



Impact of Artificial Insemination Technology Adoption on Milk Yield and Livelihoods of the Household in Saesie-Tsaedaemba District Eastern Zone, Tigray, Ethiopia

Yemane Hailu Gebre¹, Gebrehiwot Weldegebrail Gebru², Kahsa Tadel Gebre³

¹Tigray Agricultural Research Institute, Humera Agricultural Research Center, Humera, Ethiopia

²Department of Rural Development and Agricultural Extension, Mekelle University, Mekelle, Ethiopia

³Department of Animal, Rangeland and Wildlife Sciences, Mekelle University, Mekelle, Ethiopia

Email: yemanehaile15@gmail.com

How to cite this paper: Gebre, Y.H., Gebru, G.W. and Gebre, K.T. (2024) Impact of Artificial Insemination Technology Adoption on Milk Yield and Livelihoods of the Household in Saesie-Tsaedaemba District Eastern Zone, Tigray, Ethiopia. *Open Access Library Journal*, 11: e12406.

<https://doi.org/10.4236/oalib.1112406>

Received: October 10, 2024

Accepted: December 28, 2024

Published: December 31, 2024

Copyright © 2024 by author(s) and Open Access Library Inc.

This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

This study was aimed at the impact of AI technology on milk production and livelihoods of the farmers in Saesie-tsaedaemba District Eastern Zone, Tigray, Ethiopia. In the study area, AI is a proven technology that has been used for genetic improvement for more than 15 years. So far, there has been little empirical information about the impact of AI on milk yield and livelihoods of the households. The purpose of this paper is therefore to estimate the impact of AI technology on milk yield and household livelihoods. The study was a survey design that used both primary and secondary data sources. The three-stage sampling procedure was employed to select 204 respondents. Both descriptive statistics and econometric models were applied to analyze the data. The result of the logit model for matching shows that family size, training, literacy, access to extension service, mobile ownership, and supplementation of concentrated feed were important variables that had positively associated and significantly influenced the adoption of AI technology whereas, farmland size, distance to FTC and distance inseminator office had shown a negative relationship. The result of PSM indicates that adopters of AI technology are seemingly better-off than non-adopters in the majority of outcome indicators such as milk yield per cow per lactation, annual income of the household, total physical asset holding which is converted into cash and non-food expenses; implying that AI technology has a considerable impact on milk yield and livelihood of the farmers. Hence, intensive work such as training, better extension service, providing a reasonable incentive to AI technicians, especially during weekends and holidays, hardship and overtime allowances should be provided to improve the adoption of AI technology as a result to improve milk production

and productivity, increase household income and achieving food security as well as overall improve well-being of the households.

Subject Areas

Agricultural Science

Keywords

Impact, Adoption, Artificial Insemination Technology, Milk Yield, Livelihood

1. Introduction

Compared to many other African countries, Ethiopia has a large potential for dairy development due to its large livestock population, which comprises 59.5 million cattle, 30.70 million sheep, and 30.20 million goat populations [1]. However, In Ethiopia, dairy cattle production does not provide the expected contribution to the national income due to several factors [2]. A study conducted by [3] indicated that the average daily milk production was only 1.8 liters with an average lactation length of about 207 days and a mean annual milk yield per cow of 376 liters. The poor milk productivity is partly due to poor livestock management practices and partly due to the poor genetic quality of the cattle.

Appropriate genetic improvement strategies are very essential to improve milk production and productivity through genetic improvement of the local cattle. Genetic improvement strategies for cattle in Ethiopia have been carried out by modifying the breed composition of local cattle populations, either by introducing genes from an external source (AI service) or through direct importation of exotic cattle from other potential countries [4]. Access to AI technology is an appropriate strategy for the dairy industry due to AI technology is simpler, quicker, and low price technology than others [5] [6].

The use of AI technology is essential for the economic purposes of smallholder dairy farms such as increasing milk production, improving income levels, generating employment opportunities and improving the nutritional standards of the rural people. As stated in the study of [7] in Zebu cows, AI technology increases the milk potential of a cow to almost double their potential per year. According to his study, the pure Zebu breed provides 900 liters per year while under the same management, the crossbred produces 1500 liters per year. According to the study of [8], the average milk yield was 9.2 liters per day per cow by using AI technology, whereas 2.3 liters per day per cow by using the natural breeding method and this is due to many socio-economic, institutional and natural factors. Similar evidence was achieved by [9] [10]. Regarding the impact of improved dairy technologies on the livelihood and welfare of the farmers, [9] found that milk consumption, milk commercialization, the number of meals consumed and monthly food expenditure were increased in a significant and robust way due to adoption of improved dairy technologies.

Historically in Ethiopia, AI was introduced in 1938 in Asmara, which was the

north part of Ethiopia and was stopped due to the Second World War and restarted in 1952 (Yemane *et al.*, 1993 as cited by [11]). It was again stopped due to unaffordable expenses of importing necessary inputs such as semen, liquid nitrogen, and other related inputs requirements. After 15 years of withdrawal an independent service was started in the Arsi region, Chilalo Awraja under the Swedish International Development Agency (SIDA). However, at the farm level, it was introduced 35 years ago as a tool for genetic improvement (Zewdie *et al.*, 2006 cited by [12]). 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) & Adigrat town [13]. According to the Office of Agriculture and Rural Development of Saesie-Tsaedaemba District (OARDSTD), AI technology has become one of the most important valuable biotechnology that has been commonly used in the district for more than 15 years [14].

However, in the study area, so far, there was little empirical information about the impact of AI on milk yield and livelihoods of the households. The purpose of this paper is therefore to estimate the impact of AI technology on milk yield and household livelihoods.

2. Research Methodology

2.1. Description of the Study Area

The study area (Saesie-Tsaedaemba district) shares a 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 Southeast. (See **Figure 1**)

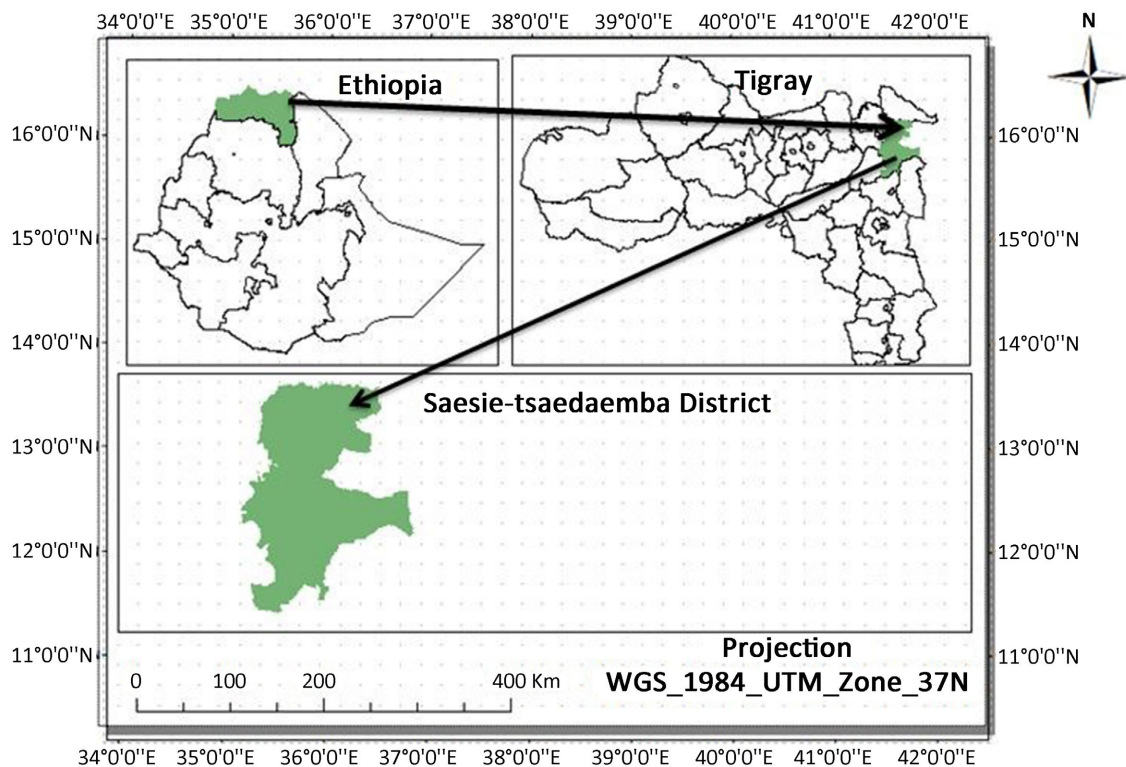


Figure 1. Location map of the study area.

The report of [14] indicated that the district has a total of 31,264 households with a population of 139,191, of whom 65,796 are male and 73,395 female; 18,933 (13.60%) are urban dwellers. Generally, its agro-ecological zone is Woynadega 92%, Dega 5%, and Kola 3%. With an area of 2511.47 square kilometers, the farmers have an average of 0.51 hectares of land. 69.31% of the farmers in the district both raised crops and livestock, while 26.28% only grew crops and 4.41% only raised livestock. The district has about 98,276 Cattle (90,990 local and 7286 hybrids) 124,997 Sheep, 46,950 Goats, 15,577 Donkeys, 96 Horses, 33 Mules, and 6 Camels.

2.2. Sample Size Determination and Sampling Procedure

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 of Tigray Rgional State (BoARDTRS). Secondly, from a total of 28 peasant association, two (2) of them were selected using simple random sampling. Finally, based on Yamane (1967) formula as cited by [15], 204 sample households were selected using systematic random sampling.

2.3. Types, Sources, and Methods of Data Collection

In this study, both the primary and secondary data sources were used to generate both quantitative and qualitative types of data. Primary data was collected through interview method, structured questionnaire and focused group discussions whereas the secondary data were collected from the report of OARDSTD, Central Statistics Agency (CSA), journals, books, and conference proceedings to supplement the primary data.

2.4. Method of Data Analysis

This study employed both descriptive statistics and; an econometric model to analyze the data. Descriptive Statistics were used to analyze and compare the socio-economic characteristics and institutional variables, between adopters and non-adopters. Data obtained from the sampled respondents were described and summarized using percentages frequencies, mean and standard deviations. The impact of AI on milk production and livelihoods of the household was analyzed using an econometric model of Propensity Score Matching (PSM) using “STATA Version 14” software which gained popularity in recent years for its potential to remove a substantial amount of bias from non-experimental data.

Many kinds of literature showed that PSM was initially invented by Rosenbaum and Rubin (1983) as cited by [16] and has been applied in many program evaluations. In observational studies, it is often not feasible to conduct a randomized controlled experiment to estimate the causal effect of a program or intervention.

However, in observational study designs, selection bias becomes a problem since it is difficult to obtain a comparison group equivalent to the group of exposed or treated individuals.

Hence, PSM is used for making a randomized experiment and reducing the selection bias in observational studies. On average, AI technology participants with the same propensity score are balanced on covariates and the counterfactual (the result for the treated observations if they were instead not treated) can be estimated within that group.

The propensity score is the conditional (predicted) probability of receiving treatment given the relevant controls X by Rosenbaum and Rubin (1983) as cited by [16]. It can be expressed as:

$$P(X) = \Pr[D = 1 / X] = E[D / X] \dots \dots \dots (1)$$

$D = [0, 1]$ is the indicator of exposure to treatment and X is the multi-dimensional vector of pre-intervention characteristics. $D = 1$ for treated observations and $D = 0$ for control observations. The propensity score was estimated using the logit model with dependent variable coded as 1 for AI technology adopters and 0 otherwise. The propensity score is a single index variable that summarizes the pre-treatment characteristics of each subject, which makes matching possible. After the propensity score is estimated, the average treatment effect on the treated (ATT) can then be estimated as follows:

$$\begin{aligned} ATT &= E\{Y_i^1 - Y_i^0 \mid D = 1\}, \\ ATT &= E[E\{Y_i^1 - Y_i^0 \mid D_i = 1, p(X)\}] \\ ATT &= E[E\{Y_i^1 \mid D_i = 1, p(X)\} - \\ &E\{Y_i^0 \mid D_i = 0, p(X)\} \mid D = 1 \dots \dots \dots (2) \end{aligned}$$

Y_i^1 and Y_i^0 are the potential outcomes in the two counterfactual situations of (respectively) treated (AI technology adopter) and untreated (non-adopter). Once the propensity scores are estimated, each AI technology adopter corresponds to a non-adopter with similar propensity score values, to estimate ATT. Although, several matching algorithms were developed to match adopters with non-adopters of agricultural technologies, asymptotically, almost all matching algorithms should yield the same results [17] and then it is worthy enough to deploy only one PSM matching method to show the impact of adoption any technology. However, for the sake of clarity and to display accuracy of the evidence the three commonly used matching algorithms (nearest neighbor matching, kernel-based matching and radius matching) were employed to choose the appropriate matching algorithm/s based on the matching quality indicators.

Although several matching quality criteria exist in the literature [18]-[21], the most widely used matching performance criteria namely mean absolute standardized bias (MASB), pseudo- R^2 , insignificant p-values of the likelihood ratio test and the number of matched sample size) identified, kernel matching algorithm (bandwidth 0.1) has been chosen in this study.

3. Results and Discussion

3.1 Descriptive Statistics

Table 1 shows data results for continuous variables of the respondents. Among the total of 204 respondents, only 23.5 % of respondents had at least one hybrid cattle via AI technology that are categorized as AI technology adopters and the rest 76.5% of households were non-adopters and did not have hybrid cattle via AI technology. Participants of the focus group discussion (FGD) revealed that poor pregnancy rate, heat detection problems, lack of awareness, communication problems, lack of incentive to the technicians and accessibility problems were the main reasons given for non-adoption of AI technology.

Table 1. Descriptive statistics for continuous variables.

Variable name	Respondents (N = 204)				t-test
	Adopters (48)		Non-adopters (156)		
	Mean	Std.Dev	Mean	Std.Dev.	
Age	50.15	6.75	51.92	11.83	0.99
Family size	6.31	1.87	5.14	2.11	-3.45
Land size	0.48	0.19	0.55	0.30	1.39
Total livestock holding in TLU	5.50	2.06	5.15	1.20	-1.51
Distance to farmer training center	41.25	6.15	48.56	9.87	4.84
Distance to AI officer	35.63	6.49	42.30	8.92	4.80

The average age of adopters and none adopters was 50.15 and 51.92 years respectively. The t-test value of age is not significant; which implies that there was not a significant age difference between adopters and non-adopters of the given technology. The average family size of adopters and non-adopters was estimated to be 6.31 and 5.14 persons respectively (**Table 1**). The t-test value of family size was significant at 1% significance level; which implies that adopter households had more family size than non-adopters.

The average landholding size for the total sample households was 0.51 ha. The mean landholding size of adopters and non-adopters was about 0.48 and 0.55 hectares respectively. The t-test value shows that there was no significant difference in the size of landholding between the two groups ($t = 1.3862$). The average livestock holding size in TLU was 5.51 and 5.15 for AI adopters and non-adopters respectively and its t-value is statistically insignificant ($t = -1.5052$). This implies that there was no difference in livestock holding between adopters and non-adopters of AI technology.

The average distance to FTC walking in minutes for the households from their home for adopters and non-adopters was 41.25 and 48.56 minutes respectively. As indicated in the table, the t-test value ($t = 4.8439$) was highly statistically significant at 1% significance level; meaning that there was a significant mean difference in the distance of FTC between the two groups implies that better adopters

lived near FTC which is similar with that of the distance of inseminator office. The descriptive result shows that the average distance of inseminator office from the household residence walking in minutes for adopters and non-adopters households was 35.63, and 42.29 minutes respectively. The t-test value indicates that distance from AI insemination officer was significant at 1% significance level ($t = 6.2100$); which implies that there was a significant difference between adopters and non-adopters on the distance of inseminator office that means; in comparison to non-adopter, better AI technology adopters were lived near to AI service station.

The descriptive result for discrete variables revealed that among the total respondents, 70.10% were male respondents and the remaining 29.90% were female respondents as it is presented in **Table 2**. Referring to **Table 2**, 64.56% and 71.79% of adopters and non-adopters respectively were male-headed households. Regarding its relationship with the adoption of the given technology, the Pearson chi-square test indicated that the sex of the household head had an insignificant relationship ($\chi^2 = 0.9107$) with the adoption of AI technology (**Table 2**).

As can be seen from **Table 2**, out of the total households interviewed majority (82.35%) were literate and the rest 17.65 % were illiterate. As indicated in the table above 93.75 % and 78.85 % of adopters and non-adopters can read and write whereas the rest of households can not. Concerning its association, the table revealed that literacy had a significant relationship at a 1 % significance level ($\chi^2 = 5.6102$) with the adoption of AI technology. This means that literacy encourages adopting AI technology.

Table 2. Descriptive result for discrete variables.

Variable name	Attribute	Respondents (N = 204)		Chi-square (χ^2)
		Adopter	None adopter %	
Sex of the household head	Male	64.56%	71.79%	0.9107
	Female	35.42%	28.21%	
Literacy level of the household head	Illiterate	6.25%	21.15%	5.6102
	Literate	93.75%	78.85%	
Access to training	Not-trained	14.58%	63.46%	35.1313
	Trained	85.42%	36.54%	
Feed Supplementation practice	No	50%	86.54%	9.7623
	Yes	50%	13.46%	
Mobile ownership	No	29.17%	71.15%	27.2704
	Yes	70.83%	28.85%	
Contact with developmental agent	No	16.67%	53.85%	20.4926
	Yes	83.33%	46.15%	

According to the result of the study, out of the surveyed 204 households, 48.04% of respondents were trained. While the rest 51.96% of the respondents were not

trained in livestock production. In this study, out of the adopters, the majority (85.42%) of them were found to be trained, whereas only 36.54% of the non-adopters were not trained. The chi-square value ($\chi^2 = 35.1313$) indicates that there is a significant relationship between being trained and AI technology adoption decisions at 1% significance level. This clearly shows the existing gap between trained and non-trained households in terms of participation in AI technology adoption.

Findings in **Table 2** indicate that, out of surveyed household respondents, only 22.06% of respondents were provided supplementary feed such as wheat bran and local drink residues called “Hatela” for their cattle/dairy cows which is lower than the finding of [22]. A research study report by him found that about 54% of farmers fed their cattle with concentrate feed. Concerning this explanatory variable, 50% of adopters and 13.46% of non-adopters give supplementary feed. The P-values of chi-square statistics ($X^2 = 30.674$; $P = 0.000$) indicate that concentrated feed supplementation practice is significantly associated with AI technology adoption means that in comparison, those households who provide supplementary feed for their cattle/dairy cows were more AI adopters than they do not provide supplementary feed.

Mobile is also an important means of verbal communication and seeking services and information. Of the total of 204 respondents, 70.83% of the adopters and only about 28.85 % of the non-adopters had mobile for seeking and delivering information about important affairs. Moreover, the chi-square value ($X^2 = 27.2704$) revealed that there was a significant difference in mobile ownership between the two groups which means adopters of AI technology have more mobile access as compared with non-adopters.

Of the total of 204 sample respondents, 54.90% of farmers reported having contact with Developmental Agents (DAs) and 45.10% of farmers reported having no contact with DAs (**Table 2**). The Table also indicates that 83.33 % of adopters and 46.15% of none adopters had contact with extension agents respectively. Whereas 16.67% and 53.85 % of non-adopters had no contact with DAs. The chi-square result ($X^2 = 20.4926$) shows a statistically significant difference between adoption categories concerning farmer's contact with an extension agent.

3.2. Results of the Econometric Model

Nine variables were statistically significant and most of the variables included in the model specification show the expected signs: The result of logit model for matching shows that except the three variables (age of the households, sex of the household heads and total livestock holding in TLU) which were not significant, all the rest variables were statistically significant. Training, feed supplementation practice and mobile ownership were positive, whereas, distance to FTC and AI inseminator office was negative and highly significant at less than 1% (**Table 3**). Moreover, literacy and family size were positively and statistically significant at a 10% significance level. Farmland size was negative and DAs contact was positively associated with adoption and both are significant at a 5% significance level.

Table 3. Results of the logit regression for AI technology adoption.

Variables	Coef.	Std. Err.	Z
Age	0.0013773	0.027459	0.05
Sex of the household head	-0.531558	0.589330	-0.90
Literacy level of the household head	1.664861	0.899185	1.85*
Family size	0.2242749	0.128694	1.74*
Land size	-3.02742	1.25144	-2.42**
Total livestock holding in TLU	0.2577997	0.186449	1.38
Mobile ownership	1.9929	0.561951	3.55***
Contact with developmental agent	1.430589	0.572916	2.50**
Access to training	2.914805	0.712688	4.09***
Feed supplementation practice	1.746305	0.673652	2.59***
Distance to farmer training center	-0.141638	0.044349	-3.19***
Distance to AI officer	-0.101806	0.037871	-2.69***
Constant	2.332677	3.23827	0.72

Table 4. Result of the matching quality indicators.

Matching algorithms	Pseudo R ²		LR χ^2 (p-value)		Mean standardized bias		Total % bias reduction	No of matched sample sizes
	Before matching	After matching	Before matching	After matching	Before matching	After matching		
NNM ^a	0.546	0.064	121.63 (0.000***)	7.15 (0.847)	58.1	11.6	80.03	196
NNM ^b	0.546	0.036	121.63 (0.000***)	3.96 (0.984)	58.1	7.9	86.4	196
NNM ^c	0.546	0.035	121.63 (0.000***)	3.90 (0.985)	58.1	9.3	83.99	196
RBM ^d	0.546	0.146	121.63 (0.000***)	11.73 (0.467)	58.1	15.2	73.84	185
RBM ^e	0.546	0.115	121.63 (0.000***)	9.90 (0.625)	58.1	17.6	69.71	187
RBM ^f	0.546	0.119	121.63 (0.000***)	10.57 (0.566)	58.1	17.8	69.36	188
KBM ^g	0.546	0.064	121.63 (0.000***)	7.15 (0.847)	58.1	8.6	85.2	192
KBM^h	0.546	0.019	121.63 (0.000***)	2.06 (0.999)	58.1	4.7	91.91	196
RBM ⁱ	0.546	0.028	121.63 (0.000***)	2.48 (0.998)	58.1	7.8	86.58	196

Note: ***significant at 1% significance level.

- ▶ NNM^a: Two nearest neighbors matching with replacement and common support.
- ▶ NNM^b: Three nearest neighbors matching with replacement and common support.
- ▶ NNM^c: Four nearest neighbors matching with replacement and common support.
- ▶ RBM^d: Radius based matching with caliper 0.04 and common support.
- ▶ RBM^e: Radius l based matching with caliper 0.05 and common support.
- ▶ RBM^f: Radius based matching with caliper 0.06 and common support.
- ▶ KBM^g: kernel based matching with band width 0.08 and common support.
- ▶ KBM^h: kernel based matching with band width 0.1 and common support.
- ▶ RBMⁱ: kernel based matching with band width 0.12 and common support.

3.3. Choosing Matching Algorithm

Looking into the result of the matching quality, although all matching algorithms lead to qualitatively similar results, the best results after matching such as the lowest mean standardized bias (4.7), almost lower Pseudo R^2 (0.019) and insignificant P-value of the likelihood ratio of $X^2(0.999)$ as well as the better matched sample size (196) were obtained by employing kernel matching with bandwidth 0.1 (Table 4). Hence, in this study, a kernel matching estimator with band size 0.1 was chosen as the best estimator for the matching exercise.

3.4. Estimating the AI Technology Adoption Effect and Interpreting Results

Following the selection of the appropriate matching algorithm, the interest is the average treatment effect for those households which had access to AI technology, *i.e.*, the average treatment effect for the treated. The impact of AI technology on milk yield and livelihood of the household is the difference between AI technology user households and non-user households. The difference in averages of the subjects who adopted AI technology and those who did not adopt is interpreted as the impact of AI technology as follows.

Table 5. Estimation of ATT of AI technology adoption on outcome indicator variables.

Variable	Sample	Treated	Control	Difference	S.E.	t-value
Milk yield	Unmatched	935.3125	224.903846	710.408654	56.8863086	12.49***
	ATT	858.375	185.639665	672.735335	84.2538051	7.98***
Income	Unmatched	10628.125	8002.05128	2626.07372	288.900966	9.09***
	ATT	10371.25	7987.80171	2383.44829	510.751252	4.67***
Asset of the household	Unmatched	8649.01042	6757.11859	1891.89183	278.136833	6.80***
	ATT	8576.0625	7153.49869	1422.56381	508.292465	2.80***
Food expenses	Unmatched	5311.47917	5058.10897	253.370192	299.746284	0.85
	ATT	5373.8	5148.70609	225.09391	543.307918	0.41
Non-food expenses	Unmatched	3955.4375	3351.16026	604.277244	296.689665	2.04**
	ATT	4179.65	2853.5593	1326.0907	542.656591	2.44***

Note: ***& ** indicates significance level at 1% and 5% respectively.

As indicated in Table 5 the average milk yield per lactation was significantly higher for adopters than non-adopters. Before matching, the average milk yield per lactation for adopters was 935.31 liters. The corresponding figure for non-adopter was 224.9 liters which was too lower than that of adopters. However, after controlling for other factors using the PSM method the average milk yield per lactation for adopters is 858.38 liters while that of non-adopter is 185.64 liters. This indicates that; the given technology has raised the average milk yield per lactation of the treated group by 672.74 liters than the average milk yield per lactation of non-adopters. The difference is statistically significant at 1% probability level.

This shows that the adoption of AI technology has a considerable impact on enhancing milk yield.

Similarly, **Table 5** indicates that the average annual income of the household for adopters was 10628.13 ETB. The corresponding figure for non-adopter was 8002.05 ETB which was 24.71% lower than that of adopters. However, after matching the average annual income of the household for the treated and control group is 10371.25 ETB and 7987.80 ETB respectively. This indicates that AI adopter increased their income by 2383.45 ETB due to adopting AI technology. The difference is statistically significant at 1% significance level. This shows that in the study area, AI technology has a significant impact on raising the household's income.

Referring to **Table 5**, the average asset holding that was converted into cash outcome indicator before matching was 8649.01 ETB and 6757.12 ETB for treated and untreated households respectively. However, keeping other factors constant, the average asset holding converted into a monetary value is 8576.06 ETB for the adopter and 7153.5 ETB for non-adopters. Moreover, the result displayed in the above table tells us that AI technology adoption had a positive and highly significant impact on asset holding of the farm households at 1 % probability level; implying AI technology has a considerable impact on asset holding of adopter households.

As indicated in **Table 5**, the average annual food expenditure by AI technology user households and non-user households was 5311.48 ETB and 5058.11 ETB respectively before matching whereas, after matching, 5373.8 ETB and 4991.25 ETB for adopters and non-adopters respectively. This indicates that; the treatment has raised the annual food expenditure of the treated group on average by 225.09 ETB, which is 4.39 % higher than the average annual food expenditure of non-adopters. However, the t-value shows that there is no statistical difference between the two groups in the mean of annual food-expenditure both before and after matching.

The estimation result of average per capita non-food expenditure which is presented in **Table 5** had shown a statistically significant difference between AI technology users and non-users groups before matching at less than 5% probability level. The average per capita non-food expenditure was 3955.44 ETB for treated households before matching, whereas, 3351.16 ETB for non-adopters which was 604.28 lower than that of adopters. However, after matching the average per capita non-food expenditure of the household for the treated and control group is 4179.65 ETB and 2853.56 ETB respectively. This indicates that AI adopters paid more money (annually 1326.09 ETB) than non-adopters for clothes, health, education, etc. which is an indicator of well-being. The difference was also statistically significant at 1 % significance level. Therefore, in the outcome of the average per capita non-food expenditure, the adoption of AI technology has shown a positive and substantial impact on the adopter's livelihood.

4. Conclusion and Recommendations

From the evidence gathered in the present study, it can be concluded that despite

the potential and existence of favorable conditions for AI technology adoption, the adoption and its level of adoption has been at a low level. The main reasons given for non-adoption of AI technology were poor pregnancy rate, heat detection problems, lack of awareness, communication problems, lack of incentive to the technicians and accessibility problems. However, the ground realities or contribution of AI technology in milk yield and livelihoods of the household are entirely different between adopters and non-adopters. According to the household-level comparisons for the outcome indicators, adopters of AI technology are seemingly better off than non-adopters in many aspects. The result of PSM on the impact of the adoption of AI technology on milk yield, income, assets of the household, food and non-food expenses of the household showed that the technology has a considerable impact on four outcome variables. Hence, intensive work such as training, better extension service, providing a reasonable incentive to AI technicians especially during weekends and holidays, hardship and overtime allowances should be provided to improve the adoption of AI technology subsequently, to improve milk production and productivity, increase household income and achieving food security as well as overall improve well-being of the households.

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] Central Statics Agency (2017) Agricultural Sample Survey. Report on Livestock and Livestock Characteristics (Private Peasant Holdings). *Addis Ababa Ethiopia*, **2**, 9-12.
- [2] Abera, Z. (2018) Review on Procedures and Utilization of Artificial Insemination Technologies in Nekemte Semen and Liquid Nitrogen Production and Distribution Centre, Western Oromia, Ethiopia. *Concepts of Dairy & Veterinary Sciences*, **1**, 1-9. <https://doi.org/10.32474/cdvs.2018.01.000117>
- [3] Duguma, B. (2021) Productive and Reproductive Performance of Crossbred and Indigenous Dairy Cows at Smallholdings in Selected Towns of Jimma Zone, Ethiopia. *Animal Production Science*, **61**, 92-100. <https://doi.org/10.1071/an19380>
- [4] Worku, D., Alemayehu, K. and Melekote, M. (2016) Comparative Reproductive Performance Evaluation of Holstein Friesian Cattle Breeds in Two Different Agro Ecological Conditions, Oromia Region, Ethiopia. *Animal Genetic Resources/ Ressources génétiques animales/ Recursos genéticos animales*, **58**, 31-42. <https://doi.org/10.1017/s2078633616000060>
- [5] Mugisha, A., Kayiizi, V., Owiny, D. and Mburu, J. (2014) Breeding Services and the Factors Influencing Their Use on Smallholder Dairy Farms in Central Uganda. *Veterinary Medicine International*, **2014**, Article ID: 169380. <https://doi.org/10.1155/2014/169380>
- [6] Ingabire, M.C., Yonggong, L., Pasha, J.C. and Hardi, A. (2018) Factors Affecting Adoption of Artificial Insemination Technology by Small Dairy Farmers in Rwanda: A Case of Rwamagana District. *Journal of Economics and Sustainable Development*, **9**, 46-53.
- [7] Elijah Kiplangat, N. (2018) Farm Gate Dairy Milk Marketing Channel Choice in Kericho County, Kenya. *Journal of World Economic Research*, **7**, 92-104.

- <https://doi.org/10.11648/j.jwer.20180703.11>
- [8] Limenih, B. (2018) Women Farmers' Adoption Challenges on Artificial Inseminations Service in Outskirt of Addis Ababa. *International Journal of Agricultural Extension*, **6**, 81-88. <https://doi.org/10.33687/ijae.006.02.2417>
- [9] Tiruneh, S. and Tegene, F. (2018) Impacts of Climate Change on Livestock Production and Productivity and Different Adaptation Strategies in Ethiopia. *Journal of Applied and Advanced Research*, **3**, 52-58. <https://doi.org/10.21839/jaar.2018.v3i3.150>
- [10] Sapkota, S., Gairhe, S., Kolakshyapati, M. and Upadhyay, N. (2016) Adoption of Artificial Insemination Technology in Dairy Animals and Impact on Milk Production: A Case Study in Nawalparasi and Chitwan Districts of Nepal. *Nepalese Journal of Agricultural Sciences*, **14**, 80-85.
- [11] Bekele, A.D., Beuving, J. and Ruben, R. (2016) How African Households Shop: Evidence from Dairy Chains in Ethiopia. *The European Journal of Development Research*, **29**, 806-826. <https://doi.org/10.1057/s41287-016-0062-3>
- [12] Kebebew, Y. and Bekele, T. (2018) Assessment of Efficiency and Major Constraint of Artificial Insemination Service in Small Holder Dairy Farmers in and around Adama Town. *International Journal of Advanced Research in Biological Sciences*, **5**, 88-99.
- [13] Ashebir, G. (2016) Status of Artificial Insemination in Tigray Regional State, "Constraints and Acceptability under Field Condition". *Journal of Dairy, Veterinary & Animal Research*, **3**, 91-95. <https://doi.org/10.15406/jdvar.2016.03.00078>
- [14] Saesitsaeda emba wereda Office of Agriculture and Rural Development (STEWBOARD) Report (2018) Annual Report.
- [15] Ahmed, M. and Rahman, M. (2020) Local Climate Change Governance and Making Climate Resilient Town: The Role of Local Authorities. *Research & Reviews: Journal of Architectural Designing*, **2**, 1-13.
- [16] Hadush, M. (2017) Implication of Animal Feed and Water Scarcity on Labor Allocation, Food Production and Per Capita Food Consumption in Tigray Region, Ethiopia. *Journal of Economic Development*, **42**, 59-93. <https://doi.org/10.35866/caujed.2017.42.4.003>
- [17] Habtewold, T.M. (2018) Adoption and Impact of Improved Agricultural Technologies on Rural Poverty. In: Heshmati, A. and Yoon, H., Eds., *Economic Growth and Development in Ethiopia*, Springer Singapore, 13-38. https://doi.org/10.1007/978-981-10-8126-2_2
- [18] Rosenbaum, P.R. and Rubin, D.B. (1985) Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *The American Statistician*, **39**, 33-38. <https://doi.org/10.1080/00031305.1985.10479383>
- [19] Dehejia, R.H. and Wahba, S. (2002) Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Review of Economics and Statistics*, **84**, 151-161. <https://doi.org/10.1162/003465302317331982>
- [20] Sianesi, B. (2004) An Evaluation of the Swedish System of Active Labor Market Programs in the 1990s. *Review of Economics and Statistics*, **86**, 133-155. <https://doi.org/10.1162/003465304323023723>
- [21] Smith, J. and Todd, P. (2005) Does Matching Overcome LaLonde's Critique of Non-experimental Estimators? *Journal of Econometrics*, **125**, 305-353. <https://doi.org/10.1016/j.jeconom.2004.04.011>
- [22] Datta, A.K., Haider, M.Z. and Ghosh, S.K. (2018) Economic Analysis of Dairy Farming in Bangladesh. *Tropical Animal Health and Production*, **51**, 55-64. <https://doi.org/10.1007/s11250-018-1659-7>