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FACTORS AFFECTING SMALL DAIRY FARMERS' ADOPTION AND INTENSITY OF ADOPTION OF ARTIFICIAL INSEMINATION TECHNOLOGY: A CASE STUDY OF SOUTHERN ETHIOPIA

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ABSTRACT

The study was carried out in Loma woreda in Dawuro zone of Southern Nations, Nationalities and Peoples Regional State with the objective of identifying factors influencing artificial insemination (AI) technology adoption and its intensity in dairy farmers. Tobit model was used to examine factors affecting probability of adoption and intensity of adoption of AI technology. Land holding, information accessibility, artificial insemination training and support had a positive and herd size had negative statistical significant effect on adoption and intensity of adoption of AI technology at 10% significance level. It was concluded by the study that strengthening of extension and research activities are needed to spread the uptake of AI technology which will be helpful to improve the yield potential of small dairy farm holders in southern Ethiopia.

KEYWORDS: Artificial Insemination (AI) Technology, Adoption, Intensity, Tobit Model & Southern Ethiopia

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INTRODUCTION

The agricultural sector in Ethiopia, engaging 80% of the population, contributes 52% of the gross domestic product and 90% of the foreign exchange (Aynalem *et al.*, 2011). The livestock sub-sector alone contributes 12% of the total and over 45% of the agricultural GDP, and over 85% and 90% of the farm and pastoral incomes, respectively, have generated by livestock (MOA, 2010). The dairy sector constitutes about 13.7% of the total agricultural production and 39.4% of the total livestock production. The livestock population in Ethiopia estimates indicates those 54 million cattle, 25.5 million sheep, 24.06 million goats, and 0.92 million camels found in the rural sedentary areas of the country (CSA, 2012-2013). However, Ethiopia has capability of high dairy cattle population resources numerically total number of dairy cows are 16,941,364 among this 9,919,360 are milking cows, 7,022,004 are dry- cows, and the total dairy cattle milk production is 2,764,794,544 litters (Land O'Lakes, 2010). The national average of daily milk yield of a local cow is 1.32 litters with a lactation period of 180 days. The estimated daily average milk yield for an improved dairy cow is 7 liter with a lactation period of 242 days. The per capita milk consumption in Ethiopia, 18.68 liters is very low as compared to the global average of 100 liters and even far below than the average consumption of Africa, 26 liters (CSA, 2012-13 and LWARDO, 2015).

The dairy industry remains a key livestock component with significant contribution to food security and income in dairy communities (FAO, 2008). The low consumption of milk and milk products coupled with the huge potential for dairy development clearly indicates that there are many opportunities to improve the sector. This is even more appealing that the considerable potential of dairy production in creating income generation opportunities and its further contribution in improving human nutrition, particularly for women and children (Mohamed *et al*., 2004). Therefore, artificial insemination (AI) plays an important role to increase the yielding capacity of cows and is the appropriate and cheapest way of genetic improvement, the realization of breeding programs has to be well organized and excited in a very reliable way, and AI is fully functional when, it corporate with good animal husbandry, such as effective heat detection (Noakes *et al.,* 2009). In order to improve the low productivity of the indigenous Zebu cattle, selection of the most promising breeds and crossbreeding of these indigenous breeds, with high producing exotic cattle has been considered as a practical solution (Mekonnen *et al.*, 2010).

According to CSA, (2012-2013) in Southern Nations, Nationalities and Peoples Regional state (SNNPRS) dairy development package as full practicing system was not introduced in all zones. In Dawuro zone, where only AI technology was applied as a dairy development practice and AI was infused by AI technician, only in insemination center (LWARDO, 2015). lomma woreda has capacity of high dairy cattle population, total number of dairy caws are 102,134 among this 61,212 are milking cows and 40,922 are dry cows and the total dairy cattle milk production 7,803,733 liter. Dairy technology through AI was introduced in this woreda from last 13 years (LWARDO, 2015). However, the achievements of the AI service are not successful. It was due to Lack of sufficient information on farmer's characteristics and the factors affecting the adoption of technology often-positioned innovative technologies on mistaken intention which affects the decision making capacity of dairy farmers. Therefore, the study has been conducted to bridge the gap with the following objectives: 1. To assess the characteristics of small dairy farmers on adoption and intensity of adoption of AI technology. 2. To identify factors which affect adoption and intensity of adoption of AI technology of small dairy farmers.

RESEARCH METHDOLOGY

SNNPRS is one of the nine regions in Ethiopia; comprises 14 administrative zones and 8 special districts. Dawuro is one of the 14 Zones in SNNPRS. The capital city of Dawuro Zone is Tarcha and it is located about 438 kilometers via Hossana, to South West of Addis Ababa, 280 Kms to the West of Hawassa, the regional states's capital. The purposive selection of zone and woreda was made after getting the information from secondary sources of Dawuro zonal agricultural and rural development annual report, (2015) due to consideration of early AI technology adoption, presence of more dairy cattle population and accessibility of technology.

Sampling Frame

In this study, multi-stage sampling technique was employed. In the first stage, Dawuro Zone was selected purposively from the SNNPRS. In the second stage, Loma woreda was selected purposively out of five woreda and 2 woreda administration, from the Dawuro Zone. In the third stage four kebeles, namely Gessa Chare, Tulama Tama, Fulassa Borize, and Fulassa Balle were randomly selected out of 36 kebeles and 4-kebele administration from the Loma woreda. In fourth stage, prior to the selection of sample household heads from selected kebeles the list of all small dairy household heads categorized into two stratum, AI adopters and AI non- adopters based on secondary data of kebeles administrations (LWARDO, 2016). AI adopters were those who had adopted AI technology, at least for one cow or heifer considered as AI

technology adopter. Similarly, AI non-adopters were those who had not adopted AI technology even at least for one cow or heifer considered as AI non-adopters. In this study, a cow that was pregnant for first time considered as a heifer.

The sample size of this study was determined, by using the Kalvolho's table (Kalvolho the national Archive, revised 2005). The total number of the population (adopters and non-adopters) of the study area was 2,380 (LWARDO, 2015), which lies in Kalvolho's table range of 1201-3200. Based on this table, there was a choice to select sample size of 50 (low), 125 (medium) and 200 (high). Thus, sample size of 200 respondents was selected to maximize the benefit of the study.

Finally, 200 small dairy household heads were allocated among adopters and non-adopters categories from selected kebeles, according to the probability proportional to their sample size. Out of 200 sample farmers, 37 were adopters and 163 were non-adopters. The study was mainly focused on primary data, collected from sample farmers. The data was collected on following aspects of study such as personal characteristics (sex, education, age, family size and experience of dairy), economic variables (income, land size and herd size), institutional variables (distance, support and AI training) and technological variable (information) from the small dairy household heads by using pre-structured questionnaire. The data relates to the agricultural year 2015-16.

ANALYTICAL METHOD

Descriptive Statistics

Descriptive statistics was used to investigate the characteristics of small dairy farmers, in the study area. Statistical Package for Social Sciences (SPSS) was used to generate descriptive statistics. For the comparison of different characteristics of sample households heads, t-test used for continuous variables and $\chi 2$-test was employed for dummy variables.

Estimation Procedure of Adoption Index

The adoption index ratio was also calculated by taking the total numbers of artificially inseminated cows and heifers divided into total numbers of cows and heifers used (natural bull + AI) under reproduction. The actual proportion of AI animals (Cows and Heifers) from total numbers of cows and heifers under reproduction score ranges from 0 to1. The result of proportion ratio score with zero point implies non-adopter of the AI technology and greater than zero (>0 and ≤ 1) implies adopters which includes three categories depending on their ratio; namely low adopters (0.1-0.33), medium adopters (0.34-0.66) and high adopters (0.67-1). On the other hand**,** mean adoption index was calculated by the submission of the proportion of the artificially inseminated cows and heifers from total number of cows and heifer under reproduction depending on each category divided by total numbers of respondents in the each respective category.

Tobit Model

Limited dependent variable model provides a good framework, to study adoption behavior of farmers. As noted by Feder *et al.,* (1985), the most commonly used qualitative models to study the adoption behavior will be the logit and the probit models. These models specify a functional relationship between the probability of adoption and various explanatory variables (Bekele *et al.,* 2000). These empirical models only explain the probability of adoption. They fail to take into account the degree of adoption. This inadequacy was overcome with the use of the Tobit model (Tobin, 1968; McDonald and Moffit, 1980), as cited by Shapiro *et al.,* (1992). Therefore, in the present study, Tobit model was used to examine

factors affecting adoption and intensity of adoption of artificial insemination technology for reproduction. In addition, as the major number of observations on dependant variable had a value zero. So, Tobit model was found to be appropriate to deal with such censored data and used to analyze the intensity of adoption of artificial insemination technology in preference to multiple regression models. The Tobit model, not only measures the probability that a farmer adopts the new technology, but also the intensity of adoption of the technology, once it was adopted.

Mathematically, the Tobit model had expressed as:

$$Y_i = \beta_i X_i + U_i, \quad Y_i = \beta_i X_i + U_i > 0$$

$$= 0 \text{, Otherwise} \tag{1}$$

Where, $Y_i =$ the observed dependent variable, in this case proportion of animals artificially inseminated from total number of cows and heifers under reproduction.

$X_i =$ Explanatory variables

$\beta_i =$ A $K \times 1$ matrix of parameters to has be estimated

$U_i =$ An independent and normally distributed error term with mean zero and constant variance

$$E(Y_i) = X\beta F(z) + \sigma f(z) \tag{2}$$

Where, $z = X\beta / \sigma$, $F(z)$ is the cumulative distribution function, $f(z)$ is the value of the derivative of the normal curve, at the given point, z is the Z -score for the area under normal curve, β is a vector of Tobit maximum likelihood estimates and σ Is the standard error of the error term. Similarly, the expected value of intensity of adoption of artificially inseminated cows and heifers by adopters had estimated by:

$$E(Y_i | Y_i^* > 0) = X\beta + \sigma f(z)/F(z) \tag{3}$$

Where, Y_i^* is the latent dependent variable, which is not- observable?

The purpose of Tobit analysis was to identify factors, that clarify variations in the adoption of artificial insemination technology. However, it was important to interpret the parameter estimates of the model with care because; Tobit parameter estimates were generated, by applying with equal sub-sample of observations. If, parameter estimates for entire population of farmers was required and necessary to compute adjusted estimates, that effectively scale the Tobit parameters, by the probability of observations falling in the uncensored sample. Following Madalla (1983), the adjusted estimates are the marginal effects of explanatory variables on the expected value of the dependent variable and given by:

$$\frac{\partial E(Y_i)}{\partial X_i} = F(z)\beta_i \tag{5}$$

The Tobit specification allows us to analyze, whether or not AI technology has adopted and the conditional level of adoption of artificial insemination technology had given the decision to adopt. The total elasticity in equation (4) had decomposed into two effects.

$$\frac{\partial E(Y_i)}{\partial X_i} = F(z)\left[\frac{\partial E(Y_i^*)}{\partial X_i}\right] + E(Y_i^*)\left[\frac{\partial F(z)}{\partial X_i}\right] \tag{5}$$

Multiplying through by $\eta = \frac{X_i}{E(Y_i)}$ and

$$\eta\left[\frac{\partial E(Y_i)}{\partial X_i}\right] = \eta F(z) + \eta E(Y_i^*) \tag{6}$$

$$\frac{\partial F(z)}{\partial X_i} = f(z)\frac{\beta_i}{\sigma} \tag{7}$$

Similarly, the change in intensity of adoption with respect to change in an explanatory variable among adopter had been Estimated by,

$$\frac{\partial E(Y_i / Y_i^* > 0)}{\partial X_i} = \beta\left[1 - z\frac{f(z)}{F(z)} - \left(\frac{f(z)}{F(z)}\right)^2\right] \tag{8}$$

VARIABLE SPECIFICATION

Dependent variable

Dependent variable used in this study is the proportion of artificially inseminated animals (cows and heifers) from the total number of cows and heifers under reproduction in the years, 2013-2016.

Independent variables

Independent variables stand-alone and were not changed by the other variables but cause change in dependent variable. These variables in this study were those variables, which had influence on adoption of artificially inseminated technology. The variables used in this study are given in table 1 with their description, types, units of measurement and their expected effects.

Table 1: Description of Variables used in the Tobit Model and their Expected Sign

Description of Variable	Type of Variable	Unit of Measurement	Expected Effect
Sex the household head	Dummy	Male=1, Female=0	+
Age of the household head	Continuous	Years	−
Education level of the household head	Continuous	Years of schooling	+
Land size of the household head	Continuous	Hectares (ha)	+
Dairying experience of the household head	Continuous	Years	+
Family size of the household head	Continuous	Number	+
Total Annual income of the household head from dairy	Continuous	Birr	+
Access to information for the household head	Dummy	If Yes = 1, Otherwise=0	+
Access to training for the household head	Dummy	if Yes = 1, Otherwise = 0	+
Distance from AI center to the household head's house	Continuous	Kilometer (Km)	−
Access to support for the household head	Dummy	if yes = 1, Otherwise = 0	+
Herd size of the household head	Continuous	Number	+

Source: Author

RESULTS AND DISCUSSIONS

Characteristics of Sample Household Heads

Descriptive statistics used to compare non-adopters from adopters of AI technology. In this study, respondents were categorized into four categories (non, low, medium and high) on the basis of adoption index. Out of the total 12 hypothesized explanatory variables, eight variables were continuous and four were dummy variables.

Description of Continuous Variables

The mean age of non-adopters and adopter's categories low, medium and high of AI technology were 44.3, 39.5, 38.4 and 40, respectively. The difference in age between two groups measured by t test was found to be negatively significant at 1 percent level of significance (t=-42.4*******p=0.001). Among non-adopters more than fifty percent respondents were in the age of >60 years. Whereas, adopter's categories of Low, medium and high all the respondents were found in between the age of 31 to 60 years. It means that lesser age respondents were adopted AI technology than old aged respondents.

Education Level indicated that in non-adopters 36.6 percent were illiterate. On the other hand, among adopter's categories of Low, medium and high all the respondents were found literate. The average education level of non- adopters and adopter's categories low, medium and high of AI technology were 1.2, 6.2, 6.2 and 5.5, respectively. Therefore, the difference in education level between both the groups measured by t- test was found to be significant (t = 31.6******* p= 0.004) at 1 percent level of significance. It indicated that AI technology was adopted by those farmers who were educated. The similar result found in the study of Wetengere (2009).

Out of total mean of land size (1.9) among non adopters and adopter's categories low, medium and high were 1.8, 2.1, 2.4 and 2.2, respectively. For the comparison between two groups t test was carried out and was significant (t = 5.2******* p= 0.002) at 1 percent level of significance. In the level of land size, 62 percent of non-adopters of AI were found in the range of <0.5 to 1 ha. Whereas, majority of low, medium and high categories of adopter's of AI technology land size were found in between 1 to > 2 ha. The result reveals that the respondents who had more land in the study area AI technology were adopted by them only.

The mean of dairying experience of non-adopters and adopter's categories low, medium and high were 7.6, 11.8, 13.7 and 14.9. To measure the difference between two groups t test was used and it was significant (t = 2.61******* p=0.003) at I percent level of significance. In dairying experience, among adopters low, medium and high categories majority of the respondents had experience in between 4 to >10 years. But among non- adopters only 57.7 percent found in the same range of experience. This indicates that those respondents who had longer dairy farming experience were in a better position to know about the potential benefits of AI technologies than those respondents with shorter dairy farming experience. The result of the study correlated with Namwata *et al.* (2010).

Out of total mean (6.01) size of family, mean for non-adopter of AI was 5.7. On the other hand, among adopter's low medium and high categories of AI was 7.5, 5.8 and 7. T statistics was stated that, the difference between two groups was negatively significant (t= -9.48******* and p = 0.001) at 1percent level of significance. Family size, 7 to >9 in non-adopter and adopter's categories of low, medium and high was 68 percent and around 28 percent, respectively. This indicates that those respondents who had less family size were shown more interest in the adoption of the AI technology than those who had more family size.

The total mean annual income of respondents was 3465.6 birr. Out of this, the mean for non-adopters of AI was 2912.4. Whereas, among adopter's categories low, medium and high mean annual income were 6365.6, 5546.8 and 5747.2, respectively. It indicates that the respondents who had adopted AI technology were significantly (t = 28.3*****,** p = 0.001) earning more income than non-adopters. The study is similar with Barry, (2005).

Out of total mean (7.14) distance of AI center from respondents house, the mean distance for adaptor's categories low (3.12), medium (3.6) and high (3.5) was comparatively less than the mean (7.99) distance for non-adopters. The difference in distance between two groups, measured by t test was found to be negatively significant at 1 percent level of significance (t=-4.011*******p=0.008). It implies that, for those respondents whose house was near to AI centre had shown more interest, for the adoption of AI technology than those for whom it was far.

Herd size, among non- adopters, 22 percent respondents had >8. Whereas, majority of the adopter's categories low, medium and high herd size was less. T statistics was used to compare the herd size of two groups and shown that herd size was negatively significant at 1 percent level of significance. It implies that the respondents who had less herd size were willing to adopt the AI technology than those who had more. The study is related with findings of Bonabana-Wabbi (2002) and Wetengere (2009).

Table 2: Descriptive Statistics of Continuous Variables of Sample Household Heads in the Study Area

Adopters	Mean	Age Distribution, Age in Years (Per cent)					
		< 30	31-45	46-60	>60	Total	
Non	44.3	9.8	4.9	30.2	55.1	100	
Low	39.5	-	18.34	16.8	-	35.14	
Medium	38.4	-	20.72	8.80	-	29.72	
High	40	-	25.44	9.7	-	35.14	
Total Mean	**43.4**	**t= -42.4 *** p = 0.001**					
Education Level							
Adopters	**Mean**	**Education Level (Per cent)**					
		Illiterate	**1-8**	**9-12**	**>12**	**Total**	
Non	1.2	36.6	37.6	25.8	-	100	
Low	6.2	-	9.34	25.8	-	35.14	
Medium	6.2	-	10.2	19	-	29.2	
High	5.5	-	8.92	10.22	16	35.14	
Total mean	**2.1**	**t = 31.6*** p= 0.004**					
Land Size							
Adopters	**Mean**	**Level of Land Size in ha.^ (Per cent)**					
		< 0.5	**0.51-1**	**1.01-1.50**	**1.51-2**	**>2.00**	**Total**
Non	1.8	8	54	26.4	9.8	1.8	100
Low	2.1	2.7	-	5.4	10.8	16.24	35.14
Medium	2.4	-	1.02	7.1	10.8	10.8	29.72
High	2.2	-	-	2.74	16.2	16.2	35.14
Total Mean	1.9	t = 5.2*** p= 0.002					
Dairying Experience							
Adopters	**Mean**	**Dairying Experience in Years (Per cent)**					
		< 3	**4-6**	**7-10**	**>10**	**Total**	
Non	7.6	42.3	18.4	27	12.3	100	
Low	11.8	4.34	12.1	8.2	10.5	35.14	
Medium	13.7	1.4	7	9.2	12.12	29.72	
High	14.9	-	4.94	11.3	18.9	35.14	
Total Mean	**8.9**	**t = 2.61*** p=0.003**					

Table 2: Contd.,

Family Size

Adopters	Mean	Family Size in No. (Per cent)				
		< 3	4-6	7-9	>9	Total
Non	5.7	12.7	19	35	33.3	100
Low	7.5	15.4	11.64	5.4	2.7	35.14
Medium	5.8	12.3	1.92	5.8	3.9	29.72
High	7	10	8.4	4.54	5.2	35.14
Total Mean	**6.01**	**t = - 9.48 *** p = 0.001**				

Total Annual Income+

Adopters	Mean	Annual Income in Birr (Per cent)				
		< 3000	**3001- 5000**	**5001- 7000**	**> 7000**	**Total**
Non	2912.4	22.7	58.3	19	-	100
Low	6365.6	2.7	8.54	23.9	-	35.14
Medium	5546.8	3	6.1	20.62	-	29.72
High	5747.2	5.74	6.1	23.3	-	35.14
Total Mean	**3465.6**	**t = 28.3*** p = 0.001**				

Distance of AI Centre from the Respondents House

Adopters	Mean	Distance from AI Centre in Km (Per cent)				
		< 3	4-6	7-9	>9	Total
Non	7.99	0.7	5.5	19.6	74.2	100
Low	3.12	19.8	15.34	-	-	35.14
Medium	3.6	21.6	8.12	-	-	29.72
High	3.5	26.4	8.74	-	-	35.14
Total Mean	**7.14**	**t = -4.011*** p = 0.008**				

Herd Size

Adopters	Mean	Herd Size in No. (Per cent)					
		1-2	**3-4**	**5-6**	**7-8**	**> 8**	**Total**
Non	6.8	11	14	16	30	22.2	100
Low	3.5	-	12.54	11.8	10.8	-	35.14
Medium	7.1	-	16.3	10.02	3.4	-	29.72
High	9.4	-	25	7.8	2.34	-	35.14
Total Mean	**6.8**	**t = -4.97 *** p= 0.003**					

Source: Survey data, 2015-16

Note: *** Indicates, significance level at 1percent, ^= Hectare and + = Currency of Ethiopia (1USD=20 Birr)

Description of Dummy Variables

The result revealed that from non-adopters, 80.98% male and others were female respondents. But in adopter's categories (low, medium and high) 94.6% male and others were female. However, out of total male respondents (94.6%) among adopter's categories of low, medium and high were 32.44%, 29.72% and 32.44%, respectively. This indicated that the dairy farming ownership was male dominated in the study area. This was because of labor-intensive nature of the dairy farming, which was very hectic and time consuming particularly for females with their domestic activity. Furthermore, the result of chi-square analysis ($\chi 2$=14.36, P=0.023) reveals that there was significant relationship between sex and the adoption of AI technology at 5% significant level. The result of the study was related with the previous researchers Degnet and Belay, (2001).

Access to information in non-adopter was availed by 34% respondents. Whereas, adopters' categories low, medium and high it was availed by 35.14%, 29.72% and 35.14% respondents, respectively. This reflected that majority (66%) of non-adopters were not received access to information regarding the AI technology. Therefore, chi-square test indicated that there was significant positive difference between adopter and non-adopter with respect to information access at ($\chi 2$ = 98.14, p = 0.002). This implies that, information had significant relationship with adoption of AI technology. The

result of the study allied, with the findings of Langyituo and Mekuria, (2005) and Feder *et al.*, (1985).

The respondents participated in training from the adopters' categories were 25% of non, 35.14% of low, 29.72 % of mid, and 34.14% of high. To know whether, there was significant relationship between AI training and AI technology adoption $\chi2$ test was conducted. However, the chi-square test result indicated that, ($\chi2$= 65.07, p=0.001) there was positive and significant association between AI training and AI technology adoption. In addition, $\chi2$ test revealed that there was significant variation in AI training among adopter and non-adopter.

Access to support services were availed by the respondents of non (25.15%) followed by medium (29.72%), low (32.43%), and high (32.43%) categories of adopters. The chi-square test ($\chi2$= 66.5, p=0.002) confirmed that there was significant difference between adoption categories with respect to small dairy farmers access to support. The result of $\chi2$ test also indicated statistically significant association between support and adoption of AI technology.

Table 3: Descriptive Statistics for Dummy Variables of the Sample Household Heads (Per cent)

Variable	Dummy Alternative	Categories of Adopter				$\chi2$	P
		Non	Low	Medium	High		
Sex	Male	80.98	32.44	29.72	32.44	14.39**	0.023
Information	Yes	34	35.14	29.72	35.14	98.14***	0.002
AI Training	Yes	25	35.14	29.72	34.14	65.07***	0.001
Support	Yes	25.15	32.43	29.72	32.43	66.5***	0.002

Source: Survey data, 2015-16
Note: ***, ** Indicates, significance level at 1 and 5 percents

Results of Analytical Model

The Tobit model was employed, to estimate the effects of the hypothesized independent variables on adoption and intensity of adoption of AI technology of small dairy farmers. Twelve independent variables were included in the model. Those were age, sex, education, land size, dairying experience, family size, total annual income, access to information, access to AI training, distance from AI center, access to support services and herd size. Out of 12 explanatory variables, 5 variables were shown significant influence on probability of adoption and intensity of adoption of AI technology by small dairy farmers.

Table 4: Tobit Regression Model Estimates for Factors Affecting Adoption of AI Technology in the Study Area

Lists of Variables	Estimated Coefficient	*Robust* Standard Error	T-Value	P-Value
Sex	0.0053733	.01593	0.33	0.736
Age	-.0006079	.00043	-1.44	0.161
Education	.0013638	.00187	0.77	0.465
Land Size	.0200166	.0103	2.14	0.05*
Dairying Experience	.0020265	.00207	1.00	0.328
Family Size	.002003	.00198	1.01	0.312
Income	.002302	.00210	1.02	0.320
Access to Information	.905117	.04996	3.50	0.053*
Access to Training	.0409011	.02451	1.77	0.095*
Distance to AI Centre	-.00010753	.00265	-0.40	0.685
Access to Support	.0457794	0.02503	1.75	0.067*
Herd Size	-.0028767	.00169	-1.84	0.088*
Sigma	.954877	.0555316		

Log likelihood = -14.38101 Prob>chi2=0.0000, Pseudo R^2=0.875
Source: Model output
Note: * Significant at 10% levels

The regression coefficients of Land size, access to information, AI training and support services were significantly positive. This reveals that with an increase in these variables, the adoption of AI technology increases. However, the regression coefficient of herd size was significantly negative which indicates that an increase in herd size results decrease in the adoption of AI technology. While, the regression coefficients of age and distance to AI centre from the household's house were negative but statistically insignificant. Thus, land size, access to information, AI training and support services are the main responsible factors to encourage the adoption of AI technology by small dairy farmers. On the other hand, large herd size is playing important role to discourage the adoption of AI technology.

Table 5: Effect of change in Explanatory Variables on Probability of Adoption and Intensity of Adoption of AI Technology

Variable	Change in Probability of Adoption	Change in Intensity of Adoption	Total Change
Land Size	0.169	0.02	0.0019
Access to Information	0.279	0.097	0.052
Access to Training	0.064	0.04	0.0085
Access to Support	0.0729	0.0696	0.0099
Herd Size	-0.0243	-0.00287	-0.000269

Source: Model output

The result indicates that a unit increase in the land size of the household heads increases the probability of change on adoption and intensity of adoption of AI technology by 1.7% and 2%, respectively. The marginal effect of land size on overall adoption and intensity of adoption of AI technology was 0.19%. Whereas, a unit increase in the information of the household heads increases the probability of change on adoption and intensity of adoption of AI technology by 2.8% and 9%, respectively. The marginal effect of information on adoption and intensity of adoption of AI technology was 5.2%. The result indicates that the estimated increase in the probability of change in adoption and intensity of adoption of artificial insemination technology resulting from a unit change in participating in AI training was 6.4% and 4%, respectively. But the overall marginal effect of AI training on adoption and intensity of adoption was 0.85%. In similar way, a unit change in support service estimated increase in the probability of change in adoption and intensity of adoption of artificial insemination technology by 7.2% and 6.9%, correspondingly. Its overall marginal effect was 0.99%. The result also reflects that, a unit increase in herd size would be decrease the probability of adoption and intensity of adoption at -2.4% and -0.28%, respectively. The overall marginal effects of herd size on probability of adoption and intensity of adoption was -0.0269%.

CONCLUSIONS

The study assessed that all the considered variables were found to have relatively more effect on the probability of adoption than intensity. There is a need to strengthen extension services for dissemination of knowledge of AI technology. Training is very essential to encourage the large herd size dairy farmers for the adoption of AI technology. It should be given by only AI technology expert. Training is a technological intervention event through which farmers get technical, theoretical and practical information for the adoption of technology. Therefore, information could play a vital role in strengthening and filing the knowledge gap of household heads to adopt AI technology. Simultaneously, there should be

time-to-time supervision by the government, in order to keep eye on the activities of experts to ensure quality services for the farmers. In order to extend door step AI facilities to the farmers' it is necessary to increase the number of AI centre in the area. So that farmer could avail the facility whenever they want. In addition, there is a need to form farmers association. These associations could provide good opportunity for farmers to interact with each other and to share their knowledge. It could play a major role to increase production and productivity from dairy sector.

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