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Adoption of farm biosecurity practices among smallholder poultry farmers in Kenya – An application of latent class analysis with a multinomial logistic regression

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ABSTRACT

Sub-Saharan Africa has a growing demand for poultry, but productivity in the sector has not increased to meet this demand. One major constraints in the sector is diseases. Many farmers currently use clinical control measures that involve treating birds with antibiotics upon detecting an infection. However, this approach has presented the misuse of antibiotics, leading to antimicrobial resistance, which could have catastrophic effects going by different projections. We evaluate 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. We find low adoption of biosecurity measures across all classes of smallholder poultry farmers in Nyanza. However, correlation analysis show 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 higher adoption of biosecurity measures. Lastly, we implement a multinomial logistic regression to assess determinants of class membership and our 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.

1. Introduction

Poultry diseases and the associated costs 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

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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 and 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 and 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 aims to evaluate the adoption patterns 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.

2. Methodology

2.1. Study site

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.

2.2. Sample selection and data collection

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). In this study we concentrate largely on the sector 3 farmers who are the majority in Nyanza. The farmers are characterized by 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).

We use the 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. The questionnaire was pretested, validated, and enumerators trained to use it appropriately. The data was obtained by 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.

2.3. Description of variables

Table 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

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

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

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

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 the 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. We use 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”. See Appendix 1 for the summary of descriptive statistics.

2.4. 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 and Ben-Akiva, 2002). Farmers, therefore, choose which biosecurity practices to implement following a utility-maximizing behavior modeled by Eq. (1).

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

Where U is a latent (unobserved/indirect) variable comprising the systematic (deterministic) part- V_{ijs}, and a stochastic component denoted by μ_{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; β_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 Eq. (2) (Vermunt, 2017).

$$P(Y_i) = \sum_{s=1}^{S} P(X' = s) P(Y_i | X' = s) \tag{2}$$

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, we can compute the probability of individual i choosing alternative n in a choice situation Y_{in}, conditioned on membership to class s as in Eq. (3).

$$\text{Prob}_{in|s}(j) = Prob(Y_{in} = j | class = s) = \frac{\exp(X^{'}_{in,j}\beta_s)}{\sum_{j=1}^{J}\exp(X^{'}_{in,j}\beta_s)} \tag{3}$$

Where β_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. Eq. (5) makes it possible to observe an individual farmer under different choice situations. We can also compute the probability of an individual belonging to a particular class s (P_{is}) as shown in Eq. (4).

$$P_{is} = \frac{\exp(w_i^{'}\theta_s)}{\sum_{s=1}^{S}\exp(w_i^{'}\theta_s)} \tag{4}$$

Where w_i to represent the observable attributes determining class membership; while θ_s represent class-specific parameters. The computation of the posterior probability follows a maximum likelihood estimation of Eq. (5).

$$\ln L = \sum_{i=1}^{N} \ln L_i = \sum_{i=1}^{Q} \ln \left[\sum_{n=1}^{N} P_{is} \left(\prod_{n=1}^{Y_i} L_{in|s} \right) \right] \quad (5)$$

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 latent class analysis 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 involve 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 Eq. (6).

$$C_i = \beta_0 + \beta_i X_i + \mu_i \quad (6)$$

Where *Ci* is a multidimensional variable representing different adoption classes. On the other hand, X_i represent a vector of covariates including socioeconomic, institutional, and technological characteristics, while β_i are estimated parameters. μ_i is a mutually exclusive error term. The model in Eq. (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. 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 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.

3. Results and discussion

3.1. Model selection

Table 2 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 Bayesian Information Criterion. 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.

3.2. Item response probabilities

Table 3 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.

3.2.1. Adoption of general biosecurity practices

The outcome probabilities summarized in the table 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

Table 2
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	19,843.39	19,661.99
LC2 – 2-classes	-8649.63	17,840.28	17,473.26
LC3 – 3-classes	-8334.97	**17,484.58**	16,931.94
LC4 – 4-classes	-8198.30	17,484.85	16,746.60
LC5 – 5-classes	-8112.727	17,587.33	**16,663.45**
LC6 – 6-classes	-8134.596	17,904.68	16,795.19

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

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

Outcome probabilities	LC1 *Low Adopters* *(n = 158)*	LC2 *Moderate Adopters* *(n = 163)*	LC3 *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
A. **Inappropriate Measures**			
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 % of households within respective classes.
Source: Survey Data 2021.

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.

Housing practices are least embraced by *low adopters* with less than 1 % having a poultry unit. This finding indicates that a majority 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.

3.2.2. *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 wash their hands and use foot disinfectant before accessing the poultry unit. Only 30.3 % of the *high adopters* insisted on farmers using protective clothing when handling the birds.

3.2.3. *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 low uptake of external biosecurity control.

3.2.4. *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 inadequate uptake of nutrition practices.

3.2.5. 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. % of the *high adopters* reported controlling external parasites. The proportions are even lower 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. de Oliveira 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 continue 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 (de Oliveira 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 de Oliveira Sidinei et al. (2021), which groups farmers into different clusters. The study by de Oliveira 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 by the use of 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.

3.3. Biosecurity adoption and key poultry health indicators

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 4 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.

Table 4
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 use of antibiotics was more common among individuals in the higher adoption classes –a positive and statistically significant correlation coefficient of 0.41. The finding contradicts Davies and Wales (2019) and Moffo et al. (2022), both of which 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. Determinants of adoption of biosecurity measures

Table 5 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 variable 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 ($0.87 \pm 0.26, p = 0.003$; $0.90 \pm 0.26, p = 0.002$). These findings agree with Yamano et al. (2015) and de Oliveira 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*

Table 5
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.

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 de Oliveira 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 agrees with Etuah et al. (2020) who argue that more years of experience enables 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 the 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 caused 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.

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.

4. Conclusion and recommendations

In this study we evaluate adoption of biosecurity measures, which have been shown to effectively and sustainably manage livestock diseases. 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, we implement an MLogit to explore the potential determinants of adoption of biosecurity measures.

Our 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, our study present empirical evidence that adoption of biosecurity measures is largely driven by access to information on such practices. Farmers who accessed information on biosecurity measures were 24.9 % more likely 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 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 can support farmers to access the resources that can 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.

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Declaration of Competing Interest

This article is submitted with the full knowledge of the listed authors and the funding bodies. There is no conflict of interest.

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Appendix 1. Table of 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.

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