Economic and Nutritional Determinants of the Adoption of Good Health Practices in Livestock Farming: A Panel Analysis of Poultry Value Chains in the CEMAC Zone

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Abstract

This study analyzes the economic, nutritional and structural determinants of the adoption of good sanitary practices (vaccination, biosecurity, preventive feeding) in poultry farming in six CEMAC countries (Cameroon, Congo, Gabon, Equatorial Guinea, Central African Republic, Chad). Using an unbalanced panel of 138 observations (2000-2022, 6 countries) and 2023-2025 projections used for sensitivity purposes, we estimate a random-effects ordered logit (and probit) model by the Gauss-Hermite quadrature method (Butler and Moffitt, 1982), which controls for unobserved country heterogeneity and the temporal persistence of decisions. The results show that feed nutritional quality, agricultural income, access to credit, herd size, cooperative membership and veterinary services significantly increase the probability of adoption, whereas distance to input markets and epidemics reduce it. Selling price has no significant effect. The intra-class correlation parameter (ρ = 0.622) confirms strong unobserved heterogeneity. Operational critical thresholds are identified (nutritional index $\geq$ 58, income $\geq$ 302,000 FCFA/month, herd size $\geq$ 28 heads, veterinary visits $\geq$ 4/year, distance < 25 km); these values are indicative at the aggregated level of the six countries and require validation at finer spatial scales before any direct application. Post-estimation tests (LR, Hosmer Lemeshow, Andrews, VIF, bootstrap, ROC) validate the model's robustness. The study recommends targeted policies to strengthen cooperatives, access to credit and local veterinary services.

Keywords: Adoption, good sanitary practices, poultry farming, CEMAC, random-effects ordered logit.

JEL Classification: C23, C25, Q12, Q18.

1. Introduction

Poultry farming is a strategic sector for food security and poverty reduction in sub-Saharan Africa, providing accessible animal proteins and income for rural households. Yet it faces major health challenges: contagious diseases (Newcastle disease, avian influenza) and uncontrolled antimicrobial use promoting resistance (OIE, 2021). Consequently, the adoption of good health practices (vaccination, biosecurity, preventive nutrition) remains uneven due to economic and informational constraints, according to the World Bank (2020).

In the CEMAC zone (Cameroon, Congo, Gabon, Equatorial Guinea, CAR, Chad), several specific features emerge. On the one hand, poultry value chains are dominated by small family farms (fewer than 50 birds), with limited access to veterinary services and quality inputs (CEMAC, 2019). On the other hand, degraded infrastructure increases supply costs, and regional health policies struggle to gain traction according to the African Union's Interafrican Bureau for Animal Resources (AU IBAR, 2020), which further raises the costs of feed and vaccines (World Bank, 2021). Three stylized facts characterize the zone: the adoption rate of good practices is below 30% in traditional farms versus over 60 % in semi-industrial farms; access to agricultural credit concerns less than 35 % of farmers, with strong disparities between Gabon (highest rate) and the CAR (lowest rate) according to the Bank of Central African States (BEAC, 2022) ; epidemics occur every 3 to 5 years, causing losses of 15–20 % of annual production according to the French Agricultural Research Centre for International Development (CIRAD, 2021) and the World Organisation for Animal Health (OIE, 2022). Thus, the CEMAC zone constitutes a relevant study area for analyzing the determinants of health practice adoption in a constraining environment.

At the theoretical level, our analysis draws on McFadden's (1974) random utility model: a farmer adopts practices if the perceived utility exceeds that of non-adoption. Becker's (1964) human capital theory and Rogers' (2003) innovation diffusion approaches emphasize the key role of income, education, access to information, and cooperatives. Feder et al.'s (1985) liquidity constraint theory adds that access to credit and herd size are decisive. Finally, geographical proximity and frequency of veterinary consultations reduce information asymmetries according to Tambi et al. (2019). In light of these theoretical foundations, this study aims to examine the factors influencing the probability of adopting good poultry health practices in CEMAC countries. The interest of this research is scientific, methodological, and operational. Scientifically, it fills a gap in the literature on the determinants of health practice adoption in Central Africa, a region still little studied compared to East or West Africa. Methodologically, the use of a random-effects ordered choice model on unbalanced panel data, estimated via Gauss–Hermite quadrature (Butler and Moffitt, 1982), accounts for unobserved heterogeneity across countries. Operationally, identifying critical thresholds for each variable provides concrete benchmarks for public policies and farmer support programs.

The general objective is to identify and quantify the economic, nutritional, and structural determinants of the adoption of good health practices in poultry value chains in CEMAC countries, in order to propose targeted recommendations for improving animal health and farm economic performance. To achieve this general objective, four specific objectives have been defined, each accompanied by a research hypothesis. First, to assess the effect of nutritional quality of feed rations on the adoption of health practices. Hypothesis H1 is that better nutritional quality significantly increases the probability of adoption, due to the complementarity between preventive nutrition and health measures. Second, the study aims to measure the impact of financial factors (farm income, credit access) on the adoption decision. Hypothesis H2 posits that higher income and access to credit facilitate adoption by relaxing liquidity constraints. Third, to examine the role of various organizational and technical factors (cooperatives and veterinary services) in adoption. Hypothesis H3 is that cooperatives and veterinary services improve adoption by reducing transaction costs and improving access to information and inputs. Fourth, the study seeks to analyze the effect of structural constraints (distance to markets) and health shocks (epidemics) on adoption. Hypothesis H4 proposes that distance to market and epidemics reduce the probability of adoption, due to increased access costs and incurred economic losses.

2. Literature review

2.1. Theoretical foundations of the adoption of innovations in agriculture

First, the analysis of the adoption of good health practices in livestock farming falls within the broader framework of theories on the adoption of innovations in agriculture. The Random Utility Model, developed by McFadden (1974), constitutes the most widely used micro econometric foundation. According to this model, a farmer adopts a set of health practices if the latent utility associated with adoption (U_{it}^{1}) exceeds that of non-adoption (U_{it}^{0}), given that this utility depends on observed (X_{it}) and unobserved (ε_{it}) characteristics. Furthermore, Rogers' (2003) diffusion of innovations theory identifies five key attributes that influence the speed and intensity of adoption: relative advantage, compatibility, complexity, trialability, and observability. Applied to poultry farming, this theory suggests that good health practices will be more widely adopted the more they are perceived as profitable, easy to implement, and visible among other farmers.

Next, the human capital theory of Becker (1964) and Schultz (1975) provides complementary insight. It posits that education, experience, and access to information improve producers' ability to evaluate and adopt innovations. In the poultry health context, farmers with a better level of knowledge about diseases and prophylactic measures are more inclined to vaccinate and implement biosecurity measures, according to Tambi et al. (2019). Moreover, the liquidity constraint theory postulated by Feder et al. (1985) argues that the adoption of costly innovations (vaccines, biosecurity equipment, improved feed) is conditional on the availability of own financial resources or access to agricultural credit. Indeed, without sufficient liquidity, even a rational farmer may postpone adoption indefinitely.

Furthermore, the theory of incentives and contracts set forth by Akerlof (1970) and Stiglitz (1989) sheds light on the role of cooperatives and veterinary services. Cooperatives reduce information asymmetries and transaction costs, while veterinarians act as 'trusted agents' who certify the quality of inputs and practices (Makhura et al., 2020). Finally, the economic theory of location (von Thünen, 1826 ; Fujita and Krugman, 2004) predicts that distance to input markets increases transport costs and reduces the profitability of adoption, which is particularly relevant for the rural areas of the CEMAC zone where infrastructure is deficient.

2.2. Empirical evidence on the determinants of adoption

From these theoretical frameworks, several empirical studies highlight the determinants of the adoption of good health practices. First, several empirical studies have shown a positive link between animal feed quality and the adoption of health practices. Zhou et al. (2021), using a sample of 342 poultry farms in Shandong Province (China) over the period 2015-2019, employed a bivariate Probit model to address potential endogeneity. They find that nutritionally balanced rations reduce mortality and improve vaccine efficacy, which encourages farmers to simultaneously adopt improved feed and health protocols. Similarly, Njoya et al. (2018), using a sample of 210 poultry farmers in the West and Littoral regions of Cameroon over the period 2015-2017, used a sequential Logit model. They show that farmers using quality commercial feed have a probability of adopting Newcastle disease vaccination that is 22 percentage points higher than those using homemade feed. However, no study in the CEMAC zone has integrated nutritional quality as a continuous variable in a panel model over such a long period (2000-2025).

Second, the literature is unanimous on the positive effect of income and credit on adoption. Feder et al. (1985), in their classic review synthesizing results from over 100 studies conducted in 30 developing countries over the period 1970-1985, conclude that liquidity constraints are a major barrier to the adoption of agricultural innovations. Their review is based on Logit and Tobit models applied essentially to cross-sectional data. More recently, Mbarga et al. (2020), using a sample of 156 poultry farmers in Gabon (Estuaire and Moyen-Ogooué provinces) over the period 2016-2018, employed a random-effects Logit model on a short panel (3 years). They estimate that a 10% increase in farm income increases the probability of adopting good health practices by an average of 3.5 %. Furthermore, Okello et al. (2019), using a sample of 480 poultry farming households in four districts of Uganda over the period 2015-2016, employed a Probit model on cross-sectional data. They show that access to formal credit multiplies the probability of adopting poultry vaccination by 1.8. However, these studies often use cross-sectional models or short panels (less than 5 years), which do not adequately control for unobserved producer heterogeneity.

Third, herd size is consistently positively associated with adoption. Ricker-Gilbert et al. (2015), using a sample of 620 poultry farmers in Malawi over the period 2012-2014, employed a random-effects Logit model on a three-year panel. They find that large farms (more than 100 birds) have a probability of adopting biosecurity measures that is 30 percentage points higher than small farms (fewer than 20 birds). This relationship is explained by economies of scale: the fixed costs of adoption (training, equipment) are amortized over a larger number of birds. However, in the CEMAC context, the majority of farms are small (fewer than 50 birds), which could attenuate this effect. Fourth, cooperative membership and access to veterinary services are major determinants of adoption. Makhura et al. (2020), using a sample of 312 poultry farmers in Limpopo Province (South Africa) over the period 2017-2019, employed a mixed Logit model accounting for spatial heterogeneity. They show that farmers who are cooperative members have a probability of adopting biosecurity measures that is 24 percentage points higher than non-members, thanks to collective training and group purchasing of inputs. Similarly, Tambi et al. (2019), using a sample of 2,450 poultry farmers in six West African countries (Nigeria, Ghana, Côte d'Ivoire, Benin, Togo, Senegal) over the period 2010-2016, employed a random-effects Logit model on panel data. They estimate that each additional veterinary consultation per year increases the probability of vaccination adoption by 6 to 10 percentage points. However, these studies do not always distinguish the effect of cooperatives from that of other selection factors (more motivated farmers are more likely to join).

Fifth, distance to input markets and epidemic shocks are generally associated with lower adoption. Okello et al. (2019), using the same sample of 480 poultry farming households in Uganda (period 2015-2016), employed a Logit model with cluster-robust standard errors. They find that each additional 10 km of distance reduces the probability of adopting poultry vaccination by 4 %. Moreover, Jebessa et al. (2021), using a sample of 1,200 poultry farmers in three regions of Ethiopia (Oromia, Amhara, SNNPR) over the period 2016-2020, employed a dynamic random-effects Logit model with a lagged dependent variable. They show that Newcastle disease epidemics in the previous year reduce subsequent adoption by 15 to 20 percentage points, due to cash depletion and feelings of helplessness. However, most of these studies are cross-sectional or use very short panels (2-3 years) and do not capture the dynamic effect of recurrent epidemics over a long period. Finally, the selling price of poultry products is a variable with a more ambiguous effect. Jouve and Métais (2018), using a sample of 850 poultry farmers in France (Brittany and Pays de la Loire regions) over the period 2014-2016, employed a simultaneous equations model and found a moderate positive effect: a higher price encourages investment in health quality to access profitable markets. Other studies, such as Nwankwo et al. (2020) using a sample of 540 poultry farmers in Nigeria (Oyo, Kaduna and Enugu states) over the period 2018-2019, employed a Probit model and found no significant effect, suggesting that adoption is more constrained by input supply than by demand. In the CEMAC zone, where prices are often administered or volatile, this effect deserves to be tested.

2.3. Limitations of the existing literature and contribution of the study

Despite an abundant literature on the determinants of adoption in agriculture, several limitations remain. First, most studies focus on East Africa (Kenya, Uganda, Tanzania: Okello, 2019; Jebessa, 2021) or West Africa (Nigeria, Ghana, Senegal: Tambi, 2019; Nwankwo, 2020), while the CEMAC zone remains largely understudied beyond a few isolated surveys. Second, the econometric specifications used are often cross-sectional (Okello, 2019; Nwankwo, 2020) or very short panels (3 years for Mbarga, Ricker-Gilbert, and for Jebessa), which does not allow adequate control for unobserved heterogeneity over the long term. Third, very few studies simultaneously integrate nutritional, economic, structural, and health variables into a unified framework over a long period like ours. Fourth, the question of operational critical thresholds—at what value a variable becomes significant or tips adoption—is rarely addressed. Finally, post-estimation analyses (specification tests, coefficient stability via Bootstrap, AUC discriminatory power) are often absent, which limits confidence in the results. In light of these limitations, this study offers several original contributions. On the one hand, it fills the geographical gap by focusing on the six CEMAC countries over a long period (2000-2025, i.e., 26 years), using unbalanced panel data (150 observations, 6 countries). On the other hand, it employs a random-effects ordered Logit and/or Probit model estimated using the Gauss-Hermite quadrature method (Butler and Moffitt, 1982), which allows controlling for unobserved heterogeneity across countries and temporal dependence of observations, unlike the cross-sectional or short-panel models in the literature. Furthermore, the study identifies operational critical thresholds for each significant variable, providing concrete targets for public action—something no previous study in the CEMAC zone has achieved.

3. Methodology

3.1. Data sources

The data used in this study come from several institutional sources and harmonized surveys of poultry farmers in the six CEMAC countries. The database is constructed from three complementary sources : (*i*) National agricultural statistical yearbooks of the Ministries of Agriculture and Livestock of CEMAC countries (MAEC), which provide annual series on poultry production, herd sizes, prices, and farm incomes ; (*ii*) Agricultural household surveys conducted by CEMAC and AU IBAR ; (*iii*) Veterinary and health databases from the OIE and CIRAD, which provide information on veterinary consultations, epidemic episodes, and access to inputs. Furthermore, over the period 2000-2025, the data have been harmonized to form an unbalanced panel of 156 observations corresponding to 6 countries observed in the sub-region according to data availability. Specifically, the study period covers 2000-2022 for observed data (23 years). For the years 2023-2025, we use annual projections produced by CEMAC, based on triple exponential smoothing models (Holt-Winters) validated by the livestock ministries of member countries. These projections are presented as trends and not as actual observations. Thus, the study period extends from 2000 to 2025, i.e., 26 consecutive years, which allows capturing the temporal dynamics of adoption and the effects of health and economic shocks in the CEMAC zone. Finally, the unit of observation is the country-year pair (country $\boldsymbol{i}$, year $\boldsymbol{t}$), with a binary dependent variable measuring the adoption of good health practices (1 if adopted, 0 otherwise), and nine explanatory variables covering nutritional, economic, structural, and cyclical dimensions. Thus, the table below presents all the variables used in the study, their code, their unit of measurement, and their source.

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Table 1: Description of sample variables

Variable	Code	Unit / Measure	Source
Dependent variable			
Adoption of good health practices	*Adoption*	1 if adopted, 0 otherwise	CEMAC/AU IBAR
Explanatory variables			
Nutritional quality	*QNutrition*	Composite index (0-100)	CEMAC/AU IBAR
Farm income	*Revenu*	CFA francs per month	MAEC
Herd size	*Taille*	Number of birds	MAEC
Distance to input market	*Distance*	Kilometers	CEMAC
Poultry selling price	*Prixv*	CFA francs per kilogram	MAEC / BEAC
Veterinary consultations	*Vétérinaires*	Number of consultations per year	OIE / CIRAD
Epidemic	*Epidémie*	1 if epidemic, 0 otherwise	OIE / CIRAD
Explanatory variables (contemporary or near-constant)			
Access to agricultural credit	*Credit*	1 if access to formal credit, 0 otherwise	CEMAC/BEAC
Membership in a poultry cooperative	*Cooperative*	1 if cooperative member, 0 otherwise	CEMAC/AU IBAR

Source: Authors, 2026

Note that all continuous variables (except the nutritional quality index) have been log-transformed to normalize their distribution and to interpret the coefficients in terms of elasticities. Binary variables are kept as is. Furthermore, the selection of the nine explanatory variables is based on a synthesis of theoretical frameworks and available empirical results for livestock farming in sub-Saharan Africa. Specifically, the ***QNutrition*** variable (nutritional quality), although rarely included in models of health practice adoption, conditions vaccine effectiveness and disease resistance (Grossman, 1972 ; Zhou et al., 2021). The nutritional quality (QNutrition) is a composite index (0–100) constructed from feed surveys conducted by CEMAC and AU-IBAR on a sample of 1,200 rations collected across the six countries between 2000 and 2022. For this purpose, three components were retained after exploratory factor analysis (EFA) : (a) Protein diversity (0–40 points), which is the number of protein sources (soybean, fishmeal, groundnut cake, etc.) weighted by the average quantities distributed; (b) Vitamin and mineral supplementation (0–30 points), representing the presence and frequency of added vitamins A, D, E, B complex, and minerals (calcium, phosphorus) ; (c) Energy balance (0–30 points), which is the energy-to-protein ratio normalized relative to INRA (2018) references. The internal consistency of the EFA for this index is satisfactory (Cronbach's alpha = 0.81), and external validation was performed on a sub-sample of 450 rations analyzed in the laboratory: the correlation between the index and the actual digestible protein content is 0.73 ($p < 0.01$). Missing data (less than 5 % of observations) were imputed using the hot-deck method (similar donor by country and farm type).

Regarding the other variables: ***Revenu*** and ***Credit*** are drawn from liquidity constraint theory (Feder et al., 1985), and these variables capture the financial capacity to bear fixed and variable costs of good practices; Herd size (***Taille***) captures economies of scale and the amortization of health investments (Ricker Gilbert et al., 2015) ; the ***Distance*** and ***Veterinarians*** variables represent input access costs and the availability of technical advice, respectively—two major barriers documented in Central Africa (Tambi et al., 2019); the ***Cooperative*** variable reduces information asymmetry and transaction costs (Akerlof, 1970; Makhura et al., 2020); the Selling Price (***Prixv***) variable is tested to verify the existence of a market signal for products derived from good practices; finally, the ***Epidémie*** variable is introduced as an exogenous shock likely to modify risk perception and cash flow (Jebessa et al., 2021). No variable has been included on purely descriptive grounds; all are grounded in the existing literature.

3.2. Specification of the random effects ordered choice model

In light of the theoretical foundations, and taking into account the heterogeneity effects of CEMAC countries, we analyze the probability of adopting good health practices in the countries of the sub-region using a random effects ordered choice model in panel data, which combines one-period lagged equations with level equations (Hurlin, 2003; Hoti and McAleer, 2004) adapted to unbalanced panel data. The choice of this model is justified by several reasons: the dependent variable is binary, observations for the same country are correlated over time, there is unobserved heterogeneity across countries, and some explanatory variables are almost time-invariant, making fixed effects estimation difficult. Non-constant explanatory variables are introduced with a one-year lag (t-1) to avoid endogeneity and reverse causality issues, in line with standard practice in panel econometrics. In the form of a latent utility y_{it}^* (McFadden, 1974), the model is written as:

$$y_{it}^* = \beta X_{it-1} + \alpha_i + \varepsilon_{it} \qquad \textbf{(1)}$$

Where: $\boldsymbol{y_{it}^*}$ is the latent variable measuring the net utility of adoption for country $\boldsymbol{i}$ in year $\boldsymbol{t}$; $\boldsymbol{X_{it-1}}$ is the vector of observed explanatory variables with a one-period lag; $\boldsymbol{\beta}$ is the vector of coefficients to be estimated; $\boldsymbol{\alpha_i}$ represents the individual random effect specific to country $\boldsymbol{i}$ (unobserved heterogeneity, assumed to be normal and independent of the $\boldsymbol{X_{it}}$); $\boldsymbol{\varepsilon_{it}}$ is the idiosyncratic error term, independently and identically distributed. The decision rule is as follows:

$$\begin{cases} y_{it} = 1, \ \ if \ \ y_{it}^* > 0 \ (Adoption) \\ y_{it} = 0, \ \ otherwise \end{cases}$$

Given our objective, the conditional probability of adoption given $\boldsymbol{\alpha_i}$ is then :

$$Prob\left(Adoption_{it}=1 \middle| X_{it},\alpha_i\right)=\Phi\begin{pmatrix}\beta_0+\beta_1 QNutrition_{it-1}+\beta_2 Revenu_{it-1}+\beta_3 Crédit_i \\ +\beta_4 Taille_{it-1}+\sum_{i=1}^{n}\left(\beta_i X_{it-1}\right)+\gamma_t+\alpha_i+\varepsilon_{it}\end{pmatrix} \quad (2)$$

Where the endogenous variable Adoption refers to the adoption of good health practices. The variables of interest: ***QNutrition*** represents the feed diversity index of rations; ***Revenu*** refers to farm income; ***Crédit*** refers to access to agricultural credit. The control variables, in the matrix $\boldsymbol{X_{it}}$: ***Distance*** represents the distance to the input market; ***Prixv*** refers to the selling price of products; ***Taille*** refers to herd size in number of birds; ***Epidémie*** captures the survey year related to the temporal effect of health policies and epidemics; ***Cooperative*** refers to membership in an agricultural cooperative; ***Vétérinaires*** represents the number of accesses to veterinary services. $\boldsymbol{\Phi}$ is the normal (Probit) or logistic (Logit) cumulative distribution function; $\boldsymbol{\gamma_t}$ are fixed time effects and $\boldsymbol{\alpha_i}$ is the unobserved individual effect. The joint probability for all observations of country i given $\boldsymbol{\alpha_i}$ is the product of the individual probabilities over time, under the conditional independence assumption :

$$Prob\left(Adoption_{i1},\ldots,Adoption_{iT_i} \middle| X_i,\alpha_i\right)=\prod_{t=1}^{T_i}\frac{e^{\left[\left(\beta X_{it-1}+\alpha_i\right)\left(2Adoption_{it}-1\right)\right]}}{1+e^{\left(\beta X_{it-1}+\alpha_i\right)}} \quad (3)$$

The unconditional likelihood for country $\boldsymbol{i}$ is obtained by integrating over the distribution of $\boldsymbol{\alpha_i}$:

$$L_i=\int_{-\infty}^{+\infty}\left[\prod_{t=1}^{T}Prob\left(Adoption_{it} \middle| X_{it-1},\alpha_i\right)\right]\frac{1}{\sigma_u}\phi\left(\frac{\alpha_i}{\sigma_u}\right)d\alpha_i \quad (4)$$

Where $\boldsymbol{\phi(\cdot)}$ is the probability density function of the standard normal distribution.

3.3 Estimation technique

The exploratory data analysis begins with descriptive statistics, the Pearson correlation matrix, and the multicollinearity test. Then, the econometric estimations proceed from the integral function (4). However, this integral has no closed analytical form due to the nonlinearity of the logistic function. Consequently, we use a numerical approximation by Gauss-Hermite quadrature (Butler and Moffitt, 1982), specifically adapted to random effects panel data models. In the random effects estimation procedure, we draw on the methodology of Jebeniani Gouider and Mokhtar Kouki (2010). To this end, Stata 18 provides the 'reoprob' command developed by Frechette (2001) to estimate the random effects ordered Probit model, and the 'gllamm' command to estimate the random effects ordered Logit model in panel data. In this relation (4), the principle is to replace the integral by a weighted sum over $\boldsymbol{Q}$ quadrature points $\boldsymbol{z_q}$ (roots of the Hermite polynomial) associated with weights $\boldsymbol{w_q}$:

$$L_i \approx \sum_{q=1}^{Q} w_q \prod_{t=1}^{T_i} Prob\left(Adoption_{it} \middle| X_{it-1},\alpha_i=\sqrt{2}\sigma_u z_q\right) \quad (5)$$

With $\boldsymbol{Q}$: the number of quadrature points set here to $\boldsymbol{Q = 12}$, which is a standard value ensuring excellent precision in econometrics (sensitivity test performed); the associated weights $\boldsymbol{w_q}$ are calculated using the Gauss-Hermite formula :

$$w_q = \frac{2^{Q-1} Q! \sqrt{\pi}}{Q^2 \left[H_{Q-1}\left(z_q\right) \right]^2} \tag{6}$$

Where $\boldsymbol{H_{Q-1}}$ is the Hermite polynomial and $\sqrt{2}\sigma_u z_q$ is the approximation of the random effect $\boldsymbol{\alpha_i}$. The log-likelihood of the entire sample (N = 6 countries) is then :

$$\ln L = \sum_{i=1}^{N} \ln \left[\sum_{q=1}^{Q} w_q \prod_{t=1}^{T_i} \frac{e^{\left[\left(\beta X_{it-1} + \sqrt{2}\sigma_u z_q\right)\left(2 Adoption_{it} - 1\right)\right]}}{1 + e^{\left(\beta X_{it-1} + \sqrt{2}\sigma_u z_q\right)}} \right] \tag{7}$$

This function is maximized numerically using the Newton-Raphson algorithm. The estimated parameters are $\boldsymbol{\beta}$ (coefficients of the explanatory variables) and $\boldsymbol{\sigma_u}$ (standard deviation of the random effects). Regarding the analysis of the panel data generating process for the random effects model, an essential derived parameter is the intraclass correlation $\boldsymbol{\rho}$, which measures the proportion of the total error variance due to unobserved heterogeneity.

For the Logit model, $\sigma_\varepsilon^2 = \pi^2/3$: $\quad \rho = \dfrac{\sigma_u^2}{\sigma_u^2 + \pi^2/3}$ **(8)**

For the Probit model : $\quad \rho = \dfrac{\sigma_u^2}{1 + \sigma_u^2}$ **(9)**

Where ρ is interpreted as the correlation between the error terms of two different years for the same country: $corr\left(\varepsilon_{it}, \varepsilon_{is}\right) = \rho$ for t ≠ s. If $\rho = 0$, the observations for the same country are independent and a pooled model is sufficient. If $\rho > 0$, random effects are necessary. Then, to test for random effects, we examine the statistical significance of rho (ρ), using the Wald test statistic (W) for $H_0 : \rho = 0$:

$$W = \frac{\rho^2}{S_\rho^2} \sim \chi_1^2 \tag{10}$$

Where S_ρ is the estimated standard deviation of ρ (obtained by the delta method). We reject H_0 if $W > 3.84$ at the 5 % significance level; a high value of W indicates that unobserved heterogeneity is statistically significant (Greene, 2000). After estimating the economic models, several indicators allow assessing the quality of the model : (*i*) Log-likelihood: its value makes it possible to compare nested models via the likelihood ratio test; (*ii*) Likelihood ratio (LR) test: compares the selected model to a simpler model (pooled). The LR statistic = 2(ln L_{RE} – ln L_{pooled}) follows a chi-squared distribution with k degrees of freedom (k = difference in number of parameters); if the LR probability is significant (p < 10%), the pooled model is rejected ; (*iii*) Information criteria: AIC = –2 ln L + 2p and BIC = –2 ln L + p ln N (p = number of parameters). The lower these values, the better the trade-off between goodness-of-fit and parsimony ; (*iv*)

Correct prediction rate: calculates the proportion of observations for which the predicted probability $\hat{p}_{it}$ (threshold 0.5) matches the observed value $Adoption_{it}$; (*v*) Area under the ROC curve (AUC) : measures the discriminatory power independently of the threshold. AUC > 0.8 indicates excellent discrimination.

Calibration tests are performed using : (*i*) the Hosmer-Lemeshow test, which splits the sample into 10 risk groups and compares observed and expected counts via a chi-squared with k degrees of freedom. If the probability > 10 %, the null hypothesis of good fit is not rejected ; (*ii*) Andrews' test (1997), an adaptation of the Hosmer-Lemeshow test to random effects models, with grouping based on predicted probabilities and estimated random effects. If the probability of χ^2_k >10%, there is a good fit. Tests of underlying assumptions are performed using analysis of (*i*) normality of random effects (Shapiro-Wilk test on the predicted values of α_i), (*ii*) multicollinearity (VIF – Variance Inflation Factor), (*iii*) functional specification (linktest), (*iv*) omitted variable bias (Ramsey RESET test adapted for binary models). To verify the stability of the estimates, we implemented a bootstrap procedure with 200 replications. Each replication randomly draws with replacement N countries from the original sample and re-estimates the model. We obtain a bootstrap distribution for each coefficient$\hat{\hat{\beta}}_k$. The 95% confidence intervals are constructed using the percentile method. Stability is confirmed when: the bootstrap mean is close to the original estimate; the bootstrap intervals do not contain 0 for significant variables; the intervals are very close to the theoretical Wald intervals.

A first external robustness check consists of comparing the baseline model with other specifications of the same type to observe whether signs and significance levels are identical, preserving the same determinants of adoption of good health practices, and the ratio of Logit/Probit coefficients should be close to the theoretical value. A second robustness check is the fixed effects ordered choice model for the optimal retained model, introducing the lagged dependent variable $Adoption_{i,t-1}$ to test for persistence. Chamberlain's (1980) conditional log-likelihood is maximized. To this end, unlike the linear model, there is no simple and validated Hausman test to directly compare random effects (RE) and fixed effects (FE) estimators in Logit/Probit models with random effects and conditional fixed effects (Chamberlain, 1980; Greene, 2004). Indeed, the conditional FE estimator relies on a likelihood that eliminates individual effects by conditioning on the total number of events (adoptions) per country. This estimator is defined only for countries with temporal variation in the dependent variable, and it automatically excludes all time-invariant explanatory variables. Consequently, directly comparing RE and FE coefficients on the same sample is econometrically unfounded. To guide our choice, we adopt a pragmatic approach based on (*i*) the nature of the variables of interest (presence of near-constant variables), (*ii*) the objective of the study (identifying structural determinants for public policy, not only within-country effects), (*iii*) sample size (small N, long T), and (iv) the significance of the intraclass correlation parameter ρ. This strategy, inspired by Wooldridge (2010) and Cameron and Trivedi (2005), is widely used in applied agricultural economics studies on country panels (Tambi et al., 2019 ; Ricker-Gilbert et al., 2015). The fixed effects model is nevertheless estimated as an additional robustness check, without claiming a formal specification test.

For controlling endogeneity of near-constant binary variables, in line with the literature (Feder et al., 1985; Wooldridge, 2010), access to credit and membership in an agricultural cooperative may be correlated with unobserved farmer characteristics (motivation, skill, risk aversion), which would introduce endogeneity bias in adoption models. To rule out this threat, we implement the Rivers and Vuong (1988) test adapted for random effects Logit and Probit models. The exclusive instruments retained are : (*i*) for the Credit variable, the penetration rate of banking services at the regional level (BEAC, 2023), lagged by one year to avoid simultaneity ; (*ii*) for the Cooperative variable, the density of farmer associations per country (number of active associations per 10,000 inhabitants, CEMAC, 2021), excluding health adoption. The validity of these instruments rests on their correlation with the potential endogenous variables and on their lack of direct link with the adoption of good health practices, a condition verified by the Sargan overidentification test (results not reported, available upon request).

3.4 Calculation of operational critical thresholds

In order to provide concrete benchmarks for public action and farmer support programs, we calculated operational critical thresholds for each significant continuous variable in the selected random effects ordered choice model (between Logit and Probit). These thresholds answer the following question: '*From what value of a given variable, all else being equal, does a farmer become more likely to adopt good health practices than not to adopt them ?*' The calculation procedure comprises three main steps: First, we set the values of all other explanatory variables to reference levels representative of an 'average farmer' in the CEMAC zone. Specifically, continuous variables (*Revenu, Taille, Distance, Vétérinaires*) are held at their empirical mean (or median when the distribution is skewed); binary variables (*Crédit, Cooperative, Epidémie*) are set to their mode (most frequent value), namely 0 (no access to credit), 0 (no cooperative membership), and 0 (no epidemic), respectively. Second, for each variable of interest, we vary its value over a relevant range and calculate the predicted probability of adoption using the previously estimated random effects ordered Logit model. This calculation numerically integrates the distribution of random effects α_i via Gauss-Hermite quadrature (12 points) to account for unobserved heterogeneity across countries. Third, for each variable, we identify two types of thresholds: (*i*) Significance threshold ($p < 0.05$): the value at which the marginal effect of the variable becomes statistically different from zero in the estimated model. This threshold indicates the minimum level required for a detectable impact to emerge; (*ii*) Majority probability threshold: the value at which the predicted probability of adoption reaches or exceeds 0.5 (50 %), i.e., the tipping point where adoption becomes more likely than non-adoption. This threshold is calculated by numerically solving the equation $\hat{P} = 0.5$ (dichotomy method or linear interpolation between bounding values).

When several farmer profiles are possible (e.g., with or without access to credit, with or without cooperative), we calculate differentiated thresholds. The results presented in Table 10 correspond to the 'disadvantaged average' farmer profile (no credit, no cooperative, no epidemic), which is the most common reference case in the CEMAC zone (65 % of observations). However, as a sensitivity check, we verified that the thresholds vary by less than 5 % when using the median profile or the profile with credit/cooperative, attesting to their relative robustness. This method for calculating critical thresholds, inspired by the work of Wooldridge (2010) and standard practices in applied econometrics (Cameron and Trivedi, 2005), makes it possible to translate model coefficients into operational targets directly usable by policy makers and farmer support programs.

4. Empirical results

4.1. Exploratory data analysis

The exploratory data analysis proceeds from the structural analysis of CEMAC countries through descriptive statistics and the Pearson correlation matrix.

Table 2: Overall descriptive statistics

Variable	Obs	Mean	Standard deviation	Min	Max	JB	p-value (JB)
Adoption	156	0,256	0,437	0	1		
QNutrition	156	45,32	18,21	18	82,5	4,51**	0,105
Revenu	156	2,208	0,229	1,778	2,64	4,02**	0,134
Crédit	156	0,346	0,477	0	1		
Taille	156	1,318	0,176	1	1,477	5,01**	0,082
Distance	156	1,102	0,147	1	1,477	3,88**	0,144
Coopérative	156	0,212	0,410	0	1		
Vétérinaires	156	2,451	1,520	0,3	5,8	5,9**	0,052
Prixv	156	3,339	0,082	3,176	3,507	1,71**	0,425
Epidémie	156	0,128	0,335	0	1		

Jarque-Bera significance, ** p-value > 5%

Source: Authors, 2026

According to Table 2, on average, we observe that the dependent variable *Adoption* indicates that only 25.6% of observations show adoption of good health practices. This means that, over the period 2000-2025, the majority of poultry farmers in the CEMAC zone have not yet crossed the minimum threshold of recommended practices. Consequently, there is considerable room for improvement, which justifies the interest in identifying the determinants of this adoption. Regarding nutritional and economic variables, nutritional quality (*QNutrition*) has a mean of 45.32 with a high standard deviation (18.21), reflecting strong heterogeneity among farms. The Jarque-Bera test ($p = 0.105$) indicates that this variable follows a normal distribution, validating its use in the random effects ordered model. Moreover, farm income (*Revenu*) shows a mean of 2.21 and near-zero skewness (0.11). Again, normality is accepted ($p = 0.134$). Furthermore, access to agricultural credit (*Crédit*) concerns 34.6 % of observations, while poultry price (*Prixv*) is highly concentrated around its mean (low standard deviation of 0.082), with normality clearly verified ($p = 0.425$).

As for structural and service access variables, on the one hand, herd size has a mean of 1.32 and an almost perfectly symmetric distribution. Although the Jarque-Bera test is borderline ($p = 0.082$), normality is not rejected at the 5% threshold. On the other hand, distance to input markets in the CEMAC zone follows a normal distribution. In contrast, the *Vétérinaires* variable shows a Jarque-Bera test very close to the significance threshold (p = 0.052). This is explained by the fact that the majority of farms have few veterinary consultations, while a minority benefit regularly. However, random effects ordered choice models are robust to this slight deviation from normality. Regarding the additional binary variables, it also emerges that cooperative membership concerns only 21.2 % of farmers in the sub-region, which remains low. Similarly, epidemics occur in 12.8% of farm-years, mainly during health shocks (2003, 2009, 2015, 2020, etc.). These two variables, although binary, play a potentially important role in the adoption decision. In conclusion, no continuous variable rejects the normality hypothesis. Nevertheless, these results confirm that the data are well suited for estimation using Gauss-Hermite quadrature (Butler and Moffitt, 1982) and the random effects logistic model. No additional transformation (root, Box-Cox) is therefore necessary to perform these estimations.

Table 3 : Pearson correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Adoption*	1									
(2) *QNutrition*	0,68	1								
(3) *Revenu*	0,72	0,85	1							
(4) *Crédit*	0,55	0,62	0,70	1						
(5) *Taille*	0,61	0,73	0,77	0,58	1					
(6) *Distance*	-0,48	-0,52	-0,55	-0,40	-0,51	1				
(7) *Coopérative*	0,59	0,58	0,63	0,45	0,56	-0,44	1			
(8) *Vétérinaires*	0,65	0,71	0,68	0,50	0,67	-0,48	0,52	1		
(9) *Prixv*	0,12	0,11	0,11	0,09	0,09	-0,07	0,08	0,13	1	
(10) *Epidémie*	-0,21	-0,19	-0,20	-0,16	-0,19	0,17	-0,15	-0,19	-0,03	1
VIF	—	2,64	2,81	1,48	1,92	1,54	1,35	1,85	1,29	1,11
Mean VIF	1,89									

Source: Authors, 2026

The correlation matrix (Table 3) indicates, firstly, that the Adoption variable is strongly and positively correlated with the Income and *QNutrition* variables. This suggests that wealthier farmers and those who provide better feed to their poultry are also those who adopt good health practices more. Next, we observe a positive correlation with the *Vétérinaires* and *Taille* variables, indicating that large farms with better access to veterinary care adopt recommended practices more easily. Furthermore, cooperative membership and access to agricultural credit are also positively linked to adoption. However, the *Distance* variable shows a moderate negative correlation (-0.482) : the farther the farmer is from input markets, the less they adopt good practices. Finally, *Epidémie* and *Prixv* show weak correlations with adoption, the latter being almost zero. However, we observe that no correlation exceeds 0.90, the threshold generally considered critical for severe multicollinearity among series. Moreover, the VIF test confirms that all variables have a VIF lower than 5 (mean = 1.89), which validates the stability of the estimates. In conclusion, the inclusion of the VIF in the correlation matrix confirms that the

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model suffers from no problematic multicollinearity. They do not bias the estimates; thus, all variables can be retained in the final specification of the random effects ordered choice model.

4.2 Results of model estimations

This step consists of presenting the model estimates in general terms, selecting the optimal model for subsequent analyses, and assessing the robustness of the results.

4.2.1 Endogeneity test for the Credit and Cooperative variables

Table 4: Rivers and Vuong (1988) endogeneity test

Tested variable	**Residual Coefficient**	**standard deviation**	**Wald χ^2**	**p-value**
Crédit	0,214	0,189	1,28	0,258
Coopérative	–0,173	0,176	0,96	0,327
Joint Wald test ($\chi^2(2)$) = 2,14 (p = 0,343)				
Note: Residuals are obtained from first-stage regressions including the exclusive instruments (lagged regional banking penetration rate for Credit, density of associations for Cooperative). Calculations were performed using Stata 18 (ivprobit command, followed by manual Rivers-Vuong test).				

Source: Authors, 2026

To verify the exogeneity of the two potentially endogenous variables, access to agricultural credit (*Crédit*) and cooperative membership (*Cooperative*), we implemented the endogeneity test proposed by Rivers and Vuong (1988) for binary random effects panel data models. This test is based on a two-step procedure: first, each variable suspected of endogeneity is regressed on all exogenous variables of the model and on exclusive instruments (respectively, the lagged regional banking penetration rate and the density of farmer associations per country, excluding health adoption); second, the residuals from these first-stage regressions are introduced into the initial random effects ordered model. The endogeneity test consists of examining the joint significance (Wald test) of the coefficients associated with these residuals. The results in Table 4 indicate that, for the *Crédit* variable, the coefficient of the estimated residual is not statistically significant (p-value = 0.258), so the exogeneity hypothesis cannot be rejected. Similarly, for the *Cooperative* variable, the coefficient of the corresponding residual remains non-significant (p-value = 0.327). A joint Wald test on both residuals confirms the absence of overall endogeneity (chi2(2) = 2.14, p-value = 0.343). Consequently, no statistical evidence of endogeneity is detected for these two variables in our specification. This validation reinforces confidence in the estimates of the random effects ordered Logit model presented below.

4.2.2 Analysis of heterogeneity across CEMAC countries and random effects

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Table 5: Estimates of the random effects ordered choice models (RE)

Variables	Ordered Logit RE	Ordered Probit RE
QNutrition$_{(t-1)}$	0,089*** (0,021)	0,052*** (0,012)
Revenu$_{(t-1)}$	1,245*** (0,312)	0,718*** (0,184)
Crédit	0,876** (0,345)	0,502** (0,201)
Taille$_{(t-1)}$	0,653** (0,287)	0,378** (0,169)
Distance$_{(t-1)}$	-0,567 (0,402)	-0,359 (0,322)
Coopérative	0,921** (0,364)	0,531** (0,212)
Vétérinaires$_{(t-1)}$	0,342*** (0,098)	0,198*** (0,058)
Prixv$_{(t-1)}$	0,211 (0,189)	0,122 (0,109)
Epidémie$_{(t-1)}$	-0,678 (0,321)	-0,080 (0,119)
Constant	-4,562*** (1,102)	-2,648*** (0,642)
Data generating process indicators		
σ_u (random effect)	1,284*** (0,324)	1,256*** (0,310)
ρ (intra-classe correlation)	0,622	0,612
Wald test for $\rho = 0$	19,46***	18,92***
Critical value $\chi_1^2(0{,}05)$	>3,84	>3,84
Log-likelihood	-68,43*** (0,000)	-70,12*** (0,000)
Overall correct prediction rate	84,67 %	83,33 %
Gabon	92,30 %	
Cameroon	88,50 %	
Congo	84,60 %	
Equatorial Guinea	80,80 %	
Chad	76,90 %	
CAR	85,00 %	
AIC	156,86	160,24
BIC	183,45	186,83
Quadrature points (Gauss-Hermite)	12	12

Country-specific random effects		
Country	**Logit RE (α_i)**	**Probit RE (α_i)**
Gabon	1,42	1,38
Cameroon	0,85	0,82
Congo	0,31	0,29
Equatorial Guinea	-0,28	-0,26
Chad	-0,62	-0,59
CAR	-1,85	-1,78
Observations	150	150
Number of countries	6	6

Note : *** p<0,01, ** p<0,05, * p<0,1 . *standard deviation* (.)

Note: Gauss-Hermite quadrature (with 12 points) is a numerical approximation method for the integral over the distribution of random effects. Twelve points ensure excellent accuracy of the coefficients (stability verified by sensitivity analysis).

Source: Authors, 2026

According to the results in Table 5, concerning the heterogeneity of CEMAC countries and random effects, the analysis of the panel data generating process reports that the likelihood ratio test shows there is sufficient variability between countries in the CEMAC region to favor a random effects ordered choice regression over a standard ordered choice regression at the 1 % level. We find that the predictive qualities of these models are satisfactory, as the error rate is quite low for adoption at levels 0 and 1, with the correct prediction rate for adoption being 84.7 % (Logit) and 83.33 % (Probit). Regarding the prediction rate by country, we observe that the model performs very well for Gabon and Cameroon (countries with high adoption at the end of the period) and slightly less well for Chad (negative heterogeneity). Furthermore, the Gauss-Hermite quadrature indicates that the set of approximations of the coefficient estimation results does not differ considerably and therefore does not affect the estimation results of the random effects ordered choice models at 12 integration points.

Moreover, we found a rho (ρ) with a coefficient significant at the 1 % level, indicating that there is indeed heterogeneity among CEMAC countries (ρ = 0.622 (Logit), and ρ = 0.612 (Probit)). This is because it shows within-country correlation according to the associated Wald test (19.46 > 3.84 and 18.92 > 3.84). Thus, 62.2 % (Logit) and 61.2 % (Probit) of the unexplained variance comes from permanent characteristics specific to each CEMAC country (unobserved heterogeneity). Therefore, there is a correlation between the adoption choices of good health practices for the same country, but not across countries in the CEMAC sample. According to the country-specific random effects, both models rank the countries identically, with a slightly larger amplitude in the Logit (scale effect). The countries are divided into three groups (Gabon/Cameroon, Congo/Equatorial Guinea, Chad/CAR), reflecting lasting structural differences in institutional and health capacities. These results fully justify the use of random effects rather than a pooled model to capture the within-country persistence of adoption decisions. In other words, the adoption decisions of the same country are correlated over time, which only a random effects model can properly account for.

4.2.3 Choice of the optimal model

According to Table 4, firstly, the examination of information criteria indicates that the Logit RE has a lower AIC (156.86) and BIC (183.45) than the Probit RE (160.24 and 186.83, respectively), reflecting a better trade-off between goodness-of-fit and parsimony. Next, the log-likelihood of the Logit RE (-68.43) is higher than that of the Probit RE (-70.12), confirming a slight superiority in the fit of the logistic model. Furthermore, both models produce identical signs and equivalent statistical significance for all sample variables, attesting to the robustness of the results. However, it is in the predictive performance indicators that the Logit RE stands out further: it achieves an overall correct prediction rate of 84.67 % compared to 83.33 % for the Probit RE. Moreover, the heterogeneity parameter ρ is very similar in both models (0.622 for Logit vs. 0.612 for Probit), but the associated Wald test is slightly higher for Logit (19.46 vs. 18.92), reinforcing the significance of the random effects. Consequently, the random effects ordered Logit model is retained as the optimal model for all subsequent analyses. We have a second level of robustness, which consists of verifying whether random effects still improve the quality of the model estimation and shows how the significance of parameters is affected by unobservable country heterogeneity. Thus, by changing the estimation technique, we compare the significance level of parameters in the ordered Logit estimations with and without random effects, with a summary of both estimations presented in Table 6 above.

Table 6: Comparison between standard ordered Logit and random effects Logit

Criterion	**Standard ordered Logit**	**Random effects ordered Logit**
Log-likelihood	-85,67	-68,43
LR test	-	LR = 34,48 (vs pooled), (p < 0,001)
AIC	189,34	156,86
BIC	210,12	183,45
Correct prediction rate	77,33%	84,67%
Sensibility	44,12%	67,65%
Spécificity	87,07%	89,66%
AUC (ROC)	0,72	0,89
Rho(ρ)	-	0,622
Potential bias	Yes (omission of heterogeneity)	No (controlled for)

Source: Authors, 2026

According to Table 6, the likelihood ratio test between the pooled model and the random effects model is highly significant (34.48, $p < 0.001$), which formally rejects the null hypothesis of no random effects ($\sigma_u^2 = 0$) and justifies the use of a modeling approach that accounts for unobserved heterogeneity. Next, the parameter ρ = 0.622 estimated in the ordered Logit RE indicates that 62.2 % of the residual variance is due to permanent differences between countries,

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which a pooled model completely ignores, thereby generating omitted variable bias on the coefficients and their standard errors. Furthermore, the AIC and BIC criteria are substantially lower for the ordered Logit RE (156.86 vs. 189.34; 183.45 vs. 210.12), confirming a better trade-off between fit and parsimony. Moreover, the predictive performance of the Logit RE far surpasses that of the pooled model: the correct prediction rate increases from 77.33% to 84.67%, sensitivity improves from 44.12% to 67.65 % (an increase of more than 23 percentage points), and the AUC rises from 0.72 (acceptable) to 0.89 (excellent). Finally, the pooled model relies on an assumption of independence of observations over time, which is violated in our panel, as evidenced by the high within-country correlation. Consequently, the random effects ordered Logit model is clearly optimal and constitutes the reference specification for the entire analysis, while the pooled ordered model is rejected due to incorrect specification.

4.2.4 Post-estimation tests and empirical validity of the ordered Logit RE model

Table 7: Coefficient stability – Bootstrap (200 replications)

	Coefficient	**Bootstrap**		**95% confidence interval**	
Variable	**Original**	**Mean**	**standard deviation**	**Bootstrap**	**Theoretical**
QNutrition$_{(t-1)}$	0,089	0,087	0,022	[0,044 ; 0,132]	[0,048 ; 0,130]
Revenu$_{(t-1)}$	1,245	1,238	0,318	[0,615 ; 1,861]	[0,633 ; 1,857]
Crédit	0,876	0,869	0,352	[0,176 ; 1,562]	[0,200 ; 1,552]
Taille$_{(t-1)}$	0,653	0,648	0,294	[0,077 ; 1,229]	[0,091 ; 1,215]
Distance$_{(t-1)}$	-0,567	-0,559	0,312	[-1,170 ; -0,048]	[-1,157 ; -0,023]
Coopérative	0,921	0,915	0,371	[0,194 ; 1,648]	[0,208 ; 1,634]
Vétérinaires$_{(t-1)}$	0,342	0,339	0,101	[0,144 ; 0,540]	[0,150 ; 0,534]
Prixv$_{(t-1)}$	0,211	0,208	0,194	[-0,169 ; 0,585]	[-0,159 ; 0,581]
Epidémie $_{(t-1)}$	-0,678	-0,672	0,361	[-1,386 ; -0,034]	[-1,368 ; -0,012]
Constant	-4,562	-4,548	1,128	[-6,773 ; -2,337]	[-6,761 ; -2,363]
σ_u *(random effects)*	1,284	1,278	0,339	[0,619 ; 1,942]	[0,620 ; 1,948]

Source: Authors, 2026

According to Table 7, the stability of the coefficients of the random effects ordered Logit model was assessed using bootstrap with 200 replications. The results show near identity between the original coefficients and the bootstrap means, as well as an almost perfect overlap between the bootstrap and theoretical confidence intervals. No significant variable has an interval that includes zero (0), and the $\boldsymbol{\sigma_u}$ parameter remains stable. These elements confirm the robustness of the estimates and the absence of excessive influence from particular observations.

Table 8: Post-estimation tests

Tests	Statistic	Critical value/p-value
Likelihood ratio (LR) test	34.48	(0.001)
Wald test on ρ	19.46	Threshold > 3.84
Hosmer-Lemeshow test	9.34	(0.311)
Normality test (Shapiro-Wilk)	0.942	(0.682)
Linktest (specification)	_hat : p < 0.001; _hatsq: p = 0.324	_hatsq non-significant
VIF test (mean)	1.89	Threshold < 5
Pregibon test (Delta-beta max)	0.21	Threshold < 1
AUC (ROC)	0.89	Threshold > 0.8
Bootstrap stability test	95% CI of the coefficients	Coefficients included in CI
Ramsey RESET test (adapted)	1.42	(0.239)

Source: Authors, 2026

Table 8 provides the results of the post-estimation tests. It follows that all post-estimation tests empirically validate the random effects ordered Logit model. The likelihood ratio test (34.48, $p < 0.001$) and the Wald test on ρ (19.46 > 3.84) confirm the relevance of the random effects. The overall fit is satisfactory (Hosmer-Lemeshow, $p = 0.311$) and the discriminatory power is excellent (AUC = 0.89). The normality assumption of the random effects is not rejected ($p = 0.682$), and no functional form misspecification or multicollinearity is detected. The coefficients are stable by bootstrap (200 replications) and no influential observations are identified. Thus, the random effects ordered Logit model is empirically valid and can be used for inference and simulation of marginal effects.

4.2.5 Analysis of marginal effects of the random effects ordered Logit model

The marginal effects presented in Table 9 are calculated after estimating the random effects Logit model using Stata's 'margins' procedure, which numerically integrates over the distribution of α_i via Gauss-Hermite quadrature (12 points). For binary variables, the marginal effect corresponds to the difference in average predicted probabilities of adoption between the two categories, after integration over α_i. Only variables with significant coefficients ($p < 0.10$) are reported. Thus, the selling price (*Prixv*), which is not significant, is excluded from the table. The values presented below are interpreted as the percentage point change in the probability of adoption for a one-unit change in the explanatory variable (or for switching from 0 to 1 for binary variables), all else equal, and after integrating over unobserved country heterogeneity via Gauss-Hermite quadrature.

Table 9: Average marginal effects on the probability of adoption

Variable	Marginal effects	Standard deviation	p-value
QNutrition$_{(t-1)}$	0,021***	0,005	0,001
Revenu$_{(t-1)}$	0,298***	0,072	0,001
Crédit	0,210**	0,082	0,011
Taille$_{(t-1)}$	0,156**	0,068	0,023
Distance$_{(t-1)}$	-0,136*	0,072	0,059
Coopérative	0,221***	0,085	0,009
Vétérinaires$_{(t-1)}$	0,082***	0,024	0,001
Epidemie$_{(t-1)}$	-0,162*	0,084	0,054
Note : Significance : *** p<0,01, ** p<0,05, * p<0,1			

Source: Authors, 2026

Analysis of Table 9 reveals that the marginal effect of nutritional quality is positive and highly significant ($p < 0.001$). Concretely, a one-point improvement in the nutritional quality index of feed rations increases the probability of adopting good health practices by 2.1 percentage points. This effect, although modest in absolute terms, is cumulative over several years: a 10-point increase in the index (e.g., from 45 to 55) raises the adoption probability by nearly 21 points. Next, the marginal effect of income is the highest among all continuous variables (+0.298, $p < 0.001$). A 10 % increase in monthly farm income increases the adoption probability by nearly 3 percentage points. Furthermore, access to credit has a substantial binary effect: farmers with access to agricultural credit see their adoption probability increase by 21 percentage points compared to those without access ($p < 0.05$). Moreover, cooperative membership produces the highest marginal effect among all binary variables (+0.221, $p < 0.01$). Farmers who are cooperative members have an adoption probability 22.1 percentage points higher than non-members. This effect is explained by cost pooling, access to health information, and collective training. In addition, veterinary services (number of consultations per year) show a positive and highly significant marginal effect (+0.082, $p < 0.001$). Each additional veterinary consultation increases the adoption probability by 8.2 percentage points, highlighting the crucial role of technical advice and prevention. Regarding distance, its marginal effect is negative and moderately significant (-0.136, $p < 0.10$). A 10 % increase in distance to input markets reduces the adoption probability by 1.4 percentage points. Although the effect is statistically less robust than the previous ones (10 % significance level), it confirms that geographical remoteness constitutes a barrier, likely due to transport costs and reduced access to veterinary inputs in CEMAC countries. Furthermore, the *Epidémie* variable reduces the adoption probability by 16.2 percentage points ($p < 0.10$). This result, although limited by the small number of epidemic years (12.8 % of observations), indicates that health shocks create a 'trauma' effect or budget constraint that delays adoption.

4.2.6 Operational critical thresholds

Table 10: Operational critical thresholds of the variables

Variable	**Mean value**	**Significance threshold (p < 0,05)**	**Probability threshold ($\hat{p} \geq 0,5$)**
QNutrition	45,3	≥ 52	≥ 58
Revenu	162	≥ 224000	≥ 302000
Taille	21	≥ 24	≥ 28
Vétérinaires	2,45	$\geq 3{,}0$	$\geq 3{,}8$
Distance	12,6	≥ 18	≥ 25
Crédit	0,35		
Coopérative	0,21		
Epidémie	0,13		

Source: Authors, 2026

Analysis of the operational critical thresholds (Table 10) of the random effects ordered logit model allows us to identify guiding values for public action. Thus, a nutritional quality below 52 (index) has no significant effect on adoption; it is above 58 that adoption becomes more likely. Similarly, a monthly income (at its real value) below 224,000 CFA francs is insufficient to generate a significant effect, whereas an income above 302,000 CFA francs makes adoption more likely. For herd size, the threshold for likely adoption is 28 birds. Veterinary services become effective from 3 annual consultations, with a shift toward likely adoption at 4 consultations. In contrast, a distance greater than 25 km reduces the probability of adoption below 0.5. Finally, access to credit and cooperative membership are powerful triggers, increasing the probability of adoption from approximately 0.32 to 0.53. These operational thresholds provide concrete targets for policies supporting the adoption of good health practices in the CEMAC zone. The non-significant Price variable is excluded from the threshold analysis.

4.3 Robustness check of the results

At a third level of robustness analysis of the results, according to the results in Table 4, the robustness check of the estimates by comparing the random effects logit model and the random effects probit model confirms the stability of the determinants of adoption. Indeed, the signs and significance levels are strictly identical between the two specifications: nutritional quality, income, credit, herd size, cooperative membership, and veterinary services significantly increase the probability of adoption ($p < 0.05$ or better), while distance to markets and epidemics reduce it ($p < 0.10$). Poultry price remains non-significant in both models. The ratio of Logit/Probit coefficients (between 1.71 and 1.76) is very close to the expected theoretical value (1.81), confirming that the magnitude differences are purely scale-related. Finally, the random effects parameters (σ_u and ρ) are almost identical, attesting that the need to control for unobserved heterogeneity does not depend on the choice of the link function. Thus, the results are robust and the random effects ordered Logit model can be confidently retained for the final interpretation. Moreover, all robustness checks that have been examined related to the importance of specific determinants of adoption of good health practices that are country-specific and may be correlated with our set of explanatory variables. As a fourth and final level of robustness verification for the importance of these factors, we estimate the following dynamic specification of the ordered Logit with unobserved country-specific effects (Table 11). The estimated model is as follows :

$$Prob\left(Adoption_{it}=1 \middle| X_{it-1}, Adoption_{it-1}, \alpha_i\right)=\frac{e^{\left(\beta X_{it-1}+\delta Adoption_{it-1}+\alpha_i\right)}}{1-e^{\left(\beta X_{it-1}+\delta Adoption_{it-1}+\alpha_i\right)}} \quad \textbf{(11)}$$

Where: $Adoption_{i,t-1}$ is the dependent variable lagged by one annual period, $\boldsymbol{\alpha_i}$ are the individual fixed effects (countries) estimated by conditional maximum likelihood according to Chamberlain's (1980) method. Observations without temporal variation in adoption are excluded (sample reduction).

Table 11: Results of the fixed effects ordered Logit model with lagged variable

Variable	**Fixed effects ordered Logit (FE)**	**Standard deviation**
Adoption$_{(t-1)}$	1,842***	0,421
QNutrition$_{(t-1)}$	0,061**	0,028
Revenu$_{(t-1)}$	0,892**	0,398
Crédit	0,512	0,412
Taille$_{(t-1)}$	0,421	0,341
Distance$_{(t-1)}$	-0,389	0,358
Coopérative	0,601	0,421
Vétérinaires$_{(t-1)}$	0,241**	0,112
Prixv$_{(t-1)}$	0,154	0,215
Epidémie$_{(t-1)}$	-0,489	0,401
Goodness-of-Fit	**Hosmer-Lemershow test**	
H-L statistic	8,76	(0,362)
LR chi2	28,46***	(0,001)
Log-likelihood	-58,21	
AIC	138,42	
Pseudo R²	0,31	
Observations	144	
Number of countries	5	1 excluded: CAR with no variation
*** p<0,01 ; ** p<0,05 ; * p<0,1		

Source: Authors, 2026

Estimating a fixed effects ordered Logit model with the introduction of the lagged dependent variable constitutes a severe robustness test (Table 11). The results show that three determinants—nutritional quality, farm income, and veterinary services—retain a positive and statistically significant effect ($p < 0.05$) even after controlling for fixed effects and temporal persistence ($Adoption_{t-1} = 1.842$, $p < 0.01$). In contrast, the variables Credit, Herd size, Cooperative, Distance, and Epidemics become non-significant in this specification, due to their low temporal variation and absorption by the fixed effects.

Furthermore, in the econometric literature on nonlinear panels (Logit, Probit), the standard Hausman test, as used in linear models, is not directly transposable for comparing random effects and fixed effects specifications. Indeed, Chamberlain's (1980) conditional fixed effects Logit estimator is not defined in the same way as the linear FE estimator, because it relies on a conditional likelihood that eliminates individual effects, but its coefficients are only comparable to random effects estimators under very restrictive assumptions (absence of near-constant variables, symmetric distribution). Consequently, a naive Hausman test on the raw coefficients is econometrically invalid (Wooldridge, 2010; Greene, 2004). To guide the choice between random effects and fixed effects in our context, we instead mobilize three complementary criteria, widely recommended for discrete choice panel models : (*i*) The nature of the explanatory variables: our model includes two near-constant variables over time (*Crédit* and *Cooperative*), as well as a lagged dependent variable in the robustness specification. However, the conditional fixed effects Logit estimator eliminates any variable that does not vary over time within a given country, which would make it impossible to estimate the effect of these key variables (Greene, 2012) ; (*ii*) Temporal persistence and unobserved heterogeneity: the intraclass correlation parameter ($\rho = 0.622$) is highly significant (Wald test: 19.46, $p < 0.001$), indicating that a large part of the residual variance comes from permanent differences between countries. A pooled model would be biased, but a random effects model correctly captures this dependence structure ; (*iii*) Information criteria and predictive ability: the Logit RE has lower AIC (156.86) and BIC (183.45) than the dynamic FE model (138.42 for a reduced sample of 144 observations vs. 156, not directly comparable). Above all, the RE model retains all 6 countries and 156 observations, whereas the conditional FE automatically excludes the CAR (lack of temporal variation in the dependent variable), thereby reducing regional representativeness. Consequently, in accordance with Wooldridge's (2010) recommendations for small nonlinear panels ($N = 6$, $T = 26$), we retain the random effects ordered Logit model as the reference specification. The robustness test using the dynamic FE model (Table 11) is presented not as a competing specification test, but as a complementary verification of coefficient stability for variables that vary sufficiently over time.

5 Discussion of results and implications

5.1 Discussion of results and validity of hypotheses

Our results are consistent with several studies, but also present notable differences. Regarding the first hypothesis (H1), our results show a positive and highly significant effect of the nutritional quality of rations on the probability of adoption. The marginal effect of 2.1 percentage points per index point is similar to that found by Zhou et al. (2021) in China (2.3 points), but our operational threshold (index ≥ 58) is a first for the CEMAC region. Our index point indicates that investment in feed quality is an operational lever for adoption. Theoretically, this falls within the health capital framework (Grossman, 1972) : better nutrition improves the overall health status of poultry, making vaccination and biosecurity measures more effective and therefore more attractive to the farmer. Thus, hypothesis H1 is fully validated.

Regarding hypothesis H2 (income and credit), our estimates very clearly confirm the expected positive effect. The high income elasticity (marginal effect of 0.298) confirms the results of Mbarga et al. (2020) in Gabon, but our financial thresholds (224,000 FCFA/month for a significant effect and 302,000 FCFA for probable adoption) provide concrete targets absent from previous work. These results are perfectly consistent with liquidity constraint theory (Feder et al., 1985): without sufficient financial resources or agricultural credit, farmers cannot cover the initial costs of good practices (vaccines, equipment, improved feed). Regarding credit, the 21-percentage-point increase in adoption probability is higher than that observed by Okello et al. (2019) in Uganda (18 points). This difference is likely explained by the greater scarcity of formal credit in the CEMAC zone (34.6 % of observations versus 42 % in the Ugandan sample). Clearly, hypothesis H2 is largely validated.

For hypothesis H3 (cooperative and veterinarians), the results are also very robust. All else being equal, and subject to the conditional exogeneity assumptions of the random effects model, cooperative membership is associated with an average adoption probability that is 22.1 points higher. The 22.1-percentage-point effect slightly exceeds that of Makhura et al. (2020) in South Africa (24 points) and confirms the key role of collective action in low-social-capital areas. However, this result should not be interpreted as a pure causal effect, as selection bias (more motivated farmers possibly self-selecting into cooperatives) cannot be completely ruled out in the absence of valid instruments. Meanwhile, each additional veterinary consultation increases the adoption probability by 8.2 points, validating the theory of incentives and contracts put forward by Akerlof (1970) and Stiglitz (1989): cooperatives reduce information asymmetries and transaction costs, while veterinarians act as trusted agents who certify the quality of inputs and practices (Makhura et al., 2020; Tambi et al., 2019). Moreover, the threshold of 3.8 consultations per year for adoption to become more likely than non-adoption provides a concrete target for policies aimed at strengthening veterinary services. Thus, hypothesis H3 is fully validated.

Regarding hypothesis H4 (distance and epidemics), the results confirm the expected negative signs, but with weaker significance (10 % level). Distance significantly reduces the probability of adoption by 1.4 points for a 10 % increase in distance, with a marginal effect of –0.136 at the 10 % threshold. The negative effect of distance is more modest than in Uganda (–4 % per additional 10 km). This difference may reflect lower spatial heterogeneity at the aggregated country level in our data. An epidemic in the previous year reduces adoption by 16.2 points ($p < 0.10$). These results are consistent with von Thünen's (1826) economic theory of location and empirical work on health shocks (Okello et al., 2019 ; Jebessa et al., 2021). However, the weaker significance (10 %) can be explained by several factors: distance is a fairly time-invariant variable for each country, which reduces identified variation; epidemics are rare (12.8 % of observations), limiting statistical power; the effect of epidemics may be partially captured by other variables (such as income and credit) via economic losses. Nevertheless, the sign and magnitude are robust, as confirmed by bootstrapping and the partial FE model. Consequently, hypothesis H4 is partially validated: distance and epidemics do reduce adoption, but their effect is less precisely estimated. An interesting result is the non-significance of poultry selling price in the sub-region across all models. The absence of a significant effect aligns with the conclusions of Nwankwo et al. (2020) in Nigeria. This is explained by the lack of 'health quality' certification on local markets in the CEMAC zone, where prices are often administered or have low volatility, unlike the French study by Jouve and Métais (2018) where a quality premium exists.

5.2 Implications and recommendations

From a theoretical perspective, our results confirm the relevance of McFadden's (1974) random utility model and Feder et al.'s (1985) liquidity constraint theory in a little-studied African context. They also show that nutritional quality deserves to be integrated as a full-fledged determinant, rather than as a mere control variable, in adoption models of health practices. Furthermore, the very large effect of cooperatives suggests that collective mechanisms are more effective than individual incentives in contexts of low social capital and imperfect information. The associations found for credit access and cooperative membership may partially reflect unobserved structural differences across countries, despite reassuring specification tests. Future studies using exogenous institutional variations (rural credit reforms or cooperative creation) would be needed to establish stronger causality.

Thus, several operational recommendations can be made for policy makers, regional organizations, and technical partners (FAO, World Bank). First, it is recommended to establish a 'Feed and Health' program (CEMAC/FAO) that aligns compound feed subsidies with achieving a nutritional index ≥ 58, with a bonus for cooperatives that train their members. Second, regarding financing, governments and microfinance institutions should set up a 'Poultry Credit' guarantee fund (BEAC) that would create a subsidized credit line (5 % instead of 12–15 %) for farmers who can justify at least three veterinary consultations per year. Third, a 'Community Veterinarian' strategy (AU-IBAR) is essential, deploying trained community agents to provide a minimum package of four visits per year, financed by a subsidized voucher system (50 % by the state, 50 % by the cooperative). Moreover, cooperative membership should be encouraged through tax advantages or priority access to subsidized inputs. Fourth, in response to distance constraints and epidemics, the existence of rural logistics platforms is important for areas located more than 25 km from an input market, implementing bi-monthly pharmacy trucks (inspired by the 'Kamayi' model in Cameroon) and cooperative-based group ordering points. Finally, the establishment of a health resilience fund is also necessary, because after a confirmed epidemic, emergency aid of 150,000 FCFA (equivalent to the loss of 20 poultry) could avoid the 'financial trauma' effect that we measure as a 16.2 percentage point decrease in the probability of adoption.
Technically, the identified thresholds are not universal laws but indicative orders of magnitude. Their translation into public policies must take local margins of maneuver into account. Regarding the nutritional threshold (QNutrition ≥ 58): a subsidy program for the purchase of compound feed should target farms with an index below 52 (significance threshold) and aim to exceed 58. For example, by setting up 'control batches' with improved feed formulations within cooperatives. Regarding the income threshold (≥ 302,000 FCFA/month): this amount corresponds to twice the average income of smallholder farmers (162,000 FCFA). Thus, social transfer policies or health amortization credit should aim for an additional income of around 140,000 FCFA per month to cross this threshold. Regarding the herd size threshold (≥ 28 poultry): mass vaccination programs can be offered free of charge to flocks of fewer than 28

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birds (where adoption is unlikely) and partially charged beyond that. The veterinary threshold (≥ 4 consultations per year) implies a seasonal flat rate (one visit every three months). Systems such as 'veterinary mutuals' or 'subsidized vouchers' can guarantee this frequency. Regarding the distance threshold (< 25 km): beyond 25 km, mobile systems (itinerant pharmacy trucks, grouped collection points) become necessary. These thresholds are provided for an 'average disadvantaged farmer' (without credit, without cooperative, without epidemic). Their application should be adjusted by region-scale studies.

5.3 Limitations of the study

Despite the methodological rigor and richness of the results, our study has several limitations that should be mentioned. First, the sample size (6 countries, 156 observations) is relatively modest, which limits the statistical power of certain tests, especially for rare variables such as epidemics (12.8 % of observations). Future studies should include more countries or sub-national data (regions, provinces, departments) to increase the number of observations. Moreover, annual series for some countries (notably Equatorial Guinea and the Central African Republic) have gaps, resulting in an unbalanced panel. The 2023–2025 projections, although based on recognized methods (Holt-Winters), are not a substitute for actual observations. Second, national aggregation masks major disparities. For example, the 25 km distance threshold does not have the same operational relevance in Yaoundé (high density of sales points) as in the Sudanese zone of Chad. Work using farm-cluster-level data is needed. Third, the lack of longitudinal data on certain variables (Cooperative, Crédit) forced us to treat them as near-constant, which may underestimate their dynamic effect. Also, there is no causal identification design for binary variables such as cooperative membership or credit access. Although the Rivers-Vuong test did not reject the exogeneity of the Crédit and Cooperative variables, the absence of perfectly exclusive instruments (only lagged variables) leaves residual uncertainty. Only a natural experiment or a longitudinal randomized follow-up would establish strict causality. Panel surveys of the same farmers over a long period would improve estimation quality. Fourth, the QNutrition variable is a composite index whose construction could be refined (e.g., by integrating indicators of protein diversity, presence of vitamin supplements). External validation of this index through nutritional analyses would be desirable. Fifth, the quality of local governance, corruption in public veterinary services, the prevalence of antimicrobial resistance, or the effectiveness of awareness campaigns could not be included due to a lack of reliable and comparable annual series for the 2000–2025 period. These factors could bias coefficients if correlated with observed variables. Sixth, the normality assumption for random effects, although not rejected by the Shapiro-Wilk test, deserves to be relaxed in future work (e.g., with non-parametric or semi-parametric random effects). Finally, our modeling assumes that adoption is a memoryless process beyond the lagged variable (in the FE model). Although the persistence effect is strong ($Adoption_{t-1}$ significant in the FE model), it would be interesting to explore richer state-dependence models (e.g., two-period Markovian models). Our results are specific to the CEMAC zone and poultry value chains. Extension to other species (pork, cattle) or other regions of Africa is not automatic.

5.4 Caveats regarding the level of geographical aggregation

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An important limitation of this study lies in its level of aggregation: the unit of observation is the country-year pair, due to a lack of harmonized data at a finer scale over the entire 2000-2025 period for the six CEMAC countries. However, this national aggregation necessarily masks considerable within-country heterogeneity, between administrative regions (coastal vs. Sahelian areas), between farm types (traditional, semi-industrial, family farms), or between urban and rural areas. For example, an operational threshold such as 'distance to input markets less than 25 km' cannot be applied uniformly across the entire Cameroonian or Chadian territory: some remote regions of northern Cameroon have distances well above this, while the western highlands concentrate farms close to markets. Likewise, the effect of herd size (threshold ≥ 28 birds) cannot have the same meaning in a small family farm in rural Equatorial Guinea as in a semi-industrial farm on the outskirts of Libreville. Consequently, the identified critical thresholds (nutritional index ≥ 58, income ≥ 302,000 CFA francs/month, veterinary consultations ≥ 4/year, distance < 25 km) should be interpreted as indicative orders of magnitude and not as universally applicable absolute values. Their use for public action requires prior disaggregation at the regional or local level, through targeted field surveys or sensitivity analyses by sub-area. National and regional policymakers (CEMAC, livestock ministries) are encouraged to conduct complementary studies to adapt these thresholds to the specific contexts of each territory.

6. Conclusion

Ultimately, this study has identified and quantified the main determinants of the adoption of good health practices in poultry and pig farming in the six CEMAC countries over the period 2000-2025. Using a random effects ordered logit model estimated by Gauss-Hermite quadrature (Butler and Moffitt, 1982), we have shown that nutritional quality of feed rations, farm income, access to agricultural credit, herd size, cooperative membership, and veterinary services significantly increase the probability of adoption, while distance to markets and epidemics reduce it. Selling price has no significant effect. Unobserved heterogeneity between countries is considerable, justifying the use of random effects. The identified critical thresholds (nutritional index ≥ 58, income ≥ 302,000 CFA francs/month, size ≥ 28 birds, veterinary consultations ≥ 4/year, distance < 25 km) provide operational targets for public policies. Recommendations include strengthening cooperatives, improving access to credit and proximity veterinary services, as well as opening up remote areas. Beyond the limitations already mentioned (modest sample size, lack of longitudinal data for certain variables), it should be emphasized that the level of national aggregation restricts the operational scope of the proposed critical thresholds. Future work using sub-national data (regions, departments, farm clusters) is necessary to validate, adjust, or refine these thresholds at a scale relevant for public intervention. As it stands, our results provide a first macro-regional mapping of the determinants of adoption, but their translation into local policies must incorporate a substantial margin of adaptation. This study brings new and robust insights for the design of poultry health policies in the CEMAC zone, while also opening up other avenues for future research, including the integration of institutional variables, sub-period analysis, and extension to other livestock sectors.

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