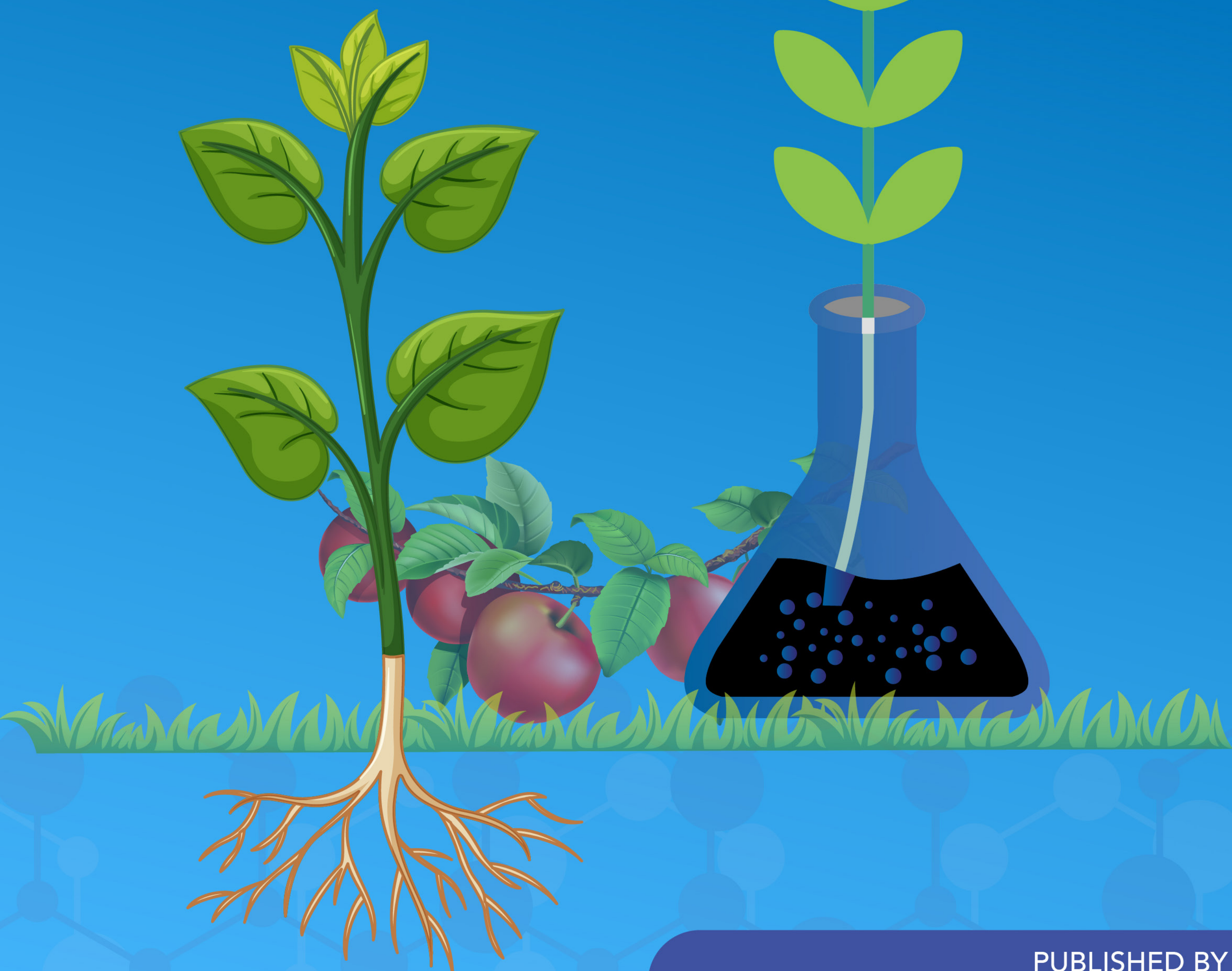
American Journal of Food Science and Technology (AJFST)

ISSN: 2834-0086 (ONLINE)

VOLUME 4 ISSUE 2 (2025)



PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of
Food Science and Technology (AJFST)

Volume 4 Issue 2, Year 2025
ISSN: 2834-0086 (Online)
DOI: https://doi.org/10.54536/ajfst.v4i2.5280
https://journals.e-palli.com/home/index.php/ajfst

From Indigenous to Improved Breeds: Adoption Dynamics and Intensity of Artificial Insemination Among Farmers in Western Kenya

G. O. Awuor[1], E. Kipkemei[1], A. Serem[1], A. K. Kipkoech[1*]

Article Information

Received: May 09, 2025

Accepted: June 14, 2025

Published: September 01, 2025

Keywords

Adoption Intensity, AI Technology, Probit, Western Kenya

ABSTRACT

Adoption of Artificial Insemination (AI) has the potential to upgrade local dairy breeds for improved milk production in western Kenya. This study employed the double hurdle probit model to analyze factors influencing the adoption and intensity of AI technology. A multistage random sampling technique was employed to identify sample units among adopters and non-adopters of AI technology. Data was obtained from cross-sectional survey of 378 farmer households. Results of the probit model showed that age, education level, experience, milk sales, AI cost, worker's skill on heat detection, semen type, AI reliability, and availability of the inseminator positively and significantly influenced AI technology adoption. Only training on livestock production negatively and significantly influenced AI technology adoption. Results of the truncated regression showed that age, education level, experience, and training on livestock production positively and significantly influenced the intensity of AI technology use. Group membership and the availability of the inseminator negatively and significantly influenced the intensity of AI technology adoption. It is concluded information is the most critical factor influencing adoption of AI. Building more trust and confidence about AI technologies will lead to increased adoption. The study recommends the improvement of farmer education through introduction of effective farmer training and information sessions. There is need to conduct training needs assessments before the trainings are carried out so as to capture the farmers' interest together with their socio-economic environments.

INTRODUCTION

The primary objective of improving the livestock sector is meeting the increasing demand for livestock products for achieving food security and the sustainability of the economy. In Kenya, the livestock sector contributes over 30% of the farm gate value of agricultural commodities, about 10% of the national Gross Domestic Product (GDP), at least 50% of the agricultural GDP, and employ 50% of the labor force in agriculture (KALRO, 2024). The dairy sub-sector are critical in the economy given the ever-increasing human demand of milk and the potential to generate frequent and sustainable household incomes. Milk contributes substantially to the economy, accounting for 27% of the value added by livestock and 10% of the total agricultural value added (FAO, 2016).

In western Kenya, dairy sub-sector faces significant challenges despite its potential to contribute to food security and economic growth. While cows are the most prevalent dairy animal, farmers typically keep just two or three cows, meaning that farmers experience a higher average cost of production compared to farmers in developed countries where average dairy herd size is around 90 cows in the UK and 300 in the USA (FAO, 2016). Herd quality is characterized by low productivity, with smallholder farms predominantly keeping exotic-zebu (indigenous breed) crosses (41.7%), Friesian (34.3%), and Ayrshire (22.4). The average milk production per cow in is estimated at 6.47 liters per day, with a lactation yield of 2,400 liters (Wanjala & Njehia, 2014). These figures are significantly lower than the global average of 40 liters per day per cow and up to 14,000 liters per lactation.

This disparity is attributed to genetic limitations of the available animal breeds Low adoption of high-yield exotic breeds due to cultural preferences of the indigenous Zebu breed and inadequate artificial insemination services (Kiplagat *et al.*, 2025), inefficient breeding services, inadequate management practices leading to poor-quality fodder production and seasonal scarcity (Odero-Waitituh, 2017) and insufficient extension and advisory services. Studies have shown that the herd quality influence the ability of farmers to improve their milk production and herd size through influencing the rate of spread of reproductive diseases, conception rates, calf mortality rates, growth and maturity rates.

The use of new technologies to improve herd quality has been found to increase productivity, lower the risk of livestock diseases, and ensures environmental sustainability in productive areas (Kimunya, 2014). There are a number of reproductive technologies available to transfer desirable genetic materials such as artificial insemination, embryo transplant, and vitro fertilization, of which only artificial insemination (AI) is the most commonly used technique in developing countries including Kenya. Particularly used as a reproduction method in dairy farming, AI provides significant economic contributions to milk production and to farmers by

[1] Department of Agricultural Economics and Resource Management, Moi University, P.O Box 3900, Eldoret, 30100, Kenya
[*] Corresponding author's e-mail: akkipkoech@gmail.com

genetically improving animals (Howley *et al*., 2012). The advancement and application of artificial insemination have significantly transformed cattle production and genetic enhancement, especially within the dairy industry in developed nations (Henning *et al*., 2010).

Potential of Artificial Insemination (AI) To Improve Herd Quality And Productivity

Artificial Insemination is the process by which semen is artificially introduced into the female reproductive tract for the purpose of conception (Shehu *et al*., 2010). The process has become a popular avenue in the endeavour to the improve herd quality and milk production in western Kenyan. The technology allows for future change of the herd breed by introducing semen from genetically superior bulls in to local cows. The semen is carefully selected to ensure they have the desired traits such as higher milk yield, disease resistance, and better adaptation to local environments.

In western Kenya, the government promote AI services on dairy cattle, highlighting the focus on boosting the productivity of the dairy sub-sector. The use of AI has helped to address challenges such spread of reproductive diseases, poor conception rates, social issues from sharing bulls, lack of control over progeny quality, limited financial resources, inadequate veterinary support, and poor performance of dairy breeds (Gahakwa *et al*., 2014). The use of AI services enables farmers to access superior genetics that would otherwise be unavailable or unaffordable through natural mating. For instance, the cost of purchasing and maintaining a bull are inhibitably high. The adoption of AI service among farmers has resulted to emergence of crossbreeds heifer cows with significantly improved milk production potential compared to indigenous Zebu breed. There has been a significant reduction in inbreeding, which was responsible for the undesirable traits inherent in the local cow breeds. For the purpose of this research the study sought to understand the frequency of use of artificial insemination by the AI expert in consultation with the farmer. There has been increase in promotional activities for the AI service by both government and private sector players through training of professionals in AI, provision of high-quality semen and training for farmers on various aspects of AI. There has also been a policy shift in to allowing for the privatization of AI services that improved accessibility. Heat synchronization of heifers and cows was tried in Siaya County among other counties, with the Government of Kenya collaborating with ILRI to upgrade the local zebus using fixed time artificial insemination (FTAI). This initiative saw the increase in the number of artificial inseminations in western Kenya (in particular at Alego-Usonga sub-County) with a peak being witnessed in 2016 as presented in Table 1. Despite the potential of AI technology to upgrade local zebus through selective breeding and meet growing milk demand, farmers have not fully embraced the technology, with sizeable number of farmers still opting for use of traditional bulls, or even preferring to maintain their traditional herd.

Several studies have explored the drivers of AI technology in different contexts, highlighting the complex interplay of socio-economic, institutional, and technical factors (Gebre *et al*., 2022; Ingabire *et al*., 2018; Bayan, 2018; Mwanga *et al*., 2019). These factors can include farmer characteristics (age, education, and experience), access to credit and extension services, cost of AI services, availability of liquid nitrogen, infrastructure, and cultural beliefs (Ayantunde *et al*., 2008). Understanding these factors is crucial for designing and implementing effective interventions to promote AI technology adoption and maximize its impact on livestock productivity.

In Alego-Usonga Sub-County, while livestock keeping is a common practice, there is a need for more in-depth research to understand the specific factors that influence adoption of AI technology. There is need to capture the local and unique context of Alego-Usonga, which might have distinct socio-economic, environmental, and cultural characteristics. A comprehensive analysis of the factors influencing AI adoption and intensity of use within this specific sub-county is essential. This study sought to address this gap by investigating the socio-economic, technical, and institutional factors that influence farmers' decisions to adopt and consistently utilize AI technology in Alego-Usonga sub-County to improve their dairy herd and ultimately milk yield.

MATERIALS AND METHODS

Study Area

The study area was Alego-Usonga sub-county that covers an area of 599 square kilometers within Siaya county in western Kenya. The areas has a population of 224,363 people according to the 2029 Kenya National Bureau of Statistics (KNBS) census of 2019 (KNBS, 2019). The population is made of smallholder farmers practicing mixed farming where they keep livestock and farm crops. There are 3,512 households in the study area producing 26% of the milk consumed in the area from the 81% of marketed of milk produce. The farmers are known to hire labour for dairy management activities. The smallholder dairy farmers keep 1-5 cows on an average of 0.5 to 3 acres. The improved cows produce 3.4 liters per cow per day compared to the indigenous zebu cows that produce an average of 2.4 liters/cow/day (ASDSP, 2014).

The area has a bimodal rainfall pattern with two rainy seasons in each year typically separated by drier periods, leading to alternating wet and dry phases throughout the year. The rains occur between March and May and again between October and December and is well distributed within the Northern parts of Ugunja, Gem and Ugenya receiving the highest amount between 1600-2000mm and rainfall gradually reducing to Southern parts of Bondo and Rarieda which receive the lowest amounts between 800-1200mm annually. The temperature ranges from 15 to 32 degree Celsius with an annual average of 28 degrees Celsius (Directorate of Livestock Production and Veterinary, 2019). The weather characterized by warm temperatures, consistent rainfall and high humidity provide reliable moisture for pasture growth, ensuring that grasses and forage crops can thrive throughout the rainy seasons.

Data Collection, Sampling Technique and Size

This study utilized a cross-sectional study design. Data was collected using a structured questionnaire administered to smallholder farmers. The questionnaire gathered information on socio-economic, technical, and institutional characteristics of smallholder farmers. The study employed a multi-stage sampling technique to identify adoptors and non-adopters of AI technology. A sample size of 378 was randomly selected. This study utilized the formula by Kothari (2004) to estimate the sample size as follows:

$$n = \frac{Z^2.p.q.N}{e^2(N-1)+Z^2p.q} \qquad \text{....(1)}$$

Where,

N = population Size; n = the desired sample size; z – Standard normal deviate at 0.05 significance level; p – the proportion in the target population estimate to have a characteristic being measured (an assumption of p =0.5 was made); q = 1 - p; e = level of statistical significance desired; z - statistic at 95% confidence level is 1.96.

The level of significance being 0.05 therefore; the sample size, n was estimated as:

$$n = \frac{(1.96)^2 \times (0.5)(0.5)(22965)}{0.0025(22964)+3.8416X0.25} = 378 \qquad \text{....(2)}$$

Data Processing and Analysis

After data collection, cleaning of the data was done using Microsoft Excel software. STATA software version 15 was utilized to analyze quantitative data collected from the household survey. Both descriptive and inferential statistics were applied to the data to identify factors influencing the adoption of AI technology and intensity of use in Alego-Usonga.

The Cragg (1971) Double Hurdle model was employed in this study to analyze factors influencing the adoption and the intensity of use of AI technology in Alego Usonga Sub County. According to Cragg (1971), adoption is a process involving two stages/tiers; the first is decision on whether or not to adopt the technology, and second is to what extent to adopt. The model assumes that the decision not to adopt is a deliberate choice, thus the zeros from non-participants are considered as corner solution in the utility maximizing model. The model curbs bias in the continuous second tier dependent variable by linking a value to the piled up data, thus maintaining all the data within the sample. The Cragg model is flexible, assuming that there are no restrictions regarding the components of independent variables in each estimation stage. The model requires a joint application of the probit and truncated regression models, sequentially or simultaneously. The probit model equation that was used in the study is given as:

$$\mathcal{Y}_i^* = \beta_i X_i + \varepsilon_i$$

$$\mathcal{Y}_i = \begin{cases} 1 \text{ if } \mathcal{Y}_i^* > 0 \\ 0 \text{ if } \mathcal{Y}_i^* \leq 0 \end{cases} \qquad \text{....(3)}$$

Where subscript i is the i[th] household, is the latent discrete adoption choice variable, Y_i^* is the observed adoption variable which takes a value of 1 if the farmer adopted AI technology and 0 otherwise, X_i is Kx1 vector of factors that influence AI technology adoption, β_i is a Kx1 vector of parameters to be estimated, ε is the error term.

These coefficients β_i represent changes in the latent variable (unobserved z-score) underlying the binary outcome and thus, the effect of each predictor on the latent propensity (z-score) to adopt AI. The change in probability that a farmer will adopt AI or not arising from the change in the variables X_i depends on their effect on the cumulative normal distribution function (Φ) evaluated at the mean predictor values.The marginal effect of an independent variable X_k on the probability is:

$$\frac{\partial P(Y=1)}{\partial X_k} = \beta k \cdot \phi(\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_x)\beta_i \qquad \text{....(4)}$$

Where, Φ is the standard normal density

The PDF of the standard normal at β_X is:

$$\phi(\beta X) = \frac{1}{2\pi} e^{-\frac{\beta X^2}{2}} \qquad \text{....(5)}$$

Marginal effect of change in $X_x = \Phi(\beta X) \times \beta_k$

In the second hurdle, the truncated regression model was employed to determine factors that influence the intensity of AI technology adoption among farmers who adopted the technology. The truncated regression is given by:

$$I_i^* = \alpha_i X_i + \mu_i \qquad \mu_i \sim N(0, \delta^2)$$

$$I_i = \begin{cases} I_i^* \text{ if } I_i^* > 0 \text{ and } \mathcal{Y}_i = 1 \\ 0 \text{ otherwise} \end{cases} \qquad \text{....(6)}$$

Where, I_i is the intensity of AI technology adoption, and depends on I_i^* is the latent variable being greater than zero on the condition that a decision is made to adopt AI technology.X_i is a vector of parameters to be estimated for the intensity of adoption, is a vector of factors that influence the intensity of use of AI technology, μ is the error term which has a normal distribution.

The double-hurdle regression equation is specified as follows:

$$Y_i \text{ or } I_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3, \ldots, \beta_n X_n + \varepsilon_i \qquad \text{....(7)}$$

Where, Y_i is the AI adoption which takes a value of 1 for adopters and 0 otherwise, I_i is intensity of use of AI measured by the number of times a farmer used the technology, β_i is a vector of parameters to be estimated, X_i is vector of the explanatory variables, and ε_i is the error term.

RESULTS AND DISCUSSIONS

Results in Table 1 presents the descriptive statistics for the variables used in the analysis. The results indicate that, on average, the majority of small-scale dairy farmers were aged 40-49 years , with 46% being male. Most of the farmers had attained primary-level education and had more than five years of experience in dairy farming. The age and education level of the farmers suggests that the typical dairy farmer in this sample is a mature adult with basic to moderate educational attainment, which can influence their ability to adopt new technologies and management practices. The gender distribution (mean of 0.46) indicates a relatively balanced representation of men and women, though slightly more women may be involved. On average, 39.5% of male small-scale dairy farmers were members of various farmer groups that is relatively low, which could affect access to shared resources, training, and collective bargaining for better prices or services. The average herd size is 3.7, with a high standard deviation (2.08), indicating significant variation in the scale of dairy operations among households. Milk sales average at Kshs. 455.5, but with a large standard deviation (267.8), showing that while some households are quite productive, others are less so, possibly reflecting differences in whether a farmer has improved or indigenous breed, differences in herd size, management skills, or market access.

The costs associated with breeding among the dairy farming are notable, with artificial insemination (AI) services of about Kshs. 2000 and the cost of a bull was Kshs. 854.5, which a high standard deviation of Kshs. 376.3 for the cost of the bull. The high standard deviation pints to lack of standard prices for breeding that expose farmers to high charges from scrupulous breeders and the high financial investment required for herd improvement and breeding.

The average worker's skill in heat detection is 1.6 (in a scale of 1-4, 1 =poor, 2=fair, 3=good, 4=excellent) with considerable variability (std. error = 0.7), suggesting that most farmers are considered to have some knowledge on heat detection but majority need additional training. This skill is crucial for effective breeding and maximizing milk production, underlining the importance of capacity building in dairy farm management. This particular variable for the success of AI technology given that a farmers ought to have an excellent heat detection skill to ensure the inseminator is called in on the right time for successful breeding.

Table 1: Descriptive Statistics and Measurement of Variables Influencing Adoption and Intensity of AI

Variable (Characteristics of household head)	**Measurement**	**Sample Mean**	**Std. Dev**
Age	1 = 20 – 29 years, 2 = 30 – 39 years, 3 = 40 – 49 years, 4 = above 50 years	3.3	0.76
Gender	1 = Male, 0 = Female	0.46	0.5
Education level	1 =non-formal, 2=primary, 3=secondary 4 = college/university	2.3	1.0
Years of experience in dairy farming	1 = less than 1 year, 2= 1 – 5 years, 3= more than 5 years	2.7	0.5
Group membership	1 = yes, 0 = no	0.4	0.49
Herd size	In numbers	3.7	2.08
Milk Sales	In Ksh	455.5	267.8
Cost of AI service	1 = Ksh. 1000 – Ksh. 2000, 2= above Ksh. 2000	1.8	1.3
Cost of bull	Cost in Ksh	854.5	376.3
Worker's skill on heat detection	1 = poor, 2 = good, 3 = very good 4 = excellent	1.6	0.7
Semen type	1 = poor, 2 = good, 3 = very good	1.8	0.4
Perception about AI reliability	If it is reliable 1 = yes, 0 = no	0.45	0.5
Supplements use	If they give supplement feeds 1 = yes, 0 = no	0.9	0.3
Farmer access to extension	Access to extension service 1 = yes, 0 = no	0.9	0.3
Farmer has attended atlease one farmer training	Attended any training 1 = yes, 0=no	0.72	0.45
Farmers access other support services (apart from extension and training)	If support services are available 1 = yes, 0 = no	0.07	0.25
Information on availability of Inseminator	If the inseminator is available 1 = yes, 0 = no	0.9	0.3

Source: Author's Computation (2025)

The results also shows high access to extension services by about 90% of the farmers. But this is surprising given that the although there is a high extension access, the perception about the reliability of AI remained low (45%). This points out at the need to re-look at the mode of extension service, the packaging of the extension information and assess the factors that influence the effectiveness of the service. Results showed that 72% of the farmers had attended at least one training by the extension service. Only 7% of farmers access other support services beyond extension and training. There is a high preference of non-sexed semen of 1.8 (in a scale of 1=sexed, 2=non sexed) pointing out to the limiting possibility of high cost of sexed semen. Results showed that there was a high awareness among farmers (90%) on the availability of AI service within reach of the farmers meaning that the adoption and non-adoption of AI was deliberate decisions by farmers.

Factors Influencing Adoption of AI Technology

Results of the probit regression from using Equation 3 used to estimate the factors influencing the adoption of AI technology in the study area is provided in Table 2 below. The results revealed that ten out of seventeen variables considered and analyzed were statistically significant and influenced adoption of AI technology in the study area. Age, education level and experience of the household head, milk sales, cost of AI service, cost of use of bull service, worker's skill on heat detection, semen type, perception about AI reliability and information on availability of inseminator positively influenced AI technology adoption. Further, only training negatively influenced AI technology adoption in the study area that calls for a further analysis of the effectiveness of training in achieving the intended outcomes of promoting genetic improvements of dairy herd in the study area. Training may negatively influence artificial insemination (AI) adoption if it is poorly designed, irrelevant, or not tailored to farmers' needs and socio-economic circumstances. Poorly designed training my lower farmers' confidence in AI technology and may cause resistance, confusion and mistrust of the technology or the AI service and service providers.

Age was established to have a positive effect and statistically significant at 5% level of significance in explaining the adoption decision of AI technology. This showed that a shift to the higher next age category increases the probability of adopting AI technology by 25.3%. The findings suggests that older farmers are more likely to adopt AI technology. The argument is that older farmers have more experience, have a better access to resources, or a greater willingness to invest in AI technology due to accumulated resources and knowledge. The current finding is in line with those on factors for adoption of artificial insemination technology among pig farmers by Sharma *et al.* (2020) who found out that age of the household head positively and significantly determined the adoption of AI technology in small scale pig production systems in India. The current finding is also consistent with those on factors influencing adoption of AI by smallholder livestock farmers in dryland production systems of Kenya by Abot (2020) who reported a positive influence of age on the adoption of AI technology.

Table 2: Probit Regression Results on Factors Influencing AI technology Adoption

Factors influencing adoption of AI (X_i)	Coef. (β_i)	St. Err.	t-value	p-value	[95% Conf	Interval]	Marginal effects
Age	0.253**	0.102	2.49	0.013	0.054	0.452	0.105
Gender	0.095	0.186	0.51	0.609	-0.269	0.459	0.039
Education level	0.201***	0.03	6.80	0.000	0.143	0.258	0.083
Years of experience in dairy farming	0.121**	0.059	2.05	0.041	0.005	0.237	0.050
Group membership	0.154	0.212	0.73	0.468	-0.262	0.569	0.064
Herd size	-0.018	0.045	-0.39	0.696	-0.106	0.071	-0.007
Milk sales	0.001***	0.000	2.94	0.003	0.000	0.002	0.000
Cost of AI service	0.542***	0.205	2.64	0.008	0.14	0.943	0.225
Cost of bull	0.001*	0.000	1.67	0.094	0.000	0.001	0.000
Worker's skill	0.198**	0.099	1.99	0.047	0.003	0.393	0.082
Semen type	0.345***	0.086	4.03	0.000	0.178	0.513	0.143
Perception about AI reliability	1.862***	0.289	6.45	0.000	1.296	2.428	0.772
Supplements	0.283	0.271	1.04	0.296	-0.248	0.815	0.117
Farmers access to extension access	-0.332	0.29	-1.15	0.252	-0.900	0.236	-0.138
Farmers attend at least one farmer training	-0.496**	0.225	-2.20	0.028	-0.937	-0.054	-0.206

Information about inseminator availability	0.85***	0.241	3.53	0.000	0.378	1.323	0.353
Farmers access other support	0.204	0.379	0.54	0.59	-0.538	0.946	0.085
Constant	-4.239***	1.095	-3.87	0.000	-6.385	-2.093	
Mean dependent var	0.696	SD dependent var				0.461	
Pseudo r-squared	0.357	Number of obs				332	
Chi-square	145.649	Prob > chi2				0.000	
Akaike crit. (AIC)	300.309	Bayesian crit. (BIC)				372.606	
	βX = 1.33	ϕ(X) = 0.414					

**** p<.01, ** p<.05, * p<.1 denotes significance at 1%, 5% and 10%, respectively.*

Education level of the household head was found to have a positive effect and statistically significant at 1% level of significance in explaining the adoption decision of AI technology. This showed that an increase in education level is likely to increase the probability of AI technology adoption by 3.9%. Studies have shown that education increases the awareness and promotes attitude change which creates a favourable environment for technology adoption (Mwanga *et al*., 2019; Okello *et al*., 2021). Farmers with high levels of education are likely to have more knowledge and skills and hence their higher probability of adopting AI technology compared to those with low levels of education. The current finding are consistent with those on the determinants of utilization of agricultural technologies among smallholder dairy farmers in Kenya by Okello *et al*. (2021) who established that education level positively influenced the utilization of AI. Similarly, a study on adoption of artificial insemination and the intensity of use in Ethiopia by Gebre *et al*. (2022) reported a positive relationship between the households' level of literacy and adoption and intensity of use of AI.

Years of experience in dairy farming was established to have positive influence on AI technology adoption at 5% level of significance. This means that for every additional years in dairying experience, the likelihood of adopting AI technology increases by 5.0%. Experienced farmers may have observed or learned about the benefits of AI over time which enhance their chances of adopting the technology. Additionally, longer involvement in dairy farming may provide farmers with better financial resources to afford AI services. The current finding is consistent with the findings on factors for adoption of artificial insemination technology among pig farmers by Sharma *et al*. (2020) who found out that farming experience positively and significantly determined the adoption of AI technology in small scale pig production systems in India. The current result is also similar to those on factors affecting the use of artificial insemination of farmers in dairy farming in Turkey by Özsayın (2020) who reported that dairy farming experience had a positive effect on the use of artificial insemination. However, other studies have reported negative influence of experience on adoption of technologies. Kaaya *et al*. (2005) reported that experience negatively influences the utilization of AI in Uganda. Similarly, a study on adoption and intensity of improved fish feeds use in Western Kenya by Wafula *et al*. (2021) established that experience negatively influenced the intensity of using improved fish feeds in Kenya. It is imperative that as farmers accumulate years of experience in dairy farming, they experiment several strategies in their quest to improve earnings, including improving dairy herd using AI. Farmers adopt and permanently use new agricultural technologies when they test them and find them working and perceive clear economic and practical benefits (Castellini *et al*. 2025).

Milk sales was found to have a positive effect and statistically significant at 1% level of significance in explaining the AI technology adoption decision. This implies that a 1 Ksh increase in milk sales is likely to influence the probability of adopting AI technology by a very low percentage (<0.1%). Income from milk is an incentive and will determine the probability that a farmer will use AI technology or not. Farmers who receive low incomes are not motivated to use this technology since they do not realize much from dairy farming as compared to those who earn more. The current finding is consistent with the findings by Tefera (2013) who reported that income from milk sales positively influenced the farmer decision to adopt AI in Ethiopia. A study on multi-country investigation of factors influencing breeding decisions by smallholder dairy farmers in sub-Saharan Africa by Mwanga *et al*. (2019) reported that income from selling dairy products positively influenced the use of AI in Ethiopia and negatively influenced the choice of AI as a breeding option in Tanzania, Uganda, and Kenya.

The cost of AI was found to be statistically significant at 1% level of significance and positively influenced AI technology adoption by 22.5%. The cost of any dairy technology will always determine its uptake and hence if the technology is affordable it will be embraced by the farmer, and if it is expensive only few farmers will adopt it. The current finding is divergent to the findings on the adoption of improved technologies and profitability of the catfish processors in Ondo State, Nigeria by Olutumise *et al*. (2020) who reported that cost of equipment negatively influenced the decision to adopt and the rate of adopting improved fish processing technologies in Nigeria. The current findings are also inconsistent with those on multi-country investigation of factors influencing breeding decisions by smallholder dairy farmers in sub-Saharan

Africa by Mwanga *et al.* (2019) who found out that cost of AI service negatively influenced the choice of AI as a breeding option. The positive relationship between cost of AI and the probability of its adoption show that adoption decisions are strongly influenced by the expected profitability and cost-benefit considerations. While high costs is expected to be a barrier, farmers are more likely to evaluate benefits and costs of a technology and adopt technologies with higher costs if these technologies promise greater returns or efficiency gains that justify the investment (Pope & Sonka 2020).

Worker's skill on heat detection was statistically significant at 1% level of significance and positively influenced the probability of adopting AI technology by 8.2%. Successful conception is determined by proper heat timing and timely insemination. Accurate heat detection leads to better reproductive management, shorter calving intervals, and increased milk production. A worker with good skill on heat detection will enhance the chances of a successful conception as compared to the one with poor skills. Additionally, the worker spends most of his/her time with the cows and monitors the behaviour of the animal and hence is able to detect the possibilities that it is on heat or not. The success of AI technology depends majorly on the ability of the farmer to detect heat and invite an inseminator on time. Without the skills, the success rate of AI can be highly compromised leading to economic losses and mistrust of the technology.

Semen type was statistically significant at 1% level of significance and positively influenced the adoption of AI technology by 14.3%. There are various types of semen available to the farmers for the select for insemination. It is important to note that farmers made deliberate decisions to adopt Ai service based on expected benefits. The sexed semen was adopted by farmers who had perceived clear pathway to improving their dairy herd and milk production and are likely to continuously use AI service. Moreover, farmers who used sexed semen were likely to be knowledgeable also preferring semen from genetically superior bulls that offer traits such as higher milk production, disease resistance, or faster growth thereby obtaining additional benefits from AI and help further promote adoption of AI.

Perception about AI reliability was statistically significant at 1% level of significance and positively influenced the adoption of AI technology by 77.2%. When farmers believe and trust the capability of a technology to improve the performance of their enterprises they are likely to adopt and continue using it. This could be attributed to the fact that farmers like trying out technologies that are believed to benefit them in the long-run. Additionally, farmers are likely to adopt a given technology if it is being promoted by the government and trusted agencies. The perception about reliability is linked to access to extension service, farmer training and the availability of information about AI service and the associated benefits. Farmers are more likely to adopt agricultural technologies if they receive correct information through the right sources (Livondo *et al.* 2015).

Training on livestock production was established to be statistically significant at 5% level of significance and negatively influenced AI technology adoption by 20.6%. Training impacts knowledge to farmers about existing technologies and hence enabling them to use them. The current finding is divergent to those on factors affecting small dairy farmers' adoption and intensity of artificial insemination technology in Ethiopia by Herana and Kumari (2017) who reported that training positively influenced adoption of AI. The current finding is also in line with the finding by Sharma *et al.* (2020) who reported that participation in training and demonstration programmes positively influenced the adoption of AI technology in small scale pig production systems in India. Moreover, the findings on adoption of artificial insemination service for cattle crossbreeding by smallholder farmers in Ethiopia by Abraha *et al.* (2020) who established that formal training positively influenced AI technology adoption contradict the current result.

Inseminator availability was statistically significant at 1% and positively influenced the probability of adopting AI technology by 35.3%. This finding could be attributed to the fact that most farmers stated that the inseminator was available when called. Conception of a cow once heat signs are detected was time bound and tend to put farmers in a panic model. The information about availability determines chances for the farmer inviting the inseminator. Supporting this findings are those on factors affecting adoption of artificial insemination technology by dairy farmers in Tanzania by Temba (2011) who revealed that proximity to AI service providers and access to information were significant factors affecting AI adoption by dairy farmers.

Factors influencing the Intensity of AI Technology Use

Table 3 presents the truncated regression results on the factors influencing the intensity of AI technology adoption in the study area. The table of results shows that nine out of seventeen variables considered and analyzed were statistically significant and influenced the intensity of AI technology adoption on the level in the study area. Among the variables that positively influenced the intensity of AI technology include; age, education level, experience, milk income, and training. Further, group membership, AI cost, worker's skill on heat detection, and availability of the inseminator negatively influenced the intensity of AI technology use.

Age positively influenced the intensity of using AI technology at 1% level of significance. This shows that a year increase in age increases the intensity of AI technology use by 5%. The argument is that as farmers increase in age their experience also adds up. Farmers with a good history with AI use are likely to intensify as opposed to those with bad experiences. The current finding conform those by Chen *et al.* (2020) who reported a positive effect of age on the intensity of tea consumption among men and women in China. The current finding however is divergent to finding by Mahoussi *et al.* (2021)

who found out that age square had a negative quadratic relationship with the intensity of use of improved maize seeds in Benin.

Education level was established to have a positive influence on the intensity of AI technology use at a 1% significance level. This implies that for each additional year in education, the intensity of using AI technology increased by 4.2%. This could be attributed to the fact that education improves the knowledge and skills of the farmer. The current finding is consistent with the findings on adoption of artificial insemination technology and its intensity of use in Ethiopia conducted by Gebre *et al*. (2022) who reported that literacy level increases the intensity of AI technology adoption. The current findings also conform to the finding by Mahama *et al*. (2020) who noted that education level positively influenced the extent of AI adoption. However, the current finding contradicts the findings on factor influencing adoption of AI by smallholder farmers in dryland production systems of Kenya by Abot (2020) who found that education level negatively influenced the extent of AI adoption.

Experience was also found to positively influence the intensity of AI technology use at 1% level of significance. This means that a year increase in dairy farming experience is likely to increase the intensity of AI technology use by 5.8%. This could be attributed to the fact that more experienced farmers tend to continue employing technologies that they perceive beneficial with time. The current finding are consistent with the findings by Olutumise *et al*. (2020) who reported a positive influence of experience on the intensity of adoption of improved technologies and profitability of the catfish processors in Nigeria. The current finding is divergent from the findings by Tefera (2013) who reported that experience of keeping crossbred cattle in the past years had negative effect on the extent of adoption of AI in Ethiopia. The current findings also contradict those on factors influencing adoption decision of AI technology and the extent of adoption by Bayan (2018) who found out that with one additional year older from start of a dairy farm, the probability of adoption and intensity of adoption goes down.

Group membership negatively influenced the intensity of AI technology use by 3.8% at a 5% level of significance. Cooperatives offer a range of benefits to its members including marketing of output, inputs, education and new technologies. The decision to adopt and intensify dairy technologies may be independent of the influence of cooperatives. The current findings is consistent with the finding on the determinants of utilization of agricultural technologies among smallholder dairy farmers in Kenya by Okello *et al*. (2021) who reported a negative influence of group membership on utilization of dairy technologies in Kenya. The current finding is also convergent to those on adoption and intensity of improved fish feeds use in Western Kenya by Wafula *et al*. (2021) who reported that group membership negatively influenced the adoption and intensity of using improved fish feeds. The current finding are inconsistent with the finding on the determinants of artificial insemination use by smallholder dairy farmers in Ethiopia by Tefera (2013) who reported that being a member of dairy cooperative positively influenced the extent of AI use. The current findings are also divergent to the findings on factors affecting adoption of artificial insemination technology by dairy farmers in Tanzania by Temba (2011) who reported that group membership positively influenced adoption and intensity of AI.

Training was established to have a positive influence on the intensity of AI technology use at a 10% level of significance. This means that attending trainings increases the intensity of AI technology use by 5.6%. The argument is that farmers who have been trained have better access to information and agricultural knowledge about dairy farming as opposed to their non-trained counterparts. The current finding is consistent with the findings on factors affecting small dairy farmers' adoption and intensity of artificial insemination technology in Ethiopia by Herana and Kumari (2017) who reported that access to AI training positively influenced intensity of AI in Ethiopia. The current finding also conforms to the findings by Gebre *et al*. (2022) who reported that access to training positively influences the intensity of AI technology adoption in Ethiopia. However, a study by Dumara and Zenbaba (2020) established that attendance in training had a positive and significant effect on the adoption and intensity of adoption of malt barley technology in Ethiopia.

Table 3: Truncated Regression Results on Factors Influencing Intensity of AI Technology Adoption

AI Intensity factors X_i	Coef. β_i	St.Err.	t-value	p-value	[95% Conf	Interval]
Age	0.05***	0.013	3.80	0.000	0.024	0.076
Gender	-0.023	0.016	-1.46	0.145	-0.054	0.008
Education level	0.042***	0.01	4.44	0.000	0.024	0.061
Experience	0.058***	0.017	3.40	0.001	0.025	0.091
Group membership	-0.038**	0.017	-2.17	0.03	-0.072	-0.004
Herd size	-0.003	0.004	-0.76	0.448	-0.011	0.005
Milk sales	0.000**	0.000	2.07	0.039	0.00	0.00
AI cost	-0.029*	0.016	-1.80	0.071	-0.06	0.002
Cost of bull	0.000	0.000	0.75	0.456	0.00	0.00

Worker's skill	-0.016*	0.009	-1.83	0.067	-0.034	0.001
Semen type	-0.003	0.007	-0.38	0.702	-0.016	0.011
AI reliability	-0.019	0.02	-0.95	0.343	-0.057	0.02
Supplements use	0.03	0.023	1.27	0.204	-0.016	0.075
Extension access	-0.021	0.023	-0.93	0.353	-0.067	0.024
Training	0.056***	0.021	2.61	0.009	0.014	0.098
Inseminator availability	-0.048**	0.021	-2.26	0.024	-0.09	-0.006
Government support	0.02	0.031	0.66	0.506	-0.04	0.08
Constant	1.096***	0.09	12.18	0.000	0.92	1.272
Sigma	0.137***	0.005	25.77	0.000	0.127	0.147
Mean dependent var	1.021	SD dependent var			0.144	
Number of obs	332	Chi-square			33.543	
Prob > chi2	0.014	Akaike crit. (AIC)			-338.117	

**** p<.01, ** p<.05, * p<.1 denotes significance at 1%, 5% and 10%, respectively.*

Inseminator availability was found to have a negative influence on the intensity of AI technology use by 4.8% at a 5% level of significance. This could be attributed to some cases of dishonesty by the inseminators. Farmers who have experienced any form of cheating from the service providers are less likely to intensify the adoption of AI technology (Kaaya *et al.*, 2005). The findings by Abot (2020) on factor influencing adoption of AI by smallholder farmers in dryland production systems of Kenya, who reported that dishonesty from the service providers negatively influenced the intensity of AI adoption supports our findings.

CONCLUSION

The study highlights key factors influencing AI adoption among small-scale dairy farmers, emphasizing the role of age, education, farming experience, and economic considerations. Older and more experienced farmers were more likely to adopt AI technology, while education and experience played a crucial role in both adoption and intensity of AI technology use. Despite having relatively small herds, farmers exhibited significant variations in milk productivity and income, with high AI costs presenting a financial barrier. Challenges such as poor heat detection skills, limited awareness of semen types, and concerns over AI reliability further impacted adoption rates. Access to extension services and training was generally high, yet government support remained minimal. Interestingly, while inseminator availability was not a major issue, group membership and livestock production training negatively influenced AI intensity, suggesting that certain collective or traditional farming practices may deter AI usage. The findings underscore the need for targeted interventions, including improved farmer education, financial support, and enhanced AI service reliability, to increase AI adoption and maximize its benefits in small-scale dairy farming.

The single important factor influencing adoption of AI services was the perception about the reliability of AI services where a unit change in this variable would increase probability of farmers adopting AI by 77.2%. Other factors with high impact in influencing adoption are information about inseminator availability (35.3%) and access to extension service (20.6%). The benefit will be increased awareness and positive impact on adoption of artificial insemination technology in the study area. Farmers should be encouraged to form more farmer groups by promoting the benefits that are likely to be accrued when people form groups, such as markets for their outputs, education and training, and dissemination of dairy technologies such as AI. Farmers should enhance the skills of their workers by allowing them also to attend trainings on livestock production and AI technology. Enhance training effectiveness by conduct training needs assessments before the trainings are carried out so as to capture the farmers' interest together with the environment. The government should support AI activities by subsidizing the cost of AI and feeds to individual farmers and groups, funding trainings and workshops, and provide capacity building for the trainers.

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