Original Research Article

The Impact of Artificial Insemination Technology on Smallholder Dairy Farmers' Livelihoods in Muheza District of the Tanga region in Tanzania

---

ABSTRACT

This study examined the effect of artificial insemination (AI) technology on the livelihoods of smallholder dairy farmers. A cross-sectional design was employed, surveying 116 randomly selected smallholder dairy farmers in Muheza district in Tanga region of Tanzania. Data analysis utilized a Probit model and Propensity Score Matching (PSM) were used to analyse livelihoods framework to account for potential biases stemming from self-selection into AI adoption. This rigorous approach allowed isolation of impact of AI from other factors influencing farmer livelihoods. The findings revealed a significant association between AI adoption and improved livelihoods. Specifically, AI-adopting farmers reported a considerable increase in daily meal consumption, a key indicator of improved food security and nutritional well-being. Furthermore, the study demonstrated a significant rise in income among AI adopters compared to their non-adopting counterparts. Increased income suggested direct AI contribution to enhanced smallholder dairy farmers' economic stability. The improved livelihoods observed in AI-adopting farmers are likely attributed to several factors. AI facilitated access to superior genetics, resulting to healthier and more productive dairy cattle. Consequently, led to increased milk production, a primary source of income for these farmers. Moreover, the adoption of AI might indirectly contribute to improved farming practices and knowledge transfer through training and support networks. Based on these findings, the study recommended increased government support in the study area focused on two key areas: (1) enhancing the availability and quality of breeding services; and (2) expanding the distribution of improved dairy cattle genetics to reach a wider range of rural smallholder dairy farmers. Thus, investing on these areas will significantly contribute to improved livelihoods, food security, and economic well-being of rural smallholder dairy farmers.

Keywords: Artificial Insemination, Dairy Cattle, Smallholder Farmers, Livelihoods, Muheza-Tanga-Tanzania.

1. INTRODUCTION

When used to farms with good breeding programs and management practices, Artificial Insemination (AI) technology has the potential to improve animals' genetic merits, increase production and incomes, reduce the risks of spreading venereal diseases as well as maximize farm's net profit. As such, AI had become a common breeding technique for genetic improvement in livestock farming. For this reason, AI is widely used in livestock breeding globally with high utilization reported in developed countries compared to developing countries.

In Tanzania, AI is one of the key breeding tool advocated by the Tanzanian government to improve dairy cattle production and consequently, genetic gain within the herds of smallholder dairy farmers (URT, 2017). To implement this, a number of different projects within the dairy sub-sector had been conducted to date involving actors from both public sector institutions such as National Artificial Insemination Centre (NAIC), Tanzania Livestock Research Institute (TALIRI), Local Government Authorities (LGAs), and private sector organizations like Land O'Lakes (URT, 2017). With regard to those projects and programs, in Tanga region, AI was used to breed high-quality bulls for distribution to the rural areas, aiming to improve dairy cattle genetics, increased milk production and incomes as well as improved farmers' livelihoods (Kim *et al.,* 2017). As a result, a significant number of smallholder dairy farmers (21,821) accounting 45.8% of households in Muheza district had adopted AI technology, reflecting its importance to the local economy (GCCA, 2019).

Currently, AI had become a widely adopted breeding technique used in dairy cattle production in Tanzania, making superior dairy cattle genetics readily available in the country (Zekarias, 2019). It has led to a 281% increase in crossbred dairy cows and a 26-42% rise in milk production per cow, facilitated by the distribution of 236,335 semen doses and 47,827.95 litres of liquid nitrogen (Msalya *et al.,* 2017). Additionally, the government had actively addressed farmers AI-related services (Riyad *et al.,* 2017), with much of the existing literature focusing on AI services to the smallholder dairy farmers (Mwanga *et al.,* 2018) and the cost-profitability of AI in beef cattle (Zekarias, 2019).Previous research had examined factors influencing AI adoption in dairy cattle farming and its impact on smallholder dairy value chain (Kanar *et al.,* 2019), nonetheless, there is scarcity of studies specifically on the impact of AI on farmer livelihoods in Tanzania. Thus, this study uniquely focuses on the livelihood outcomes of AI adoption to smallholder dairy farmers in Muheza district of the Tanga region in Tanzania.

2. METHODOLOGY

2.1 Research Design

The study employed a cross-sectional research design to collect data at a single point in time due to resource constraints (Maninder, 2016). Kate (2006) also used this design to investigate the relationship between influencing factors and outcomes. This approach is cost-effective and requires a relatively short completion time.

2.1.1 Study Area and Sample Size

The study was conducted in Muheza District, Tanzania, a region with widespread artificial insemination practices in dairy cattle. A probability sampling technique called simple random sampling was used to select 116 respondents. This means that every individual in the population of interest had an equal chance of being chosen for the study. The method ensured that the sample was representative of the entire population of dairy farmers in the district, minimizing the risk of bias. Muheza district is located in northeastern Tanzania, west and south of Tanga city. It is bordered by Mkinga district to the north, Pangani to the south, and Korogwe District to the west. The district's geographical coordinates are 4° 54' 18" S latitude and 38° 55' 23" E longitude. Covering 1,497 square kilometers, it comprises approximately 7% of Tanga region's total land area of 28,055 square kilometers (URT, 2017). Muheza district experiences a predominantly hot climate with significant rainfall. February is the driest month, with an average rainfall of 40 mm, while April sees peak rainfall averaging 199 mm, a difference of 159 mm. February also experiences the highest average temperature at 27.2 °C, while July is the coolest month at 22.8 °C. The district's climate is influenced by several factors, including the Usambara Mountains and their associated highlands and foothills (URT, 2009; URT, 2017).

2.1.1.1 ***Statistical Data Analysis Technique***

The probit analysis yielded statistically significant results regarding the factors influencing the probability of artificial insemination technology adoption.

Model Specification

The probit model used in this study takes the following form:

$$Pr\ (BAI = 1|X) = \Phi\ (\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8)$$

where:

BAI (Beneficiaries of Artificial Insemination) is a binary dependent variable (1 = beneficiary, 0 = non-beneficiary).

X represents a vector of explanatory variables:

X_1: Educational level of farmers

X_2: Farmers' experience/knowledge

X_3: Farmers' household size

X_4: Time

X_5: Age of farmers

X_6: Knowledge about artificial insemination practices

X_7: Frequency of extension contact

X_8: Availability of artificial inseminators (1 = available, 0 = unavailable)

β_0, β_1, β_2, β_3, β_4, β_5, β_6, β_7, and β_8 are the model parameters to be estimated.

Φ is the cumulative standard normal distribution function.

This model estimates the probability of a farmer being a beneficiary of artificial insemination based on these explanatory variables. The study also considered additional investigating variables such as gender, occupation, perception of artificial insemination profit, and participation in off-farm activities, although these were not included in the final model specified above. The initial implicit form of the model, $Y = f\ (\sum \beta_i x_i)$, was made explicit by assuming Φ follows a standard normal distribution.

The Propensity Score Matching (PSM)

The study investigated the causal relationship between artificial insemination (AI) adoption and the livelihoods of dairy farmers. The average treatment effect (ATE) of AI on farmer livelihoods (Y) was estimated as the difference between the outcome with AI ($D_i = 1$) and the counterfactual outcome without AI ($D_i = 0$): $T_i = Y_i (D_i = 1) - Y_i (D_i = 0)$ (3.4). Since the counterfactual outcome cannot be directly observed, the analysis shifted from individual treatment effects to the average treatment effect (ATE) for the population. The ATE was defined as: $ATT = E [Y_1 (D = 1)] - E [Y_0 (D = 0)]$ (3.5). This represented the average benefit of AI adoption compared to the expected outcome without adoption. However, self-selection bias existed because farmers who adopt AI may differ systematically from non-adopters even before AI adoption. To address this, the study employed propensity score matching (PSM). PSM relied on two key assumptions: conditional independence and common support. Under these assumptions, the ATT is estimated as: $ATT = E [Y_1 - Y_0|D = 0, p(x)] = E [Y_1|D = 1, p(x)] - E [Y_0|D = 0, p(x)]$ (3.7). This was the average difference in outcomes within the common support region, weighted by the propensity score, p(x). The propensity score, represented the probability of AI adoption given observed characteristics, was estimated using a probit model. The model included pre-intervention characteristics such as gender, occupation, education level, experience, household size, age, knowledge of AI, frequency of extension contact, perceived AI profit, and participation in off-farm activities. A binary dependent variable (AI adoption: 1 = adopted, 0 = not adopted) was used. The use of a probit model, rather than a logit model, was justified by Gujarati (2004) who suggested that both models yield similar results.

Matching Estimators of the ATT Based on the Propensity Score

Propensity score matching (PSM) began by estimating propensity scores to ensure the balancing condition was met. This allowed estimation of the average treatment effect (ATT) on the outcomes of interest. While various matching estimators exist in the literature, this study employed nearest neighbor matching (NNM), radius matching (RM), and stratification matching to estimate the ATT based on the propensity scores.

Validity and reliability of data collection instruments

The study ensured validity accurate measurement of the intended constructs and reliability consistent measurement of results following the definitions provided by Taherdoost (2016) and Raudeliuniene (2018), respectively. A questionnaire was used as the data collection method to support the exploration of artificial insemination's effects on dairy farmers' livelihoods, thus guaranteed the validity and reliability of the findings.

3. RESULTS AND DISCUSSION

Table 1 (a): summary statistics and mean/proportion difference tests for continuous and categorical variables.

Variable	Artificialinsemination(N=73		Non- artificial insemination (N=43)	
	Mean	Std.Dev.	Mean	Std.Dev.
Income	2.273	0.534	1.372	0.691
Meals	2.643	0.674	1.721	0.935
Age	2.315	0.6845	1.814	0.588
Gender(1=female)	1.767	0.426	1.302	0.465
Maritalstatus(1=married)	0.918	0.277	0.814	0.394
Education(1=primary)	2.192	0.680	1.465	0.767
Breeds(1=local)	1.973	0.623	2	1
Acresland(1=small)	1.890	0.315	1.256	0.441

Distance(0=lowmileage)	0.205	0.407	0.884	0.324
Training	2.178	1.109	3.047	0.924

Table 1 (a) The sample included 73 artificial insemination beneficiaries and 43 non-beneficiaries. Analysis of the first objective revealed that age group ($P < 0.01$) and education level ($P = 0.05$) were positively and significantly associated with AI adoption. Specifically, a higher education level increased the probability of AI adoption (coefficient = 0.721). Acreage of grazing land was also positively and significantly associated with AI adoption ($P < 0.01$, coefficient = 2.095). Conversely, distance to the nearest AI centre showed a negative and significant relationship ($P < 0.01$). Gender ($P = 0.97$) and marital status ($P = 0.724$) were not significantly associated with AI adoption.

Table 2 (b): Chi-Squareresults

Variable	Category	Adaptor (N=73)	Non-adopter (N=43)	Total frequency (N=116)	Pearson Chi - square (p_value)
Gender	Male	56	13	69	0.000
	Female	17	30	47	
Age	20-40	9	12	21	0.000
	41-60	32	27	59	
	61-80	32	4	36	
Marital status	Unmarried	6	8	14	0.097
	Married	67	35	102	
Education	Primary	11	30	41	0.000
	Secondary	37	6	43	
	Collage/university	25	7	32	
Breed	Lacal	15	21	36	0.000
	Exotic	45	1	46	
	Crosses	13	21	34	
Training	Cattlebreeding	27	5	32	0.000
	Extensionservices	18	2	20	
	Diseases management	16	22	38	
	Haymaking	12	14	26	
Distanceto AIcentre	Lowmileage	58	5	63	0.000
	Largemileage	15	38	53	
Access to land	Smallarea	8	32	40	0.000
	Largearea	65	11	86	
Food securit	Onemealperday	8	26	34	0.000
	Twomealperday	10	3	13	

y	Threemealperday	55	14	69	
Income	Lowincome	3	32	35	0.000
	Medium income	47	6	53	
	Highincome	23	5	28	

Table 3. Probit regression

AI	**Coef.**	**Std.Err.**	**z**	**P>z**	**dy/dx**
Age	0.841309	0.321093	2.62	0.009*	0.2513
Gender(1=female)	0.017892	0.475229	0.04	0.970	0.0053
Maritalstatus(1=married)	0.238833	0.675093	0.35	0.724	0.0760
Education(1=primary)	0.721354	0.33048	2.18	0.029**	0.2154
Breeds(1=local)	-0.29693	0.246048	-1.21	0.228	-0.0886
Acresland(1=largegrazingland)	2.094835	0.496273	4.22	0.000*	0.6256
Distance	-1.28041	0.469108	-2.73	0.006*	-0.3847
Training	-0.25096	0.212955	-1.18	0.239	-0.0749
_cons	-4.32187	1.684765	-2.57	0.01	
Numberofobs= 116 LRchi2(8) = 103.19 Prob> chi2 = 0.0000 Pseudo R2 = 0.6746 Loglikelihood=-24.886778					

Table 3. Presents results from a probit regression model based on data from 116 dairy farmers in Muheza district. The likelihood ratio test (LR chi² = 103.19, P < 0.05) indicated a significant relationship between at least one independent variable and the dependent variable (AI adoption). The model's log-likelihood was -24.886778, and the pseudo R² of 0.6746 suggested a good model fit, explaining a substantial proportion of the variance in AI adoption.

Table 4. Estimation of ATT: Impact of AI on Income and Meal

Outcome		Outcome(Income)	Outcome(Meal)
Nearestneighbour matching	No.treatment	73	72
	No.control	8	37
	ATT	1.274	1.102
	Std.Err.	0.062	0.323
	t	20.389	3.415
Radiusmatching estimators	No.treatment	73	72
	No.control	8	37

	ATT	1.301	1.061
	Std.Err.	0.776	0.423
	t	1.678	2.506

Table 4 presents average treatment effect (ATT) estimates for the impact of artificial insemination on dairy farmer income. Nearest neighbor matching yielded an ATT of 1.274, while radius matching yielded an ATT of 1.301 (standard error = 0.776). Both positive ATT estimates suggest that artificial insemination is associated with higher income for dairy farmers.

This study investigated the factors influencing AI adoption among Tanzanian smallholder dairy farmers and its subsequent impact on their livelihoods. The findings revealed that older age (P = 0.009), higher education levels (P = 0.029), and larger grazing land acreage (P< 0.01) were significantly and positively correlated with AI adoption. Conversely, greater distance to AI centers (P = 0.006) negatively impacted adoption rates. Interestingly, gender, marital status, dairy cattle breed, and access to extension services training showed no significant association with AI adoption. Employing propensity score matching (nearest neighbor and radius matching), the study demonstrated a significant positive effect of AI on both farmer income and daily meal consumption, suggesting improved livelihoods for those who adopted the technology. This aligned with the findings from similar studies conducted elsewhere.

For instance, research in Kenyaby Ngugi *et al*. (2017) showed a similar positive correlation between smallholder dairy farmers' educationand AI adoption. This suggests that access to information and understanding of AI's benefits are crucial drivers of adoption. Furthermore, studies in Uganda(Nalunga *et al*., 2018)have highlighted the importance of proximity to AI services. The negative correlation between distance to AI centers and adoption observed in this study echoes these findings, emphasizing the logistical challenges associated with AI implementation in remote areas. The positive impact on farmer livelihoods, as measured by increased income and improved nutrition, is consistent with broader literature on the economic benefits of AI in dairy farming Ouma *et al*. (2019) However, the lack of significant association between extension services and AI adoption suggests conduction of further studies, potentially indicating a need for more targeted and effective extension programs tailored to the specific needs and contexts of smallholder dairy farmers in the study area. Future research could explore the effectiveness of different extension strategies, focusing on overcoming perceived barriers to AI adoption, such as cost, access to quality semen, and technical expertise. Comparative studies across different regions of Tanzania, considering variations in infrastructure, access to resources, and farming practices, would also provide valuable insights.

4. CONCLUSION

The study concluded that artificial insemination technology significantly improved dairy farmers' livelihoods, increased both income and daily meal consumption compared to non-adopters. The government should prioritize the development and accessibility of artificial insemination technology to enhance the dairy industry and improve farmers' well-being. Specifically, efforts should focus on producing and distributing high-quality bulls to rural areas to improve dairy cattle genetics and production. Future research should expand beyond Muheza district to encompass a broader range of geographical and socioeconomic contexts, thereby enhancing the generalizability of findings and informing more effective policy development at regional or national levels.

8. ETHICAL APPROVAL

Ethical research standards were maintained by obtaining necessary permits from Mzumbe University's Directorate of Publication and Postgraduate Studies, thus facilitating access to participating institutions. Informed consent was obtained from all respondents prior to data collection, ensuring freedom from coercion. Respondents were informed that the study was for academic purposes only and that all data would remain confidential.

9. REFERENCES

GCCA. (2019). Supporting communities in the east Usambara Mountains to adapt to climate change. Tanzania integrated approaches for climate change adaptation in the east Usambara Mountains

Gujarati, D.N. (2004) Basic Econometrics. 4th Edition, McGraw-Hill Companies.

Kim S.J., Ka, S., Ha J.-W., Kim J., Yoo D., Kim K. (2017). Cattle genome-wide analysis reveals genetic signatures in trypanotolerant N'Dama. BMC Genomics 18:371. 10.1186/s12864-017-3742-2

Kanar, D., Derek, B., & Amos, O (2019). Upgrading the smallholder dairy value chain: a dynamics ex-ante impact assessment in Tanzania's Kilosa district. Journal of Dairy Research 86

Kate, A.L. (2006). Study Design III: cross-sectional studies. Article in Evidence-based Dentistry.DOI: 10.1038/sj.ebd.6400375

Maninder, S. S. (2016). Methodology Series Module 3: Cross-sectional Studies. Article in Indian Journal of Dermatology -DOI: 10.4103/0019-5154.182410

Msalya, G., Lutatenekwa, D., &Chenyambuga, SW. (2017) Possibilities of utilizing biotechnology to improve animal and animal feeds productivity in Tanzania – review of past efforts and available opportunities. Journal of Dairy, Veterinary & Animal Research Volume 5

Mwanga, G., Mujibi, F. D. N., Yonah, Z. O., & Chagunda, M. G. G. (2018). Multi-country investigation of factors influencing breeding decisions by smallholder dairy farmers in sub- Saharan Africa. Tropical Animal Health and Production vol.51:395–409.

Nalunga, J., Mugenyi, E., & Buyinza, M. (2018). Factors influencing adoption of improved dairy farming technologies in Uganda: A case study of Kamuli District. African Journal of Agricultural Research, 13(33), 1736-1745.

Ngugi, L. W., Mburu, J., Kahi, A. K., Peters, K. J., & Recha, J. W. (2017). Factors influencing the adoption of artificial insemination among smallholder dairy farmers in Kenya. Tropical animal health and production, 49(2), 377-384.

Ouma, E. A., Abdulai, A., & Barrett, C. B. (2019). Agricultural input adoption and income inequality among smallholder farmers in rural Kenya. Food Policy, 89, 101749. https://doi.org/10.1016/j.foodpol.2019.101749.

Raudeliuniene, J. (2018). Basic Research Methods. Modernizing the Academic Teaching and Research Environment: Methodologies and Cases in Business Research, 47.

Riyad, J., Anwar H., Jelalu, K., & Kiros, W (2017). Assessment on problems associated with artificial insemination service in dairy cattle in Tullo district, West Hararghe, Ethiopia. Ethiop. Vet. J, 21 (2), 62-74.

Taherdoost, H. (2016). Validity and Reliability of the Research Instrument: How to test the validation of questionnaire/survey in research. International Journal of Academic Research Management (IJARM). Vol.5, No. 3. Retrieved from: http://doi.org/ 10.2139/ssrn.3205040/10/12/2020/10:20pm.

URT. (2017). Muheza district strategic plan and operational plan for the year2018/19-2012/23.
URT. (2017). Tanzania livestock master plan (2017/2018 – 2021/2022).

URT, (2009) Supporting Communities to Adapt to Climate Change in Usambara mountains

Zekarias, M (2019). A Review on Artificial Insemination of Cattle in Ethiopia. Glob J Repro'd Med 6(4):