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# Adoption of artificial insemination technology and its intensity of use in Eastern Tigray National Regional State of Ethiopia

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## Abstract

**Background:** The study was focused on the adoption and intensity of adoption of artificial insemination (AI) Technology in Saesie-tsaedaemba District of Tigray Region, Ethiopia. AI is one of the most important and valuable dairy technology that has been used for genetic improvement for several years in the study area. However, there was little empirical information about major factors affecting adoption decision and intensity of AI in the study area. The purpose of this study was to evaluate the status of AI technology adoption and its intensity and to identify major factors influencing the adoption and intensity of use of AI technology.

**Methods:** A multistage sampling technique was applied to select study sites and sample households. A structured interview was used to collect data from a total of 204 sample farmers. Besides, key informants interview was used to triangulate, validate, and enrich the findings of the household interview.

**Results:** Results of the tobit model regression revealed that households' level of literacy, milk yield, income, training, access to extension service, mobile ownership, supplementation of concentrated feed and hybrid cattle ownership were found to have a positive and statistically significant relationship with adoption and intensity of AI technology, whereas distance to farmer training centre (FTC) office had shown a negative relationship.

**Conclusions:** Adoption of context-based AI technology plays a paramount importance in achieving farm household's food security. The extension system should give more emphasis to the capacity building which is pivotal for introducing, adoption, and scaling out of best practices of dairy technologies. Besides the effort of the government, the participation of the private sector in AI technology is important to achieve wider adoption of AI technology.

**Keywords:** Artificial insemination technology, Adoption, Intensity, Determinants, Tobit model

## Background

Many empirical studies showed that Ethiopia is a resourceful country endowed with the estimated the largest livestock population in Africa [1–8]. The current cattle population of Ethiopia is estimated to be about 60.39 million. Out of this total cattle population, the female

cattle constitute about 54.68% and the remaining 45.32% are male cattle. About 98.24% of the total cattle in the country are local breeds. The remaining 1.76% are hybrid and exotic breeds that accounted for about 1.54 and 0.22%, respectively [7, 9]. This shows that the proportion of crossbreed cattle compared to the total cattle population is still negligible.

According to the Ethiopian Institute of Biodiversity Conservation [10], there are 25 indigenous cattle breeds. Though the indigenous breeds are well-adapted to the local environment, they have low productivity potential; Indigenous cows give birth nearly every 2 years; and

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produce an average of only 147 L of milk/year. Whereas, in areas where there are adequate feed and better management practices, crossbreeds can give birth almost every year and produce on average about 2600–4600 L of milk/year [11]. Similarly, a study conducted by [12] reported that under the present Ethiopian conditions, crossbred dairy cattle can increase milk per lactation sixfold in pre-urban dairy systems and tenfold in commercial dairy systems compared to local breed cattle managed in traditional dairy production systems.

In Ethiopia, modifying of breed composition of local cattle either by introducing genes from an external source (AI service) or through direct importation of exotic cattle from other potential countries were major strategies for genetic improvement [13]. The supply of crossbred heifers, providing of AI service, and setting up of bull service stations were major components of livestock genetic improvement. However, among the others, AI is simple, quick, and low price technology [8, 9]. On the other hand, Refs. [10, 14] stated that since livestock breeding is generally uncontrolled in Ethiopia; right bull selection criteria have not been applied and controlled which makes genetic enhancement difficult. Hence, AI was recognized as the primary tool for genetic improvement in cattle breeding. Similar studies in many African developing countries, where agro-climatic conditions are similar to Ethiopia and where there are good market access and adequate feed, genetic improvement can best be achieved through crossbreeding using AI and hormone synchronization [8, 14, 15]. As stated in the study of Ref. [16] in Zebu cows, AI technology increases the milk potential of a cow to almost double their potential per year. In addition, Ref. [16] affirmed that the pure Zebu breed provides 900 L per year, while under the same management, the crossbreed produces 1500 L per year. This indicates that AI plays an important role to increase the yielding capacity of cows; and is the appropriate and cheapest way of genetic improvement when it is incorporated with good animal husbandries, such as effective heat detection, feeding, and health management [6, 8, 17, 18]. In the same way, Ref. [19] explained that genetic improvement of cattle is essential for economic purposes, particularly milk production, and AI technology is an important component of an overall strategy to improve the profitability and sustainability of dairy cattle operations as well as to improve the livelihood of the farmers. A research report by Ref. [20] also pointed out that access to AI technology is an appropriate strategy of the dairy industry to improve milk production and productivity through genetic improvement of the local cattle.

In addition, a study by [2, 21] found that AI is the most commonly used and valuable biotechnology that has been used in Ethiopia for over 4 decades (40 years). AI

technology has been pushed by extension agencies to the farmers but its adoption and its intensity are yet to be identified. The provision of AI technology in the National Regional State of Tigray was started 21 years back in the capital city of the region (Mekelle) and Adigrat town. The current types of breeds used for crossbreeding in the region are pure HF, Jersey, Begait, and cross HF Begait cross (50%) [22].

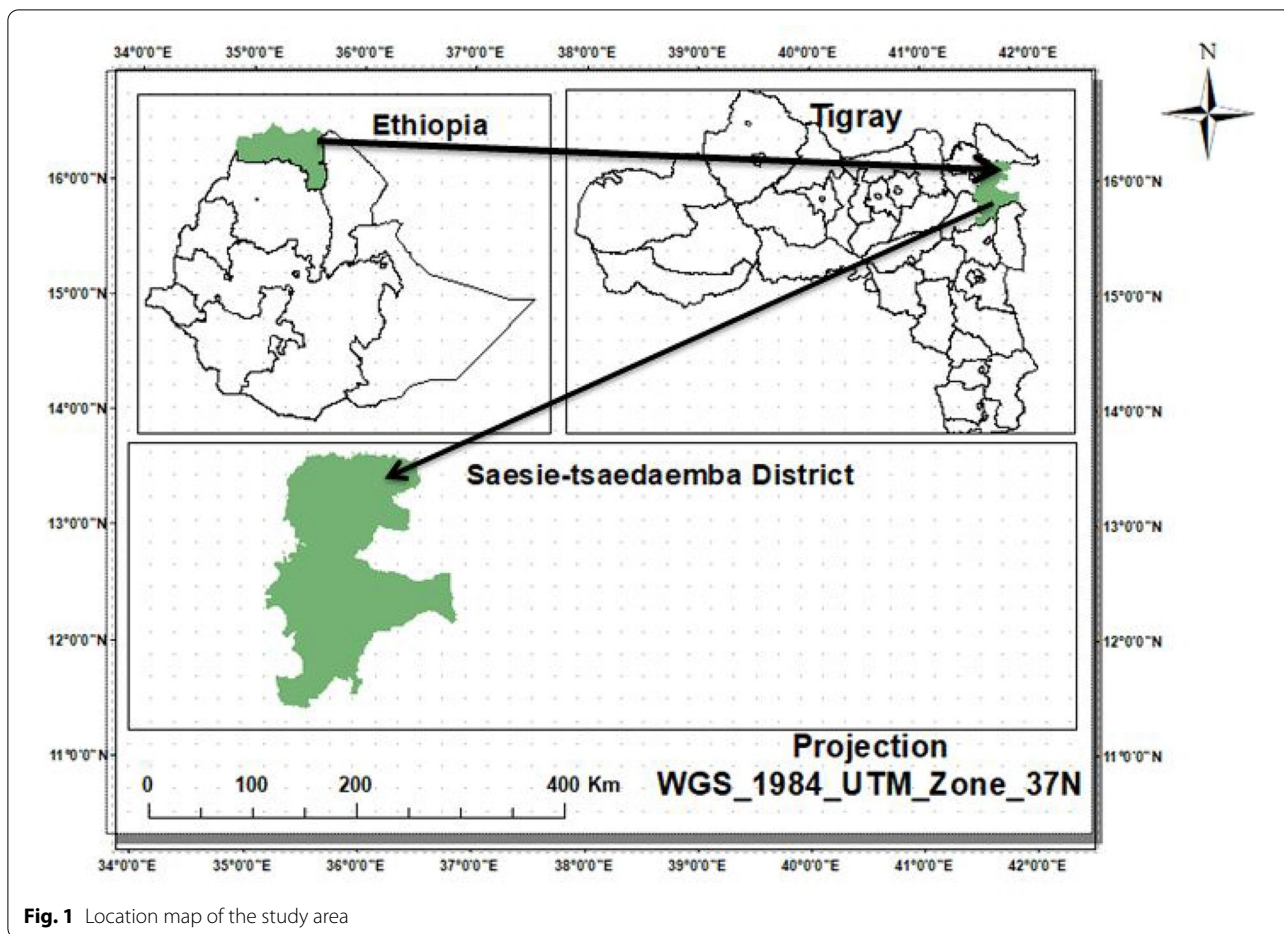
Furthermore, according to the office of agriculture and rural development Wereda Saesie-tsaedaemba and Central statistical agency (CSA) report CSA [9, 22, 23], AI technology has become one of the most important and commonly used as well as valuable biotechnology that has been used in the district for more than 15 years. On contrary, even though large efforts have been made to disseminate AI service, the adoption of AI service by farm households may vary widely across different agro-ecologies and within the similar agro-ecology and it might depend on the perceptions and awareness of farmers towards the technology. Moreover, adoption of different technologies across space and time are influenced by different factors and their associations. As stated in the study of Ref. [24], the probability of adoption of improved dairy technologies is hindered by demographic, economic, institutional, and social factors. A decision to adopt or reject agricultural technologies depends on smallholder farmer's objectives, cost, and benefits of the technology [25, 26]. Although there have been several technology adoption studies undertaken in Ethiopia, there is limited empirical information about the major factors affecting the adoption decisions of farmers and the intensity of adoption of AI technology. Therefore, the main purposes of the current study were to assess the status of adoption and intensity of use of AI technology and to analyze the major factors influencing the adoption and intensity of use of AI technology in the study area.

## Research methods

### The study sites

The study was conducted during the year 2019 in Saesie-tsaedaemba district Eastern Zone National Region State of Tigray, Ethiopia which is located at about 883 km north of Addis Ababa. It shares border with Afar Region in the East, Irob in the North, Ganta Afeshum in the Northwest, Hawzen in the Southwest, Klite Awulaelo in the South. Atsbi Wenbrta in the South East. The study site map is presented in Fig. 1.

Saesie-tsaedaemba district has 26 rural and two urban peasant associations with a total of 31,264 households with an estimated total population of 139,191. Besides, out of the total household heads in the district, 69.31% of them both raised crops and livestock, while 26.28% only grew crops and 4.41% only keeps livestock. The total



**Fig. 1** Location map of the study area

livestock population in the district is estimated; Cattle 98,276 (local 90,990 and hybrid 7,286), Sheep 124,997, Goat 46,950, Donkey 15,577, Horse 96, Mule 33 and Camel 6 [27, 28].

**Sampling procedure and sample size**

In this research study, survey design and a three-stage sampling technique were adopted to select the study sites and the sample households. Out of the districts in the Eastern Zone, Saesie-tsaedaemba district was selected purposively in which many cattle are existed and reared and due to the district is recognized as a milk corridor by many developmental agencies, such as bureau of agriculture and rural development (BoARD). Second, from a total of 28 Peasant Association (PAs), two (Sikata and Hadushhiwot) were selected using simple random sampling. Finally, sample households were selected from the two PAs. To select sample households, a systematic sampling method was applied.

The sample size was specified based on Yemane, 1967 as cited by [28] simplified formula. The formula was used at

a 95% confidence interval to the determination of a representative sample. It is described as follows:

$$n = \frac{N}{1 + N(e)^2}$$

where

*n* = the sample size drawn from the total cattle owner households in two peasant associations.

*N* = the total number of cattle owner household heads in two peasant association (1798).

*e* = margin of error tolerance (0.066).

1 = the probability of an event occurring.

Based on the above sample size determination calculation, 204 sample households were obtained. From the total household heads in the study area only 48 households were adopters and the remaining were non-adopters. This is due to the reason that despite the long introduction of AI technology and its usefulness to the farmers of the study area its adoption rate among the farmers remains very low. Accordingly, as a researcher, we did not want to ignore the adopters (48) of the AI

technology and the crucial role of the technology for improving the livelihood of the farmers and ensuring household food security. Consequently, the authors decided to use uncensored data which is the whole 48 adopters of the AI technology knowingly and 156 non adopters to achieve the objective of the study.

#### Type, source and method of data collection

The study involved both qualitative and quantitative types of data from the primary and secondary sources to get the overall image on the adoption and intensity of AI technology. The primary data was collected through the interview method, structured questionnaire, and focus group discussions. In addition, 20 respondents who have the willingness to share their experience towards the genetic improvement of livestock were selected from the two peasant associations to conduct two focus group discussions (FGD) based on the checklist. The target size for each FGD was 10 individuals, and it was assumed that some invitees would not respond. In the case of key informant interviews, four men and two women, who included agricultural officers and experts and experienced farmers, were interviewed. These key informants were regarded to be community experts with first-hand knowledge and ability to provide deep insight into AI technology in the study area. The secondary data were also collected from relevant literature, such as published books, peer-review journals, conference papers, and governmental and non-governmental office reports as deemed necessary (e.g., STEOARD and CSA).

#### Method of data analysis

This study was employed both descriptive statistics and econometric model to analyze the data. Quantitative data was obtained from the sampled respondents that were described and summarized using percentages frequencies, mean and standard deviations. The qualitative data was analyzed by narrating and content analysis.

Looking into the empirical studies in the literature, many researchers have employed the tobit model to identify factors influencing the adoption decision and intensity of technology use. For example from adoption studies conducted in Ethiopia [29, 30] used a tobit model to identify determinants of Adoption and intensity of use of coffee technology package in Yerga-cheffe district, Gedeo zone, Southern Nations Nationalities Peoples Regional State, Ethiopia. Similarly, [31–33] used tobit model to assess factors affecting adoption and intensity of adoption of improved haricot bean production package in Alaba special woreda, Southern Ethiopia, and other authors [34] also used tobit model

to assess determinants of adoption and intensity of use of vetiver grass /*Vetiveria Zizanioides*/ technology in Mettu district, Ilu Abba Bora Zone, Oromia, Ethiopia.

The model was chosen, because tobit model has an advantage over other analytical models (logistic or probit) in that, it reveals both the probability of adoption and intensity of use of the technology [25]. The dependent variable that was used in the tobit model is the proportion of hybrid cattle via AI from the total number of cattle owned by the household, as used by [35]

Dependent variable

$$= \frac{\text{Number of hybrid cattle via AI}}{\text{Number of total cattle owned}} = 0 \leq a \leq 1,$$

where 'a' = the scored value of the proportion of hybrid cattle via AI technology.

It is a continuous variable measured with the scored value of the proportion of hybrid cattle via AI technology. The respondents are assigned 1 if adopters, and 0 non-adopters. Where, the adopter is the farmer who has at least one hybrid cattle via AI technology owned, whereas non-adopters are those who do not have hybrid cattle via the technology. The final adoption result of adopter households were categorized into three groups based on the use of AI technology, namely, low, medium, and high. The non-adopter group was given a score of 0 and kept as a separate category to investigate factors influencing the adoption of AI technology and its intensity. This makes up 4 distinct categories across which the adoption and intensity of AI technology are assessed. The adoption index score ranges used to classify respondents into non-adopters, low, medium and high adopters were 0, 0.01–0.33, 0.34–0.66 and 0.67–1.00, respectively, as used by [29, 31]. This implies the actual adoption intensity score ranges from 0 to 1. Adoption score of 0 points implies non-adoption of AI technology and adoption score value of 1 implies the adoption of AI technology all cattle owned by the household are hybrid via AI technology.

#### Specification of the Tobit model

Tobit model was useful for analyzing main factors affecting adoption and intensity of use of AI technology. Following [35–37], the tobit model which tests factors influencing adoption and intensity of adoption AI technology can be specified as

$$\begin{aligned}
 Y_i^* &= \beta X_i = u_i & i = 1, 2 \dots n \\
 Y_i &= Y_i^* & \text{if } Y_i^* > 0 \\
 &= Y_i^* & \text{if } Y_i^* \leq 0,
 \end{aligned}
 \tag{1}$$

where

$Y_i$  = The observed dependent variable, i.e., the total number of hybrid cattle via AI technology;

$Y_i^*$  = The non-observable latent (existence) variable representing the use of AI technology.

$X_i$  = Vector of factors affecting adoption and intensity use of AI technology.

$\beta_i$  = Vector of unknown parameters.

$u_i$  = Residuals that are independently and normally distributed with mean zero and a common variance  $\sigma^2$ .

The model parameters are estimated by maximizing the tobit likelihood function of the following form [25, 27]:

$$L = \prod_{y_i^* > 0} \frac{1}{\sigma} f\left(\frac{Y_i - \beta_i X_i}{\sigma}\right) \prod_{y_i^* \leq 0} F\left(-\frac{\beta_i X_i}{\sigma}\right), \tag{2}$$

where  $f$  and  $F$  are the density function and cumulative distribution function of  $Y_i^*$ , respectively.

$\prod_{y_i^* \leq 0}$  means the product over those  $i$  for which  $Y_i^* \leq 0$ , and

$\prod_{y_i^* > 0}$  means the product over those  $i$  for which  $Y_i^* > 0$ .

It may not be sensible to interpret the coefficients of a tobit in the same way as one infers coefficients in an uncensored linear model [36]. Hence, one has to compute the derivatives of the estimated tobit model to predict the effects of changes in the variables.

A study by Ref. [38] proposed the following techniques to decompose the effects of explanatory variables into adoption and intensity effects. Thus, a change in  $X_i$  (explanatory variables) has two effects. It affects the conditional mean of  $Y_i$  in the positive part of the distribution. A similar approach was used in this study.

1. The marginal effect of an explanatory variable on the expected value of the dependent variable is

$$\frac{\partial E(Y_i)}{\partial X_i} = F(Z) \frac{\beta_i}{\sigma}, \tag{3}$$

where

$\frac{\beta_i X_i}{\sigma}$  is denoted by  $Z$ , following [38]

2. The change in the probability of adopting technology as independent variable  $X_i$  changes  $Y_i^*$  is

$$\frac{\partial F(Z)}{\partial X_i} = f(z) \frac{\beta_i}{\sigma} \tag{4}$$

3. The change in intensity of adoption with respect to a change in an explanatory variable among adopters is

$$\frac{\partial E\left(\frac{Y_i}{Y_i^* > 0}\right)}{\partial X_i} = \beta_i \left[ 1 - Z \frac{f(z)}{F(Z)} - \left(\frac{f(z)}{F(Z)}\right)^2 \right]. \tag{5}$$

To avoid the problem of multi-collinearity, both continuous and dummy variables were checked before executing the tobit model. Different methods are often suggested to detect the existence of multi-collinearity in continuous explanatory variables and contingency coefficient (CC) for dummy variables [39].

According to Refs. [36, 39] VIF ( $X_i$ ) can be defined as  $VIF = \frac{1}{1-R_i^2}$ , where:  $R_i^2$  is the multiple correlation coefficients between  $X_i$  and other explanatory variables. For each selected continuous explanatory variable,  $X_i$  is regressed on all other continuous explanatory variables, the coefficient of determination  $R_i^2$  constructed for each case. The higher the value of  $R_i^2$  is the greater the value of VIF  $X_i$  causing greater collinearity in the variables  $X_i$ . As a rule of thumb, for continuous variables, if the value of VIF is ten and above, the variables are said to be collinear (if the value of  $R_i^2$  is one, it would result in greater VIF and causes perfect multi-collinearity between the variables), whereas for dummy variables said to be collinear [39].

Similarity, contingency coefficients were computed for dummy variables from chi-square ( $\chi^2$ ) value to detect the problem of multicollinearity (the degree of association between dummy variables:

$$C.C = \sqrt{\frac{\chi^2}{n + \chi^2}}, \tag{6}$$

where  $C.C$  = contingency coefficient,  $n$  = sample size,  $\chi^2$  chi-square value.

## Results and discussion

### Status of adoption and intensity of adoption of AI technology

As we explained in the methodology section, the adoption intensity score was calculated by dividing the number of hybrid cattle via AI technology owned to the total number of cattle owned by the respective household that enables us to know the level of adoption of each sample farm households. The result of mean adoption scores across adoption categories is provided in Table 1.

A close look at the adoption score of sample households reveals that the majority (76.47%) of the sample

**Table 1** Distribution of the respondents by level of adoption score

Adoption category	N <sup>o</sup>	%	Adoption score	Mean	SD	F	P
Non-adopters	156	76.47	0.00	0	0		
Low-adopters	20	9.80	0.01–0.33	0.26	0.05		
Medium-adopters	25	12.26	0.34–0.66	0.47	0.13		
High-adopters	3	1.47	0.67–1.00	0.75	0		
Total	204	100	0.00–1.00	0.09	0.19	1019.17***	0.0000

\*\*\*Significant at 1% significance level

respondents had an adoption score of 0 (non-adopters). Of the total sampled household heads, 9.80% had adoption intensity scores ranging from 0.01 to 0.33, and 12.26% of the respondents had ranging from 0.34 to 0.66 and only 1.47% of them had ranging from 0.67 to 1.00. Of the 48 adapters, 41.67% respondents fall under low adopter category and 52.08% of them fall under medium adopters category and 6.25% respondents had adoption score that ranges from 0.67 to 1 and categorized as high adopters (Table 1). One way analysis of variance revealed that there is a significant mean difference ( $F=1019.17$ ;  $P=0000$ ) among the adoption score of the four adoption categories at a 1% significance level which indicates there is variation in the level of adoption among the sample respondents. The adoption of AI technology in the study area is still low.

#### Demographic, socio-economic and institutional characteristics of sample households by adoption category of AI technology

The descriptive statistical analysis result of demographic, socioeconomic, and institutional characteristics of respondents are summarized in Tables 2 and 3. Table 2 shows the influence of continuous variables on the adoption and intensity of adoption AI technology.

Family size (FAMSZ) is one of the demographic factors that are useful to describe respondents and provide a clue about the availability of labor of the sample and the population. Based on these assumptions, the family size was hypothesized to have a positive and significant relationship with the adoption and intensity of adoption of AI technology. Results of descriptive statistics in Table 2 indicated that the average family size of the sample population, none, low, medium and high adopters' categories was 5.42, 5.14, 6.45, 6.16 and 6.67, respectively, and the  $F$  value has shown that there is a significant mean difference among adopter categories at 1% significance level. The result of the finding suggests that in line with the hypothesis, the adoption of AI technology was necessarily associated with family size. Large family size is an indicator of the availability of labor, provided that the proportion of those within the age range of active labor force is high. Even some unproductive labor family members participated in easy farm activities, such as cattle rearing, feeding, and following cows when they come into heat.

The descriptive result shows that the average distance of inseminator office (DSAI) walking in minutes from the residence of the sampled households, non-adopters, low adopters, medium adopters, and high adopters

**Table 2** Socio-economic characteristics of sample household's for continuous variables

Variables	Mean for adoption category					F
	Non	Low	Medium	High	Total	
AGE	51.92	51.4	49.72	45.33	51.50	0.62
FAMSZ	5.14	6.45	6.16	6.67	5.42	4.03***
LANDSZ	0.55	0.56	0.52	0.46	0.54	0.19
DSAI	43.23	38	35.20	23.33	41.45	14.50***
DFTC	48.56	43.50	41.20	26.67	46.83	11.15***
YIELD	2.30	5.35	5.32	11.33	3.10	101.46***
TLU	5.15	6.38	5.12	2.9	5.23	7.69***
INCOMHH	8002.05	10,374.5	10,349.60	14,640	8619.95	35.80***
HYBRIDC	0.35	2.2	2.2	3	0.79	73.38***

\*\*\*Significant at 1% significance level

**Table 3** Socio-economic characteristics of sample Household's for categorical variables

Variables		Adoption category					$\chi^2$
		Non %	Low %	Medium %	High %	Total %	
GEND	Male	71.79	55	68	100	70.10	3.7215
	Female	28.21	45	32	0	29.90	
LITERAT	Illiterate	21.15	15	0	0	17.65	7.4165*
	Literate	78.85	85	100	100	82.35	
TRAIN	Trained	36.54	95	80	66.67	48.04	36.5836***
	Not-trained	63.46	5	20	33.33	51.96	
EXTEN	Yes	46.15	70	92	100	54.90	23.0236***
	No	53.85	30	8	0	45.10	
FEDSUPP	Yes	13.46	40	56	66.67	22.06	30.6742***
	No	86.54	60	44	33.33	77.94	
MOBILE	Yes	28.85	55	80	100	38.73	31.3443***
	No	71.15	45	20	0	61.27	

\*\*\*, \*Indicates significance level at 1% and 10%, respectively

household were 41.45, 48.56, 43.50, 41.20 and 26.67 min, respectively. The *F* test indicates that distance from the inseminator office was significant at a 1% significance level; which implies that there was a significant difference among adopter categories on the distance of inseminator office that means; in comparison to adoption categories, better AI technology adopters were lived near to AI service station.

The average distance to Farmer Training Center (DFTC) walking in minutes for the household's from their home for sampled households, non-adopter, low adopter, medium adopter, and high adopters was 46.83, 48.56, 43.50, 41.20 and 26.67 min, respectively. As indicated in Table 2, the one way ANOVA was highly statistically significant at 1% significance level; meaning that there is a significant mean difference of distance of FTC among the four groups implies that better adopters were lived near to FTC which is similar with that of the distance of inseminator office.

Livestock production is an integral part of mixed farming systems. Livestock is a source of power, manure, and cash income. Following [32], types and heads of livestock owned by the sample households were converted into tropical livestock units (TLU), so as to facilitate comparison among the farm households. The average livestock holding size in TLU for the entire respondents, none, low, medium, and high adopters was 5.23, 5.15, 5.12, 5.32, and 11.33, respectively, and its *F* value is statistically significant. This implies that the difference in terms of TLU ownership among adopter's categories is highly statistically significant at a 1% significance level.

The average hybrid cattle size (HYBRIDC) of sampled households, none, low, medium, and high adopters

were 0.79, 0.35, 2.2, 2.2, and 3 cattle, respectively, and its *F* value was statistically significant at less than 1% significance level. This implies that there is a significant mean difference in hybrid cattle holding among none, low, medium, and high adopters meaning there is a positive association between owning hybrid cow/heifer and adoption and intensity AI technology.

In the study area, the average daily milk yield of dairy cattle (YIELD) was 3.10, 2.30, 5.35, 5.32, and 11.33 L per cow per day for sampled households, none, low, medium and high adopters, respectively. The difference among none, low, medium, and high adopters with respect to daily milk yield level was significant at 1% significance level which means that hybrid cattle via AI provide more milk than natural matted (a combination of local and hybrid via natural matting). Key informants reported that high milk producer cows remain the underlying attribute for increasing the rate of technological adoption among small dairy farmers in the study area.

Similarly, Table 2 clearly shows that sampled households had an average income (INCOMHH) of 8619.95 Ethiopian Birr (ETB). The mean farm income of none, low, medium, and high adopters was 8002.05, 10,374.5, 10,349.60, and 14,640 ETB, respectively. The results of the analysis also clearly indicated that there is a significant annual farm income difference among the sample AI technology adopter categories at 1% significance level. This shows that farm income has a positive relationship with the adoption decision of AI technology and statistically significant effect.

The summary results of the overall findings of a dummy variable in Table 3 shows that, out of the

hypothesized variables considered, except sex of the HHH, all the dummy variables, namely, access to training, mobile ownership, concentrated feed supplementation practice and access to extension service/ DAs visit, were found to be significant at less than 1% probability level, whereas literacy of the HHH was found significant at 10% significance level.

As can be seen from Table 3, out of the total households interviewed majority (82.35%) of them were literate and the rest 17.65% (36) were illiterate. Moreover, 78.85% of the non-adopters, 85% of the low adopters, 100% of the medium and 100% high adopters can write and read. Concerning its association, literacy had a significant relationship ( $\chi^2=7.4165$ ;  $df=3$ ;  $p=0.060$ ), with adoption and intensity of adoption of AI technology that implies literate households are more encouraged to adopt AI technology.

Regarding access to training, the results of the study revealed that 48.04% of the total respondents were trained in livestock production, while the rest 51.96% of the respondents did not get training. It is also revealed that 36.54% non-adopters, 95% low adopters, 80% medium adopters, and 66.67% high adopters were trained in livestock production either in PAs or at the District level. Similarly, the Pearson chi-square test indicated that access to training had a significant relationship with the adoption of AI technology at less than a 1% significance level. This clearly shows the existing gap between trained and non-trained households in terms of participation in AI technology adoption. Therefore, the result of the study clearly shows that households who have access to training adopt AI technology better as compared to non-trained households.

Of the total of 204 sample respondents, 54.90% of farmers reported having contact with DAs, while the rest 45.10% of farmers reported have no contact with development agents for the last 1 year (Table 3). The study also revealed that 46.15%, 70%, 92%, and 100% of non-adopters, low adopters, medium, and high adopters had contact with extension agents, respectively. The chi-square result shows a statistically significant difference between adoption categories with respect to farmer's contact with an extension agent.

Table 3 further shows that out of the total sample households, only 22.06% respondents were found providing supplementary feeds such as wheat bran and local drink residues called "Hatela" for their cattle/dairy cows which is lower than the finding of [40] that found about 54% farmers fed their cattle with concentrate feed. Of the total sample households, 13.46% of non-adopters 40% low adopters, 56% medium adopters, and 66.67% high adopters give supplementary feed. The  $P$  values of Chi-square statistics indicate that concentrated feed

supplementation practice is significantly associated with adoption categories means that in comparison, those households who provide supplementary feed for their cattle/ dairy cows were more AI adopters than those who do not provide supplementary feed.

Access to mobile is also an important means of verbal communication used to seek updated agricultural extension services. Results of the study revealed that 38.73% of the total sample households are mobile owners, while the remaining 61.27% were not owners of personal mobile for calling of AI technician when his cows come into estrus. In addition, non-adopters (28.85%), low adopters (55%), medium adopters (80%), and 100% of the high adopters were found to be owners of personal mobile phones. The result of this study shows ownership of mobile phones has a positive and statistically significant effect on enhancing farmer's adoption decisions on AI technology in the study area.

#### **Determinant factors influencing farmer's adoption and intensity of adoption of AI technology**

A total of fifteen independent variables were hypothesized to influence the adoption of AI technology in the study area. However, the result of the tobit model revealed that only nine independent variables, namely, literacy level of the household head (LITERAT), access to training (TRAIN), number of hybrid cattle owned by the household head (HYBRIDC), extension contact (EXTEN), average daily milk yield (YIELD), income of the household head (INCOMHH), distance to farmer training center (DFTC), supplementation of feed (FED-SUPP) and access to mobile (MOBILE) were found significantly affecting farmers adoption (Table 4). Except for the distance to FTC office that had shown a negative relationship, all significant variables were found to have a positive relationship with the adoption and intensity of AI technology.

All variables that were found to influence the adoption and intensity of the use of AI technology might not have a similar contribution in influencing the decision of farm households. Hence, using a decomposition procedure suggested by [37], the results of tobit model was used to assess the effects of changes in the explanatory variables into adoption and intensity of use and the result is presented in Table 5.

#### **Literacy of the household head (LITERAT)**

As hypothesized, the model indicated that literacy was found to have a positive relationship and statistically significant at less than a 5% significance level in explaining the adoption decision and intensity use of AI technology. Table 4 indicates that literacy increases the probability of



**Table 4** Maximum likelihood estimates of Tobit model

Explanatory variables	Estimated coefficients	Standard Error	t value
GEND	- 0.0621088	0.0531717	- 1.17
AGE	0.0014681	0.0027197	0.54
LITERAT	0.1679711	0.1009549	1.66*
TRAIN	0.1671775	0.0628579	2.66***
FAMSZ	- 0.0102478	0.0118136	- 0.87
LANDSZ	- 0.1819922	0.136215	- 1.34
TLU	0.001158	0.0136056	0.09
HYBRIDC	0.0870001	0.0262046	3.32***
EXTEN	0.1530046	0.0585533	2.61***
YIELD	0.0330968	0.0161248	2.05**
INCOMHH	0.0000348	0.0000138	2.51**
DFTC	- 0.0084901	0.0037525	- 2.26**
DSAI	- 0.0053998	0.0036274	- 1.49
FEDSUPP	0.1580401	0.0508528	3.11***
MOBILE	0.1212236	0.0508699	2.38**
Constant	- 0.3962038	0.3336673	- 1.19
/sigma	0.1871436	0.0205291	

Number of observations = 204  
 LR chi<sup>2</sup>(15) = 197.73  
 Prob > chi<sup>2</sup> = 0.0000  
 PseudoR<sup>2</sup> = 0.9068

\*\*\*, \*\*, \*Significant at 1% 5% and 10% significance level, respectively

adoption and intensity of adoption of AI technology by 9.79% and 2.35%, respectively. This implies that literacy leads to have better access to information synthesis and understand the benefits of new agricultural technology (AI technology) better than illiterate households then leads to adopting the technology. This result is in line with the studies conducted by [16, 41].

**Access to training (TRAIN)**

Training was found to be one of the significant variables in explaining the adoption decision. The tobit model result

indicates that it was statistically significant at less than a 1% significance level in explaining the adoption decision and intensity use of AI technology. Partial derivation was also used to test the influence of this variable on the probability and the extent of the use of AI technology. The result from this test in the model shows that when farm household heads are trained, the probability of adoption and intensity use of the AI technology increases by 14.97% and 2.78%, respectively. This probably could be, because trained farmers have better access to information and agricultural knowledge about a dairy farm in general and specifically in AI technology than non-trained. This result conforms with the results of Refs. [5, 42].

**Number of hybrid cattle (HYBRIDC)**

The result from the tobit model indicated above revealed that in line with the hypothesis that it was statistically significant at less than 1% significance level in explaining the adoption decision and intensity use of AI technology. The result is consistent with other studies done by [43, 44]. Analysis of its marginal effect indicated that an increase in the number of hybrid cattle by one unit results in an increase in the probability and intensity of adoption of AI technology by 7.43% and 1.41%, respectively. A possible reason for this finding is that the farmers with hybrid cattle might have more knowledge about the importance of hybrid cattle and are encouraged to use AI technology intensively.

**DAs contact (EXTEN)**

DAs contact (EXTEN) was the most important explanatory variable with the sign of consistent to our prior expectation which was positive and statistically significant at 5% and 1% significance level that influences the probability of adoption and intensity use AI technology, respectively. Households who had visited by extension workers had increased their interest in using AI technology as they access to valuable information, knowledge, and skill. This

**Table 5** Summary of decomposition of marginal effects from significant Tobit model results

Explanatory Variables	Change in the probability of adoption		Change in intensity of adoption		Change among the whole	
	dy/dx	P >  z	dy/dx	P >  z	dy/dx	P >  z
Literacy	0.0979368	0.019	0.0235037	0.043	0.1679711	0.096
Training	0.1497203	0.008	0.0277786	0.005	0.1671775	0.008
Hybrid cattle holding	0.0742772	0.008	0.0141307	0.001	0.0870001	0.001
DAs visit	0.1267358	0.015	0.0245562	0.006	0.1530046	0.009
Milk yield	0.0282567	0.077	0.0053756	0.045	0.0330968	0.040
Income of the HHH	0.0000297	0.034	5.65e-06	0.013	0.0000348	0.012
Distance to FTC	- 0.0072485	0.044	- 0.001379	0.023	- 0.0084901	0.024
Feed supplement	0.1817601	0.021	0.0297354	0.006	0.1580401	0.002
Mobile ownership	0.1151668	0.048	0.0206641	0.023	0.1212236	0.017

intern could influence the benefit of the farmer by enhancing the use of the AI. The model result shows households that were visited by extension workers have better and updated information that increases the probability of adopting and intensity of AI technology used by 12.67% and 2.46%, respectively. The result agrees with the findings of adoption studies in Nigeria [20, 45].

#### **Annual milk yield (MLKYLD)**

Like the model output result shows, this variable had a positive and significant influence on the likelihood of adoption of AI technology and intensity use of AI technology at 10% and 5% significance level, respectively. A marginal change in daily milk yield increases the probability of adoption and intensity of use of AI technology by 2.83% and 0.54%, respectively. The possible reason could be due to the fact that households who gain better milk production are more encouraged for adopting dairy technologies/AI technology. The result is consistent with the study was done by [16] that shows the adoption of AI is related to milk production and the productivity level of the cattle. It is clear that agriculture produces the nourished food human beings consume and the food consumption determines the nutritional status of the households. As a result, well nourished households have strong and healthy body that enables them to be easily adopter, innovative and productive in the agricultural production and productivity.

#### **Income of the household head (INCOMHH)**

Result of the Tobit model shows that the annual income of the household was a positive and significant influence on the likelihood of adoption of AI technology and intensity use of AI technology at 5% significance level. As the income of the household head increases by one unit, the probability of adoption and intensity of AI technology increases by 0.003% and 0.00056%, respectively. The above finding implies that those household heads that have relatively better annual income usually purchase and have a cow with better body size and conformation which are suitable for insemination. If a small size cow is inseminated with semen which is collected from a large bull, calving difficulty might have occurred. Then those small body size cows which are owned by poor farmers are restricted from using the technology. This result is in conformity with the studies done by [45]. This implies the probability of households to have better annual income and able to ensure food self-sufficient.

#### **Distance to farmer training Center (DFTC)**

Distance of the household head from FTC was assumed to influence the adoption and level adoption negatively. The model result in Table 4 shows that this variable influences the probability of adoption and the extent of use of AI technology negatively and statically significant at 5%

significance level with the marginal effect of  $-0.0072485$  and  $-0.001379$  for probability and intensity of adoption of AI technology, respectively; mean that for one unit increase in distance of FTC from the households, the probability of adoption and intensity of adoption decreases by about 0.73% and 0.14%, respectively. The possible reason might when the residence of farm households far away from FTC, they had no or limited information about new technology. Moreover, when they require extension service such as calling AI technician when his/her cow is coming into heat and had not a mobile number, a farmer goes to FTC and receives a mobile number and then called to the technician on time either themselves or by the help of the DAs if their resident is near to FTC.

#### **Feed supplementation practice (FEDSUPP)**

The decision to adopt any single innovation (technology) depends on the availability of interrelated inputs [45]. This suggests that the decision to adopt a current technology may be conditional on the utilization of previously available complementary inputs. The provision of concentrated supplementary feed in the farm rather than letting to grazing and only roughages is considered as a complementary practice in dairy production and is expected to influence the adoption of AI technology positively as it is considered as interrelated technology. As the tobit model output shows feed supplementation practice had a positive and significant influence on the likelihood of adoption of AI technology and its intensity at 5% and 1% significance level, respectively. The decomposed result from the tobit model indicates that with the assumption of keeping of other factors constant, the probability of adoption and intensity of use of AI technology increases by 18.18% and 2.97%, respectively, in households who supplement concentrated feed than do not. The result is consistent with the hypothesis, which argues that feed supplementation gives better yield and improves profitability as it has higher responses in the livestock industry. The result was strongly supported by FGD participants. For example, during FGDs, they strongly narrated that: *"The chance of AI success is greatly increased when it is incorporated with good animal husbandry's. Adequate feeding enables us to have cows with good body conformation that are suitable for insemination artificially with better semen quality"*. This study is similar to the study of Refs. [6, 46] on the Adoption of artificial insemination technology in dairy animals and the impact on milk production which was conducted in Nawalparasi and Chitwan districts of Nepal.

#### **Mobile ownership (MOBILE)**

In the regression output, owning mobile was found to be a positive factor that affects AI technology adoption

decision and intensity and statistically significant at a 5% significance level; which means having mobile support to AI technology adoption decision and intensity. Key informants of the study affirmed that among the prominent reasons for facilitating AI technology mobile ownership was mentioned first. The marginal effect of this variable showed that AI technology adoption probability and its intensity for a household that has mobile increases by 11.52% and 2.07%, respectively, than those who do not have. The main reason for that positive impact could be; when the cow comes into estrus, farmers who have mobile called to AI technician then, the technician would arrive on time. On the other hand, households who do not have mobile access would walk on foot to the inseminator office and arrived too late after the estrus already passed. According to many authors, timing during insemination is very crucial for a successful pregnancy rate [47–49]. Moreover, it suggests that having mobile improves accessing information so that farmers could easily understand the benefit of AI technology.

### Conclusions and recommendations

Adoption context-based AI technology plays an indispensable role in improving the productivity of cattle in general and dairy production, in particular, that plays paramount in improving the livelihoods and achieving food security of the farm households. However, the findings of the study revealed that the adoption of AI technology by farm households is at the infant stage. Out of the total of 204 sample respondents, only 48 (23.5%) of the sampled households were found as adopters of AI technology.

Results of the tobit regression model revealed that households' level of literacy, training on livestock

production, hybrid cattle holding, access to extension service, milk yield of the cows, the income of the household, mobile ownership and supplementation of concentrated feed were found to a positive relationship and significantly affecting the probability of households adoption of AI technology and intensity of its adoption. Similarly, distance to FTC was found negatively affecting the likelihood of farmers in AI technology and its intensity.

To enhance the adoption and intensity of adoption of AI technology among the farm households, the authors of this study recommends the following so as to improve their livelihood. (1) The government should create an enabling environment for effective and efficient participation of the private sector. (2) Appropriate training and awareness creation about AI technology such as reporting early when the cow of the farmer is at an early stage of heat is important and should be given to overcome this problem. Hence Developmental agencies and extension workers should provide more emphasis for training and livestock farm visits with better provision of relevant technical advice and support. (3) AI technology technicians should post their mobile number to be accessible easily by the livestock owner famers. (4) Further scaling-up of the high milk producers' milk cow with better body conformation and condition will play crucial role on the improvement of their living standard. (5) AI technicians should follow up and checked the viability of semen to improve the conception rate of the cows in the study area.

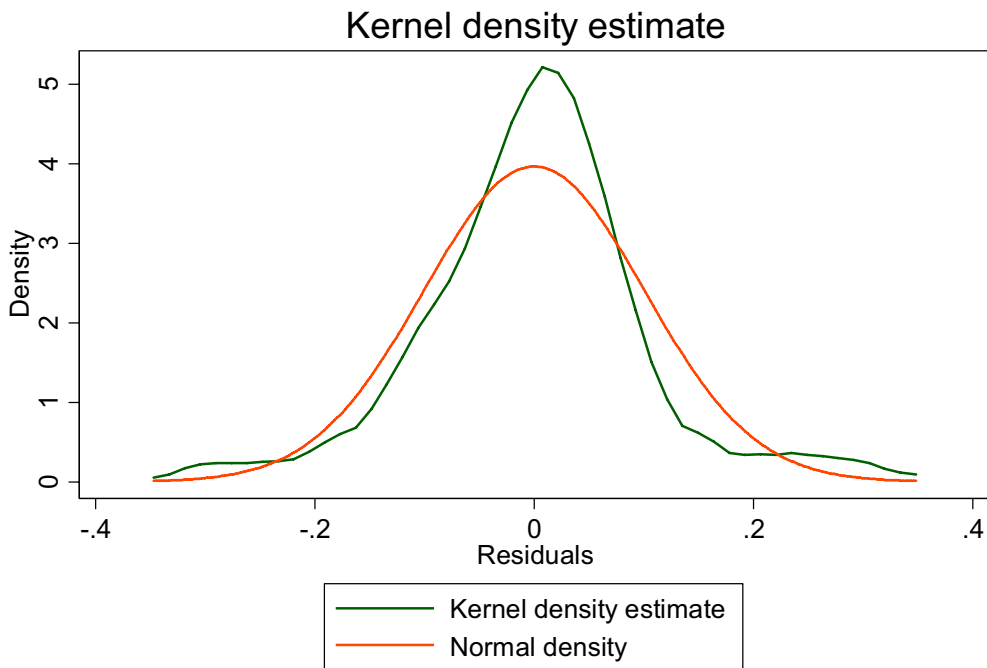
### Appendix

List of hypothesized Independent variables (Table 6).

**Table 6** Independent variables

No.	Independent variables with their measurements		
	Variables code	Definition of variable	Measurement
1	GEND	Sex of the household	Dummy
2	AGE	Age of the household measured in years	Continuous
3	LITRAT	literacy of the household head	Dummy
4	TRAIN	attending training on livestock production	Dummy
5	FAMSZ	Family size of the household	Continuous
6	LANDSZ	Total farm size owned by the household	Continuous
7	TLU	Total livestock holding in TLU	Continuous
8	HYRIDC	Number of cross breed cattle	Continuous
9	EXTEN	Access of the household to extension services	Dummy
10	YIELD	Average daily milk yield in liters	Continuous
11	INCOMHH	Income of the household in Ethiopian Birr (ETB)	Continuous
12	DFTC	distance to FTC walking in minutes	Continuous
13	DSAI	distance to AI service station walking in minutes	Continuous
14	FEEDSUPP	Feed supplementation practice	Dummy
15	MOBILE	Mobile ownership	Dummy

Variable	VIF	1/VIF
yield	3.00	0.333272
hybridc	2.77	0.361536
incomhh	1.80	0.556662
train	1.38	0.726359
dsai	1.29	0.773271
dftc	1.19	0.841203
famsz	1.17	0.853358
tlu	1.15	0.868922
mobile	1.13	0.883253
fedsupp	1.12	0.894639
extns	1.12	0.894725
litrat	1.10	0.905952
gend	1.10	0.909187
landsz	1.08	0.922420
age	1.05	0.949232
Mean VIF	1.43	



kernel = epanechnikov, bandwidth = 0.0249

```

. estat htest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of intens

chi2(1)          =          2.25
Prob > chi2      =          0.1333

```

### Abbreviations

AI: Artificial insemination; TLU: Tropical livestock unit; FTC: Farmer training center; STEOARD: Saesie-tsaedaemba office of agriculture and rural development.

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### Author contributions

Gebre designed the study, analyzed the data, and drafted the manuscript. Gebre and Gebre revised the manuscript and conducted some analysis and interpretation. All authors read and approved the final manuscript.

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### Availability of data and materials

The data set for this study is available from the corresponding author on request.

### Declarations

#### Ethics approval and consent to participate

Not applicable.

#### Consent for publication

All authors wrote, read, revised and approved the final manuscript.

#### Competing interests

The authors declare that they have no competing interests.

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