Original Research Article

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

ABSTRACT

This study investigated artificial insemination (AI)'s impact on Tanzanian smallholder dairy farmers' livelihoods. 116 farmers in Muheza district were surveyed using a cross-sectional design. Data analysis employed a Probit model and Propensity Score Matching (PSM) to account for self-selection bias in AI adoption. This rigorous approach allowed isolation of impact of AI from other factors influencing farmer livelihoods. AI adoption significantly improved smallholder dairy farmers' livelihoods, notably increasing daily meal consumption and income.Substantially higher incomes were reported from AI adopters than non-adopters, indicating enhanced economic stability. This improvement is likely due to superior genetics leading to healthier, more productive cattle and increased milk production. Additionally, AI adoption may indirectly boost farming practices through knowledge transfer and support networks. Therefore, to significantly boost food security and economic well-being, the Tanzanian government should prioritize expanding access to superior dairy genetics and high-quality breeding services for smallholder farmers. This targeted investment will dramatically improve livelihoods not only in Muheza district of the Tanga region but also in other rural communities in Tanzania.

Keywords: Artificial Insemination, Dairy Cattle, Livelihoods,Smallholder Farmers.

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). Its use has led to increased milk production per cow in some of the dairying areas in the country, facilitated byaccessibility of reliable AI services (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 respondentsfrom a population of 164 smallholder dairy farmers. 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 :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 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 : 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 security	Onemealperday	8	26	34	0.000
	Twomealperday	10	3	13	
	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 examined the factors influencing artificial insemination (AI) adoption among Tanzanian smallholder dairy farmers and its impact on their livelihoods. The findings reveal a complex interplay of factors affecting technology adoption within this specific context.

Several statistically significant factors influenced AI adoption. Positive correlations existed between adoption and older age (P = 0.009), suggesting experience and understanding of long-term benefits may be key. Further research could explore whether this correlation is linked to access to information or established social networks. Higher education levels also positively correlated with AI adoption (P = 0.029), highlighting the importance of education in comprehending and utilizing new technologies. Literacy and numeracy skills are crucial for understanding AI's technical aspects and evaluating its potential. Finally, farmers with larger grazing land acreages showed a greater likelihood of AI adoption (P < 0.01), potentially due to economies of scale where the returns on improved breeding justify the investment. Larger operations might also facilitate easier access to AI services (Anthony et al., 2014; Omondi et al., 2017).

Conversely, distance to AI centers negatively impacted adoption rates (P = 0.006), emphasizing the critical role of geographical accessibility.The costs and logistical challenges of traveling long distances create significant barriers for many farmers. Interestingly, gender, marital status, cattle breed, and access to extension services training showed no significant association with AI adoption, suggesting the influence of other, less easily quantifiable factors.

Employing propensity score matching, the study demonstrated a significant positive impact of AI adoption on farmer livelihoods. AI adoption led to statistically significant increases in farmer income, likely due to improved breeding practices resulting in higher milk production (Gebre et al., 2024). Furthermore, it positively affected daily meal consumption, indicating improved nutritional status and food security. These findings align with similar studies conducted elsewhere, reinforcing the positive impact of AI on dairy farming and farmer well-being. However, the specific factors influencing adoption vary across contexts, underscoring the need for localized research.

Future research should investigate the non-significant factors (gender, marital status, breed, extension services) to understand their potential indirect influence on AI adoption. It should also explore the cost-effectiveness of AI adoption across different farm sizes and geographical locations, and develop targeted interventions to address barriers to adoption, particularly those related to geographical accessibility and information dissemination. Addressing these limitations will provide a more comprehensive understanding of AI adoption and its impact on the livelihoods of Tanzanian smallholder dairy farmers(Mathewos et al., 2023).

The findings of this study resonate with existing literature on AI adoption in sub-Saharan Africa. For example, research conducted in Kenya by Ngugi et al. (2017) demonstrated a similar positive correlation between smallholder dairy farmers' education levels and AI adoption. This reinforces the crucial role of access to information and understanding of AI's benefits as drivers of technology adoption. Farmers with higher levels of education are better equipped to comprehend the technical aspects of AI, assess its potential benefits, and navigate the adoption process effectively. This suggests that literacy programs and targeted educational initiatives focused on the practical applications of AI in dairy farming could significantly enhance adoption rates (Chelkeba et al., 2016).

Furthermore, the importance of proximity to AI services, highlighted in this study's negative correlation between distance to AI centers and adoption rates, is echoed by research in Uganda (Nalunga et al., 2018). These findings underscore the significant logistical challenges associated with AI implementation in remote areas. The cost and time involved in transporting animals to AI centers, coupled with potential losses incurred during transit, act as substantial barriers to adoption. Strategies to improve accessibility, such as mobile AI services or the establishment of strategically located AI centers in underserved areas, are crucial for promoting wider adoption (Chelkeba et al., 2016; Mathewos et al., 2023).

The positive impact of AI adoption on farmer livelihoods, as evidenced by increased income and improved nutrition in this study, aligns with broader literature on the economic benefits of AI in dairy

farming (Ouma et al., 2019). Improved breeding practices through AI lead to increased milk production, higher milk quality, and ultimately, greater income for farmers. This increased income directly translates into improved food security and overall well-being for farming families. However, the consistent observation across multiple studies of a lack of significant association between access to extension services and AI adoption warrants further investigation. This suggests that current extension programs may not be effectively addressing the specific needs and contexts of smallholder dairy farmers (Chelkeba et al., 2016).
Future research should explore the effectiveness of different extension strategies, focusing on overcoming perceived barriers to AI adoption. These barriers include the cost of AI services, access to high-quality semen, and the lack of technical expertise among farmers. Tailored training programs that address these specific challenges, combined with practical demonstrations and ongoing support, could significantly improve the effectiveness of extension services. Comparative studies across different regions of Tanzania, incorporating variations in infrastructure, access to resources, and farming practices, would provide valuable insights into the factors that influence AI adoption and its impact on livelihoods. Such comparative analysis would allow for the identification of best practices and the development of region-specific strategies to promote sustainable AI adoption. This nuanced understanding is crucial for designing effective policies and interventions to support the growth and sustainability of the smallholder dairy farming sector in Tanzania.

4. CONCLUSION

The study provides valuable insights into the factors influencing the adoption of artificial insemination (AI) among smallholder dairy farmers in Tanzania and highlights its significant impact on their livelihoods. The identified relationships between AI adoption and variables such as age, education, and land size underscore the importance of knowledge and resource availability in facilitating technological advancements in agriculture. Furthermore, the negative correlation with distance to AI centers emphasizes the logistical challenges that farmers face, which can hinder their ability to adopt beneficial practices. The findings align with existing literature from other regions in sub-Saharan Africa, reinforcing the notion that education and accessibility are critical drivers of technology adoption. The positive outcomes associated with AI adoption, including increased income and improved nutrition, illustrate the potential benefits that can be derived from enhanced dairy farming practices. However, the lack of significant associations with extension services indicates a need for more effective and targeted support programs that cater to the specific contexts of smallholder farmers. Future research is essential to address the gaps identified in this study, particularly concerning the exploration of non-significant factors and the effectiveness of various extension strategies. By investigating the perceived barriers to AI adoption and developing tailored interventions, stakeholders can enhance the adoption rates of AI technologies among smallholder dairy farmers. Additionally, comparative studies across different regions of Tanzania will contribute to a more comprehensive understanding of the diverse factors influencing AI adoption and its impact on livelihoods. Ultimately, the insights gained from this research can inform the development of effective policies and interventions aimed at promoting sustainable practices within the smallholder dairy farming sector. By fostering an environment that facilitates access to information, resources, and training, we can help elevate the livelihoods of Tanzanian farmers, ensuring food security and economic stability in rural communities. This study serves as a foundation for ongoing discussions and efforts to understand and support the transformative potential of AI in livestock development, paving the way for future advancements in the sector.

ETHICAL APPROVAL AND CONSENT

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.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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