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Adoption and intensity of integrated agriculture aquaculture among smallholder fish farmers in Kenya

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This paper examined the adoption and intensity of using integrated agriculture aquaculture (IAA) among smallholder fish farming households in Kenya. The analysis was based on cross-sectional farm-level data collected from four counties in Kenya: Nyeri, Kakamega, Siaya, and Busia. Results showed that risk plays a central role in farmers' decisions through the direct effect of the sample moments of the profit distribution. Specifically, the first moment (mean profit) had a highly significant positive effect on the adoption and intensity of IAA. Profit variability, as reflected by the second moment, negatively impacted adoption and the intensity of IAA. Other factors that were important in IAA adoption included the proportion of economically active members, full-time land ownership, awareness of IAA, accessibility to irrigation, and flat farm topography, all of which were statistically significant in influencing IAA adoption positively. Other factors which were found to influence the intensity of IAA positively and significantly were: age, education level, number of economically active members, full-time land ownership, awareness of IAA, flat farm topography, and clay soil type. Thus, IAA should be promoted alongside farmers' education, farm size, access to affordable and accessible credit, number of farm enterprises, and IAA awareness as a mechanism for enhancing smallholder IAA adoption and intensity of use.

KEYWORDS

IAA adoption, IV2SLS estimation, Kenya, Africa, policy

1. Introduction

Smallholder farmers in Kenya, constituting around 70–80% of the agricultural workforce, play a critical role in ensuring the country's agricultural productivity and food security [[Kenya Bureau of National Statistics \(KNBS\), 2016](#)]. However, these farmers face significant challenges due to their limited access to resources, which hampers their ability to lead healthy and productive lives. The value of land as a vital source of income for rural farmers exceeds that of other forms of physical capital, making it a crucial asset. Unfortunately, this valuable asset is threatened by deterioration, posing risks to both food security and overall agricultural productivity. To address these challenges, the Kenyan government has taken steps to modernize the agricultural sector by adopting innovative technologies ([Jairo and Korir, 2019](#)). For instance, the Kenyan government has been actively taking measures to support and expand the

aquaculture sub-sector. The efforts encompass technical and financial assistance to farmers, along with the implementation of policies and regulations that foster the sub-sector's long-term development (Obiero et al., 2019). Collaborating with private companies, the government has prioritized enhancing farmer training, skill improvement, and better access to markets.

Between 2009 and 2012, the Kenyan government launched a significant aquaculture subsidy program known as the Economic Stimulus Program (ESP; Ole-Moiyoi, 2017). The aim was to boost aquaculture development by providing subsidies for various aspects such as pond construction, fish feeds, fingerlings supply, post-harvest management, and capacity building for fish farmers and related institutions. Before the ESP project in 2008, Kenya's aquaculture production was 4,452 metric tonnes (MT). However, by 2010, production surged to 12,153 MT, with the number of farmers reaching 49,050 at the peak of the subsidy program in 2012 (Nyandat and Owiti, 2013). These impressive achievements were a result of government policies and investments, leading to rapid growth in aquaculture production, reaching 24,096 MT in 2014 (Obiero et al., 2019). Notably, even regions with little history in fish production or consumption experienced growth in the industry (Ole-Moiyoi, 2017). Following the ESP program, Kenya's aquaculture production faced a decline to 12,356 MT in 2017, down from the peak of 24,096 MT in 2014. Several factors contributed to this decline, including inadequate water holding capacity of ponds in selected counties, particularly in the Eastern and Coastal regions, poor extension services, ineffective management practices, limited fish farm inputs, weak marketing structures, over-reliance on government and donor support, and the absence of value addition (Munguti et al., 2017; Obwanga and Lewo, 2017; Opiyo et al., 2018). However, since 2018, aquaculture production has been gradually increasing, and as of 2022, it stands at 22,140 MT, showing improvement from 15,180 MT in 2018 [Kenya Bureau of National Statistics (KNBS), 2023]. Despite the challenges faced, the government's continued efforts and investments have contributed to the recovery and growth of the aquaculture industry in Kenya.

To enhance aquaculture production, it is crucial to identify key areas that promote collaboration at the national, regional, and county levels while bolstering technical skills in inland aquaculture. These priorities involve mapping suitable sites for aquaculture and estimating their carrying capacity. Moreover, more research is needed to ensure the sustainability of inland aquaculture production, considering both profitability and socio-economic aspects. Integrated Agriculture Aquaculture (hereafter IAA) can also contribute to increased profitability and overall production efficiency (Musa et al., 2020). It was introduced to Sub-Saharan Africa (SSA) from Asia due to its successful outcomes. IAA operates on the principle of leveraging synergies among different subsystems to enhance overall farm productivity. It involves integrating a small pond stocked with suitable fish and utilizing farm resources such as crop residues and by-products as feed and pond fertilizer (Brummett and Noble, 1995). IAA presents a sustainable intensification option for small-scale farmers and holds great promise as a technology to address long-standing agricultural challenges. It offers a solution to sustainably increase agricultural productivity while simultaneously promoting food and nutrition security through integrated resource management (Lightfoot et al., 1993; Brummett and Noble, 1995; Lightfoot and Noble, 2001; Sugunan et al., 2006; Dey et al., 2010; FAO, 2022). By adopting the IAA approach, small-scale farmers can engage in mixed-enterprises,

extending beyond fish production alone. This integrated approach allows for mutually beneficial interactions among various farm enterprises, resulting in increased farm productivity (Edwards, 1998; Prein, 2002; Pant et al., 2005).

In Kenya, IAA is widely practiced through three main types: crop-fish integration, livestock-fish integration, and crop-fish-livestock integration. In crop-fish integration, fish and crops are combined in a mutually beneficial system. Fish raised in ponds provide fertilizer for crops like vegetables, fruits, and grains, while the crops offer shade and cover for the fish, supporting their growth. Livestock-fish integration is prevalent in rural areas, where smallholder farmers keep livestock and fish together in small-scale systems. Animal manure from the livestock serves as a nutrient source for fertilizing fish ponds, leading to enhanced fish growth and production, while also reducing manure waste on the farm, benefiting the environment. In some areas with limited water resources, fish can be integrated into livestock systems. Small ponds or tanks connected to livestock enclosures allow water from fish ponds to be used for livestock watering, reducing the need for additional fresh water resources. Crop-fish-livestock integration takes a comprehensive approach by combining fish, livestock, and crop production. Fishponds provide fertilizer for crops, while livestock contribute manure and other nutrients for the fish. The crops, in turn, offer food and shelter for the livestock. These various IAA systems offer sustainable alternatives for small-scale farmers in Kenya, promoting increased productivity and resource optimization (Lightfoot et al., 1993; Brummett and Noble, 1995; Lightfoot and Noble, 2001; Sugunan et al., 2006; Dey et al., 2010; FAO, 2022).

In recent years, several studies (Dey et al., 2010; Islam et al., 2015; Shoko et al., 2019) have been conducted to explore the adoption of IAA. These studies have investigated various factors, including demographics, economics, and institutional aspects, that influence farmers' decisions to adopt or reject this farming method. However, the role of risk in agricultural decision-making, especially when adopting new practices, is of significant importance. Smallholder farmers, who tend to be risk-averse, may hesitate to invest in modern technologies, potentially perpetuating their poverty unless effective strategies are implemented to mitigate negative consequences. Production risk is particularly critical in developing countries where smallholder farmers heavily rely on their crops for sustenance and income. It involves the uncertainty and variability associated with agricultural processes, including potential negative outcomes and fluctuations in crop yields, livestock production, and overall agricultural productivity. Factors like weather conditions, pests, diseases, market fluctuations, and unforeseen events contribute to production risk. Addressing this risk is challenging for farmers, as they must consider the uncertainties and potential negative impacts on resource allocation, technology adoption, and investment decisions. Given the potential effects on farmers and their families, it is essential to minimize exposure to risk, especially for those who are risk-averse and prefer more stable conditions. While previous studies have provided insights into socio-economic, population, and structural factors influencing IAA adoption decisions (Dey et al., 2010; Islam et al., 2015; Obiero et al., 2019; Shoko et al., 2019), they often overlook the risk-averse nature of smallholder farmers. To enhance the understanding of IAA adoption and its implications, it is crucial to consider the risk aversion factor in smallholder farmers and its influence on decision-making processes.

This study contributes to the existing research on farm IAA adoption among smallholder farmers by emphasizing the significance of considering risk exposure through robust estimation procedures. It focused on Kakamega, Nyeri, Busia, and Siaya to investigate how production risk influences smallholders' decisions regarding the adoption and intensity of IAA. While the study's findings are specific to these counties, the policy recommendations derived from the research can be applied in other rural areas where IAA is feasible. By addressing the issue of risk exposure and understanding its implications, policymakers and stakeholders can gain valuable insights into the challenges faced by smallholder farmers. Consequently, they can develop effective strategies to support the adoption and intensity of IAA practices in various contexts, ultimately promoting sustainable and improved agricultural outcomes.

2. Data and methods

2.1. Methods

2.1.1. Theoretical framework

The expected utility maximization theory informed this study. This theory is based on the idea that farmers in developing countries like Kenya work in significant market imperfections and uncertainty (Ogada et al., 2014). Smallholders tend to be less willing to take risks, so they are not likely to be the first to use new technologies. They instead take a "wait-and-see" approach (Ghadim et al., 2005). A farmer may face production risks, such as bad weather. Risk is shown by ε , and the distribution $G(\cdot)$ is independent of what the farmer does. Assuming risk-averse farmers who use conventional inputs \mathbf{x} and water x_w in a given production season to produce output q in a well-behaved production function $f(\cdot)$. In IAA, water is an essential input. Areas with a lot of water are good places to raise fish and, by extension, to combine with crops/livestock. Smallholder farmers would use water to grow high-value crops, which would help them make more money on their farms (Dey et al., 2010). A function $l(\alpha)$ is added to the production function to account for how efficiently water is used. The fact that water efficiency depends on management practices and the characteristics of the farmer shows how different farmers are. Unobserved heterogeneity may include unreported farm management skills, land fertility, measures to reduce risk, and discount rates, which have the potential of affecting how much inputs are used and how productive a farm is. So, the production function is written as follows:

$$y = f[l(\alpha)x_w, \mathbf{x}, \varepsilon] \tag{1a}$$

Given a risk aversion scenario, maximization of the expected profit utility is denoted as:

$$\max_{x, x_w} E[U(\bar{\omega})] = \max_{x, x_w} \int \left\{ U \left[pf(\varepsilon, l(\alpha)x_w, \mathbf{x}) - r_w x_w - r' \mathbf{x} \right] \right\} dG(\varepsilon) \tag{1b}$$

Where $U(\cdot)$ is the von Neumann-Morgenstern utility function. Getting the first-order condition for water input choice. Where $\dot{U} = \partial U(\bar{\omega}) / \partial(\bar{\omega})$ is:

$$E[r_w \dot{U}] = E \left\{ p \frac{\partial f(\varepsilon, l(\alpha)x_w, \mathbf{x})}{\partial x_w} \dot{U} \right\} \Leftrightarrow \tag{2a}$$

$$\frac{r_w}{p} = E \left\{ \frac{\partial f(\varepsilon, l(\alpha)x_w, \mathbf{x})}{\partial x_w} \right\} + \frac{\text{cov} \left[\dot{U}; \partial f(\varepsilon, l(\alpha)x_w, \mathbf{x}) / \partial x_w \right]}{E[\dot{U}]} \tag{2b}$$

Where p and r are the prices of output and the vector of inputs, respectively, assumed to be non-random (meaning farmers do not influence prices in the markets). The First Order Conditions (FOC) for the other variables in equation (1) are derived similarly. The farmer's choices are demonstrated as a binary choice such that $P=1$ to adopt or not to adopt $P=0$. The optimum input choices upon adoption or otherwise were represented as x^1 and x^0 respectively for adopters and non-adopters. An IAA adopter is defined as a farmer who has a fishpond as part of their farming activities and recycles resources among different enterprises. The expected utility of an individual who adopts an improved farming system is higher than for a non-adopter and is given by:

$$E[U(\bar{\omega}^1)] - E[U(\bar{\omega}^0)] > 0 \tag{3}$$

$$\begin{aligned} \max_{x^1, x_w^1} E[U(\bar{\omega})] = \\ \max_{x^1, x_w^1} \int \left\{ U \left[pf(\varepsilon, l^1(\alpha)x_w^1, \mathbf{x}^1) - r_w^1 x_w^1 - r' \mathbf{x}^1 - \mathbf{I}^1 \right] \right\} dG(\varepsilon) \end{aligned} \tag{4}$$

and

$$\begin{aligned} \max_{x^0, x_w^0} E[U(\bar{\omega})] = \\ \max_{x^0, x_w^0} \int \left\{ U \left[pf(\varepsilon, l^0(\alpha)x_w^0, \mathbf{x}^0) - r_w^0 x_w^0 - r' \mathbf{x}^0 - \mathbf{I}^0 \right] \right\} dG(\varepsilon) \end{aligned} \tag{5}$$

Equation (4) and equation (5) are the expected utility for adoption and non-adoption.

$$\frac{r_w^1}{p} = E \left\{ \frac{\partial f(\varepsilon, l(\alpha)x_w^1, \mathbf{x}^1)}{\partial x_w^1} \right\} + \frac{\text{cov} \left[\dot{U}; \partial f(\varepsilon, l(\alpha)x_w^1, \mathbf{x}^1) / \partial x_w^1 \right]}{E[\dot{U}]} \tag{6}$$

$$\frac{r_w^0}{p} = E \left\{ \frac{\partial f(\varepsilon, l(\alpha) x_w^0, x^0)}{\partial x_w^0} \right\} + \frac{\text{cov} \left[\dot{U}; \partial f(\varepsilon, l(\alpha) x_w^0, x^0) / \partial x_w^0 \right]}{E \left[\dot{U} \right]} \quad (7)$$

Equations (6) and (7) show the FOC for a risk-averse farmer’s water input, considering whether or not to adopt. The exact process is used to find the FOC for the other variables. Assuming that the farmers do not know how well the technology works or are more likely to make mistakes when using it, future profit flows are unknown after the farmers adopt it. The investment cost is fixed, meaning the extra information may be worth more than it costs. Because of this, farmers who use the technology may be hesitant to learn more about it. Assuming $VI \geq 0$ is a value of new knowledge that depends on the fixed investment cost, the level of risk attached to technology utilization, and the farmer’s features, the farmer will adopt if and only if:

$$E \left[U(\bar{\omega}^1) \right] - E \left[U(\bar{\omega}^0) \right] > VI; VI > 0 \quad (8)$$

2.1.2. Empirical model

2.1.2.1. Choice and uptake of IAA

The analysis began by calculating the mean, variance, and skewness of profits, which are indicators of production risk. These variables, along with independent variables, were then used in a discrete choice model to examine how production risks influence adoption decisions.

2.1.2.2. Calculating profit moments

Following the technique fronted by [Koundouri et al. \(2006\)](#), consider a risk-averse farm household seeking output y by employing inputs x in the presence of risk in a well-behaved stochastic production function $y = h(x, m)$. m is a vector of random risk variables. Consider:

$$h(x, m) = f_i(x, \beta_i) + u \quad (9)$$

Where: $f_i(x, \beta_i) \equiv E[h(x, m)]$ is the mean of (x, m) (first central moment); and $u = h(x, m) - f_i(x, \beta_i)$ is a random variable having a zero mean zero with an exogenous distribution to farmers’ actions. To get higher moments, the study follows:

$$E \left\{ [h(x, m) - f_i(x, \beta_i)]^k | x \right\} = f_k(x, \beta_k) \quad (10)$$

For $k = 2, 3$ implying $f_2(x, \beta_2)$ the second central moment (variance), and $f_3(x, \beta_3)$ is the third (skewness). A rise in skewness implies a lessening in exposure to downside risk such that:

$$\hat{\mu}_i^2 = h(x_{wi}, x_i, z_i, \delta) + \hat{\mu}_i \quad (11)$$

Applying Ordinary Least Square (hereafter called OLS) to equation (11) gives consistent estimates δ . $\hat{\mu}_i^2$ are consistent estimates

of the variance. The same criteria was applied to estimate the third and fourth central moments. The four estimated moments and other variables were plugged in the discrete adoption model.

To get the discrete model, assume the i^{th} household faces the decision to adopt or not IAA. Let P^* symbolize the benefit difference derived from the adoption U_{iA} and non-adoption U_{i0} . A household adopts IAA if $P^* = U_{iA} - U_{i0} > 0$. P^* is unobservable and can be denoted as:

$$P_i^* = Z_i \beta + m_i + \varepsilon_i; P_i = 1 \text{ if } P_i^* > 0 \text{ and } P_i^* = 0, \text{ otherwise} \quad (12)$$

The first stage of the analysis employed a selection model, estimated using the probit model, to determine the factors affecting IAA adoption. The two-step Heckman estimation was conducted, and the coefficient of the Mills ratio (used to correct for selection bias) was found to be statistically insignificant and negative. This suggested that technology selection bias was not a significant concern in the analysis. Consequently, the Instrumental Variable Two-Stage Least-Squares (IV2SLS) technique model was used to estimate the relationship between technology adoption and the intensity of adoption while accounting for suspected endogeneity and heterogeneity.

2.1.2.3. Sampling and sample size determination

The study population was all fish farmers in the selected study areas. The sampling frame selected a list of adopters and non-adopters of IAA in four sub counties with the highest aquaculture production in each of the four counties. To achieve the sampling size, the study employed the computation formula proposed by [Kothari \(2004\)](#) for a finite population stated as:

$$n = \frac{Z^2 \cdot p \cdot q \cdot N}{e^2 (N - 1) + Z^2 \cdot p \cdot q} \quad (13)$$

Where: n = sample size; p = Sample proportion; $q = 1 - p$; N is the estimated population which comprises all pond-based fish farming households from the four selected counties (approximately 2,500 active fish farming households) according to the 2019 Kenya Population Census; e is the acceptable margin of error/precision rate: Hence, the desired precision was $100/23 = 4.34$. Say, $e = 4\%$. $Z = 1.96$; The estimated standard variation at 95% confidence interval. Therefore, the estimated sample size was 484. To recruit the 484 individuals, automated randomization was adopted to the 2,500-population size of active fish farming households in the four study areas. The study employed the RAND Function in Microsoft Excel. The randomly selected households were highlighted for interview. All the selected households were interviewed. However, in unlikely cases of missing households after repeat visits, they were replaced. The study employed a margin between 5 and 10 households for replacements per county.

2.2. Data

The study followed an analytical study design given that there were comparison groups of study, that is adopters and non-adopters. The model was assessed on a cross-sectional data from a survey on

Kenya's smallholder fish farmers in the selected regions in the central and western Kenya. These are Nyeri (in Central) and Kakamega, Busia and Siaya in Western Kenya (Figure 1). The areas were selected based on their high concentrations of aquaculture activities, presence of aquaculture development projects, high production potential, existing infrastructure such as processing and research facilities, sufficient water resources, and adequate marketing prospects, among other factors.

2.2.1. Data collection

A competent team of three experienced research assistants were engaged for data collection. They went through a standard recruitment process, focusing on factors such as knowledge of research methodologies, experience in similar studies, familiarity with the study sites, proficiency in English, Kiswahili, and the local language, troubleshooting skills during data collection, teamwork abilities,

post-secondary education, discretion, attention to detail, and availability during the study period. The recruited team received training to ensure a clear understanding of the study objectives and their roles. Role-play sessions were conducted to practice using the research instruments and ensure their effectiveness. A 5-day centralized training session took place at the Kenya Marine and Fisheries Research Institute (KMFRI-Sagana). Additionally, a pilot exercise was conducted with fish farmers in Kirinyaga county to provide the research assistants with practical experience in a natural setting. A debriefing session followed the practice interviews to address any issues before the main data collection. Insights from the training sessions were used to improve the study instruments and inform the planning phase. The data collection process started in the western region, which had more counties, and was phased accordingly. Out of the sample size of 484 household, data on 427, represented by 88.22% was obtained and the questionnaires completely filled, which implied a good response rate. However, the remaining

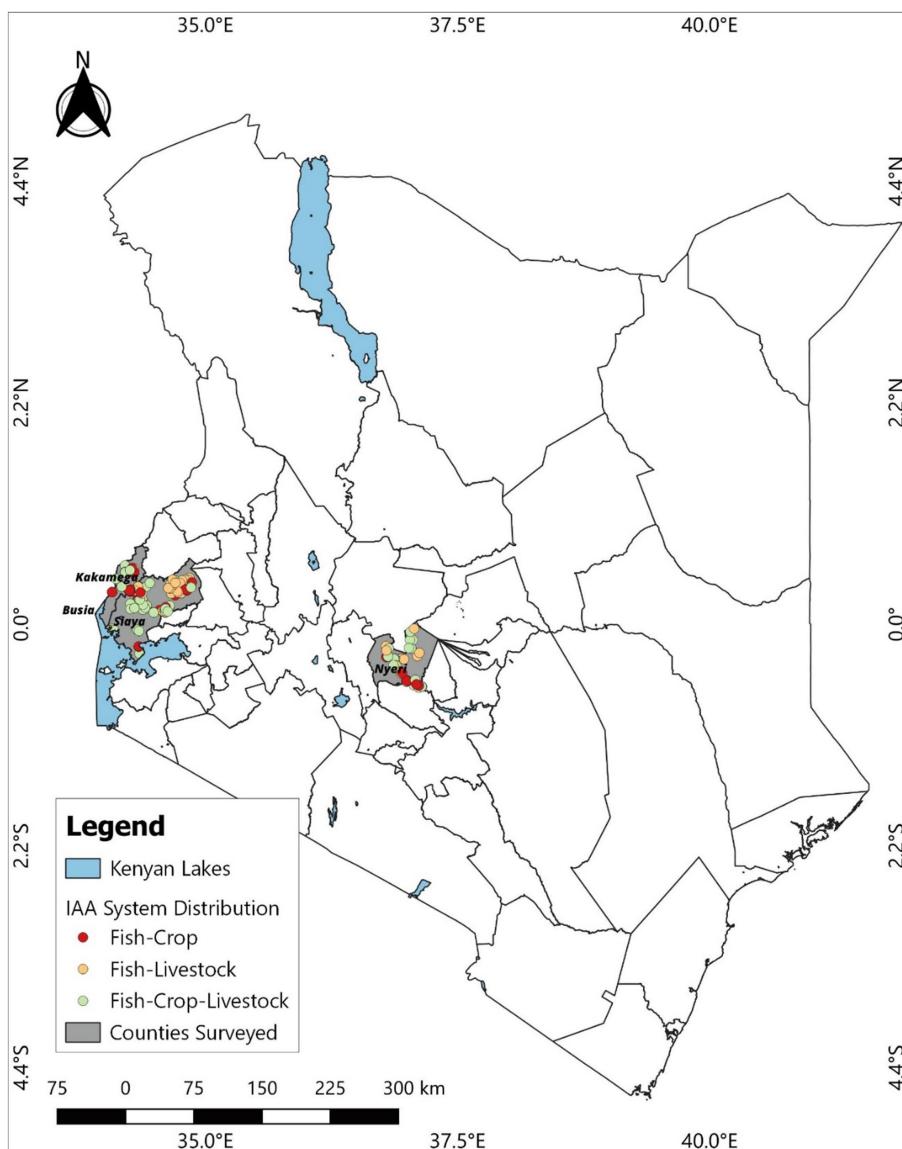


FIGURE 1 Map of the study area showing the distribution of IAA farming system in the study areas.

11.78% (based on sample determination) were either found to having many missing observations/incomplete. Proceeding household level data analysis was carried out on these 427 households. 208 households had adopted IAA, which is approximately 48.71% of the total households. The survey was conducted in the second quarter of 2021 using digitized semi-structured questionnaires. Requisite primary data from a cross-section of households was collected on sociodemographic, conventional inputs, social and human capital, detailed production data, and risk exposure. This was collected through farm visits (face to face) and using an open access Kobo tool box application¹ installed on android smartphones to ensure quality check and data safety. Data from farmers were collected for their production season August 2020–March 2021. Key informant interviews with different stakeholders supplemented survey data through an in-depth exploration of the subject matter and discover information that would otherwise not be revealed in a survey. Focus group discussions were adopted to triangulate and interpret results from the survey by understanding the impact of production risk on the welfare of smallholder adopters of integrated aquaculture technology. Secondary data were garnered from various sources like case studies, peer-reviewed journal articles, books, national government publications, county integrated development plans, and gray literature.

3. Results and discussion

Table 1 shows the average differences between people who use IAA (adopters) and those who do not (non-adopters) in the study area. Adopters have bigger farms, more educated household heads, more economically active members, more farm businesses, and are more aware of IAA. The average household head age of non adopters was 64 years while adopters was 66 years. The lower part of Table 1 presents the average differences in variance, skewness, kurtosis, and farm net returns. Adopters (KES 239,733.3) make significantly higher profits compared to non-adopters (KES 224,943.3).

Table 2 presents the distribution of IAA among adopters in the study areas, categorized by county, depicting the prevalence and regional variations in the adoption of this sustainable and integrated farming techniques, contributing to the overall understanding of IAA practice in the study areas. The table shows the number of adopters engaged in different combinations of IAA within each county, as well as the overall total for each county and the grand total for all counties. In Busia County, a total of 42 adopters were identified, and they were engaged in various IAA combinations. The distribution provides researchers and policymakers with information to better understand the implementation of IAA and its potential impact on sustainable aquacultural practices. Specifically, 18 adopters implemented a combination of fish-crop, five adopters practiced fish-livestock integration, and 19 adopters adopted crop-fish-livestock. In Kakamega County, a larger number of adopters were observed, totaling 69. Among these adopters, seven individuals adopted fish-crop, 28 individuals implemented fish-livestock integration, and 34 individuals embraced the holistic crop-fish-livestock IAA. In Nyeri County, a total of 48 adopters were identified. Out of these, nine adopters were

engaged in fish-crop IAA, 12 adopters practiced fish-livestock integration, and 27 adopters embraced the comprehensive crop-fish-livestock IAA approach. Siaya County had a total of 49 adopters. Among them, 11 adopters practiced fish-crop IAA, eight adopters implemented fish-livestock integration, and 30 adopters followed the holistic crop-fish-livestock IAA. Overall, among these, 46 adopters were engaged in fish-crop IAA, 53 adopters implemented fish-livestock integration, and the largest group, consisting of 110 adopters, adopted the comprehensive crop-fish-livestock IAA.

3.1. The adoption model results

The central role of risk in farmer's decision is highlighted through the significance of the sample moments. The first moment, which is the mean profit, had a highly significant positive effect on IAA adoption (Table 3). This implies that smallholder farmers are driven by profit maximization and would be motivated to apply profit-increasing methodologies whenever they are guaranteed higher returns (Ogada et al., 2014). Higher returns can incentivize farmers to invest in the necessary resources, technology, and training required for successful IAA adoption. The same positive effect was also reflected in the intensity of IAA application. As reflected by the second moment, that is profit variability negatively impacts IAA adoption and the intensity of IAA use. This suggests that farmers are dissuaded from using IAA in uncertain profitability. They prefer stability to the risk of chasing a more significant but speculative profit. While farmers are motivated by profit maximization, they are also risk averse and will avoid making large bets on uncertain outcomes. A unit increase in changes in skewness reduced the probability of adopting IAA. The statistical significance of the third moment of profit (skewness) indicates that farmers take downside yield uncertainty into account when they decide whether to adopt IAA. Skewness captures the probability of output failure, where negative skewness reflects a greater exposure to downside risk, meaning there is a high probability of technological failure hence the low likelihood of adoption and intensity of use (Kassie et al., 2008; Juma et al., 2009; Ogada et al., 2014). As indicated in Table 3, the sample moments of the profit distribution, in particular mean, variance and skewness affect the decision of the farmer to adopt and use IAA thus confirming that farmers are not risk-neutral.

Besides production risk variables, age, education, the proportion of economically active members, farm size, full-time land ownership, access to credit services, awareness of IAA, number of persons trained per household, number of farm enterprises, accessibility to irrigation, natural water source, flat and topography, and variance profit moments were found to positively influence the probability of adopting technology. Furthermore, among these variables, the proportion of economically active members, full-time land ownership, awareness of IAA, accessibility to irrigation, and flat farm topography were the variables which were found to be statistically significant in influencing the intensity of using IAA positively.

The current body of literature presents mixed evidence regarding the correlation between age and aquacultural technology adoption. For instance, Obiero et al. (2019) found that farmers' age is negatively associated with aquaculture technology adoption, whereas this study found age to positively influence the probability of adopting IAA. It is essential to recognize that aquacultural technology adoption is influenced by a complex interplay of various factors, including

¹ <https://www.kobotoolbox.org/>

TABLE 1 Descriptive statistics and mean difference between adopters and non-adopters.

Variable	Non-adopters	Adopters	Difference	Pr (T > t)
Age of household head (HH) (Years)	64.27 (21.67)	65.88 (20.24)	-1.61	0.2966
Household head education (Number of years)	2.56 (1.2)	2.69 (1.44)	-0.13	0.1772
Economically active members	0.60 (0.24)	0.64 (0.27)	-0.04*	0.0334
HH male gender (1/0)	0.37 (0.48)	0.44 (0.5)	-0.07*	0.0481
Farm size (ha)	2.54 (2.74)	3.38 (3.67)	-0.84***	0.0007
Fulltime land ownership (1/0)	0.14 (0.35)	0.27 (0.45)	-0.13***	0.0000
Received credit (1/0)	0.24 (0.43)	0.29 (0.45)	-0.05	0.1254
IAA awareness (1/0)	0.46 (0.5)	0.66 (0.47)	-0.2***	0.0000
Distance to the nearest input market (KM)	3.45 (6.63)	3.16 (3.03)	0.29	0.4137
Land per person (Ratio)	1.37 (1.39)	1.14 (1.39)	0.23*	0.0230
Number farm enterprise	0.00 (0.00)	2.29 (0.06)	-2.29*	0.000
Access to irrigation	0.22 (0.42)	0.38 (0.49)	-0.16***	0.0000
Presence of wetland (1/0)	0.51 (0.5)	0.68 (0.47)	-0.17***	0.0000
Natural water source (1/0)	0.55 (0.5)	0.49 (0.5)	0.06	0.1209
Flat farm topography (1/0)	0.36 (0.48)	0.4 (0.49)	-0.04	0.3251
Clay soil type (1/0)	0.31 (0.46)	0.24 (0.43)	0.07*	0.0170
Land type	0.51 (0.5)	0.43 (0.49)	0.08*	0.0307
Seed input	8641.88 (10683.99)	20059.92 (64987.25)	-11418**	0.0029
Labor input	58.49 (42.08)	81.19 (97.5)	-22.7***	0.0002
Chemical fertilizer input	12960.46 (21651.82)	20624.64 (46425.35)	-7664.18**	0.0000
Organic fertilizer input	5320.82 (5648.47)	10687.98 (12669.49)	-5367.16**	0.0000
Land input	20.89 (98.15)	14.6 (188.73)	6.29	0.5968
Capital input	6024.46 (28585.33)	3589.47 (32195.45)	2434.99	0.2860
Irrigation input	1617.75 (8645.45)	2120.98 (15799.56)	-503.23	0.6157
Net farm income (KES)	224943.3 (867995.5)	239733.3 (2.28E+06)	-14790**	0.0002
Expected profit (Mean profit)	357775.4 (769610.6)	361464.4 (557556.4)	-3688.98*	0.0191
Profit variance (Profit variability)	197189.4 (355783.4)	168853.9 (915428.9)	28335.53*	0.0102
Downside risk (Skewness of profit moment)	1 (2.19)	0.26 (1.97)	0.74	0.0000

***Significant at 1% level; **significant at 5% level, and *significant at 10% level. Bold values mean putting emphasis on the statistically significant values.

TABLE 2 Distribution of IAA among adopters in the study areas by county.

County	County				Grand Total
	Busia	Kakamega	Nyeri	Siaya	
Fish-crop	18	7	9	11	46
Fish-livestock	5	28	12	8	53
Crop-fish-livestock	19	34	27	30	110
Grand total	42	69	48	49	209

economic, social, and cultural aspects. Different regions, contexts, and types of technology can lead to varied results. In the case of IAA, the positive influence of age on adoption could be attributed to several reasons. Older farmers might have accumulated more experience and knowledge in traditional farming practices, making them more open to trying innovative approaches like IAA. Additionally, older farmers may have greater access to resources, networks, and support systems that facilitate adoption. It is also possible that the positive correlation

between age and IAA adoption is specific to the study area and its unique characteristics. Factors such as the availability of training and extension services, the presence of government incentives, and the presence of local markets can all influence adoption decisions (Kumar et al., 2018).

The finding that education positively influences the likelihood of adopting IAA aligns with existing research and is consistent with the general understanding of technology adoption in aquaculture (Läpple

TABLE 3 Selection model for technology adoption and intensity of adoption.

Variable	First stage probit model	Marginal effects results	IV2SLS model
	Adoption (1/0)		Intensity
Household characteristics			
Age of household head (HH) (Years)	0.000979 (0.00305)	0.000265 (0.000825)	0.0140*** (0.00484)
Household head education (Number of years)	0.0563 (0.0435)	0.0152 (0.0118)	0.196*** (0.0739)
Economically active members	1.170*** (0.279)	0.317*** (0.0735)	1.091** (0.512)
HH male gender (1/0)	-0.0131 (0.111)	-0.00354 (0.0299)	0.00341 (0.133)
Farm characteristics			
Farm size (ha)	0.00156 (0.0275)	0.000421 (0.00743)	-0.165** (0.0678)
Fulltime land ownership (1/0)	1.214*** (0.186)	0.329*** (0.0449)	0.941*** (0.244)
Received extension services (1/0)	-0.0576 (0.137)	-0.0156 (0.0370)	—
IAA awareness (1/0)	1.230*** (0.146)	0.333*** (0.0336)	3.614*** (0.897)
Land per person (Ratio)	-0.101** (0.0340)	-0.0275*** (0.00899)	-0.383*** (0.141)
Person trained (Number)	0.183*** (0.0477)	0.0494*** (0.0128)	—
Farm enterprises (Number)	0.0232 (0.0861)	0.00627 (0.0234)	—
Gained access to irrigation (1/0)	0.460*** (0.138)	0.125*** (0.0363)	—
Presence of wetland (1/0)	0.113 (0.173)	0.0306 (0.0468)	-0.724*** (0.276)
Natural water source (1/0)	0.271 (0.141)	0.0733* (0.0384)	0.103 (0.172)
Flat farm topography (1/0)	0.390** (0.150)	0.106*** (0.0401)	0.514*** (0.190)
Clay soil type (1/0)	-0.386** (0.140)	-0.105*** (0.0374)	0.884*** (0.172)
Lowland land type (1/0)	-0.715*** (0.151)	-0.193*** (0.0396)	—
Institutional factors			
Distance to the nearest input market (KM)	-0.0235* (0.0107)	-0.00636** (0.00288)	-0.0386 (0.0313)
Received credit (1/0)	0.200 (0.142)	0.0541 (0.0384)	0.116 (0.172)
Production risk measures			
Expected profit (Mean profit)	0.000000361* (0.000000171)	9.78e-08** (4.62e-08)	1.04e-07* (3.73e-07)
Profit variance (Profit variability)	-0.000000119** (0.000000131)	-3.23e-08** (3.56e-08)	-5.88e-07*** (2.23e-07)
Downside risk (Skewness of profit moment)	-0.0908*** (0.0233)	-0.0246*** (0.00631)	-0.206*** (0.0434)
Constant	-1.755*** (0.456)	—	-2.156** (1.064)

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

et al., 2015; Ngoc et al., 2016). Education plays a crucial role in shaping farmers' attitudes, knowledge, and skills, making them more receptive to new and innovative practices. With higher levels of education, farmers are more likely to be aware of the benefits and potential of IAA, leading to a greater interest in adopting these practices. Educated farmers often have better access to information, extension services, and training programs, which can enhance their understanding of IAA and its implementation. They are also more likely to be open to trying new approaches and adapting their farming methods based on scientific evidence and recommendations. Furthermore, education empowers farmers to critically evaluate the potential risks and benefits associated with adopting IAA (Cofre-Bravo et al., 2018). They can better assess the economic viability, resource requirements, and potential returns on investment, which are essential factors in the decision-making process. Education can also contribute to the adoption of sustainable and environmentally friendly practices. In the case of IAA, educated farmers may be more aware of the importance of conserving natural resources, reducing waste, and promoting

ecological balance, all of which are integral to successful and sustainable IAA implementation. It is important to acknowledge that education alone may not guarantee technology adoption (Amankwah et al., 2016). Other factors, such as access to resources, market opportunities, institutional support, and risk considerations, can also influence adoption decisions. However, education can act as a catalyst, enabling farmers to overcome barriers and embrace innovative practices like IAA.

The finding that a unit increase in the proportion of economically active members positively influenced the probability of adopting IAA underscores the importance of family dynamics and labor availability in aquacultural decision-making (Danso-Abbeam et al., 2018). The positive correlation between the proportion of economically active members and IAA adoption can be attributed to several factors: More economically active members in the household mean that there is a larger labor pool available for agricultural activities, including the implementation and management of IAA practices (Suvedi et al., 2017). With sufficient labor, farmers may feel more confident in

adopting labor-intensive practices like aquaculture, which can require regular attention and care. Economic activities of family members can contribute to the pooling of resources, which can then be invested in agricultural diversification, including IAA. Financial resources from the economically active members can facilitate the purchase of necessary inputs, infrastructure, and training required for successful IAA adoption. With more economically active members, there may be a higher ability to share risks associated with IAA ventures. Diversifying income sources through IAA can provide a safety net in case of output failure or market fluctuations, reducing the overall financial risk for the household. Economically active members who have exposure to external markets, information, and new ideas may bring valuable knowledge and insights to the household. This can facilitate the adoption of innovative practices like IAA, as they can better understand its potential benefits.

The finding that the number of persons trained per household positively influenced the adoption of IAA suggests that training plays a significant role in promoting the uptake of this agricultural practice (Engle, 2017; Kumar et al., 2018). Training programs are crucial in equipping farmers with the knowledge, skills, and technical know-how required to implement IAA effectively (Kuehne et al., 2017). When more members of a household receive training in IAA techniques, the overall capacity and understanding of the family increase, leading to a higher probability of adoption.

The finding that distance from the market was inversely proportional to the likelihood of adoption and the extent to which IAA is used emphasizes the significant influence of market proximity on farmers' decisions. This proximity offers several advantages that impact IAA adoption. For instance, farmers near the market can easily transport and sell their produce, reducing transportation costs and post-harvest losses. This accessibility encourages farmers to engage in IAA, knowing that their products can be readily sold and fetch better prices. Proximity to the market often means a steady demand for agricultural products. Farmers are more confident in adopting IAA when they can count on consistent demand and stable prices for their products. Being close to the market means easier access to inputs, such as fish fingerlings, feed, and crop seeds. This availability of resources facilitates the adoption and ongoing management of IAA practices. Farmers near the market can access timely information on market trends, consumer preferences, and price fluctuations. This information empowers them to make informed decisions about the adoption of IAA.

Other covariates were also found to influence the intensity of IAA integration positively and statistically significantly. These include age, education level, number of economically active members, full-time land ownership, awareness of IAA, flat farm topography, and clay soil type. The findings are in conjunction with other studies such as Kassie et al. (2011), Teklewold et al. (2013), and Mukasa (2018), who established a positive and significant correlation between technology adaptation and variables, such as age, flat farm topography, and education. Older farmers are more likely to undertake fish farming because they have the required skills, resources, and experience (Dey et al., 2010). The positive impact of economically active members on IAA integration can be explained by the fact that the more active members in the household, the more labor savings it becomes, hence an increase in IAA integration (Asfaw et al., 2014). Conversely, the variables that were found to be statistically and significantly negatively affecting the integration of IAA included farm size, person-to-land ratio, and presence of wetlands. Similarly, Dey et al. (2010) established

that a unit increase in the ratio of person to land led to a reduction in the levels of IAA integration by 38.3%. However, Mukasa (2018) found a positive impact of land size on IAA integration. This study found that an increase in farm size by 1 ha reduced the level of technology integration by 16.5%, which can be explained by the fact that the land may be used for other non-farm activities.

4. Conclusion and recommendation

Among smallholder farmers in rural Kenya, the empirical analysis found that production risk plays a central role in farmers' decisions through the direct effect of the sample moments of the profit distribution in the adoption model. The sample moments of the profit distribution, in particular mean, variance and skewness affect the decision of the farmer to adopt and use IAA thus confirming that farmers are not risk-neutral. The first moment (mean profit) had a highly significant positive effect on IAA adoption. This implies that smallholder farmers are driven by profit maximization and would be motivated to apply profit-increasing methodologies whenever they are guaranteed higher returns. The same positive effect was also reflected in the intensity of IAA application. Profit variability, as reflected by the second moment, negatively impacted IAA adoption and the intensity of IAA use. This implies that farmers are discouraged from employing IAA when profits are less certain. They would rather accept a low profit than invest heavily in pursuit of a higher but uncertain profit. As much as farmers are driven by profit maximization, they are also risk averse and will minimize investment in risky ventures. The statistical significance of the third moment of profit indicates that farmers take downside yield uncertainty into account when they decide whether to adopt IAA. Other factors that were important in IAA adoption were the proportion of economically active members, full-time land ownership, awareness of IAA, accessibility to irrigation, and flat farm topography, all of which were statistically significant in influencing IAA adoption positively. Other factors which were found to influence the intensity of IAA positively and significantly were: age, education level, number of economically active members, full-time land ownership, awareness of IAA, flat farm topography, and clay soil type. These results have important policy implications. First, neglecting risk considerations (particularly for risk-averse farmers) when assessing the impact could provide misleading guidance to policy makers. Second, IAA should be promoted alongside farmer's education, farm size, access to affordable and accessible credit, number of enterprises, and IAA awareness as a mechanism for enhancing smallholder adoption and intensity of adoption.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The study was conducted in accordance with an approval granted by the Kenyatta University Ethics Review Committee (protocol code

PKU/2290/I1431, 12th August 2021 and the Research License 295677 granted by the National Commission for Science, Technology. Informed consent was obtained from all subjects involved in the study.

Author contributions

FA, IM, and RM contributed substantially to the study's conception and design, data collection, analysis, interpretation, manuscript revision, and final approval. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fsufs.2023.1181502/full#supplementary-material>

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