics of healthy, decent, and safe dwellings to construct two-fuel endowment latent classes. They justify the use of LCA on account that fuel-poverty as estimated is a multidimensional phenomenon difficult to capture by one indicator. The LCA allows for probabilistic-based clustering, assuming the population consists of subpopulations with different probability density functions. Biosecurity practices as measured in this study follow a similar pattern to the constructs estimated by Charlier et al. (2021) and Oyinbo et al. (2019); hence the use of LCA achieves an appropriate clustering that describes adoption.

Where the characteristic of interest takes composite discrete measurements, other studies suggest the use of mixed logit models (MLM). For instance, Otieno et al. (2011) argue that an MLM also known as random parameter logit (RPL) is appropriate for modeling multiple discrete choices. They postulate that the MLM overcomes the three weaknesses of a multinomial logit, including accounting for heterogeneity in preferences, resolving unrestricted substitution patterns, and fixing the issue of dependence across panels of repeated choices. Moreover, MLM does not suffer from the problem of independence from irrelevant attributes (IIA) which is inherent in multinomial logistic regression models (MLogit). Other studies (Hsu et al., 2014; Siderelis et al., 2011; Huo et al., 2021) have also used mixed logit to model multiple discrete choice behaviors. The MLM compares with LCA except for a few distinctions. In MLM, the parameters of the model follow a continuous joint distribution (Greene, 2003), while the latter assumes that a discrete number of classes are sufficient to account for unobserved heterogeneity across classes (Shen, 2009). The two models offer alternative ways of capturing unobserved latent variables from the observed variables. However, LCA has been observed to perform better under different circumstances. The studies by Greene (2003) and Shen (2009) both agree that latent class specification may provide superior estimates; hence the preference for LCA.

Based on the preceding discussion, this study uses LCA to classify households based on homogeneous groups that adopt combinations of practices. LCA assumes that the behavior of individuals follows observable attributes and latent heterogeneity that vary with the unobserved factors (Laanen et al., 2014). The first step in the estimation involves building models that explain the probability of belonging to a latent class. Secondly, individuals are assigned classes based on the posterior probabilities. Lastly, the study uses the assigned classes for predictions, including correlations with key animal health indicators, regression with determinants of adoption, and comparing cost efficiencies by adoption category.

Farrel (1957) was the first to estimate efficiency using a deterministic non-parametric approach. The study distinguished between technical and allocative efficiency. Following Farrell's paper, Boles (1966) and Shephard (1970) proposed mathematical programming strategies to estimate the model. However, the non-parametric approach only gained traction with the publication of Charnes et al. (1978) study that introduced the term "data envelopment analysis" (DEA). DEA constructs a non-parametric linear piece-wise frontier over the data points (Coelli et al., 2005). Inefficiency is computed as a measure of the distance between the firm and an efficient frontier. Several studies estimating the efficiency of poultry enterprises have used DEA with different extensions (Yusuf & Malomo, 2007; Begum et al., 2012; Heidari et al., 2011). These studies justify the use of DEA on the premise that it does not require any preliminary assumption on the functional form of the production function. However, DEA assumes that all deviations from the frontier are attributable to inefficiency. This assumption ignores the influence of random effects (statistical noise). The data used in this study was obtained through a household survey, with respondents expected to recall information. Therefore, the use of DEA is inappropriate in this study.

Besides DEA, efficiency can also be synthesized parametrically using a stochastic frontier analysis (SFA). SFA originated with Aigner et al. (1977) and Meeusen and van Den Broeck (1977). The researchers argued that production functions fitted on survey data are stochastic rather than deterministic. Therefore, SFA decomposes the error term into two; one component capturing inefficiency effects and the other handling random effects (statistical noise) (Miriti et al., 2021).

In other words, SFA adds a symmetric error term to account for statistical noise arising from the omission of relevant variables, or measurement errors associated with the choice of functional form (Coelli et al., 2005). Battese and Coelli's (1995) extension of the SFA model allows for simultaneous estimation of efficiency scores with the inefficiency effects. This study considers SFA sufficient in estimating farmers' efficiency.

SFA has been applied in various studies focusing on poultry enterprise efficiency (Luvhengo et al., 2015; Etuah et al., 2020). While some of these studies focus on technical efficiency (TE), others consider allocative efficiency (AE). TE is an estimate of resource use efficiency, while AE considers input cost optimization. Dziwornu and Sarpong (2014) note that TE can still be achieved at a much higher cost. Etuah et al. (2020) argue on this account the need to consider both TE and AE in computing a comprehensive farm performance measure otherwise referred to as cost or economic efficiency. Notably, smallholder farmers are cost-minimizing entities; hence, the study estimates cost efficiency as a comprehensive measure of poultry farm performance.

# CHAPTER THREE: EVALUATING ADOPTION OF FARM BIOSECURITY MEASURES AMONG SMALLHOLDER POULTRY FARMERS IN NYANZA, KENYA

## 3.1. Abstract

Sub-Saharan Africa has a growing demand for poultry, but productivity in the sector has not increased to meet this demand. One major constraint in the sector is disease. Many farmers currently use clinical control measures that involve treating birds with antibiotics upon detecting an infection. However, this approach has led to the misuse of antibiotics, leading to antimicrobial resistance, which could have catastrophic effects going by different projections. This study evaluates the uptake of preventive approaches to disease management, otherwise known as biosecurity measures and the effect of the adopted practices on animal health outcome among poultry farmers in Nyanza region of Kenya. The study applies latent class analysis, which is a model-based clustering approach to categorize poultry farmers into *low, moderate,* and *high* biosecurity adoption classes. The results show low adoption of biosecurity measure across all classes of smallholder poultry farmers in Nyanza. Correlation analysis shows that increased uptake of biosecurity measures is associated with positive poultry health outcomes: this is as demonstrated by lower mortality rates among farmers characterized by increased adoption of biosecurity measures. Lastly, the study implements a multinomial logistic regression to assess determinants of class membership and the analysis shows that information access is the greatest driver of biosecurity adoption. Farmers who had access to information on biosecurity measures were 25% more likely to belong to the class of farmers adopting more biosecurity practices – h*igh adoption class*– and 21% less likely to be in the *moderate adopters* class. As such, the study recommends enhanced information dissemination to improve the uptake of biosecurity measures.

***Keywords**:* Antimicrobial resistance, Biosecurity adoption, Latent class analysis, Multinomial logistic regression

## 3.2. Introduction

Poultry diseases and the associated cost are among the major constraints in the sustainable production of chicken (Byaruhanga et al., 2017). Diseases reduce productivity and result in losses at farm and industry levels. Some economic burdens of diseases include a reduction in egg production, low quality of poultry meat, increased production costs associated with clinical treatments, and higher flock mortality. Many poultry diseases are categorized as transboundary animal diseases (TADs): these are highly contagious or transmissible epidemic diseases with the potential to spread rapidly across the globe and cause substantial socioeconomic and public health consequences (Lysholm et al., 2022). While options to treat some of the diseases exist, clinical approach to managing animal diseases have often resulted in antimicrobial resistance (AMR) due to the misuse of antibiotics (Laanen et al., 2014).

In human health, AMR has overtaken many diseases to become one of the top causes of death globally (World Health Organization, 2014). In 2019 alone there were 4.95 million deaths associated with AMR, with 1.27 million directly attributable to bacterial AMR (Murray et al., 2022). World Bank (2017) projects that the number of deaths associated with AMR may rise to over 10 million annually by 2050, thus causing a decline of 3.8% in global GDP. Notably, Sub-Saharan Africa (SSA) is most affected with the western Sahara recording up to 27.3 deaths per 100,000 attributable to bacterial AMR (Murray et al., 2022). Interestingly, food animals are major reservoir of drug resistant bacteria and are thus a major risk for transmission of AMR bacteria in the developing world, Africa included (Ayukekbong et al., 2017). Moreover, the bulk of antimicrobials consumed the world over are given to animals for food production rather than consumed directly by humans (Mitema et al., 2001). Elmanama et al. (2019) and Moffo et al. (2022) note that the use of antibiotics in poultry production is a driver of AMR.

This study was motivated by the need to promote sustainable management of poultry health. It considers two broad strategies that are addressed in literature: preventive and control measures. Control measures are used when an animal exhibits clinical signs pointing to the existence of an infection. An appropriate treatment, mostly using antibiotics, is recommended following diagnosis. Notably, most smallholder poultry farmers lack the resources to engage veterinarians: they resort to self-diagnosis and purchase antibiotics from local stores (Alhaji et al., 2018). Rather than being a solution, control measures have amplified the AMR problem among smallholder poultry farmers in addition to the cost associated with such measures.

The preventive measures otherwise known as biosecurity are more efficient and cost-effective in managing livestock health. Fasina et al. (2012) demonstrated that implementing biosecurity measures is 8.45 times, 4.88 times, and 1.49 times better than doing nothing in controlling highly pathogenic avian influenza (HPAI), Newcastle disease, and coccidiosis, respectively. Yoo et al. (2022) found similar results for poultry farmers using select biosecurity practices to control HPAI. Robertson (2020) also argues that biosecurity is critical in maintaining a farm, region, or country free from diseases. These measures not only prevent entry and establishment of infection but also boost the animal's immune response (Ingvartsen & Moyes, 2013). Additional benefits of biosecurity measures include improved animal welfare, improved vaccine effectiveness, reduced antimicrobial and anthelmintic resistance, better control of transboundary animal diseases (TADs), and higher profit margins (Brennan & Christley, 2013).

Given the benefits highlighted above, adopting biosecurity practices is arguably the most sustainable way of managing poultry health. These biosecurity measures are complementary as noted by Musungu et al. (2021) and should be implemented as a combination rather than separate measures. In practice though, farmers are likely to maintain some, while ignoring others. The studies conducted so far have focused on examining the level of awareness of biosecurity measures among poultry farmers in Kenya. However, these studies have provided limited information on the actual implementation and adoption of these measures. Many of these studies have reported low levels of awareness among farmers, as evidenced by the works of Nyokabi (2015), Nantima et al. (2016), and Nyokabi et al. (2018). The other studies outside SSA focused on commercial poultry farming based on exotic breeds without looking at similar practices among farmers rearing improved indigenous chicken.

In view of the mixed and inconclusive findings in previous literature, the present study evaluates the adoption of biosecurity practices among poultry farmers in four counties of Nyanza, including Migori, Homabay, Kisumu, and Siaya. The study seeks to answer the following question: do the perceived benefits and institutional factors influence the uptake of biosecurity practices among poultry farmers in the region? To address this question, a latent class analysis (LCA) is applied to categorize farmers into homogeneous classes representing different biosecurity adoption behaviors. LCA allows for a detailed description of adoption behavior within classes. The study also undertakes pairwise correlation to understand the relationship between the adoption of biosecurity practices and key animal health indicators. Lastly, a multinomial logistic regression (MLogit) model is applied to predict the potential determinants of the observed adoption patterns.

This study contributes to the literature in various ways: first, it documents evidence on the adoption of biosecurity measures among poultry farmers in Kenya and by extension the SSA. Secondly, it explores more biosecurity indicators compared to other studies and considers all poultry farmers irrespective of breeds. Thirdly, this is the first study to implement a model-based clustering of farmers based on the biosecurity measures they have adopted. Other studies use cluster analysis, which cannot be evaluated for model fit. Lastly, the study demonstrates the link between biosecurity adoption and the effect on animal health outcomes and uses a larger sample of farmers with different poultry breeds.

## 3.3. Methodology

### *3.3.1. Study site, sampling, and data collection*

This study uses data from a household survey of smallholder poultry producers from the four counties of Nyanza – Migori, Siaya, Homabay, and Kisumu– in Kenya. The study is part of a project dubbed USAID-TRANFORM (Transformational Strategies for Farm Output Risk Mitigation). The project is being implemented in partnership with Cargill Inc., Heifer Project International (HPI), Ausvet, and the International Poultry Council. It aims to strengthen animal sourced foods through the promotion of preventive healthcare to increase productivity and reduce antimicrobial resistance.

Respondents in this study were selected from four counties in the Nyanza region of Kenya. Nyanza region was chosen for the study due to its substantial contribution to the overall poultry population in Kenya: the region is among the top producers of poultry in Kenya, accounting for up to 33.6% of the 59 million chicken birds in the country (FAOSTAT, 2022; Omiti,2016). Furthermore, poultry farming has been identified as a key value chain that can transform the livelihood of smallholder farmers in Nyanza (Odula et al., 2010). The choice of the four counties was also intended to leverage the presence and network of Heifer in the region.

Poultry producers in Kenya can be categorized into: sector 1 (industrially integrated), sector 2 (commercial), sector 3 (semi-commercial), and sector 4 (village/backyard) (Omiti, 2016). This study concentrates largely on the sector 3 farmers who are the majority in Nyanza. The farmers are characterized by the sale of live birds, minimal to low biosecurity and low inputs. There is a broad literature indicating that the poultry production system in other parts of the Sub-Saharan Africa is not different from Kenya (Sime, 2022; Yusuf et al., 2014).

The study uses systematic random sampling method to select respondents from a sampling frame provided by HPI-Kenya. The farmers are organized into producer organizations (Pos) and have been targeted by previous interventions from HPI-Kenya. To determine the sample size, McClave et al. (2014) formula was used, which generated 502 farmers after a 10% adjustment to cover for possible non-response. The use of McClave's formula was justified on the premise that the information on the target population is known, including average income. Structured questionnaire programmed in the SurveyCTO software was used to collect data. The questionnaire captured data on household characteristics; information on poultry enterprise; knowledge, attitude on- and practice of biosecurity; cost and revenue from the poultry enterprise; and the household annual income –on-farm and non-farm income (*See Appendix 3*). The questionnaire was pretested, validated, and enumerators trained to use it appropriately. The data was obtained with informed consent from all the respondents. Data from each respondent was assessed for completeness and reliability: in exceptional cases where there were doubts, individual respondents were called for clarifications. The statistical analysis was done using R software (for latent class analysis) and Stata v16 for descriptive and regression analysis.

### *3.3.2. Description of variables*

Table 3.1 partly adopted from Higgins et al. (2018) highlights key biosecurity measures and the corresponding practices considered in the study. All biosecurity indicators were measured as binary variables –1 if one follows the practices and 0, otherwise. Mortality rate is computed as a proportion of birds that died out of the flock, hence a proportion. Use of antibiotics is a binary variable –1 if the farmer had used poultry antibiotics within the year, and 0 otherwise. The perception index used in this study was computed using principal component analysis (PCA) of statements describing the perceived benefits of biosecurity practices –administered on a 5-point Likert scale. Age of the farmer, education of the household head, and years of experience in poultry production are all continuous variables measured in years. The study uses the inverse hyperbolic sine (arcsinh) as noted by Bellemare and Wichman (2020) and Kirui et al. (2022) to derive the log transformation of on-farm and non-farm income without losing the zero observations. Access to information and gender of the household head are binary variables, “1=yes” and “1=household head is male”.

Table 3. 1**:** Principles of poultry biosecurity measures and the associated recommended practices

| Measures | Recommended practices |
|---|---|
| **Measure 1**: Introduction and movement of birds<br>*The introduction and movement of animals should be managed to prevent introduction or spread of diseases.* | • Test birds for specific diseases before introducing them to the flock.<br>• Separate new birds before introducing to the flock.<br>• Follow additional biosecurity practices before introducing new birds to the flock |
| **Measure 2:** People, vehicles, and equipment<br>*Control the entry of people vehicles or equipment entering the farm to reduce possible contamination.* | • Restrict unnecessary movement of authorized persons or vehicles into the farm.<br>• Disinfect vehicles and equipment entering the farm.<br>• Maintain a functional footbath and handwashing stations.<br>• Wear protective clothing when accessing the poultry unit. |
| **Measure 3**: Weed/wildlife control.<br>*Reduce the potential interaction of wild or domestic animals with birds.* | • Monitor and manage vermin, domestic animals, and wildlife to prevent infection to birds.<br>• Clear bushes around the poultry facility.<br>• Erect a fence around the poultry unit.<br>• Control drainage in the poultry unit. |
| **Measure 4:** Carcass and waste disposal<br>*Dispose dead birds appropriately to minimize the spread of diseases.* | • Dispose carcasses by burning, burying, or in segregated areas.<br>• Have a dedicated slaughterhouse or area away from the flock.<br>• Dispose litter or slaughter waste appropriately. |
| **Measure 5:** Animal health management<br>*Implement practices to prevent and control diseases in the farm.* | • Maintain a veterinarian-recommended vaccination schedule.<br>• Deworm the birds regularly.<br>• Maintain all farm records.<br>• Seek advice from veterinarian or government officials in case of sickness or unusual deaths in the farm.<br>• Inspect the birds regularly to detect ill-health before establishment in the farm.<br>• Segregate sick and injured animals.<br>• Observe withdrawal period following treatment of birds i.e., discard eggs following treatment. |
| **Measure 6:** Holistic nutrition<br>*Administer a balanced and wholesome diet composed of basal feeds and additional elements such as concentrates, mineral salts and other supplements.* | • Feed a balanced diet consisting of basal feeds and additional supplementation.<br>• Use quality water to avoid contamination and spread of diseases. |
| **Measure 7:** Poultry unit<br>*Ensure the birds are housed appropriately* | • Have a unit to house the birds separately from humans and other animals.<br>• House should have laying nests.<br>• Clean the poultry house regularly with water and disinfectants.<br>• Construct the poultry house in an East-West orientation.<br>• Follow an all-in-all-out principle. |

Source: Partly adopted from Higgins et al. (2018)

### 3.3.3. *Theoretical and empirical frameworks*

To analyze the adoption behavior of poultry producers, a random utility model (RUM), which assumes that an individual $i$ derives utility $U$ by adopting practice $j$ from choice set $s$ of practices, was applied (Walker & Ben-Akiva, 2002). Farmers, therefore, choose which biosecurity practices to implement following a utility-maximizing behavior modeled by Equation (3.1).

$$U_{ijs} = V_{ijs} + \mu_{ijs} = ASC + \sum_{k=1}^{K} \beta_i X_{ijs} + \mu_{ijs} \tag{3.1}$$

Where $U$ is a latent (unobserved/indirect) variable comprising the systematic (deterministic) part- $V_{ijs}$, and a stochastic component denoted by $\mu_{ijs}$, which is independent and identically distributed. The deterministic component can be decomposed further to $X_{ijs}$, representing the vector of attributes of the choice for all the covariates *K*, and *ASC* which denotes alternative-specific constant –preference for status quo; $\beta_i$ are the associated parameters. The model can be extended to capture the population's unobserved heterogeneity through latent class analysis (LCA). This extension is justified on the premise that discrete segments of decision-makers exist who are not immediately identifiable. The LCA extension enables the derivation of class-specific utility functions and the associated choice behaviors. The specification leads to a class-specific choice model as noted by Walker and Ben-Akiva (2002).

LCA identifies hidden subpopulations to which different farmers belong by finding patterns in the indicator variables. It is superior to other clustering approaches because it can be evaluated for model fit. Assuming a latent class with *N* categorical variables, the response of individual *i* on an item *n* is denoted by $Y_{in}$, with a full response vector $Y_i$. The probability $P(Y_i)$ representing a class response pattern can be defined as shown in Equation (3.2) (Vermunt, 2017).

$$P(Y_i) = \sum_{s=1}^{S} P(X' = s)P(Y_i|X' = s) \tag{3.2}$$

Where $X'$ denote the observable variables, while $s$ is a latent class of $S$ classes. The next step involves describing class-specific adoption patterns –outcome probabilities. Assuming individuals are distributed through a set of classes, it is not initially known who belongs to what group. However, the study computes the probability of individual $i$ choosing alternative $n$ in a choice situation $Y_{in}$, conditioned on membership to class $s$ as in Equation (3.3):

$$\text{Prob}_{in|s}(j) = Prob(Y_{in} = j|class = s) = \frac{\exp\left(X'_{in,j}\beta_s\right)}{\sum_{j=1}^{J} \exp\left(X'_{in,j}\beta_s\right)} \tag{3.3}$$

Where $\beta_s$ represent class-specific parameters implying homogeneity within each latent class. The size of the choice set varies by the number of indicators adopted by members. Equation (3) makes it possible to observe an individual farmer under different choice situations. The probability of an individual belonging to a particular class $s$ ($P_{is}$) –posterior probability– can be computed as shown in Equation (3.4).

$$P_{is} = \frac{\exp\,(w_i'\theta_s)}{\sum_{s=1}^{S} \exp\,(w_i'\theta_s)} \tag{3.4}$$

Where $w_i$ represent the observable attributes determining class membership, while $\theta_s$ represent class-specific parameters. The computation of the posterior probability follows a maximum likelihood estimation of Equation (3.5):

$$lnL = \sum_{i=1}^{N} \text{ln}L_i = \sum_{i=1}^{Q} ln\left[\sum_{n=1}^{N} P_{is}\left(\prod_{n=1}^{Y_i} L_{in|s}\right)\right] \tag{3.5}$$

A critical issue with latent class analysis is choosing the number of classes ($S$). Shen (2009) argues that $S$ is not a parameter and cannot be decided by a direct test of the hypothesis. He recommends the use of information criteria and selecting the most parsimonious model. Two of the most common information criteria are the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Where AIC and BIC suggest different class models, Beath (2017) recommends selecting models by BIC. The study argues that BIC is superior because it considers the number of observations and selects the model with fewer classes. Notably, BIC gives the most reasonable class model in this study. The resulting outcome probabilities and class enumeration from posterior probabilities are saved for further analysis. See Nylund-Gibson et al. (2023) for a detailed description of the LCA modeling approach.

In the succeeding analysis, the study constructs a pairwise correlation matrix to establish the relationship between the level of biosecurity adoption and key animal health indicators. The study also specifies a multinomial logistic regression model (MLogit) to predict the potential determinants of the observed pattern of biosecurity adoption. The use of an MLogit is part of a three-step latent class modeling as noted by Vermunt (2017). In the first step, the LCA model is built using observable attributes. The step not only involves a decision on variables to include and the number of latent classes, but also model specification, including the distribution of items within classes. In the second stage, individuals are assigned to latent classes based on posterior probabilities. Lastly, a standard regression model is specified that predicts the probability of belonging to a particular class given the exogenous variables. Regression is preferred with more explanatory studies, but step 3 can also involve constructing simple correlation matrices for descriptive analysis. This study uses both explanatory and descriptive analysis in the third step, including employing a one-way ANOVA and the Tukey post hoc test to show the statistical differences in variables across the estimated latent classes.

Some studies that follow regression-based approaches implement a multivariate probit (MVP) using class enumeration as the dependent variable. However, this approach is inappropriate since LCA assumes conditional independence which means the classes are independent of irrelevant attributes (IIA). In other words, the latent class specification removes confounding factors that might cause heterogeneity within classes: this means that an individual can only belong to one latent class. Consequently, the study specifies an MLogit model as shown in Equation (3.6).

$$C_i = \beta_0 + \beta_i X_i + \mu_i \tag{3.6}$$

Where $Ci$ is a multidimensional variable representing different adoption classes; $X_i$ represent a vector of covariates including socioeconomic, institutional, and technological characteristics, while $\beta_i$ are estimated parameters. $\mu_i$ is a mutually exclusive error term. The Equation (3.6) is also computed following a maximum likelihood estimation as noted by Carpita et al. (2013). The model is implemented in Stata v.16 which normalizes the likelihood function to ensure the sum of the regression coefficients over the classes is zero (Yang, 2019): This is done to ensure the model is identifiable.

One of the variables hypothesized to influence adoption patterns is farmers' perceived benefit of biosecurity measures. Perception is assessed by gauging farmers' responses to multiple Likert-Scale statements on biosecurity practices (*See Appendix 3*). These statements are summarized using PCA, after which an index is computed following the weighted sum score formula as noted by Okello et al. (2021).The use of PCA in this study was validated by the Kaiser Meyer Measure of sampling adequacy (KMO) which returns a value of 0.74 falling within the recommended threshold. Further, Bartlett's test of sphericity was significant (Chi-square=1868.22; $p$= 0.000) indicating that items included in the PCA contribute to the overall perception score. The study derived 4 components with eigenvalues greater than 1 contributing 53.13% of the cumulative variation. These components were used to generate a continuous score where positive values indicate positive perception, zero means the farmer is indifferent, while negative values indicate negative perception (*See the summary descriptive statistics – Perceived Benefits*).

## 3.4. Results and Discussion

### *3.4.1. Descriptive statistics*

Table 3. 2: Descriptive statistics for the study respondents

| **Variables** | **Low Adopters (n=157)** | **Moderate Adopters (n=163)** | **High Adopters (n=181)** | **Pooled Sample (n=501)** |
|---|---|---|---|---|
| | Mean (Std. Dev) | Mean (Std. Dev) | Mean (Std. Dev) | Mean (Std. Dev) |
| Perceived Benefits (Index) | -0.281 (2.234) | -0.333 (2.721) | 0.566 (2.296) | 0.008*** (2.456) |
| Flock Size | 29.025 (26.931) | 49.699 (43.349) | 141.088 (174.222) | 76.238*** (119.224) |
| Education of HH | 9.924 (4.202) | 11.393 (4.154) | 13.293 (3.444) | 11.619*** (4.160) |
| Age of HH | 51.172 (11.180) | 53.528 (10.216) | 48.713 (13.135) | 51.050*** (11.786) |
| Household Size | 5.032 (2.395) | 5.853 (2.542) | 5.389 (4.504) | 5.427* (3.361) |
| Years of Experience | 4.694 (6.414) | 6.172 (6.535) | 6.266 (7.169) | 5.743* (6.759) |
| Farm Size (Acres) | 1.993 (1.593) | 2.480 (2.852) | 3.381 (11.901) | 2.653 (7.400) |
| HIST of on-farm income | 6.493 (4.997) | 6.618 (5.081) | 8.681 (4.850) | 7.324*** (5.067) |
| HIST of non-farm income | 5.351 (5.650) | 5.954 (6.088) | 6.649 (6.445) | 6.016 (6.100) |
| Information access (1=yes) | 0.745 (0.437) | 0.712 (0.454) | 0.856 (0.352) | 0.774*** (0.418) |
| Gender of HH (1=Male) | 0.446 (0.499) | 0.638 (0.482) | 0.635 (0.483) | 0.577*** (0.495) |

Source: Survey Data 2021

### 3.4.2. *Model selection*

*Table 3.3* shows the summary of fit indices for different classes of LCA. As noted earlier, an appropriate model is chosen following the values of the information criterion. In this study, a 3-class model was the most parsimonious following the BIC. In contrast, AIC suggested selecting a 5-class model. This variation is common in LCA models but the more reasonable model is preferred. Hasking et al. (2011) argue that good models are selected at saturation point, $k$, beyond which there is weak identifiability: at point $k+1$ there would be too many classes and few indicators. Choosing a 5-class model, in this case, would have resulted in classes having approximately 25% of the members, assuming a uniform distribution. Since the distribution is not uniform, some classes would have very few individuals. Such cases are not desirable since few individuals with many indicators can potentially affect the estimation of outcome probabilities. Therefore, the study specifies a latent class model with 3 classes. The next section summarizes the outcome probabilities.

Table 3. 3: Fit indices of latent class analysis of adoption of farm biosecurity measures (n=502)

| **Number of Classes** | **Log-likelihood ($L^2$)** | **BIC** | **AIC** |
|---|---|---|---|
| LC1 – 1-class | -9787.99 | 19843.39 | 19661.99 |
| LC2 – 2-classes | -8649.63 | 17840.28 | 17473.26 |
| **LC3 – 3-classes** | -8334.97 | **17484.58** | 16931.94 |
| LC4 – 4-classes | -8198.30 | 17484.85 | 16746.60 |
| **LC5 – 5-classes** | -8112.727 | 17587.33 | **16663.45** |
| LC6 – 6-classes | -8134.596 | 17904.68 | 16795.19 |

*Notes: The figures in bold represent the optimal class model by the AIC and the BIC criteria; Source: Survey Data 2021*

### 3.4.3. *Item response probabilities*

*Table 3.4* shows the class proportions and class-specific item response probabilities. Latent class 2 (LC2) had the highest membership at 36.7%, followed by LC3 at 31.8% and LC1 with 31.5% of the farmers. The distribution of individuals to the three latent classes follows posterior probabilities.

### 3.4.4. Adoption of general biosecurity practices

The outcome probabilities summarized in Table 3.4 are interpreted as proportions of members in different classes using the corresponding practices. For instance, 0.997 in the housing practices of LC3 signifies that 99.7% of individuals in the class have a poultry house. In LC1, only 4 appropriate biosecurity practices are followed by more than 50% of the members. The number is slightly higher in LC2 with 8 appropriate measures being followed by at least 50% of the members. LC3 represents the latent class with the highest uptake of biosecurity practices with 12 appropriate measures being followed by at least half of the members. Notably, individuals in the lower classes also feature prominently among those using improper health practices. For instance, 71.7% of households in LC2 continue consuming eggs during the withdrawal period. Another 51.2% reported slaughtering for meat the sick birds which they fear may not recover. In LC1, 72.0% reported consuming eggs during the withdrawal period, while 44.3% were found to slaughter sick birds. Based on the observed pattern of adoption of biosecurity measures, LC1 is labeled as '*low adopters*'; LC2 as '*moderate adopters*'; and LC3 as '*high adopters*. Notably, the *high adopters* also have the lowest proportion of households using inappropriate measures. For instance, only 55.5% compared to 72.0% and 71.7% in the first two classes consumed eggs during withdrawal.

Table 3. 4: Item response probabilities of adoption of biosecurity practices by poultry farmers according to their latent class membership

| Outcome probabilities | LC1<br>*Low Adopters (n=158)* | LC2<br>*Moderate Adopters (n=163)* | LC3<br>*High Adopters (n=181)* |
|---|---|---|---|
| **A. Appropriate Measures** | | | |
| ***General biosecurity practices*** | | | |
| Do you have a poultry Housing Unit | 0.003 | **0.997** | **0.997** |
| East-West orientation for the side walls | 0.003 | **0.648** | **0.777** |
| Houses have laying nests | 0.003 | 0.010 | 0.057 |
| Well-maintained vegetation | 0.003 | **0.975** | **0.994** |
| The poultry housing unit has a fence around it | 0.003 | 0.194 | 0.458 |
| Cleans the Poultry Housing Unit | 0.003 | **0.984** | **0.992** |
| Cleaning routine: water with soap or detergents | 0.003 | 0.215 | 0.256 |
| Have a hand washing station | 0.160 | 0.262 | **0.560** |
| Have a foot disinfection facility | 0.022 | 0.055 | 0.373 |
| Use of dedicated protective clothing | 0.016 | 0.073 | 0.303 |
| Separates chicken by groups | 0.167 | 0.413 | **0.710** |
| ***Health management practices*** | | | |
| Insist on receiving health records of new birds | 0.016 | 0.017 | 0.147 |
| Insist that added birds must be vaccinated | 0.160 | 0.117 | 0.390 |
| Isolate new birds before introducing them into the flock | 0.135 | 0.224 | 0.459 |
| Test new birds for specific diseases of concern | 0.009 | 0.003 | 0.057 |
| Feed eggs to other animals during withdrawal | 0.009 | 0.024 | 0.060 |
| Dispose of eggs during withdrawal | 0.167 | 0.144 | 0.205 |
| Buries dead carcasses | **0.915** | **0.860** | **0.841** |
| Burn dead carcasses | 0.217 | 0.166 | 0.212 |
| Deworms the birds | 0.362 | 0.480 | **0.787** |
| Control external parasites like ticks and fleas in Poultry | 0.141 | 0.092 | 0.342 |
| Vaccinate against Poultry diseases | **0.676** | **0.701** | **0.979** |
| Keep Poultry Records | 0.091 | 0.123 | **0.698** |
| Clean equipment with water and soap after use | **0.531** | **0.655** | **0.765** |
| Follows the all-in all-out principle | 0.028 | 0.023 | 0.228 |
| ***Nutritional practices*** | | | |
| Feeds Commercial concentrates | 0.154 | 0.299 | **0.917** |
| Feeds Home-formulated feeds | 0.116 | 0.124 | 0.114 |
| Feeds Grains such as maize and rice | **0.657** | **0.703** | 0.189 |
| Provides additional feed supplements | 0.123 | 0.079 | 0.320 |
| **B. Use of the non-recommended practices** | | | |
| Consume eggs at home during withdrawal | **0.720** | **0.717** | **0.555** |
| Sell eggs as usual during withdrawal | 0.110 | 0.102 | 0.219 |
| Slaughters and consumes sick birds that may not recover | 0.443 | **0.512** | 0.247 |
| Sell sick chicken as live birds | 0.054 | 0.063 | 0.027 |
| Do not intervene when birds are sick | 0.494 | **0.522** | **0.691** |
| Feed dead carcasses to other animals | 0.098 | 0.093 | 0.146 |
| Slaughter and consume dead carcasses | 0.098 | 0.026 | 0.032 |
| Dump dead carcasses in rubbish pits | 0.406 | 0.388 | 0.301 |
| **Class Proportion** | **0.315** | **0.367** | **0.318** |

*Notes: The outcome probabilities in bold indicate biosecurity practices that have been adopted by more than 50 percent of households within respective classes; Source: Survey Data 2021*

Housing practices are least embraced by *low adopters*, with less than 1% having a poultry unit. This finding indicates that most of the households in class 1 had their chicken either sharing a house with people or other livestock species. Lack of housing limits the implementation of internal biosecurity controls. While most farmers in the *moderate* and *high adopters* had poultry units, only 64.8% and 77.7% were constructed in the recommended East-West orientation. The results also show that less than 10% of individuals in classes 2 and 3 had dedicated laying nests. Cleaning practices were well-adopted across classes with most households using water and detergents to wash the poultry unit. Similarly, up to 97.5% and 99.4% of the *moderate and high adopters,* respectively reported having well-maintained vegetation around the poultry housing facility. These findings indicate better uptake of housing practices among individuals in classes 2 and 3.

### *3.4.5. Adoption of internal biosecurity controls*

The results indicate low adoption of internal biosecurity controls across all classes. Only 16.0% and 2.2% in the *low* adoption categories had hand washing stations and foot disinfection facilities, respectively. The *moderate adoption* category had a slightly higher number of farmers owning handwashing and foot disinfection units; 26.2% and 5.5%, respectively. A similar pattern is observed in class 3 with 56.0% and 37.3% having handwashing and foot disinfection units, respectively. Despite owning the requisite facilities, only a few farmers reported implementing a strict regulation to ensure visitors washed their hands and used foot disinfectant before accessing the poultry unit. Only 30.3% of the *high adopters* insisted on farmers using protective clothing when handling the birds.

### 3.4.6. *Adoption of external biosecurity control*

Only 16.7% of class 1 and 41.3% of class 2 members reported separating birds into distinct categories. The practice of separating the birds by groups was highly adopted in class 3 with 71.0% of the farmers applying this practice. Among individuals who brought new stock, only 1.6%, 1.7%, and 14.7% in the *low*, *moderate*, and *high* adoption classes reported insisting on receiving the health records of the birds before introducing them to the flock. Other measures were inadequately practiced with 16.0%, 11.7%, and 14.7% of the *low*, *moderate*, and *high adopter* categories undertaking vaccination, respectively. Similarly, 13.5%, 22.4%, and 45.9% of the three adopter categories were isolating new birds when introduced to their flocks. Less than 1% of farmers in all three classes reported testing birds for specific diseases of concern before introducing them to an existing flock. These results indicate a low uptake of external biosecurity control.

### 3.4.7. *Adoption of nutrition measures*

Nutrition measures are among the least practiced by individuals across classes. Households in the *low* and *moderate* adoption categories mostly fed grains. Only 12.27% and 7.9% of the *low* and *moderate adopters* used feed supplements. This nature of feeding limits birds from developing adequate immunity to fight infection. The use of concentrates is highest among the *high adopters*, with 91.7% of the members, followed by *moderate adopters* at 29.9% and *low adopters* at 15.4%. Notably, proper nutrition also requires farmers to use supplements for components that may be lacking in the basal feeds. The results revealed that only 12.3%, 7.9%, and 32.0% of the individuals in the *low*, *medium*, and *high* adoption categories provided feed supplementation. These figures suggest an inadequate uptake of nutrition practices.

*3.4.8. Adoption of health management practices*

The other set of practices that were poorly adopted is poultry health management measures. Only deworming and vaccination scored highly across classes. Up to 78.7%, 48.0%, and 36.2% of *high, moderate,* and *low adopters* respectively reported using poultry deworming services. Likewise, 97.9%, 70.1%, and 67.6% of individuals in the three classes indicated that they vaccinate their birds against diseases. In contrast, only 34.2% of the *high adopters* reported controlling external parasites. The proportions are even lesser in the lower adoption categories. External parasites often carry pathogens that spread infectious diseases, hence the need to control them (Robertson, 2020). It was also alarming that only 53.1%, 65.5%, and 76.6% of individuals in the respective order from *low* to *high adopters* kept records. Sidinei et al. (2021) argue that keeping records, including visitors' logs, can minimize the entrance of infectious pathogens in broiler farms. On withdrawal practices, there was low uptake of the recommended practices, with 72.0% of the *low adopters* reporting that they continued consuming eggs during treatment. Alhaji et al. (2018) note that noncompliance with antimicrobial withdrawal period can cause low therapeutic doses and high concentration of antimicrobial residues in poultry. The residues can lead to emergence of pathogens with antimicrobial resistant genes. The behavior of farmers failing to follow the withdrawal mostly rises from the fear of financial losses that arise from discarding poultry products.

The results also indicate that burying was the most common carcass disposal practice with 91.5%, 86.0%, and 84.1% of *low, moderate,* and *high adopters,* respectively. Notably, a larger proportion of *low adopters* (9.8%) compared to *moderate* and *high* adopter groups –2.6%, and 3.2% respectively– indicated following the undesirable practice of consuming the meat of birds that die from diseases. Good flock health management requires farmers to either bury, burn, or dispose of dead carcasses in appropriate pits. Slaughtering is not recommended because it can potentially spread diseases. Feeding carcasses to other animals also reflects poor biosecurity. One of the most important biosecurity practices in poultry involves following the all-in-all-out (AIAO) principle, which reduces the chances of microorganisms remaining viable after disinfection (Sidinei et al., 2021). Some farmers sometime include a fallow period as part of AIAO principle, but this is not a requirement. The results demonstrate low uptake of the all-in-all-out principle with only 22.8% of the individuals in the *high adoption* class following it.

The approach taken by this study agrees with previous studies, including Alhaji et al. (2018) and Sidinei et al. (2021), which group farmers into different clusters. The study by Sidinei et al. (2021) applied cluster analysis to group broiler farmers into two biosecurity clusters: G1(low biosecurity level) and G2 (high biosecurity level). Besides evaluating fewer biosecurity indicators, the study does not also report any statistics justifying the use of two clusters. This study has demonstrated using model-based latent class analysis that poultry farmers in the study area belong to 3 classes with distinct adoption behavior. The study observes, however, that farmers have not fully embraced biosecurity measures, with some practices being followed by as low as 1% of the farmers. The next section explores the link between the observed pattern of biosecurity adoption and the key animal health indicators.

### *3.4.9. Biosecurity adoption and key poultry health indicators*

Table 3. 5: The correlation between predicted classes and key poultry health indicators

| | **Predicted class** | **Mortality Rate** | **Used antibiotics** |
|---|---|---|---|
| **Predicted class** | 1.0000 | | |
| **Mortality Rate** | -0.3564*** | 1.0000 | |
| **Used antibiotics** | 0.4118*** | -0.2026*** | 1.0000 |

*Note: *, **, *** Significant at 10%, 5%, and 1%, respectively; Source: Survey Data 2021*

The study conducted a pairwise correlation analysis to understand the relationship between biosecurity adoption and key poultry health indicators. Two indicators highlighted by World Bank (2021) including, mortality rate and antibiotics use were analyzed against biosecurity classes. Table 3.5 summarizes the results of the pairwise correlation matrix. Both indicators had statistically significant correlations with the predicted classes of biosecurity adoption. The mortality rate was found to have a negative relationship with the level of adoption, suggesting that individuals in higher adoption categories experienced lower stock deaths. This finding confirms the conclusion of Laanen et al. (2014) that biosecurity can improve poultry health.

The use of antibiotics was more common among individuals in the higher adoption classes –a positive and statistically significant correlation coefficient of 0.41 level. The finding contradicts Davies and Wales (2019) and Moffo et al. (2022), both of who conclude that biosecurity reduces antimicrobial use. A more plausible explanation is that farmers who have adopted more biosecurity practices are risk averse and are using antibiotics to prevent infection. This finding should, however, not be over-interpreted since the use of antibiotics is not necessarily bad; it is the overuse or inappropriate use that should be a concern. Future studies may want to characterize the use of antibiotics among these farmers to understand the amount, frequency, and type of antibiotics used. Notably, many farmers in the lower adoption group reported taking no intervention to cushion sick birds. As poultry production in SSA intensifies, it is likely that overuse of antibiotics may increase, leading to increased antimicrobial residues in eggs and meat. Previous studies show high level of antimicrobial drug residues in meat meant for consumption in Kenya (Mitema et al., 2001).

*3.4.10. Determinants of adoption of biosecurity measures*

Table 3.6 summarizes the regression results for potential determinants of biosecurity adoption. The Pearson's correlation test conducted on the covariates of MLogit indicated no serious cases of multicollinearity. Mwololo et al. (2019) note that the pairwise correlation coefficients of the explanatory variable should be less than 0.5 for MLogit to produce consistent estimates. In this case, all the explanatory variables had coefficients less than 0.5. Further, the data satisfies the requirement of independence from irrelevant attributes (IIA) by the specification of LCA, which ensures mutual exclusivity among classes.

The econometric results indicate that information access, perceived benefits, on-farm income, education of the household head (HH), age of household head, years of experience, flock size, gender of the household head, and household size had statistically significant effect on the uptake of biosecurity practices. Access to information was the greatest driver of adoption and increased the probability of belonging to the '*high adopters*' category by 24.9%. Further, farmers who accessed information on biosecurity practices were 20.9% less likely to belong to *moderate adopters*. Information access improves the awareness, enhances adoption, and hence the observed pattern. Kagoya et al. (2018) find that awareness facilitates the adoption of agricultural technologies.

The perceived benefit of biosecurity measures increased and reduced the probability of being in the *high and moderate* adoption category in equal measure. The finding is consistent with those obtained through a one-way ANOVA, which indicates that farmers in the higher adoption categories were more positive about the benefits of biosecurity measures. A further breakdown of the differences by Tukey post hoc test reveals that individuals in the *high adopters'* category had a more positive view of biosecurity measures compared to those in the *low* and *moderate* classes (0.87±0.26, $p$=0.003; 0.90±0.26, $p$=0.002). These findings coincide with Yamano et al.(2015) and Sidinei et al. (2021) both of who identify perception as a strong predictor of adoption.

Education is statistically significant with a negative sign in the *low* and *moderate* adoption classes and a positive sign among the *high* adopters. More educated farmers were 1.1% less likely to belong to the *low* and *moderate* adoption categories. In contrast, one extra year of formal education increased the probability of belonging to the *high* adoption class by up to 2.1%. These findings agree with Robertson (2020) who argues that education and training are essential for the success of biosecurity on the farm. Other studies, including Moore et al. (2008), Wolff et al.(2017), and Sidinei et al.(2021) also conclude that education facilitates the adoption of the recommended animal health practices. Farmers with more years of experience in poultry production had a 0.8% lower probability of belonging to the *low adopters'* class. This finding coincides with Etuah et al. (2020) who argue that more years of experience enable farmers to acquire ideas: these ideas can facilitate the uptake of good practices.

The effect of age on adoption of biosecurity measures was statistically significant in the *moderate* and *high* adoption classes. However, the sign on the marginal values differs between the two classes, indicating that younger and medium aged farmers are more likely to have a high adoption behavior, while older farmers moderately implement biosecurity practices. The impact of age on the adoption of technology varies in empirical literature. For instance, Kagoya et al. (2018) find that younger farmers are significantly more aware with a higher probability of adopting technologies. They further argue that younger farmers are more energetic, dynamic, and flexible to use new technologies. In contrast, Fisher et al. (2018) find that the age of the household head does not matter in the adoption of technology. This study agrees with the findings of Kagoya et al. (2018). The interaction variable between age, experience, and years of formal education was not significant in any adoption class.

Flock size was significant in all the categories with a negative sign among the *low* and *moderate adopters* and a positive effect on the *high adoption* class. This pattern can be explained by the fact that increasing the number of birds makes them more vulnerable to diseases with a risk of huge losses, hence better adoption of biosecurity measures. It is also possible that smaller flock sizes in classes with low adoption of biosecurity measures is the result of reverse causality instigated by higher mortality rate –lower adoption of biosecurity practices leading to smaller flock sizes. A more plausible explanation is that larger flocks are associated with commercialization, loss reduction measures and hence the higher likelihood of adopting biosecurity practices.

Male-headed households were 12.4% more likely to belong to the *moderate* adoption class. The results suggest possible gender gaps in the uptake and implementation of biosecurity measures. Gebre et al. (2019) make similar conclusions, arguing that male-headed households have a higher propensity to adopt the technology. The household size also reduced the probability of belonging to the *low* adoption class. A possible explanation of this pattern is that more members in the household represent additional labor required to implement biosecurity measures.

Table 3. 6: Effect of household characteristics on probability of latent class membership – multinomial logistic regression model

| **Variable** | **Low Adopters (n=157)** | | | **Moderate Adopters (n=163)** | | | **High Adopters (n=181)** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Margin dy/dx w.r.t (Std. Err.)** | **[95%Conf Interval]** | | **Margin dy/dx w.r.t (Std. Err.)** | **[95% Conf Interval]** | | **Margin dy/dx w.r.t (Std. Err.)** | **[95%Conf Interval]** | |
| Information access (1=yes) | -0.040 (0.033) | -0.104 | 0.025 | -0.209*** (0.067) | -0.341 | -0.077 | 0.249*** (0.070) | 0.111 | 0.387 |
| Perceived Benefits (Index) | -0.001 (0.005) | -0.011 | 0.009 | -0.022** (0.012) | -0.044 | 0.001 | 0.022* (0.013) | -0.002 | 0.047 |
| HIST of on-farm income | -0.005** (0.003) | -0.010 | -0.000 | -0.011* (0.006) | -0.022 | 0.001 | 0.016** (0.006) | 0.003 | 0.028 |
| Flock Size | -0.004*** (0.000) | -0.005 | -0.003 | -0.001* (0.001) | -0.003 | 0.000 | 0.005*** (0.001) | 0.004 | 0.006 |
| Education of HH (years) | -0.011** (0.004) | -0.019 | -0.002 | -0.011 (0.010) | -0.030 | 0.008 | 0.021** (0.011) | 0.000 | 0.043 |
| Gender of HH (1=Male) | -0.026 (0.026) | -0.077 | 0.026 | 0.124** (0.061) | 0.005 | 0.243 | -0.098*** (0.067) | -0.230 | 0.033 |
| Age of HH (years) | 0.006 (0.010) | -0.013 | 0.026 | 0.070*** (0.026) | 0.019 | 0.121 | -0.076*** (0.025) | -0.125 | -0.027 |
| Age of HH squared | -0.000 (0.000) | -0.000 | 0.000 | -0.001** (0.000) | -0.001 | -0.000 | 0.001*** (0.000) | 0.000 | 0.001 |
| Household Size | -0.009* (0.005) | -0.019 | 0.001 | 0.004 (0.008) | -0.012 | 0.019 | 0.005 (0.008) | -0.011 | 0.022 |
| Years of Experience | -0.008* (0.004) | -0.017 | 0.000 | 0.006 (0.010) | -0.015 | 0.026 | 0.002 (0.012) | -0.021 | 0.028 |
| HIST of non-farm income | -0.003 (0.002) | -0.007 | 0.001 | -0.001 (0.005) | -0.010 | 0.009 | 0.004 (0.005) | -0.006 | 0.014 |
| Farm Size (Acres) | -0.005 (0.006) | -0.016 | 0.006 | -0.001 (0.008) | -0.018 | 0.015 | 0.006 (0.009) | -0.011 | 0.024 |
| Age.exp.educ | -0.000 (0.000) | -0.000 | 0.000 | -0.000 (0.000) | -0.000 | 0.000 | 0.000 (0.000) | -0.000 | 0.000 |
| genint | 0.000 (0.000) | -0.000 | 0.000 | 0.000 (0.000) | -0.000 | 0.000 | 0.000 (0.000) | -0.000 | 0.000 |

Note: HIS stands for 'Inverse Hyperbolic Sine Transformation'; Age.exp.educ is an interaction variable between age, experience, and years of formal education; genint is an interaction term for gender, education, and flock size; HH is a short form of Household; *dy/dx* is the marginal effect; ***, **, * means the marginal value is significant at 1%, 5%, and 10%, respectively; *Source: Survey Data 2021*

The results indicate further that on-farm income is among the key variables influencing adoption of biosecurity measures. On-farm income increased the probability of belonging to the *high adopters* category, while having an inverse effect on the *low* and *moderate* adoption classes. These findings are consistent with the argument that farmers are rational and will attempt to improve enterprises that earn income. Further, on-farm income provides the resources required to implement biosecurity practices.

These results provide insight into factors influencing biosecurity adoption. Access to information on biosecurity measures and poultry production is the greatest driver of biosecurity. Consequently, intensive dissemination of information can facilitate the rapid uptake of biosecurity measures among poultry farmers in Nyanza region and other places in SSA and beyond. Information performs multiple roles, including improving the perception of farmers toward biosecurity measures.

## 3.5. Conclusion and recommendations

This study evaluates adoption of biosecurity measures, which have been shown to manage livestock diseases effectively and sustainably. The study implements a model-based clustering approach – *the latent class analysis*– to describe adoption patterns among poultry farmers. This approach is superior to other methods for cluster analysis because it can be evaluated for model fit. Besides LCA, the study constructs a correlation matrix to illustrate the link between adoption of biosecurity measures and key animal health indicators. Lastly, the study implements an MLogit to explore the potential determinants of adoption of biosecurity measures.

The results demonstrate that poultry farmers in Nyanza belong to three biosecurity classes characterized by *low*, *moderate*, and *high* adoption behaviors. These findings mirror adoption patterns for biosecurity practices among poultry farmers in Kenya and other Sub-Saharan African countries. The evidence from the study indicates generally low uptake of preventive veterinary approaches. There is a strong correlation between increased uptake of biosecurity and poultry health outcomes. Farmers implementing more biosecurity practices had significantly lower mortality rates (-0.3564; *p-value – 0.000*). The finding that individuals in the higher adoption classes had increased use of antibiotics was contrary to the expectation. However, such results indicate that the antibiotics may be beneficial in the short term, but continued use may lead to antibiotic resistance. The greater use of antibiotics can also be explained by the risk averse nature of farmers who implement better biosecurity measures. Lastly, this study presents explicit evidence that adoption of biosecurity measures is largely driven by access to information on such practices. Farmers who accessed information on biosecurity measures were 25% more likely to have high biosecurity adoption behavior.

Based on the forgoing discussions, it is evident that information access is the major driver of biosecurity adoption among small-scale poultry farmers. Therefore, policies aimed at improving poultry production in general biosecurity adoption should prioritize increasing information access and improving awareness on the benefits of biosecurity measures. This can be achieved by promoting and investing in targeted education and extension programs that provide farmers with information about biosecurity measures and their benefits. Further, the county and national government could support farmers to access the resources that may enable them to implement the measures more effectively. The government can also subsidize extension services and promote biosecurity measures in different platforms accessible to poultry farmers. These measures will not only improve the poultry health and productivity but also support the growth of the sector to meet local demand.

# CHAPTER FOUR: ASSESSING THE EFFECT OF FARM BIOSECURITY ADOPTION ON COST EFFICIENCY OF SMALLHOLDER POULTRY FARMERS IN NYANZA, KENYA

## 4.1. Abstract

As the demand for poultry products continues to rise in Sub-Saharan Africa (SSA), productivity has remained generally low. One of the key constraints to better productivity is poultry diseases. Farmers attempts to manage diseases through clinical treatment are not only costly but have also contributed to the increasing concern of antimicrobial resistance. This study was motivated by the need to assess the cost efficiency of alternative strategies for disease management, otherwise referred to as biosecurity measures. These measures have been shown to improve the health of livestock and are associated with reduced need for antibiotic treatments. However, empirical literature suggests low uptake of the measure among poultry farmers in SSA, Kenya included. Understanding the cost efficiency of these measures is key to their promotion as strategies to tackle health concerns and improve productivity. This study employs a three-step estimation procedure: first, it uses latent class analysis (LCA) model to describes adoption patterns. Secondly, a stochastic frontier analysis is used to generate cost efficiency scores and the inefficiency effects. Lastly, a one-way ANOVA is used to compare efficiency between adoption categories. The results of the LCA model reveal three patterns of biosecurity uptake with *low, moderate*, and *high* adoption behaviors. The average cost efficiency scores are 0.492, 0.610, 0.692 for the *low, moderate,* and *high adopters,* respectively. While the overall score of 0.603 indicate that poultry farmers in Nyanza are largely cost efficient, the observed pattern illustrate better cost efficiency by increased use of biosecurity measures. The inefficiency model shows that more years of experience in poultry farming and owning larger stock sizes reduces farm cost inefficiency. The findings of this study form ground for the promotion of biosecurity measures.

**Keywords**: Poultry biosecurity; latent class analysis; stochastic frontier analysis; cost efficiency; Sub-Saharan Africa

## 4.2. Introduction

Steady growth in the global population coupled with shrinking agricultural productivity has escalated the crisis of malnutrition. The crisis is more severe in Sub-Saharan Africa (SSA), which hosts at least 23% of food-insecure households worldwide (Erdaw & Beyene, 2022). Consumption of animal proteins even in very low quantities has been shown to improve the nutrition status (Erdaw & Beyene, 2022). Poultry is the best source of animal sourced protein for poor households for various reasons; (1) poultry products are affordable, (2) they are accessible, (3) poultry meat has low-fat content, and (4) the products have minimal religious restrictions. For these reasons, the demand for poultry products outstrips that of other livestock.

Despite the rising demand for poultry products in SSA, production quantities have not grown to match the trend. The low production is partly blamed on the cost and quality of feed or stocking the less productive breeds. But besides these, diseases are a major constraint that causes poor performance among smallholder poultry farmers (Erdaw & Beyene, 2022). Diseases like Newcastle are highly infectious and have been reported to cause huge losses among poultry farmers. Diseases do not only lead to shrinking stock sizes, but also lower chicken productivity and increase enterprise costs associated with control measures.

There are two broad strategies for managing diseases: preventive –otherwise referred to as *biosecurity measures*– and control measures. The control measures involve diagnosing infections and applying the necessary treatment, mostly using antibiotics. Some challenges associated with this approach are the high cost of clinical procedures, poor health outcomes caused by the improper diagnosis, and misuse of antibiotics leading to antimicrobial resistance. In contrast, biosecurity measures prevent the entry and establishment of infectious agents, and has been shown to improve health outcomes (Fasina et al. 2012; Sidinei et al. 2021; Yoo et al. 2022);Otieno et al., 2023).

Despite the benefits of biosecurity measures, different studies report low awareness and uptake of the respective practices (Nantima et al. 2016;Nyokabi et al., 2018; Otieno et al., 2023). The low awareness and adoption mean that farmers lack information on the usefulness of such practices in combating poultry diseases. Notably, implementing full farm biosecurity measures requires additional investment. It is not clear whether adoption of such measures confer any cost benefits to the farmers. Farmers may be hesitant to put up more investment required to ensure biosecurity compliance on grounds that they are more costly. This link has not yet been established in the existing empirical literature. This study tests the hypothesis that increased uptake of biosecurity measures do not influence poultry enterprise cost efficiency.

An entity is cost-efficient if it is both technically and allocatively efficient (Kumbhakar & Tsionas, 2021). Such entities achieve optimum output levels with a least-cost input combination. Technical efficiency means producing the maximum possible output from a given set of inputs, utilizing the existing technology. In contrast, allocative efficiency reflects the ability of a firm to use inputs optimally given their prices. Although inefficiency may result from farmer socioeconomic characteristics, empirical evidence suggests that technology adoption can improve efficiency (Shrestha et al., 2014; DeLay et al., 2022). Using better technologies allow farmers to operate on higher production frontiers, optimizing outputs and inputs.

There is an extensive literature tackling the efficiency of poultry farms (Ojo et al. 2013; Luvhengo et al. 2015; Pilar et al., 2018; Etuah et al. 2020). However, most of these studies are in the developed countries and focus on technical efficiency. While technical efficiency provides information on the optimal use of resources, it does not consider the cost of inputs. Notably, smallholder farmers are financially constrained with several needs competing for limited funds. Therefore, understanding the cost-minimizing input combination is crucial for optimum farm performance.

This study examines the effect of increased uptake of biosecurity measures on poultry farmers' cost efficiency. This is achieved in three stages: first, latent classes representing various levels of biosecurity adoption are constructed. Secondly, cost efficiency scores are estimated using stochastic frontier analysis. Lastly, a one-way ANOVA and Tukey post-hoc test are used to compare the mean cost efficiency of the resulting adoption classes. This approach is explicit and conclusively captures both elements of adoption and the corresponding effect on cost efficiency. The study also evaluates the inefficiency model to predict the sources of deviation from the optimal cost frontier.

## 4.3. Methodology

### 4.3.1. Analytical framework

A three-stage estimation strategy is employed: first, a latent class analysis (LCA) model that describes biosecurity adoption patterns is constructed. The model uses the observed indicators of biosecurity: introduction and movement of birds, control of people and equipment, control of wild animals, proper carcass and waste disposal, hygienic measures, poultry health management routines, and holistic nutrition practices. Each practice under these measures is a discrete variable labeled "1" for a farmer who implements it, and "0" otherwise. Latent class modeling assumes that the population can be subdivided into uniform segments consisting of individuals with similar adoption behaviors. These segments are known as classes and cannot be directly observed (latent). However, individuals can be assigned classes following the patterns observed in the biosecurity indicators they use.

In step two, the study employs stochastic frontier analysis (SFA) to predict farmers' cost efficiency scores. SFA is preferred in this study over data envelopment analysis (DEA) for two reasons. First, it relaxes the stringent assumption on the nature of outputs and inputs. DEA is sensitive to inconsistencies in data measurement or errors arising from statistical noise (Mugera, 2013). In contrast, this study relies on household survey data, which are bound to errors since farmers must recall past information. Secondly, DEA is extremely sensitive to outliers or changes in data. Yet, in practice, outliers are inevitable as targeted farmers have varied input use and attain different output levels. SFA accounts for outliers and statistical variations by decomposing the error term into statistical noise and inefficiency effects. This strategy ensures a more accurate estimation of cost efficiency scores, accounting for deviations caused by statistical errors. Lastly, SFA makes it possible to include the inefficiency component.

Since farmers use different levels of biosecurity, it is possible to construct separate frontiers for each adoption category. However, the difference in technology must be discernible as noted by Oumer et al. (2022). Such estimation also requires large datasets to avoid sample fragmentations. In this study, there are no apparent technological differences, hence there is no need to estimate separate frontiers. Since differences in cost efficiency are sometimes attributed to socioeconomic and institutional factors –access to information, income, age, experience, gender of the farmer, and size of land– it is important to account for them. The SFA model controls for these observed farm heterogeneities by specifying an inefficiency component. This strategy eliminates bias in the parameters of cost efficiency as noted by Oumer et al. (2022).

In the last stage, a one-way ANOVA and Tuckey post-hoc tests are used to compare differences in cost efficiency scores between classes. The one-way ANOVA also helps to test the hypothesis that cost efficiency does not differ significantly by the level of biosecurity adoption. This hypothesis is rejected if the *p-value* is less than the level of significance. Rejecting the null hypothesis would mean that the use of more biosecurity measures does not lead to better cost efficiency.

### 4.3.2. Empirical model

*4.3.2.1.Latent class model specification*

For the empirical application of LCA, two sets of probabilities are specified: the posterior and outcome probabilities, as shown in Equations (4.1) and (4.2), respectively:

$$P_{is} = \frac{\exp\,(w_i'\theta_s)}{\sum_{s=1}^{S}\exp\,(w_i'\theta_s)} \tag{4.1}$$

$$\mathrm{Prob}_{in|s}(j) = Prob(Y_{in} = j|class = s) = \frac{\exp\left(X'_{in,j}\beta_s\right)}{\sum \;\; _{j=1}^{J}\left(X'_{in,j}\beta_s\right)} \tag{4.2}$$

Where $\beta_s$ and $\theta_s$ are class-specific parameters, while $w_i$ is a vector of the observable biosecurity attributes. $\mathrm{Prob}_{in|s}$ is the outcome probability; it represents the likelihood of a farmer *i* following biosecurity measure *n* in $Y_{in}$ choice situations. The outcome probabilities can be interpreted as the proportion of individuals in a class who follows the corresponding biosecurity practice. In contrast, $P_{is}$ is a posterior probability: the likelihood of an individual belonging to a specific latent class.

Both outcome and posterior probabilities are computed following the maximum likelihood estimation (MLE) of Equations (4.3) and (4.4), respectively:

$$P_{i|s} = \prod_{Y_{in}}^{Y_i} P_{i|s} \tag{4.3}$$

$$lnL = \sum_{i=1}^{N} \ln L_i = \sum_{i=1}^{Q} ln\left[\sum_{n=1}^{N} P_{is}\left(\prod_{n=1}^{Y_i} L_{in|s}\right)\right] \tag{4.4}$$

The resulting posterior probabilities are used to assign individuals to adoption classes, while the outcome probabilities describe class-specific adoption behavior. The decision on the number of classes is determined by the values of information criteria. Two of the most common information criteria include the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). In case of disparity between the values of AIC and BIC, an appropriate model is selected by BIC which applies strict penalties on extra classes.

*4.3.2.2.Stochastic cost frontier*

The cost frontier is of the general form shown in Equation (4.5) as specified by Coelli et al. (2005).

$$c_i \geq c\left(w_{1i}, w_{2i}, \dots, w_{Ji}; q_{1i}, q_{2i}, \dots, q_{Ni}; \beta_i\right). \exp\{v_i + u_i\} \tag{4.5}$$

Where $c_i$ represent the cost of $i^{th}$ farmers; *c(.)* is a linearly homogenous, non-decreasing cost function with concave prices; $w_{ji}$is a vector of $j^{th}$ input prices; $q_{ni}$ represent $n^{th}$ output; while $v_i$

and $u_i$ are error terms, representing the random effects –factors outside the control of a farmer, also referred to as statistical noise– and cost inefficiency components, respectively.

The two error terms $v_i$ and $u_i$ have different assumptions on their distribution. $v_i$ is independently and identically distributed with a univariate normal distribution ($v_i \sim iidN(0, \sigma_v^2)$), while $u_i$ has a truncated-normal distribution ($N^+(\mu_i, \sigma_u^2)$, respectively. The values of statistical noise and inefficiency effects are distributed independently of each other (Etuah et al., 2020). $v_i$ is assumed to be symmetric, whereas $u_i$ is asymmetric. The non-symmetric nature of $u_i$ makes ordinary least squares (*OLS*) inappropriate in estimating the model. *OLS* produces intercepts with downward bias and no farmer-specific cost inefficiencies (Etuah et al., 2020). The bias can be adjusted using three approaches: the modified ordinary least squares (MOLS), corrected ordinary least squares (COLS), or the maximum likelihood estimation (MLE) (Kumbhakar & Lovell, 2000). However, MLE as specified by Battese and Coelli (1995) is asymptotically more efficient.

The assumptions on the distribution of the error terms introduce two variances: $v_i = \sigma_v^2$ and $u_i = \sigma_u^2$ that must be estimated alongside the parameter estimate, $\beta_i$. These variances are parameterized as $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $(\Upsilon) = \frac{\sigma_u^2}{\sigma_v^2} + \sigma_u^2$ (Etuah et al., 2020). The parameter $\Upsilon$ is the indicator of cost inefficiency. Battese and Coelli (1995) note that $\Upsilon$ lies between 0 and 1, where $\Upsilon = 0$ implies no cost inefficiency; meaning that all deviations from the frontier are a result of random effects. On the other hand, $\Upsilon = 1$ signifies that all deviations are due to cost inefficiency; in such cases, SFA produces similar estimates to those of the DEA model.

The value of $\Upsilon$ can be confirmed by a generalized likelihood ratio (*GLR*) test of the form $\lambda = -2lnLk$. *GLR* tests the null hypothesis of non-stochastic inefficiency effects (that is, $\Upsilon = 0$). This hypothesis provides further ground to justify the use of the stochastic cost frontier and the MLE as opposed to OLS (Etuah et al., 2020). The presence of stochastic inefficiency effects justifies the use of SFA and MLE, in which case, individual cost efficiency ($CE_i$) can be computed as a ratio of minimum cost to the corresponding enterprise costs *–see Equation (4.6)*. $CE_i$ ranges between 0 and 1, where 1 represents a fully efficient farm.

$$CE_i = \frac{c\left(w_{1i}, w_{2i}, \dots, w_{Ji}; q_{1i}, q_{2i}, \dots, q_{Ni}; \beta_i\right).\exp\{v_i\}}{c\left(w_{1i}, w_{2i}, \dots, w_{Ji}; q_{1i}, q_{2i}, \dots, q_{Ni}; \beta_i\right).\{v_i + u_i\}} = \exp(-u_i) \tag{4.6}$$

The first step in estimating cost efficiency via SFA involves specifying the functional form that can disintegrate the error terms. The correct specification of a model's functional form is necessary for consistent estimates of cost efficiency as noted by Oumer et al. (2022). Two of the most common functional forms are the Cobb-Douglas and Transcendental-logarithmic –Translog– models. Trans-log performs better with large samples because it has greater degrees of freedom. In contrast, studies that employ smaller samples mostly specify a Cobb-Douglas model. Another advantage of Cobb-Douglas over Trans-log is its simplicity and ease of interpreting the coefficient estimates –the parameters of a Cobb-Douglas function are simply a measure of elasticity response. A further assessment of the form that best fits the data can be achieved through the likelihood ratio (*LR*) test: the results of the *LR* test are summarized in Table 4.1.

The *p-value* of the Chi-Square statistic provides evidence to reject the null hypothesis; suggesting that the Translog functional form provides a better model fit. This conclusion can also be reached by the values of AIC and BIC, which are both parsimonious for the Translog functional form.

Table 4. 1 Likelihood-ratio test

| Model | N | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| cb | 501 | . | -813.408 | 7 | 1640.816 | 1670.332 |
| tr | 501 | . | -528.835 | 17 | 1091.670 | 1163.352 |

Note: *cb –Cobb-Douglas Model, tr –Translog Model; LR chi2(10) = 569.15 Prob > chi2 = 0.0000 (Assumption: cb nested in tr); AIC –Akaike's information criterion and BIC –Bayesian information criterion; (Source: Survey Data 2021)*

Consequently, the study specifies a Translog cost frontier in its compact form as shown in Equation (4.7):

$$\ln\left(\frac{c_i}{w_{iJ}}\right) = x_i'\beta + (v_i + u_i) \tag{4.7}$$

In a single-output three inputs scenario, the frontier in Equation (4.7) above can be linearly expressed as shown in Equation (4.8)(Coelli et al., 2005; Stratopoulos et al., 2000):

$$lnC_i = \beta_0 + \beta_q lnq + 0.5\beta_{qq}(lnq_i)^2 + \sum_{j=1}^{3}\beta_j lnw_j + 0.5\sum_{j=1}^{3}\sum_{m=1}^{3}\gamma_{jm}lnw_m lnw_j$$

$$+ 0.5\sum_{j=1}^{3}\phi_j(lnw_j)^2 + \sum_{j=1}^{3}\beta_{qj}lnq\ lnw_j + (v_i + u_i) \tag{4.8}$$

Where $C_i$ represent the total cost of the poultry enterprise; $w_j$ is the price of inputs –there are three inputs, hence the value of 3. $q$ is a single output measured here as total revenue of the poultry enterprise. The study assumes that all farmers realize homogeneous output at a price of 1 KShs per unit: at the time of this study, 1 USD was exchanged at 117 KShs.

Equation (4.8) is estimated following a maximum likelihood estimation (MLE). Further, the study species an inefficiency model, as shown in Equation (4.9) to capture socioeconomic and institutional characteristics, including the perceived usefulness of biosecurity measures.

$$U_i = \delta_0 + \sum_{n=1}^{11}\delta_n Z_{ni} \tag{4.9}$$

where $Z_{ni}$ represent the *n=11* inefficiency effects, while $\delta_n$ is a vector of the parameters being estimated; $\delta_0$ is the constant term. SFA allows for a one-step estimation of Equations (4.9). The specification of an inefficiency component is justified by the results of the generalized likelihood ratio test (*see Table 4.2*), which indicate the model with inefficiency components is more appropriate.

Table 4. 2 The generalized likelihood ratio test

| Model | N | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| null | 501 | . | -528.835 | 17 | 1091.670 | 1163.352 |
| full | 501 | . | -492.853 | 30 | 1045.705 | 1172.203 |

*Note: null –The null model; full –the model with inefficiency components; LR* $\chi^2(13) = 73.65$ *(Assumption: null nested in full); Prob >* $\chi^2 =$ *0.0000; (Source: Survey Data 2021)*

The farm cost efficiency scores are estimated via $\exp\{-E(u \mid \varepsilon)\}$, the estimator of Battese and Coelli (1988). A one-way ANOVA is used to compare the mean cost efficiencies by biosecurity adoption category. One-way ANOVA tests the null hypothesis that cost efficiencies do not differ by the level of biosecurity adoption. If the results show significant differences, a Tukey post-hoc test is conducted to reveal the classes that differ significantly and by how much.

*4.3.2.3.Description of data*

This study uses a subset of household data collected through the USAID-TRANSFORM Project. The overall goal of the project is to sustainably strengthen animal-sourced food systems to prevent antimicrobial residues, zoonoses, and transboundary diseases. It hopes to achieve this objective through the promotion of practices that embed preventive healthcare, thus reducing the use of antimicrobials while optimizing feed resources to enhance productivity and increase income from livestock enterprises in the intermediate term. The project targets both poultry in Nyanza with biosecurity information. The choice of Nyanza was intended both to leverage on the presence and network of Heifer Project International and because of the significant role poultry plays in the region (Otieno et al., 2023).

McClave's (2014) formula was used to sample 502 poultry farmers in Nyanza after applying a contingency of 10%. The use of McClave's actual income indicator formula was necessary because baseline information was available for the target farmers. Some of the key inputs in the formula are the baseline mean and standard deviation of income. The sample was obtained through a systematic random sampling method. The sampling frame consisted of poultry farmers organized into producer organizations and operating in the four counties of Nyanza: Migori, Homabay, Siaya, and Kisumu. The frame was provided by Heifer Project Kenya from previous projects that targeted the same farmers. The data was collected through a structured questionnaire programmed in the SurveyCTO software. The variables of interest are described in Table 4.3, including how they were measured. One observation was dropped due to many missing values, hence 501 in the succeeding analysis. The inverse hyperbolic sine transformation was applied to linearize the log-transformed variables. The strategy ensures that individuals with zero observations can be retained in the analysis (Bellemare & Wichman, 2020).

## 4.4. Results and discussions

### *4.4.1. Descriptive analysis*

The latent class model generates three categories of biosecurity adoption. Following the patterns of response probabilities, these classes are defined as "*low*", "*medium*" and "*high*" adopters. The results indicate a uniform distribution of individuals within classes with *medium adopters* accounting for 36.74% of farmers, followed by *high adopters* at 31.79%, and *low adopters* having 31.48%. The outcome probabilities reveal that at least 50% of *low adopters* follow

4 biosecurity practices. The *medium adopters* come second with at least 50% of the members observing 9 measures. The *high adopters* also represent the best adoption behavior with at least 50% following 13 biosecurity practices. Despite the distinct patterns of adoption, a generally low uptake of biosecurity among poultry farmers was observed.

Posterior probabilities that assign classes based on individual response patterns are generated. *Table 4.3* summarizes the descriptive statistics by adoption category. The results present a notable pattern of the socioeconomic, institutional, and technological characteristics within the different levels of biosecurity adoption. Individuals in high and moderate adoption classes had significantly higher revenues. A further breakdown of the production costs indicates that farmers in the *moderate* and *high* biosecurity adoption categories incurred significantly higher feeding costs and lower health expenditures. Contrary to the notion that biosecurity measures are labor-intensive, it was observed that there are no statistically different expenditures on labor. The finding that male-headed households dominate high and moderate classes indicates that there are gender gaps in the uptake of biosecurity practices.

The difference in age was also statistically significant, with younger farmers dominating the *high adopters* category. Farmers in the *high* and *moderate* adoption classes had significantly more years of formal schooling compared to those in low adoption category. Similarly, the higher adoption classes were dominated by individuals with more years of experience in poultry production. Up to of households in the *high* adoption class had access compared to 71% and 75% in the *moderate* and *low* adoption categories, respectively. It was also observed that individuals practicing more biosecurity measures had significantly higher on-farm income compared to their colleagues.

Table 4. 3 Descriptive statistics of variables used in the study.

| Variable | Description | Low Adopters | Medium Adopters | High Adopters | Pooled Sample |
|---|---|---|---|---|---|
| | | ***Mean (Std. Dev)*** | ***Mean (Std. Dev)*** | ***Mean (Std. Dev)*** | ***Mean (Std. Dev)*** |
| Revenues | Total income from the sale of chicken and chicken products (KShs). | 7477.83 (34823.33) | 27433.44 (181334.60) | 107148.87 (284062.36) | 49979.27 (204932.10) *** |
| Total cost | Total Cost (KShs). | 103176.02 (711046.90) | 231684.32 (1476570.70) | 128384.67 (161428.72) | 154093.40 (936240.00) |
| Feeds cost | Expenditure on feeds per chicken (KShs/chicken). | 444.18 (1757.67) | 572.27 (1739.68) | 868.19 (1538.83) | 639.04 (1682.07) * |
| Wage rate | Wage rate per hour (KShs/hour). | 31.73 (25.14) | 37.19 (27.02) | 35.53 (30.60) | 34.88 (27.85) |
| Health cost | Cost of healthcare services per chicken. | 40.93 (104.13) | 27.56 (77.33) | 28.69 (65.62) | 32.16 (83.10) *** |
| Gender | Gender of the household head. | 0.44(0.50) | 0.64(0.48) | 0.64(0.48) | 0.58(0.49) *** |
| Age | Age of the household head. | 51.17(11.18) | 53.53(10.22) | 48.71(13.14) | 51.05(11.79) *** |
| Education | Years of formal schooling by the household head. | 9.92 (4.2) | 11.39(4.15) | 13.29(3.44) | 11.62 (4.16) *** |
| Farm size | Size of the farm. | 1.99(1.59) | 2.48(2.85) | 3.38(11.90) | 5.74(6.76) |
| Experience | Years of experience in poultry production. | 4.69(6.41) | 6.17(6.54) | 6.27(7.17) | 6.76 (0.42) * |
| Information | Access to poultry production information during the year. | 0.75(0.44) | 0.71(0.45) | 0.86(0.35) | 0.77(0.42) *** |
| Non-farm income | Income earned for other non-farm enterprises. | 85617.96 (646561.62) | 206429.88 (963133.40) | 195067.76 (759939.98) | 164465.80 (801091.90) |
| On-farm Income | Income earned in the farm enterprises. | 37268.93 (127001.79) | 43370.15 (192331.27) | 113658.13 (282732.88) | 66851.65 (216893.60) *** |

*Source: Survey data (2021); note: ***, **, *, shows that the differences in mean are significant at 1%, 5%, and 10% levels of significance, respectively*

### 4.4.2. *Cost efficiency*

#### ***4.4.2.1. Estimated cost frontier***

Table 4. 4 Determinants of cost frontier

| **Variables** | **Regression output *with respect to* one-step stochastic frontier and inefficiency estimates** | | | |
|---|---|---|---|---|
| **Log (Total cost)** | **Parameters** | **Coef. (Robust Std. Err.)** | **[95% Conf. Interval]** | |
| Log (revenues) | $\beta_1$ | -0.006(0.023) | -0.051 | 0.039 |
| Log (health) | $\beta_2$ | 0.133(0.091) | -0.045 | 0.311 |
| Log (feed) | $\beta_3$ | 0.745(0.081) *** | 0.586 | 0.903 |
| Log (wage) | $\beta_4$ | 1.061(0.114) *** | 0.837 | 1.285 |
| log (revenues_health) | $\beta_5$ | 0.007(0.003) ** | 0.001 | 0.013 |
| log (revenues_feed) | $\beta_6$ | 0.005(0.004) | -0.003 | 0.014 |
| log (revenues_wage) | $\beta_7$ | -0.004(0.003) * | -0.009 | 0.001 |
| 0.5*log (revenues Sq) | $\beta_8$ | -0.004(0.003) | -0.010 | 0.003 |
| 0.5*log (health_feed) | $\gamma_1$ | -0.095(0.020) *** | -0.133 | -0.056 |
| 0.5*log (health_wage) | $\gamma_2$ | -0.056(0.014) *** | -0.084 | -0.029 |
| 0.5*log (feed_wage) | $\gamma_3$ | -0.285(0.018) *** | -0.320 | -0.250 |
| 0.5*log (health Sq) | $\phi_1$ | 0.116(0.019) *** | 0.080 | 0.153 |
| 0.5*log (feed Sq) | $\phi_2$ | 0.047(0.014) *** | 0.019 | 0.075 |
| 0.5*log (wage Sq) | $\phi_3$ | 0.081(0.037) ** | 0.008 | 0.154 |

*Note: *, **, *** Significant at 10%, 5%, and 1%, respectively; Source: Survey Data 2021*

*Table 4.4* summarizes the maximum likelihood estimates of cost efficiency, robust standard errors, usigma, vsigma, and lambda values with the levels of statistical significance. The logged coefficients of wages, the price of feeds, and square of all inputs are positive and statistically significant. This finding is consistent with the weakly monotonic tendency of cost functions (Nies, 2017): that is, input prices are positively related to the enterprise total costs. Interestingly, feeds and labor expenses are among the major cost centers for poultry enterprises in SSA (Erdaw & Beyene, 2022). The interaction term between the costs of health and prices of feeds is -0.095(0.020) and statistically significant. It means that increasing investment in health and holistic nutrition reduces the impact on total cost. A similar explanation can be given of the other interactions between inputs. In contrast, the impact on cost upon more health expenses increasing with higher outputs: this could mean that farmers who stock more chicken incur higher costs on health leading to greater enterprise costs. The interaction between revenues and wages produces an opposite and statistically significant effect on total cost.

### *4.4.2.2. Cost efficiency estimates*

*Table 4.5* summarizes the average cost efficiency estimates by adoption categories. Individuals in class 1, representing *low adopters* are by far the least cost-efficient with an average of 0.492 (49.2%). These are followed by the moderate adoption category with a mean cost efficiency of 0.610 (61.0%). The *high adopters* are also the most cost-efficient with an average of 0.692 (69.2%). These results agree with Shrestha et al. (2014) that the adoption of technology can improves efficiency. An ANOVA test shows that the estimates of cost efficiency differ significantly between classes (*F= 31.76, Prob(F)=0.000*). A further analysis of the Tukey post-hoc test reveals that cost efficiency is significantly higher in class 3 compared classes 2 and 1 (*0.082±0.024; 0.201±0.024*). Similarly, the cost efficiency estimates in the *moderate adopters* category are significantly higher than the *low adopters* category (*0.119±0.025*). The pooled mean cost efficiency of 0.603 (60.3%) is generally high suggesting that poultry farmers in Nyanza are largely cost-efficient.

Table 4. 5 Average cost efficiency scores by adoption category

| **Assigned Class** | **Summary of Cost efficiency Via E[exp(-u) e] (bc '88)** | | | **Tukey post-hoc test** | | |
|---|---|---|---|---|---|---|
| | **Mean (ce)** | **Std. Dev.** | **Freq.** | **Cost efficiency estimates (ce)** | **Contrast** | **Std. Err.** |
| Low Adopters (1) | 0.492 | 0.243 | 157 | 2_vs_1 | 0.119*** | .025 |
| Moderate Adopters (2) | 0.610 | 0.204 | 163 | 3_vs_1 | 0.201*** | .024 |
| High Adopters (3) | 0.692 | 0.215 | 181 | 3_vs_2 | 0.082*** | .024 |
| Total | 0.603 | 0.235 | 501 | | | |

*Bartlett's test for equal variances:* $\chi^2$ = 5.5592; Prob> $\chi^2$ = 0.062*; F= 31.76, Prob(F) =0.000; (Source: Survey Data 2021)*

### *4.4.2.3. Inefficiency effects*

The variance of the idiosyncratic error ($\boldsymbol{\sigma_v}$) is statistically significant indicating that the effects of statistical noise cannot be ignored. This outcome provides a further justification for specifying an inefficiency component.

The regression outcomes for determinants of inefficiency are summarized in *Table 4.6* below. Only experience and flock size were statistically significant. The impact of an extra year of experience in poultry production reduced inefficiency by -0.256(0.098). Etuah et al. (2020) and Aravindakshan et al. (2018) find similar results on the impact of experience: it equips farmers with more ideas and practices that lead to optimal resource utilization. The results of descriptive statistics provide a further justification for this fact. Farmers with more years of experience tended to belong to classes with better adoption of biosecurity measures. These farmers realized higher output with averagely lower costs.

Table 4. 6 Farm-specific inefficiency effects

| **Variables** | **Regression output *w.r.t* one-step stochastic frontier and inefficiency estimates** | | | |
|---|---|---|---|---|
| **Log (Total cost)** | **Parameters** | **Coef. (Robust Std. Err.)** | **[95% Conf.** | **Interval]** |
| Accessed information | | 0.661(0.602) | -0.519 | 1.842 |
| Experience in poultry production | | -0.256(0.098) *** | -0.448 | -0.063 |
| Flock Size | | -0.067(0.024) *** | -0.114 | -0.019 |
| Farm Size | | 0.019(0.046) | -0.071 | 0.109 |
| Education of HH | | 0.001(0.067) | -0.132 | 0.133 |
| HH is Male | | 0.235(0.587) | -0.916 | 1.386 |
| Age of HH | | 0.001(0.013) | -0.024 | 0.026 |
| Household Size | | 0.104(0.079) | -0.050 | 0.258 |
| Arcsinh_onfarm_inc | | -0.086(0.078) | -0.238 | 0.067 |
| Arcsinh_nonfarm_inc | | 0.009(0.043) | -0.075 | 0.093 |
| sigma_u | | 1.819 (0.312) *** | 1.300 | 2.547 |
| sigma_v | | 0.355 (0.043) *** | 0.279 | 0.451 |
| lambda | | 5.123 (0.336) *** | 4.464 | 5.781 |

*Note: *, **, *** Significant at 10%, 5%, and 1%, respectively; Source: Survey Data 2021*

The impact of flock size is -0.067(0.024), which is statistically significant at $\alpha = 0.01$, meaning that farmers with larger chicken flock had significantly lower cost inefficiency. This outcome can be explained by the fact that keeping more chicken makes the flock more susceptible to diseases, hence such farmers are likely to adopt more biosecurity practices which results in optimal resource use. A more plausible explanation of these findings is that farmers with higher stocks benefit from economies of scale.

Access to information, farm size, education level, gender, household size, and income were not statistically significant. The finding on the impact of education on inefficiency differs between studies. For instance, Etuah et al. (2020) and Miriti et al. (2021) find that education does not influence firm inefficiency. On the other hand, Henderson (2015) and Zhang et al. (2019) find education to positively influence inefficiency estimates, which is unexpected. However, Henderson (2015) argues that households with higher educational levels have greater opportunity costs to become wage earners, hence hasty production. In contrast, Watto and Mugera (2014) find that more educated individuals have lower inefficiency: they conclude that the impact of education on inefficiency estimates depends on its relevance to the enterprise.

The finding on the impact of gender on cost inefficiency agrees with the conclusion of Etuah et al. (2020). In contrast, Mohammed and Abdulai (2022) report a negative coefficient for the impact of gender on cost inefficiency. These findings indicate that no gender gaps exist that make one category more cost inefficient. The findings on the impact of age agree with the conclusions of Watto and Mugera (2014). Ideally, middle-aged farmers may perform better than their younger colleagues, but they can become more complacent as age increases. In such cases, age becomes either inconsequential or it increases inefficiency.

As an overview, the analysis reveals that there are three levels of biosecurity adoption: *low, moderate,* and *high adopters.* The SFA reveals that farmers who have adopted more biosecurity measures have better cost efficiency estimates compared to those with fewer measures. The specification of an inefficiency model shows that years of experience in poultry farming and the flock size are the determinants of inefficiency. In both cases, there were reduced inefficiencies with increased years of experience and higher flock sizes.  These findings provide useful information supporting the promotion of biosecurity measures for increased productivity and reduced health risks.

### 4.5. Conclusions and policy recommendations

The Poultry sector productivity in Sub-Saharan Africa has not grown to meet the rising demand. One of the major challenges ailing the poultry sector are diseases and their associated costs. Farmers' attempts to control diseases through clinical treatment has led to the increasing risk of antimicrobial resistance. This study was motivated by the need to explore the cost efficiency of alternative disease management mechanisms, otherwise referred to as biosecurity measures.

A three-step estimation procedure was employed. First, a latent class analysis model was constructed to describe adoption patterns. Secondly, a stochastic cost frontier was constructed to estimate cost efficiency and predict the inefficiency effects. Lastly, a one-way ANOVA was used to summarize the mean cost efficiency between adoption categories. The latent class model reveals three classes with *low, moderate,* and *high* biosecurity adoption behaviors. The SFA model reveals a weakly monotonic cost frontier. There was an improvement in cost efficiency with increased adoption of biosecurity measures: this is illustrated by higher average cost efficiency estimates in the *moderate* and *high* adoption classes. The differences in cost efficiencies were statistically significant between all the three classes. The inefficiency model shows that more years of experience in poultry farming and higher stock sizes both reduce farm cost inefficiency. The findings of this study form the basis for promoting biosecurity measures. The measures not only improve health outcomes but also facilitate optimal resource utilization considering price constraints.

# CHAPTER FIVE: GENERAL CONCLUSIONS AND RECOMMENDATIONS

## 5.1. General conclusions

The poultry sector in SSA suffers multiple challenges, including diseases, the associated risks and costs, and low farm productivity. Diseases are among the major causes of low poultry productivity hence the mismatch between local demand and production. To curtail diseases, farmers intensify the use of antibiotics which has contributed to the growing concern about antimicrobial resistance. This study considered alternative disease management strategies, otherwise known as biosecurity. The study sought to understand the adoption pattern for biosecurity measures among poultry farmers in Nyanza. A latent class analysis model was applied to identify the sub-populations of poultry farmers based on adoption behavior. The results indicate that poultry farmers Nyanza belong to three classes of biosecurity with "*low*", "*moderate*", and "*high*" adoption behaviors. Despite the distinct patterns of adoption, the study generally demonstrates low uptake of biosecurity practices among poultry farmers.

The MLogit regression results show that differences in the pattern of adoption can be explained by several factors, including access to information, the perceived benefits of biosecurity measures, education of the household head (HH), age of HH, years of experience in poultry production, flock size, gender of the HH, and household size. Access to information and perceived benefits are among the key drivers of biosecurity adoption, with the former increasing the probability of belonging to the *high adopter's* category by 25.3% and reducing that of being in the *moderate* adoption category by 20.8%.

The results of the Pearson correlation matrix indicate better animal health outcomes with increased uptake of biosecurity practices. Individuals in the upper biosecurity adoption classes reported significantly lower mortality rates as compared to others. This finding provides empirical evidence to support the position of earlier studies that hypothesized a positive relationship between preventive health practices and animal health outcomes. The finding that individuals in the higher adoption classes had increased use of antibiotics was contrary to expectations. However, such results indicate that the use of antibiotics may be beneficial in the short term, but a continued application may lead to antibiotic resistance. A more plausible explanation is that farmers in the higher biosecurity categories are risk averse, hence the use of antibiotics to prevent infection.

This study also sought to establish a link between the adoption of biosecurity measures and poultry farm cost performance. There is hardly any information in the published literature on the usefulness of biosecurity measures in managing the costs of poultry farms. The study demonstrates by use of stochastic cost frontier that increased uptake of biosecurity measures improves poultry farm cost efficiency. In the model, "*high adopters*" have significantly higher cost efficiency estimates compared to the "*moderate*" and "*low adopters*". The pattern is replicated between the "*moderate*" and "*low adopters*". On determinants of inefficiency, the results indicate that more years of experience and increased flock sizes reduces cost inefficiency. Farmers with higher flock sizes benefit from economies of scale, hence a better cost performance.

## 5.2. General recommendations

The findings that biosecurity improves poultry health outcomes and leads to better cost performance form the basis for the promotion of such practices among smallholder poultry farmers. Secondly, there is need for gender inclusion in the promotion of biosecurity measures. Lastly, the finding that accesses to information is the greatest driver of adoption necessitate enhanced measures to sensitize farmers on the importance of implementing biosecurity measures. Such promotion can be done through targeted measures, public barazas, or media platforms.

## 5.3. Recommendation for further research

This study adds to the list of literature seeking alternative ways of managing livestock diseases. The conventional strategy of diagnosing infection and treating it with antibiotics has become a risk to livestock production and human health through antimicrobial resistance. To provide further evidence for promoting alternative strategies, the study recommends an evaluation of the economic burden of drug resistance in poultry production in sub-Saharan Africa, including quantifying antibiotics usage among poultry farmers. In this study, the major limitation was in identifying clear-cut farmers with uniform input and output bundles. Farmers were found to be using different feed types, which led to the need to analyze feed prices in terms of cost per bird instead of cost per unit of feed. This factor also meant selecting only farmers with uniform inputs and output bundles. The study recommends that the number of inputs studied could be increased to account for all the centers contributing to the total cost.

## References


Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21–37.

Alexandratos, N., & Bruinsma, J. (2012). *World agriculture towards 2030/2050: The 2012 revision*.

Alhaji, N. B., Haruna, A. E., Muhammad, B., Lawan, M. K., & Isola, T. O. (2018). Antimicrobials usage assessments in commercial poultry and local birds in North-central Nigeria: Associated pathways and factors for resistance emergence and spread. *Preventive Veterinary Medicine*, *154*, 139–147.

Aravindakshan, S., Rossi, F., Amjath-Babu, T. S., Veettil, P. C., & Krupnik, T. J. (2018). Application of a bias-corrected meta-frontier approach and an endogenous switching regression to analyze the technical efficiency of conservation tillage for wheat in South Asia. *Journal of Productivity Analysis*, *49*(2), 153–171.

Ayukekbong, J. A., Ntemgwa, M., & Atabe, A. N. (2017). The threat of antimicrobial resistance in developing countries: Causes and control strategies. *Antimicrobial Resistance & Infection Control*, *6*(1), 1–8.

Battese, G. E., & Coelli, T. J. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics*, *38*(3), 387–399. https://doi.org/10.1016/0304-4076(88)90053-X

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, *20*(2), 325–332. https://doi.org/10.1007/BF01205442

Beath, K. J. (2017). randomLCA: An R package for latent class with random effects analysis. *Journal of Statistical Software*, *81*, 1–25.

Begum, I. A., Alam, M. J., Buysse, J., Frija, A., & Van Huylenbroeck, G. (2012). Contract farmer and poultry farm efficiency in Bangladesh: A data envelopment analysis. *Applied Economics*, *44*(28), 3737–3747.

Bellemare, M. F., & Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, *82*(1), 50–61.

Boles, J. N. (1966). Efficiency squared–Efficient computation of efficiency indexes. *Proceedings of the Annual Meeting (Western Farm Economics Association)*, *39*, 137–142.

Brennan, M. L., & Christley, R. M. (2013). Cattle producers' perceptions of biosecurity. *BMC Veterinary Research*, *9*(1), 1–8.

Byaruhanga, J., Tayebwa, D. S., Eneku, W., Afayoa, M., Mutebi, F., Ndyanabo, S., Kakooza, S., Okwee-Acai, J., Tweyongyere, R., Wampande, E. M., & Vudriko, P. (2017). Retrospective study on cattle and poultry diseases in Uganda. *International Journal of Veterinary Science and Medicine*, *5*(2), 168–174. https://doi.org/10.1016/j.ijvsm.2017.07.001

Can, M. F., & Altuğ, N. (2014). Socioeconomic implications of biosecurity practices in small-scale dairy farms. *Veterinary Quarterly*, *34*(2), 67–73.

Carpita, M., Sandri, M., Simonetto, A., & Zuccolotto, P. (2013). Football mining with R. *Data Mining Applications with R*, 397–433.

Charlier, D., Legendre, B., & Ricci, O. (2021). Measuring fuel poverty in tropical territories: A latent class model. *World Development*, *140*, 105278.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Clemmons, E. A., Alfson, K. J., & Dutton III, J. W. (2021). Transboundary animal diseases, an overview of 17 diseases with potential for global spread and serious consequences. *Animals*, *11*(7), 2039.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An Introduction to Efficiency and Productivity Analysis*. Springer Science & Business Media.

Dadgostar, P. (2019). Antimicrobial resistance: Implications and costs. *Infection and Drug Resistance*, *12*, 3903.

Davies, R., & Wales, A. (2019). Antimicrobial resistance on farms: A review including biosecurity and the potential role of disinfectants in resistance selection. *Comprehensive Reviews in Food Science and Food Safety*, *18*(3), 753–774.

de Oliveira Sidinei, M. E. A., Marcato, S. M., Perez, H. L., & Bánkuti, F. I. (2021). Biosecurity, environmental sustainability, and typological characteristics of broiler farms in Paraná State, Brazil. *Preventive Veterinary Medicine*, *194*, 105426. https://doi.org/10.1016/j.prevetmed.2021.105426

De Roover, K., Vermunt, J. K., Timmerman, M. E., & Ceulemans, E. (2017). Mixture simultaneous factor analysis for capturing differences in latent variables between higher level units of multilevel data. *Structural Equation Modeling: A Multidisciplinary Journal*, *24*(4), 506–523.

DeLay, N. D., Thompson, N. M., & Mintert, J. R. (2022). Precision agriculture technology adoption and technical efficiency. *Journal of Agricultural Economics*, *73*(1), 195–219.

Dziwornu, R. K., & Sarpong, D. B. (2014). Application of the stochastic profit frontier model to estimate economic efficiency in small-scale broiler production in the Greater Accra region of Ghana. *Review of Agricultural and Applied Economics (RAAE)*, *17*(395-2016–24332), 10–16.

Elmanama, A. A., Al-Reefi, M. R., Shamali, M. A., & Hemaid, H. I. (2019). Carbapenem-resistant Gram-negative bacteria isolated from poultry samples: A cross-sectional study. *The Lancet*, *393*, S21.

Erdaw, M. M., & Beyene, W. Ts. (2022). Trends, prospects and the socio-economic contribution of poultry production in sub-Saharan Africa: A review. *World's Poultry Science Journal*, *78*(3), 835–852. https://doi.org/10.1080/00439339.2022.2092437

Etuah, S., Ohene-Yankyera, K., Liu, Z., Mensah, J. O., & Lan, J. (2020). Determinants of cost inefficiency in poultry production: Evidence from small-scale broiler farms in the Ashanti

Region of Ghana. *Tropical Animal Health and Production*, *52*(3), 1149–1159. https://doi.org/10.1007/s11250-019-02115-6

FAO. (2017). *Africa Sustainable Livestock 2050*. 36.

FAOSTAT. (2022). *Crops and livestock products*. https://www.fao.org/faostat/en/#data/QCL

Farrel, M. J. (1957). The measure of productive efficiency. *Journal of the Royal Statistical Society*, *120*, 28.

Fasina, F. O., Ali, A. M., Yilma, J. M., Thieme, O., & Ankers, P. (2012). The cost–benefit of biosecurity measures on infectious diseases in the Egyptian household poultry. *Preventive Veterinary Medicine*, *103*(2), 178–191. https://doi.org/10.1016/j.prevetmed.2011.09.016

Fatch, P., Masangano, C., Hilger, T., Jordan, I., Mambo, I., Kamoto, J. F. M., Kalimbira, A., & Nuppenau, E.-A. (2021). Holistic agricultural diversity index as a measure of agricultural diversity: A cross-sectional study of smallholder farmers in Lilongwe district of Malawi. *Agricultural Systems*, *187*, 102991.

Fisher, M., Holden, S. T., Thierfelder, C., & Katengeza, S. P. (2018). Awareness and adoption of conservation agriculture in Malawi: What difference can farmer-to-farmer extension make? *International Journal of Agricultural Sustainability*, *16*(3), 310–325.

Garcia-Migura, L., Hendriksen, R. S., Fraile, L., & Aarestrup, F. M. (2014). Antimicrobial resistance of zoonotic and commensal bacteria in Europe: The missing link between consumption and resistance in veterinary medicine. *Veterinary Microbiology*, *170*(1–2), 1–9.

Gebre, G. G., Isoda, H., Amekawa, Y., & Nomura, H. (2019). Gender differences in the adoption of agricultural technology: The case of improved maize varieties in southern Ethiopia. *Women's Studies International Forum*, *76*, 102264.

Greene, W. H. (2003). *Econometric analysis*. Pearson Education India.

Hasking, P. A., Scheier, L. M., & Abdallah, A. ben. (2011). The three latent classes of adolescent delinquency and the risk factors for membership in each class. *Aggressive Behavior*, *37*(1), 19–35.

Heidari, M. D., Omid, M., & Akram, A. (2011). Using nonparametric analysis (DEA) for measuring technical efficiency in poultry farms. *Brazilian Journal of Poultry Science*, *13*, 271–277.

Heider, F. (1944). Social perception and phenomenal causality. *Psychological Review*, *51*(6), 358.

Henderson, H. (2015). *Considering Technical and Allocative Efficiency in the Inverse Farm Size–Productivity Relationship*. Wiley Online Library. https://onlinelibrary.wiley.com/doi/full/10.1111/1477-9552.12086?casa_token=MVJyv-Gxew0AAAAA%3AIdwwO5arC7mbVk8oHmdJibebWr4U-F0FoqErRz3eUYOcic6z3Sm_RLc2i-DjQP0Pai05rSLHTgHjUjyG

Higgins, V., Bryant, M., Hernández-Jover, M., Rast, L., & McShane, C. (2018). Devolved responsibility and on-farm biosecurity: Practices of biosecure farming care in livestock production. *Sociologia Ruralis*, *58*(1), 20–39.

Hsu, Y.-C., Chou, P.-L., Chen, Y.-M. J., & Lin, J.-J. (2014). Mixed Logit Model of Voluntary Selection of Automobile Insurance. *Journal of Information and Optimization Sciences*, *35*(5–6), 503–528.

Huo, X., Leng, J., Luo, L., & Wang, D. (2021). A mixed logit model with mean-variance heterogeneity to investigate factors of crash occurrence. *International Journal of Injury Control and Safety Promotion*, *28*(3), 301–308.

ILRI. (2021). *Prosperity*. International Livestock Research Institute. https://www.ilri.org/research/themes/prosperity

Ingvartsen, K. L., & Moyes, K. (2013). Nutrition, immune function and health of dairy cattle. *Animal*, *7*(s1), 112–122.

Kagoya, S., Paudel, K. P., & Daniel, N. L. (2018). Awareness and adoption of soil and water conservation technologies in a developing country: A case of Nabajuzi Watershed in Central Uganda. *Environmental Management*, *61*(2), 188–196.

Kelley, H. H. (1967). Attribution theory in social psychology. *Nebraska Symposium on Motivation*.

Khan, S. H., & Iqbal, J. (2016). Recent advances in the role of organic acids in poultry nutrition. *Journal of Applied Animal Research*, *44*(1), 359–369.

Kirui, L. K., Jensen, N. D., Obare, G. A., Kariuki, I. M., Chelanga, P. K., & Ikegami, M. (2022). Pastoral livelihood pathways transitions in northern Kenya: The process and impact of drought. *Pastoralism*, *12*(1), 1–12.

Kleyn, F. J., & Ciacciariello, M. (2021). Future demands of the poultry industry: Will we meet our commitments sustainably in developed and developing economies? *World's Poultry Science Journal*, *77*(2), 267–278.

Kompas, T., Nguyen, H. T. M., & Ha, P. V. (2015). Food and biosecurity: Livestock production and towards a world free of foot-and-mouth disease. *Food Security*, *7*(2), 291–302.

Kumbhakar, S. C., & Lovell, C. K. (2000). *Stochastic Frontier Modeling*. Cambridge University Press.

Kumbhakar, S. C., & Tsionas, M. G. (2021). Estimation of costs of technical and allocative inefficiency. *Journal of Productivity Analysis*, *55*(1), 41–46. https://doi.org/10.1007/s11123-020-00596-4

Laanen, M., Maes, D., Hendriksen, C., Gelaude, P., De Vliegher, S., Rosseel, Y., & Dewulf, J. (2014). Pig, cattle, and poultry farmers with a known interest in research have comparable perspectives on disease prevention and on-farm biosecurity. *Preventive Veterinary Medicine*, *115*(1), 1–9. https://doi.org/10.1016/j.prevetmed.2014.03.015

Léger, A., De Nardi, M., Simons, R., Adkin, A., Ru, G., Estrada-Peña, A., & Stärk, K. D. (2017). Assessment of biosecurity and control measures to prevent incursion and to limit spread of emerging transboundary animal diseases in Europe: An expert survey. *Vaccine*, *35*(44), 5956–5966.

Luvhengo, U., Senyolo, M. P., Belete, A., & Lekunze, J. N. (2015). Resource Use Efficiency: A Stochastic Frontier Production Analysis of Smallholder Broiler Farmers in Capricorn District, Limpopo Province. *Journal of Human Ecology*, *52*(1–2), 97–103.

Lysholm, S., Lindahl, J. F., Dautu, G., Johansson, E., Bergkvist, P. K., Munyeme, M., & Wensman, J. J. (2022). Seroepidemiology of selected transboundary animal diseases in goats in Zambia. *Preventive Veterinary Medicine*, *206*, 105708.

McClave, J. T. (2014). *STATISTICS FOR BUSINESS AN ECONOMICS 12th ed*. Pearson.

McClave, J. T., Benson, P. G., Sincich, T., & Sincich, T. (2014). *Statistics for business and economics*. Pearson Boston.

McFadden, D. (1974). *Conditional logit analysis of qualitative choice behavior, pp105-142 in Frontiers in Econometrics. Edited por P. Zarembka*. Academic Press, New York en Hosmer, D., Lemeshow, S. (2000). Applied Logistic ….

Meeusen, W., & van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, 435–444.

Menz, J., Olsson, O., & Kümmerer, K. (2019). Antibiotic residues in livestock manure: Does the EU risk assessment sufficiently protect against microbial toxicity and selection of resistant bacteria in the environment? *Journal of Hazardous Materials*, *379*, 120807.

Merrill, S. C., Koliba, C. J., Moegenburg, S. M., Zia, A., Parker, J., Sellnow, T., Wiltshire, S., Bucini, G., Danehy, C., & Smith, J. M. (2019). Decision-making in livestock biosecurity practices amidst environmental and social uncertainty: Evidence from an experimental game. *PLOS ONE*, *14*(4), e0214500. https://doi.org/10.1371/journal.pone.0214500

Miriti, P., Otieno, D. J., Chimoita, E., Bikketi, E., Njuguna, E., & Ojiewo, C. O. (2021). Technical efficiency and technology gaps of sorghum plots in Uganda: A gendered stochastic metafrontier analysis. *Heliyon*, *7*(1), e05845. https://doi.org/10.1016/j.heliyon.2020.e05845

Mitema, E. S., Kikuvi, G. M., Wegener, H. C., & Stohr, K. (2001). An assessment of antimicrobial consumption in food producing animals in Kenya. *Journal of Veterinary Pharmacology and Therapeutics*, *24*(6), 385–390.

Moffo, F., Mouiche, M. M. M., Djomgang, H. K., Tombe, P., Wade, A., Kochivi, F. L., Dongmo, J. B., Mbah, C. K., Mapiefou, N. P., & Mingoas, J.-P. K. (2022). Associations between antimicrobial use and antimicrobial resistance of Escherichia coli isolated from poultry litter under field conditions in Cameroon. *Preventive Veterinary Medicine*, *204*, 105668.

Mohammed, S., & Abdulai, A. (2022). Do Egocentric information networks influence technical efficiency of farmers? Empirical evidence from Ghana. *Journal of Productivity Analysis*, 1–20.

Moore, D. A., Merryman, M. L., Hartman, M. L., & Klingborg, D. J. (2008). Comparison of published recommendations regarding biosecurity practices for various production animal species and classes. *Journal of the American Veterinary Medical Association*, *233*(2), 249–256.

Mugera, A. W. (2013). Measuring technical efficiency of dairy farms with imprecise data: A fuzzy data envelopment analysis approach. *Australian Journal of Agricultural and Resource Economics*, *57*(4), 501–520. https://doi.org/10.1111/1467-8489.12008

Murray, C. J., Ikuta, K. S., Sharara, F., Swetschinski, L., Aguilar, G. R., Gray, A., Han, C., Bisignano, C., Rao, P., & Wool, E. (2022). Global burden of bacterial antimicrobial resistance in 2019: A systematic analysis. *The Lancet*, *399*(10325), 629–655.

Musungu, A. L., Otieno, D. J., Muriithi, B. W., Nyikal, R., Masiga, D., & Okal, M. N. (2021). Are the current animal trypanosomiasis management methods in Kenya complementary or substitutes? Evidence from Kwale County. *African Journal of Agricultural and Resource Economics Volume*, *16*(1), 46–63.

Mutua, E. N., Bett, B. K., Bukachi, S. A., Estambale, B. A., & Nyamongo, I. K. (2022). From policy to practice: An assessment of biosecurity practices in cattle, sheep and goats production, marketing and slaughter in Baringo County, Kenya. *PLOS ONE*, *17*(4), e0266449. https://doi.org/10.1371/journal.pone.0266449

Mwololo, H., Nzuma, J., & Ritho, C. (2019). Do farmers' socio-economic characteristics influence their preference for agricultural extension methods? *Development in Practice*, *29*(7), 844–853.

Nantima, N., Davies, J., Dione, M., Ocaido, M., Okoth, E., Mugisha, A., & Bishop, R. (2016). Enhancing knowledge and awareness of biosecurity practices for control of African swine fever among smallholder pig farmers in four districts along the Kenya–Uganda border. *Tropical Animal Health and Production*, *48*(4), 727–734. https://doi.org/10.1007/s11250-016-1015-8

Ngai, D. G., Nyamache, A. K., & Ombori, O. (2021). Prevalence and antimicrobial resistance profiles of Salmonella species and Escherichia coli isolates from poultry feeds in Ruiru Sub-County, Kenya. *BMC Research Notes*, *14*(1), 41. https://doi.org/10.1186/s13104-021-05456-4

Nies, A. (2017). Calculus of cost functions. In *The Incomputable* (pp. 183–216). Springer.

Nylund-Gibson, K., Garber, A. C., Singh, J., Witkow, M. R., Nishina, A., & Bellmore, A. (2023). The Utility of Latent Class Analysis to Understand Heterogeneity in Youth Coping Strategies: A Methodological Introduction. *Behavioral Disorders*, *48*(2), 106–120. https://doi.org/10.1177/01987429211067214

Nyokabi, S., Birner, R., Bett, B., Isuyi, L., Grace, D., Güttler, D., & Lindahl, J. (2018). Informal value chain actors' knowledge and perceptions about zoonotic diseases and biosecurity in Kenya and the importance for food safety and public health. *Tropical Animal Health and Production*, *50*(3), 509–518. https://doi.org/10.1007/s11250-017-1460-z

Nyokabi, S. N. (2015). *Biosecurity measures in meat and milk value chains: A study in Bura Sub-County, Kenya.* [PhD Thesis].

Odula, O. P., Ogara, W. O., Okuthe, S. O., Muchemi, G., Okoth, E., Odindo, M. O., & Adhiambo, R. F. (2010). Assessing the productivity of indigenous chickens in an extensive management system in southern Nyanza, Kenya. *Tropical Animal Health and Production*, *42*, 283–288.

Ojo, M. A., Ojo, A. O., Jirgi, A. J., & Ajayi, O. J. (2013). *Non-parametric analysis of production efficiency of poultry egg farmers in Delta State, Nigeria*.

Okello, A. O., Nzuma, J. M., Otieno, D. J., Kidoido, M., & Tanga, C. M. (2021). Farmers' Perceptions of Commercial Insect-Based Feed for Sustainable Livestock Production in Kenya. *Sustainability*, *13*(10), Article 10. https://doi.org/10.3390/su13105359

Omiti, J. (2016). *OVERVIEW OF THE KENYAN POULTRY SECTOR & ITS HPAI STATUS*.

Otieno, D. J., Ruto, E., & Hubbard, L. (2011). Cattle Farmers' Preferences for Disease-Free Zones in Kenya: An application of the Choice Experiment Method. *Journal of Agricultural Economics*, *62*(1), 207–224.

Otieno, W. A., Nyikal, R. A., Mbogoh, S. G., & Rao, E. J. O. (2023). Adoption of farm biosecurity practices among smallholder poultry farmers in Kenya – An application of latent class analysis with a multinomial logistic regression. *Preventive Veterinary Medicine*, *217*, 105967. https://doi.org/10.1016/j.prevetmed.2023.105967

Oumer, A. M., Mugera, A., Burton, M., & Hailu, A. (2022). Technical efficiency and firm heterogeneity in stochastic frontier models: Application to smallholder maize farms in Ethiopia. *Journal of Productivity Analysis*, *57*(2), 213–241. https://doi.org/10.1007/s11123-022-00627-2

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Vranken, L., Kamara, Y. A., Craufurd, P., & Maertens, M. (2019). Farmers' preferences for high-input agriculture supported by site-specific extension services: Evidence from a choice experiment in Nigeria. *Agricultural Systems*, *173*, 12–26.

Pareto, V. (1906). Manual of Political Economy. 1971 translation of 1927 edition. *New York: Augustus M. Kelley*.

Pilar, P.-G., Marta, A.-P., & Antonio, A. (2018). *Profit efficiency and its determinants in small and medium-sized enterprises in Spain*. BRQ Business Research Quarterly.

Prestinaci, F., Pezzotti, P., & Pantosti, A. (2015). Antimicrobial resistance: A global multifaceted phenomenon. *Pathogens and Global Health*, *109*(7), 309–318.

Robertson, I. D. (2020). Disease control, prevention, and on-farm biosecurity: The role of veterinary epidemiology. *Engineering*, *6*(1), 20–25.

Roy Chowdhury, I., Yeddula, S. G. R., & Kim, S.-H. (2019). Pathogenicity and Transmissibility of North American H7 Low Pathogenic Avian Influenza Viruses in Chickens and Turkeys. *Viruses*, *11*(2), Article 2. https://doi.org/10.3390/v11020163

Sharma, C., Rokana, N., Chandra, M., Singh, B. P., Gulhane, R. D., Gill, J. P. S., Ray, P., Puniya, A. K., & Panwar, H. (2018). Antimicrobial resistance: Its surveillance, impact, and alternative management strategies in dairy animals. *Frontiers in Veterinary Science*, *4*, 237.

Shen, J. (2009). Latent class model or mixed logit model? A comparison by transport mode choice data. *Applied Economics*, *41*(22), 2915–2924.

Shephard, R. W. (1970). *Theory of cost and production functions*. Princeton University Press.

Shrestha, R. B., Huang, W.-C., & Ghimire, R. (2014). Production efficiency of smallholder vegetable farms in Ilam district, Eastern Hill, Nepal. *American-Eurasian Journal of Agricultural and Environmental Sciences*, *14*(2), 150–154.

Siderelis, C., Moore, R. L., & Lee, J.-H. (2011). A mixed logit model of visitors' national park choices. *Society & Natural Resources*, *24*(8), 799–813.

Sime, A. G. (2022). Review on poultry production, processing, and Utilization in Ethiopia. *Int J Agric Sc Food Technol*, *8*(2), 147–152.

Sordillo, L. M. (2016). Nutritional strategies to optimize dairy cattle immunity. *Journal of Dairy Science*, *99*(6), 4967–4982.

Stratopoulos, T., Charos, E., & Chaston, K. (2000). A translog estimation of the average cost function of the steel industry with financial accounting data. *International Advances in Economic Research*, *6*(2), 271–286. https://doi.org/10.1007/BF02296108

Swaggerty, C. L., Callaway, T. R., Kogut, M. H., Piva, A., & Grilli, E. (2019). Modulation of the immune response to improve health and reduce foodborne pathogens in poultry. *Microorganisms*, *7*(3), 65.

Taitt, C. R., Leski, T. A., Erwin, D. P., Odundo, E. A., Kipkemoi, N. C., Ndonye, J. N., Kirera, R. K., Ombogo, A. N., Walson, J. L., & Pavlinac, P. B. (2017). Antimicrobial resistance of Klebsiella pneumoniae stool isolates circulating in Kenya. *Plos One*, *12*(6), e0178880.

Torres-Velez, F., Havas, K. A., Spiegel, K., & Brown, C. (2019). Transboundary animal diseases as re-emerging threats–Impact on one health. *Seminars in Diagnostic Pathology*, *36*(3), 193–196.

Uwishema, O., Alshareif, B. A., Yousif, M. Y., Omer, M. E., Sablay, A. L., Tariq, R., Zahabioun, A., Mwazighe, R. M., & Onyeaka, H. (2021). Lassa fever amidst the COVID-19 pandemic in Africa: A rising concern, efforts, challenges, and future recommendations. *Journal of Medical Virology*, *93*(12), 6433–6436.

Vass, M., Hruska, K., & Franek, M. (2008). Nitrofuran antibiotics: A review on the application, prohibition, and residual analysis. *Veterinarni Medicina*, *53*(9), 469.

Vermunt, J. K. (2017). Latent Class Modeling with Covariates: Two Improved Three-Step Approaches. *Political Analysis*, *18*(4), 450–469. https://doi.org/10.1093/pan/mpq025

Walker, J., & Ben-Akiva, M. (2002). Generalized random utility model. *Mathematical Social Sciences*, *43*(3), 303–343. https://doi.org/10.1016/S0165-4896(02)00023-9

Watto, M. A., & Mugera, A. W. (2014). Measuring Production and Irrigation Efficiencies of Rice Farms: Evidence from the Punjab Province, Pakistan. *Asian Economic Journal*, *28*(3), 301–322.

Weiner, B., & Kukla, A. (1970). An attributional analysis of achievement motivation. *Journal of Personality and Social Psychology*, *15*(1), 1.

Windsor, P., Khounsy, S., Earp, F., MacPhillamy, I., Young, J., & Bush, R. (2020). Managing welfare and antimicrobial-resistance issues in treating foot-and-mouth disease lesions: A new therapeutic approach. *Veterinary Medicine: Research and Reports*, *11*, 99.

Witte, W. (2000). Selective pressure by antibiotic use in livestock. *International Journal of Antimicrobial Agents*, *16*, 19–24.

Wolff, C., Boqvist, S., Ståhl, K., Masembe, C., & Sternberg-Lewerin, S. (2017). Biosecurity aspects of cattle production in Western Uganda, and associations with seroprevalence of brucellosis, salmonellosis, and bovine viral diarrhoea. *BMC Veterinary Research*, *13*(1), 1–16.

World Bank. (2017). *Antimicrobial Resistance (AMR)* [Text/HTML]. World Bank. https://www.worldbank.org/en/topic/health/brief/antimicrobial-resistance-amr

World Bank. (2021). *Safeguarding Animal, Human and Ecosystem Health: One Health at the World Bank* [Text/HTML]. World Bank. https://www.worldbank.org/en/topic/agriculture/brief/safeguarding-animal-human-and-ecosystem-health-one-health-at-the-world-bank

World Health Organization. (2014). *Antimicrobial resistance: Global report on surveillance*. World Health Organization. https://apps.who.int/iris/handle/10665/112642

Yamano, T., Rajendran, S., & Malabayabas, M. L. (2015). Farmers' self-perception toward agricultural technology adoption: Evidence on adoption of submergence-tolerant rice in Eastern India. *Journal of Social and Economic Development*, *17*(2), 260–274.

Yang, X.-S. (2019). *Introduction to algorithms for data mining and machine learning*. Academic press.

Yoo, D., Lee, K., Chun, B.-C., Lee, H., Park, H., & Kim, J. (2022). Preventive effect of on-farm biosecurity practices against highly pathogenic avian influenza (HPAI) H5N6 infection on commercial layer farms in the Republic of Korea during the 2016-17 epidemic: A case-control study. *Preventive Veterinary Medicine*, *199*, 105556. https://doi.org/10.1016/j.prevetmed.2021.105556

Yun, J., Muurinen, J., Nykäsenoja, S., Seppä-Lassila, L., Sali, V., Suomi, J., Tuominen, P., Joutsen, S., Hämäläinen, M., & Olkkola, S. (2021). Antimicrobial use, biosecurity, herd characteristics, and antimicrobial resistance in indicator Escherichia coli in ten Finnish pig farms. *Preventive Veterinary Medicine*, *193*, 105408.

Yusuf, S. A., & Malomo, O. (2007). Technical efficiency of poultry egg production in Ogun state: A data envelopment analysis (DEA) approach. *International Journal of Poultry Science*, *6*(9), 622–629.

Yusuf, S. F. G., Latihan, F. S., & Masika, P. J. (2014). Characterization of indigenous poultry production systems in the Nkonkobe municipality, Eastern Cape Province South Africa. *Journal of Agricultural Sciences*, *5*(1–2), 31–44.

Zhang, X., Yu, X., Tian, X., Geng, X., & Zhou, Y. (2019). Farm size, inefficiency, and rice production cost in China. *Journal of Productivity Analysis*, *52*(1), 57–68.

# APPENDICES

## Appendix 1: Rotated factors from the principal component analysis

| Perception statement | PC1 | PC2 | PC3 | PC4 | Mean | Std. Dev |
|---|---|---|---|---|---|---|
| Livestock keeping is a major contributor to your income | 0.061 | 0.125 | -0.087 | 0.080 | 4.171 | 1.097 |
| Feeding additives like supplements is a critical component of balanced feeding | 0.277 | 0.062 | 0.037 | -0.130 | 4.317 | 0.687 |
| The best way to keep animals healthy and protected from diseases is through balanced feeding | 0.350 | -0.105 | 0.072 | -0.060 | 4.390 | 0.592 |
| Farm management and biosecurity are linked to animal health | 0.341 | -0.084 | -0.003 | 0.002 | 4.390 | 0.618 |
| You are familiar with farm management or biosecurity practices to reduce the spread of disease between animals or from animals to humans | 0.208 | 0.234 | -0.123 | -0.138 | 4.038 | 0.929 |
| Practicing farm hygiene and sanitation will protect your herd from diseases | 0.216 | -0.083 | -0.035 | 0.166 | 4.410 | 0.568 |
| You currently use antibiotics as part of my farm management | -0.007 | 0.071 | 0.242 | 0.001 | 3.705 | 1.069 |
| Antibiotics should be added to feeds at any time to prevent animals from becoming sick | 0.006 | -0.100 | 0.455 | -0.009 | 3.536 | 1.077 |
| Antibiotics should be added to feeds at any time to promote animal growth or productivity | 0.011 | -0.085 | 0.447 | -0.024 | 3.456 | 1.084 |
| You have heard the term antimicrobial resistance | 0.075 | 0.261 | -0.053 | -0.051 | 3.102 | 1.235 |
| The use of antibiotics without animal health service provider has negative consequences to the animal and or human heath | -0.117 | 0.033 | 0.006 | 0.459 | 3.960 | 0.886 |
| Not following dosages and withdrawal periods on treatment has negative consequences on human and animals consuming livestock products | -0.066 | -0.124 | 0.076 | 0.538 | 4.181 | 0.735 |
| I am confident making choices on the antibiotics I give to my livestock | -0.056 | 0.330 | 0.012 | -0.058 | 3.363 | 1.121 |
| I like to be among the first to adopt improved production practices when trained | 0.023 | -0.026 | -0.082 | 0.337 | 4.512 | 0.677 |
| It is easy to contact animal health service provides if there is disease in my farm | -0.108 | 0.315 | -0.015 | -0.016 | 3.448 | 1.257 |
| You avoid visiting other farms or households when their livestock contract a contagious disease | -0.055 | 0.324 | -0.054 | -0.010 | 3.484 | 1.231 |

Notes: *Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy =0.740; Bartlett's test of sphericity: Chi-square (df) = 1868.22 (190); p = 0.000; Source: Survey data (2021)*

## Appendix 2: The study sites

| County | Producer organizations | Membership | Sampled farmers |
|---|---|---|---|
| Homabay | Great Wang'chieng Poultry Producers CBO/ Mbita Wealth Creation | 3581 | 62 |
| | Homabay Farmers Financial Service | 3,008 | 24 |
| | KAPOFA Cooperative Society Limited | 1501 | 30 |
| | Kago Farmers' Cooperative Society | 1553 | 14 |
| | The Mango Tree Farmers Cooperative | 1672 | 21 |
| Kisumu | East Kajulu CBO | 783 | 27 |
| | Glory Disability CBO | 1636 | 45 |
| | Osiepe Practical Action CBO | 1423 | 6 |
| | Semeki Cooperative | 1302 | 28 |
| Migori | Sakwa Poultry Farmers' Cooperative | 1616 | 56 |
| | Sokamwa Poultry CBO | 1125 | 28 |
| Siaya | Got Ramogi COSALO/ Green Heroes CBO (GHCBO) | 1905 | 62 |
| | Siaya Seed Saving and Credit Cooperative | 1220 | 38 |
| | Upendo Siaya (FSA) Saving and Credit Cooperative | 2119 | 61 |
| **Total** | | **24444** | **502** |

## Appendix 3: Informed consent and the study questionnaire

### *A. Informed consent form*

The purpose of this interview is to collect information that will help to understand the current practices used by farmers as well as challenges experienced in poultry productions before beginning project implementation. This will help Heifer International Kenya to design interventions that are aligned to the needs of the farmers. We encourage you to speak candidly to help us design the most effective, relevant project.

We will first explain what we are going to do.

**Procedures:** We will begin with an interview now. If you are willing, we will ask questions on topics such as your family background, dwelling characteristics, household expenditures and assets This interview will take an hour of your time. With your permission, we may record the proceedings.

**Risks:** We will take precautions to keep any information you give us during the interview confidential. For example, your name or other identifying information will not appear on any of our records of responses. During the interview, you can decline to answer any particular question, or stop the interview at any point. Your responses will be available only to the team conducting this study. There is also the possibility that someone may approach us during the interview to find out what we are discussing. We intend to do this interview in private; if someone approaches us, we will stop the interview until we can continue in private.

**Benefits:** There are no direct and immediate benefits to you for participating in this interview. There may be indirect benefits later from the project inputs for selected beneficiaries.

**Confidentiality:** At the end of the study, we will put all the answers together and make a report. We will not identify you by name, nor identify your business in the report. Your responses to this interview will be seen *only* by the researchers and will be stored in a locked place under our control. What you share with us will be used for our research work as well as for designing programs to help Agro-dealers and farmers.

**Compensation:** You will not receive money for participating in the interviews and the training.

**Voluntary Participation:** Taking part in this study is completely voluntary. If you choose to take part, you may stop at any time or skip any questions that you do not want to answer. Please note that your choice to take part in this interview or not to take part in this interview will in no way affect or hinder your business, or your participation in the training. If you have any questions or concerns about taking part in this study, please feel free to talk to me and I will be happy to answer your questions to the best of my abilities. You can also ask questions at any time about the project. You can take this consent form with you if you want to review it further.

**I certify that I have read and discussed the consent procedures above with the interviewee/participants and continued only on consent.**

**Name of Enumerator: _______________________**

**Signed: _____________________________** **Date: ______________**

*B. The study questionnaire*

**SECTION A: FARM/ER INFORMATION**

| **No.** | **Question** | **Response** |
|---|---|---|
| **A1** | Date of interview | |
| **A2** | Enumerator Code/Name | |
| **A3** | Respondent's name | |
| **A4** | Respondent phone number | |
| **A5** | Respondent Gender | 1= Male; 2= Female |
| **A6** | Age of respondent | 1= 10– 29; 2 = 30 – 49; 3 = 50 – 64; 4 = >60; |
| **A7** | Relationship with the HH head | 1= HH Head; 2= Spouse; 3= Son; 4= Daughter; 5= Employee/hired worker; 6 = Other (specify) |
| **A8** | County name | 1=Kisumu, 2= Migori, 3=Siaya, 4 =Homabay |
| **A9** | Name of household head | |
| **A10** | Gender of Household Head | 1= Male; 2= Female |
| **A11** | Age of HH Head | 1= 10– 29; 2 = 30 – 49; 3 = 50 – 64; 4 = >60 |
| **A12** | Highest Level of education for HH Head (***use codes Below***) | |
| **A13** | Sub county name | |
| **A14** | Ward name | |
| **A15** | Name of the PO | |
| **A16** | Total Farm Size (in acres) owned | |
| **A17** | GPS precision | |
| | **A11: CODES - Level of Education**<br>1 = Some primary school; 2 =Completed Primary School; 3 = Some High School; 4= Completed Form 4; 5= Village polytechnic and vocational trainings; 6 = College Certificate/Diploma; 7 = University; 8=Adult Literacy education<br>7 = No formal school attended | |

**SECTION B: INFORMATION ON POULTRY ENTERPRISE**

**General characteristic of poultry farming enterprise**

B1. How long has the household been involved in poultry production? ______________ years

B2. Flock structure: How many chickens do you have?

| **Type of chicken** | **Adults owned** | **Chicks owned** | **Growers** |
|---|---|---|---|
| Local/Indigenous chicken | | | |
| Improved Kienyeji | | | |
| Layers | | | |
| Broiler | | | |

B3. Type of housing: Please provide details of your chicken house.

| | |
|---|---|
| What is the floor made of? | Check codes below |
| What is the roof made of? | Check codes below |

| | |
|---|---|
| What are the walls made of? | Check codes below |
| Does the poultry house have a functional footbath? ____ 1 = Yes; 0 = No | |
| Is the house constructed on an East-West direction for the slid walls? ____ 1 = Yes; 0 = No | |
| | |
| If the house is for layers, does it have laying nests? ____ 1 = Yes; 0 = No | |
| How is the drainage system around the chicken house? | Check codes below |
| How is the state of vegetation around the chicken house | Check codes below |
| Does the poultry housing unit have a fence around it? *1 = Yes; 0 = No* | |

| **Wall material** | **Roofing material?** | **Floor material** | **Quality of drainage system** |
|---|---|---|---|
| 1) Thatch, straw<br>2) Mud and poles<br>3) Timber<br>4) Bricks<br>5) Cement blocks<br>6) Stones<br>7) Other: Specify | 1) = Thatch/straw<br>2) = Mud<br>3) = Wood, planks<br>4) = Asbestos<br>5) = Iron sheets<br>6) = Tiles<br>7) = Tin<br>8) = Cement<br>9) = Others: Specify | 1) = Earth<br>2) = Cement<br>3) = Tiles<br>4) = Bricks<br>5) = Stone<br>6) = Wood<br>7) = Others: Specify | 1) Lacking<br>2) Poor<br>3) Fair<br>4) Good |
| **State of vegetation**<br>1. Overgrown/bushy<br>2. Well maintained<br>3. No vegetation | | | |

B4. If you keep improved chicken and/or improved kienyeji breed of chicken, please give details regarding poultry breeding and productivity.

| | |
|---|---|
| Number of Hens owned (which are used for breeding and not for sale and consumption) | |
| No. of cocks owned for breeding purpose (which are used for breeding and not for sale and consumption) | |
| Where do you source replacement/starter flocks | |
| If you produce your own chicks, what is the method of hatching? | |
| Which method of brooding do you use? (?) | |

| **Source of chicken** | **Hatching methods** | **Brooding methods** |
|---|---|---|
| 1. = Hatcheries | 1. = Single bird natural incubation | 1. = Natural Brooding |

| | | |
|---|---|---|
| 2. = Local breeders/multipliers<br>3. = Own hatching<br>4. = Agro vets<br>5. = Others: Specify ___________ | 2. = Serialized hatching<br>3. = Synchronized Hatching<br>4. = Artificial incubators<br>5. = Others: Specify _____________ | 2. = Use of electric Bulb<br>3. = Charcoal burners<br>4. = Kerosene Lumps<br>5. = Others: Specify______ |

**Access to poultry farming information**

B5. Have you accessed information on poultry production for the last one year (Oct 2020 – Sept 2021)? _____ 1 = Yes; 0 = No

B6. If yes, please select and specify below

| Source | Frequency of getting Information (Use codes) |
|---|---|
| | |
| **Information source**<br>1. = Radio<br>2. = Newspaper<br>3. = TV<br>4. = Public extension<br>5. = Local cooperative/producer organization<br>6. = NGO/project<br>7. = Other farmers<br>8. = Institutions – colleges, etc.<br>9. = Digital media (internet, mobile platform/App)<br>10. = Digital media (Facebook, WhatsApp, Twitter, etc.) | **Frequency of accessing information**<br>1. = Daily<br>2. = Weekly<br>3. = Monthly<br>4. = On need<br>5. = Incidentally<br>6. = Others: Specify __________________ |

E&. Production system used: For each chicken type owned, please indicate the feeding system used.

| Type of chicken | Free range/scavenging 1 = Yes; 0 = No | Semi-intensive (Mainly intensive with some scavenging) 1 = Yes; 0 = No | Semi-intensive (Mainly scavenging with some intensive feeding) 1 = Yes; 0 = No | Pure intensive feeding 1 = Yes; 0 = No |
|---|---|---|---|---|
| | | | | |
| | | | | |
| **Chicken type**<br>1) = Local chicken<br>2) = Improved kienyeji<br>3) = Improved/exotic chicken breeds<br>4) = Others: Specify | | | | |

**SECTION C: POULTRY GROSS MARGIN**

**Poultry productivity**

C1. Have you been keeping laying chicken in the past 1 year (Oct 2020 – Sept 2021)? _____ 1 = Yes; 0 = No

C2. If yes, please provide the following information on the layers kept in the past 1 year.

| Chicken Type | Management type (1=Free range; 2= semi-intensive; 3=intensive system | Total no. of hen layers in the cycle | Age at first laying (months) | Average Number of Clutches per bird | Average number of eggs laid per hen per clutch/Year | Average no. of eggs per hen per year |
|---|---|---|---|---|---|---|
| Layers | | | | | | |
| Improved Kienyeji | | | | | | |
| Indigenous chicken | | | | | | |

C3. Have you been rearing broilers in the past 1 year (Oct 2020 – Sept 2021)? _____ 1 = Yes; 0 = No

C4. If yes, please provide the following information on the broilers reared in the past 1 year.

| Production cycle | What was the average number of broilers in each of the cycle | Length of each cycle (days) | Average market weight attained at sale? | Number marketed per cycle | Price per Kg of broiler Sold |
|---|---|---|---|---|---|
| Cycle 1 | | | | | |
| Cycle 2 | | | | | |
| Cycle 3 | | | | | |
| Cycle 4 | | | | | |

C5. Have you been rearing local chicken or improved *kienyeji* in the past 1 year (Oct 2020 – Sept 2021)? _____ 1 = Yes; 0 = No

C6. If yes, please provide the following information on the local chicken or improved *kienyeji* reared in the past 1 year.

| | Indigenous/local chicken | Improved kienyeji |
|---|---|---|
| Management system | | |
| Average number of hens that were laying the last one year | | |
| Average number of chicks that are hatched per hen in one cycle | | |
| Average number of chicks per hen that reach one month old | | |
| Average number of chicks per hen that reach maturity | | |
| Average number of birds that are sold per year | | |
| Average price per bird sold | | |
| Average number of months taken to reach market weight | | |
| **Management system**<br>1. = Free range<br>2. = Semi-intensive<br>3. = Intensive | | |

C7. Did you buy any local chicken or improved *kienyeji* chicks for rearing in the past 1 year (Oct 2020 – Sept 2021)? _____ 1 = Yes; 0 = No

C8. If yes, please provide the following information on purchases.

| | Indigenous/local chicken | Improved kienyeji |
|---|---|---|
| Management system | | |
| Average number of chicks purchased into the farm | | |
| Average number of chicks purchased into the farm | | |
| Average age of the purchased chicks in days | | |
| Average number of chicks that reached 1 month old | | |
| Average number of chicks purchased that reached maturity | | |
| Average number of birds that are sold per year, out of the number purchase? | | |
| Average number of months taken to reach market weight | | |
| **Management system**<br>4. = Free range<br>5. = Semi-intensive<br>6. = Intensive | | |

**Additional revenue from poultry related enterprises**

C9. Please provide sales revenue from other poultry related activities.

| QNO | Revenue stream | Unit of Measure | Units | Unit cost (KShs) |
|---|---|---|---|---|
| | Sale of broilers | Number | | |
| | Sale of layers | Number | | |
| | Sale of cocks/rooster/cockerel | Number | | |
| | Sale of hen | Number | | |
| | Sale of chicks | Number | | |
| | Sales of eggs | Number | | |
| | Sale of manure | Kgs | | |
| | Farmer training services (model farm) | KShs | | |
| | Income from hired out equipment | | | |
| | Other (Specify) | | | |

**Poultry feeding**

C10. What do you feed your chicken on?

| Chicken type | Feed type | Number of months used | Source | Quantity used/month | | Price/unit if purchased |
|---|---|---|---|---|---|---|
| | | | | Units | Quantity | |
| | | | | | | |

| **Chicken type** | **Feed type** | **Source** | **Units** |
|---|---|---|---|
| 1) Local chicken | 1) Commercial concentrates<br>2) Home formulated feeds<br>3) Growth stimulators/promoters | 1) Own/home formulated | 1. Kgs<br>2. Tons<br>3. Bags |

| | | | |
|---|---|---|---|
| 2) Improved kienyeji<br>3) Layers<br>4) Broilers<br>5) Others: Specify | 4) Crop waste/byproduct<br>5) Industrial waste<br>6) Natural feed scavenged by chicken<br>7) Others: Specify | 2) Purchased/commercial<br>3) Mixed – part home, part purchased | 4. Wheelbarrow/cart load<br>5. Others: Specify |

C11. Besides main/basal feed (formulated feeds, crop or industrial by-products) have you used any feed additives in the last one (1) year (October/2020-September /2021)? [__] 1= Yes; No =0.

C12. If yes, please provide the following details for each feed additives used.

| Number of months used | Feed additives used | Chicken type fed? | Source:<br>1. Own farm;<br>2. Other farm;<br>3. Purchased<br>4. Mix of purchased and own- | **If purchased** | | | |
|---|---|---|---|---|---|---|---|
| | | | | Monthly cost during months when purchased | | | Where purchased? (code) |
| | | | | Weight of pack | Number of packs | Price /pack | |
| | | | | | | | |

| | Feed additive type | Chicken fed | Mesurément unit | Where purchased? |
|---|---|---|---|---|
| | 1. Growth boosters/promoters<br>2. Vitamin supplements<br>3. Oilseed by-product (Sesame seed, cotton seed, copra, sunflower etc.)<br>4. Agro industrial byproducts (vegetable waste, | 1. = All<br>2. = Chicks<br>3. = Broilers<br>4. = Layers<br>5. = Kienyeji<br>6. =Other (specify) | 1. <=1 Kg<br>2. = 2 kg<br>3. = 5 kg<br>4. = 10 kg<br>5. = 20kg pack<br>6. = 25 kg pack<br>7. = 50 kg pack<br>8. = Other (specify) | 1. = Agro vet shop<br>2. = Other farmers<br>3. = Market, trader<br>4. = Posho mills<br>5. =Other (specify) |

C13. Is there anything that you would like to be changed about the feed additives that you use? _______ *1 = Yes; 0 = No*

C14. If yes, please provide details below.

| Product | Desired change (*choose from code below*) |
|---|---|
| | |

| |
|---|
| **Desired change**<br>1) = Manner of delivery<br>2) = Manner of administration<br>3) = Shelf life<br>4) = Enhanced content |

| |
|---|
| 5) = Others: Specify |

**Other poultry enterprise expenditures in the past one year**

C15. Animal health services and expenses

| | Vaccination | Deworming/parasite control | Curative/clinical treatment | Other (specify) |
|---|---|---|---|---|
| Do you access this service? (0= NO; 1=YES) | | | | |
| What type of chicken received the service in the past 1 year | | | | |
| How many times have used this service in last one (1) year? | | | | |
| No of chicken attended to per service | | | | |
| Total expenditure for treatment for last one (1) year | | | | |
| Who provided the main service? | | | | |
| Type of disease treated | | | | |
| Which drug/medicine was used for treatment | | | | |
| Was the bird subjected to full dose of treatment? _____ 1 = Yes; 0 = No | | | | |
| Did the treated bird recover? _____ 1 = Yes; 0 = No | | | | |
| If no, what did you do the sick bird | | | | |

| **Type of chicken** | **Service provider** | **Type of disease** |
|---|---|---|
| 1. = Chicks<br>2. = Layers<br>3. = Broilers<br>4. = Kienyeji<br>5. = Other (specify)_____ | 1. = Self/ Neighbor with professional advice<br>2. = Self/ Neighbor without professional advice<br>3. = Animal health service provider/para-vet.<br>4. = Government veterinarian/AHA<br>5. = Other Project/ NGO staff<br>6. = Coop/ group staff (AHAs attached to cooperatives)<br>7. = Agro-vet shop)<br>8. = Community dip<br>9. = Other (specify) ____________________ | |

| **Type of drugs/medicine administered** | **What happened to the treated birds?** |
|---|---|
| 1.= Antibiotic<br>2. = Multivitamin<br>3.= I don't know<br>4.= Others: Specify ___________ | 1. = Treated with new drugs and recovered<br>2. = Treated with new drugs and succumbed<br>3.= Did nothing and they succumbed<br>4.= I don't remember |

C16. Has any chicken died from your flock over the past 1 year (October 2020 – September 2021)? ____ *1 = Yes; 0 = No*

C17. If yes, please provide the following information for the chicken that have died.

| | |
|---|---|
| Causes of death | |
| Type of chicken that has died | |
| Number of chickens that died | |
| Was the chicken treated? *1 = Yes; 0 = No* | |
| Cost of treatment (KSH) | |
| **Cause of death**<br>1. = Disease<br>2. = Accident<br>3. Predation<br>4. = Others: specify ______ | **Type of chicken**<br>1. = Chicks<br>2. = Layers<br>3. = Broilers<br>4. = Improved Kienyeji<br>5. Indigenous Chicken<br>6. Others: Specify ____________ |

**Labor use and expenses**

C18. Did you employ a **monthly paid laborer** in your chicken enterprise in the past one (1) year (Oct 2020 – Sept 2021)? [__] (0=No 1=Yes).

C19. If yes, enter the following details for laborers used: -

| | Gender of labourer<br>0 = Male<br>1 = Female | Average working hours per day | monthly wage | Months engaged (Codes) | Number of hours per day dedicated to poultry activities |
|---|---|---|---|---|---|
| 1 | | | | | |
| 2 | | | | | |
| 3 | | | | | |

C20. Have you employed any casual laborer(s) in your chicken enterprise in the past one (1) year (Oct 2020 – Sept 2021)? (0=No 1=Yes).

C21. If yes, enter the following details: -

| Gender of Workers | Number of workers | Average hours worked per day | Actual hours worked in poultry enterprise | Average no of days worked in a month | Daily wage | Number of months worked in the last 12 months |
|---|---|---|---|---|---|---|
| Male – non household member | | | | | | |
| Female – non household members | | | | | | |

C22. Has any household member been involved in chicken production related activities in the past one (1) year (Oct 2020 – Sept 2021)? (0=No 1=Yes).

C23. If yes, enter the following details: -

| QNO | HH member (a) | Gender | No. people | Hrs./person/day in poultry work | Average no of Months worked | Number of Months worked |
|---|---|---|---|---|---|---|
| | Adult male | M | | | | |
| | Adult female | F | | | | |
| | Children <15 yrs. | M/F | | | | |
| | | | | | | |

C24. Other Costs in the dairy enterprise

| QNO | Type of Input/Service | Type of Units | Frequency | Unit cost (KShs) | Total Cost (KShs) |
|---|---|---|---|---|---|
| | Water | Per month | | | |
| | Value of poultry house | | | | |
| | Total Value of poultry equipment | | | | |
| | Interest on credit/loan | Per month | | | |
| | Coops fees | Per month | | | |
| | Equipment lease costs | | | | |
| | Loss due to theft | | | | |
| | Electricity costs | Per month | | | |
| | Storage costs | | | | |
| | Slaughtering costs | | | | |
| | Licenses and fees | | | | |
| | Communication costs (Poultry related) | Per month | | | |
| | Other (Specify) | | | | |
| | | | | | |
| **Frequency**<br><br>1. = ___ per day; 2. = ___ per week; 3. = ___ per month; 4. = ___ per year | | | | | |

**SECTION D: HOUSEHOLD NET ANNUAL INCOME**

I would now like to discuss with you about your income from various household activities/enterprises.

**ON-FARM INCOME**

D1. Crops revenue from October 2020 to September 2021: Please share production and consumption information for crops grown in the past 12 months (October 2020 – September 2021).

| Crop | Unit of measure | Quantity produced last | Quantity consumed home | Quantity wasted/ spoilt | Average Price per Unit? (KShs) | Quantity sold | Quantity set aside for seed |
|---|---|---|---|---|---|---|---|
| | | | | | | | |
| | | | | | | | |
| | | | | | | | |
| **Crop code**<br>1. Maize<br>2. Banana<br>3. Beans<br>4. Cassava<br>5. Passion fruit<br>6. Sweet potatoes<br>7. Coffee | 8. vegetables<br>9. Tomatoes<br>10. Sorghum<br>11. Peas<br>12. Groundnuts<br>13. Simsim<br>14. Others: Specify _____________ | | | | **Measurement unit**<br>1. Kilograms<br>2. Tons<br>3. Bunches<br>4. Bags<br>5. Others: Specify ____________ | | |

D2. Please share how much your household spent in crop production inputs/operations for the past 12 months (October 2020 – September 2021).

| Input/operation | Total expenses from October 2020 – September 2021 |
|---|---|
| | |
| **Input or operation**<br>1. Land preparation<br>2. Planting<br>3. Seeds<br>4. Fertilizer<br>5. Pesticides<br>6. Weeding costs<br>7. Herbicides<br>8. Machinery/equipment rent<br>9. Crop insurance | 10. Land rent<br>11. Interest on credit (agriculture use only)<br>12. Water/irrigation<br>13. Draught animal services (Donkeys, bullocks, etc.)<br>14. Harvesting costs<br>15. Transportation fees<br>16. Capital Expenditure (Specify)<br>17. Other (Specify)____________ |

D3. In the following table, please capture the average hours per day worked on crop production by family members.

| Household member | Number of months worked | Average hours per day worked |
|---|---|---|
| | | |
| **Household member**<br>1. = Wife<br>2. = Husband<br>3. = Another household male<br>4. = Another household female | | |

D4. Please share information on the cost of hired labor that worked on crop production over the past 12 months.

| Gender Male = 1; Female = 0 | Number of months worked | Average monthly salary | Additional monthly cost to hire labor | Additional monthly benefits given to hired labor |
|---|---|---|---|---|
| | | | | |

D5. Livestock, off-springs and by products revenues

| Livestock category/product | Unit of measure | Quantity produced/kept last 12 months | Quantity consumed at home | Quantity Wasted / dead | Quantity sold in the last 12 months | Average Price per Unit |
|---|---|---|---|---|---|---|
| | | | | | | |
| | | | | | | |
| **Livestock category**<br>1. = Cattle<br>2. = Goats<br>3. = Sheep<br>4. = Donkeys<br>5. = Pigs<br>6. = Poultry<br>7. = Others: Specify ____ | **Livestock products**<br>1. = Milk<br>2. = Eggs<br>3. = Honey<br>4. = Hides/skins | | **Production unit**<br>1. = Pieces/Number<br>2. = Kgs | | | |

D6. Please share how much your household spent in animal husbandry from October 2020 – September 2021.

| Input/service | Number of Months used | Total cost (KES) |
|---|---|---|
| | | |
| **Input/service**<br>1. = Livestock nutrition: Minerals<br>2. = Livestock nutrition: Concentrates<br>3. = Livestock nutrition: Water<br>4. = Livestock nutrition: Fodder<br>5. = Poultry feed – poultry covered later<br>6. = Veterinary services: Animal health<br>7. = Breeding services: Artificial Insemination<br>8. = Livestock shelter<br>9. = Farm equipment<br>10. = Interest on credit (for livestock only)<br>11. = Transportation fees<br>12. = Capital expenditure/depreciation specify<br>13. = Others: Specify ______________ | | |

D7. In the following table, please capture family labor use for animal husbandry.

| Persons involved | Activity done | Frequency units | Days/unit | Hours per day |
|---|---|---|---|---|
| | | | | |

| Persons | Activity | Frequency |
|---|---|---|
| 1. = Wife<br>2. = Husband<br>3. = Another household male<br>4. = Another household female | 1. = Grazing<br>2. = Feeding (collecting & preparation)<br>3. = Fodder/feed production on farm<br>4. = Providing water to the animals<br>5. = Cleaning of animal shed/shelter<br>6. = Collection of Farm -yard manure (FYM)<br>7. = Milking and milk processing<br>8. = Selling milk<br>9. = Selling animals/ animal products (except milk)<br>10. Others: Specify __________ | 1. = Daily<br>2. = Weekly<br>3. = Monthly<br>4. = Annually |

D8. In the following table, please capture information on use of hired labor for animal husbandry.

| Activity done | Frequency units | Days/unit | Hours per day | Pay/wage rate | Payment regime |
|---|---|---|---|---|---|
| | | | | | |

| Activity | Frequency | Payment regime |
|---|---|---|
| 1. = Grazing<br>2. = Feeding (+ collecting & preparation)<br>3. = Fodder/feed production on farm<br>4. = Providing water to the animals<br>5. = Cleaning of animal shed/shelter<br>6. = Collection of Farm -yard manure (FYM)<br>7. = Milking and milk processing<br>8. = Selling milk<br>9. = Selling animals/ animal products (except milk)<br>10. = Others: Specify ________________ | 1. = Daily<br>2. = Weekly<br>3. = Monthly<br>4. = Annually | 1. Daily<br>2. Monthly |

**OTHER ON-FARM INCOME SOURCES**

D9. Do you have other on-farm income sources? _____ 1 = Yes; 0 = No

D10. If yes, please provide the following information on your enterprises

| On-farm enterprise | Unit of measure | Quantity produced last 12 months | Quantity consumed at home | Quantity sold | Quantity Wasted | Average Price per Unit? |
|---|---|---|---|---|---|---|
| Organic Fertilizer | | | | | | |
| Organic pesticide | | | | | | |
| Mala | | | | | | |
| Sale of Hay | | | | | | |
| Sale of Silage | | | | | | |
| Other (Specify) | | | | | | |

**NON-FARM INCOME**

**Wage employment**

Wage income is defined as income received from ALL activities off the household's farm. This implies a remuneration, and it can be earned from agricultural (*e.g., doing farming activities for other farms*) or non-agricultural (*e.g., teacher, lawyer, working at the municipality, etc.*) sources.

D11. Did any household member engage in any such employment? _____ 1 = Yes; No = 0

D12. If yes, please provide detailed information on each of the wage employment that members of household engage in over the past 12 months.

| Household member | Type of wage employment | Number of months worked on wage employment | Days per month worked | Frequency of payment | Pay received each time |
|---|---|---|---|---|---|
| | | | | | |
| | | | | | |

| **Persons** | **Wage employment type** | **Frequency of payment** |
|---|---|---|
| = Wife<br>= Husband<br>= Another household male<br>=Another household female | = Farm laborer<br>= Formal employment<br>= Others: Specify _________ | = Monthly<br>= Weekly<br>= Daily<br>= Others: Specify _________ |

D13. Did the household members engaged in wage employment above incur any expenses related to the employment identified above? ____

1 = Yes; 0 = No

D14. If yes, please identify the expense type and the amount spent over the past 12 months

| Expense type | Number of months when incurred | Total expense for each month |
|---|---|---|
| | | |
| | | |
| | | |

| Expense type |
|---|
| 1. = Clothing for work<br>2. = Transportation<br>3. = Meals<br>4. = Shelter/rent<br>5. = Communication |

**Income from businesses and/or retail activities**

D15. Do you or any other family member carry on a business? _______ 1 = Yes; 0 = No

D16. If yes, please identify the type of business and kindly share with us the total revenue obtained over the past 12 months. *Please only include non-farm related businesses/enterprises*.

| Business type | Business operator | Number of months when operated | Revenue collected for each month operated |
|---|---|---|---|
| | | | |
| **Business type**<br>1. = Trading of livestock and livestock products (not own produce)<br>2. = Trading in agricultural products (excluding livestock!) (Not own produce)<br>3. = Non-Agricultural - Trade or services<br>4. = Trading of livestock and livestock products (not own produce)<br>5. = Sale of animal feed, pasture, fodder (not own produce)<br>6. = Draught animal/tractor services<br>7. = Tractor services<br>8. = Tree sale business<br>9. = Sale of natural resources (not won produce)<br>10. = Rentals<br>11. = Other: Specify _____________ | | **Business operator**<br>1. = Wife<br>2. = Husband<br>3. = Another household male<br>= Another household female | |

D17. In the following table please capture the total cost incurred associated with the businesses operated by household business identified above.

| Business type | Input | Number of months when incurred | Amount incurred for every month |
|---|---|---|---|
| | | | |
| | | | |

| **Business type** | **Input type** |
|---|---|
| 1. = Trading of livestock and livestock products (not own produce)<br>2. = Trading in agricultural products (excluding livestock!) (Not own produce)<br>3. = Non-Agricultural - Trade or services<br>4. = Trading of livestock and livestock products (not own produce)<br>5. = Sale of animal feed, pasture, fodder (not own produce)<br>6. = Draught animal/tractor services<br>7. = Tractor services<br>8. = Tree sale business<br>9. = Sale of natural resources (not won produce)<br>10. = Rentals<br>11. = Other: Specify _____________ | 1. = Labor (direct)<br>2. = Raw materials<br>3. = Utilities (electricity, gas, etc.)<br>4. = Equipment rent<br>5. = House rent<br>6. = Land rent<br>7. = Transportation services<br>8. = Marketing services<br>9. = Financial services (such as interest on loans)<br>10. = Technical assistance<br>11. = Packaging<br>12. = Capital expenditure* specify<br>13. Others: Specify _________________ |

D18. In the following table, please capture the labor provided by the family for all non-farm business activities. Please ensure you capture all family members involved in all businesses operated by the household.

| Household member | Number of months worked | Days per month worked | Average hours per day worked |
|---|---|---|---|
| | | | |
| **Household member**<br>1. = Wife<br>2. = Husband<br>3. = Another household male<br>4. = Another household female | | | |

H19. In the following table, please capture the hired labor for all non-farm business activities. Please ensure you capture hired labor for all businesses operated by the household.

| Gender Male = 1; Female = 0 | Number of months worked | Average monthly wage | Additional monthly cost to hired labor | Additional monthly benefits given to hired labor |
|---|---|---|---|---|
| | | | | |

**Income from Organization Profit Sharing and Dividends/Bonus**

D20. Did any household member receive payment in form of profit sharing (dividends, etc.) over the past 12 months? 1 = Yes; 0 = No

*Dividends/Bonus are the benefits received on a regular basis by a company/cooperative out of its profits*

| Household member | Source | Number of months when received | Amount received each time |
|---|---|---|---|
| | | | |
| | | | |

| Household member | Source |
|---|---|
| **Household member**<br>1. = Wife<br>2. = Husband<br>3. = Another household male<br>4. = Another household female | **Source**<br>1. = Dividend<br>= Other: Specify _____________ |

**Income from Transfers**

D21. Did your household receive any cash or in-kind benefits from the government, NGOs or family members that are not part of the household over the past 12 months? _______ 1 = Yes; 0 = No

D22. If yes, please provide information on the income transfers received. *In case of public (government) transfers, please enlist only those that are known in frequency and amount*

| Household member | Source of transfer | Number of months when received | Amount received each time |
|---|---|---|---|
| | | | |
| **Household member**<br>5. = Wife<br>6. = Husband<br>7. = Another household male<br>8. = Another household female | **Source**<br>2. = Pension<br>3. = Family allowance/remittance<br>4. = Cash transfer program<br>5. = NGO support program<br>= Other: Specify ________ | | |

**SECTION E: KNOWLEDGE, ATTITUDE, AND PRACTICES**

E1. Please respond to the following statement about your chicken feeding

| | Strongly agree (1) | Agree (2) | Neither agree nor disagree (3) | Disagree (4) | Strongly disagree (5) |
|---|---|---|---|---|---|
| Livestock keeping is a major contributor to your income | | | | | |
| Feeding additives like supplements, vitamin premixes, protein premixes) is a critical component of balanced feeding | | | | | |
| The best way to keep animals healthy and protected from diseases is through balanced feeding | | | | | |
| Farm management and biosecurity are linked to animal health | | | | | |
| You are familiar with farm management or biosecurity practices to reduce the spread of disease between animals or from animals to humans | | | | | |
| Practicing farm hygiene and sanitation will protect your herd from diseases | | | | | |
| You currently use antibiotics as part of your farm management | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Antibiotics should be added to feed/water at any time to prevent animals from becoming sick | | | | | |
| Antibiotics should be added to feed/water at any time to promote animal growth or productivity | | | | | |
| You have heard the term ‘antimicrobial resistance’/Antibiotic Resistance | | | | | |
| The use of antibiotics without animal health service provider has negative consequences to the animal and or human heath | | | | | |
| Not following dosages and withdrawal periods on treatment has negative consequences on human and animals consuming livestock products | | | | | |
| You are confident making choices on the antibiotics you give to your livestock | | | | | |
| You like to be among the first to adopt improved production practices when trained | | | | | |
| You only want to adopt practices that others have tested and confirmed that they work | | | | | |
| Efforts to improve biosecurity (segregation; cleaning and disinfection) did not prevent the disease in the past | | | | | |
| It is easy to contact animal health service provides if there is disease in my farm | | | | | |
| Reporting disease in my farm will get me help so that the disease doesn’t spread within my farm or other farms | | | | | |
| You can get information on disease outbreaks within your area | | | | | |
| You avoid visiting other farms or households when their livestock contract a contagious disease | | | | | |

**This implies feeding a balanced and wholesome diet composed of basal feeds and additional feed elements such as concentrates, mineral salts/blocks and other feed additives.*