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Factors Affecting Adoption of Artificial Insemination Technology by Small Dairy Farmers in Rwanda: A Case of Rwamagana District

Marie Claire Ingabire[1.2.*] Yonggong Liu[1] John Chrisostom Pesha[1.3] Alhassan Hardi[1]
1.College of Humanities and Development Studies, China Agricultural University P.O. Box 100083, Beijing Haidian, Qinghua DongLu, P.R. China
2. Rwanda Agricultural Board (RAB)
3. Stella Maris Mtwara University College - St. Augustine University of Tanzania

Abstract
The dairy industry plays a crucial role in the rural community's economy and farmers' livelihoods. However, the level of dairy productivity in Rwanda remains relatively low since the industry is dominated by the indigenous Ankole cattle which have poor genetic potential and low productive capacity. The use of Artificial Insemination Technology in the country is intended to allow rapid genetic improvement of dairy herds in order to ensure high productivity and better livelihood status among small dairy farmers and other stakeholders involved in the value chain system. Despite the efforts made by the responsible authorities to disseminate the respective breeding technology to small dairy farmers in the countryside, the level of adoption in some productive areas is still low. This study therefore focused on assessing factors affecting adoption of Artificial Insemination Technology by small dairy farmers in Rwanda; where Rwamagana district was chosen as a study area. Semi-structured questionnaires and in-depth interviews were used to collect raw data from small dairy farmers (AI users and non-users) and key informants respectively while secondary data were gathered from the responsible public authorities. Descriptive statistics and binary regression model were used for analyzing quantitative data whereas content analysis was employed to analyze qualitative data. The findings show that Artificial Insemination Technology remains an essential attribute for improving reproductive performance which may ultimately lead to high dairy productivity. Through binary logistic regression, the study depicted that age, gender, education status, extension services, household income, distance from AI centers and access to credit were statistically significant implying their positive contributions to the adoption of AI technology among small dairy farmers. For enhancing farmers' knowledge and skills on AI technology, the responsible authorities should allocate more resources for capacity building in productive areas. This intervention would increase the rate of AI adoption and ultimately, increase productivity in the dairy industry.
Keywords: Dairy Industry; Artificial Insemination; Technology Adoption; Small Dairy Farmers

1. Introduction

The livestock sector plays a significant role in sustainability of the world's economy and attainment of food security. According to Steinfeld et al (2006), livestock production systems occupy about 30% of the planet's ice-free terrestrial surface area. This sector employs more than one billion people in the world of which 60% of them are from rural households (Braun, 2010). Livestock production accounts for more than one third of the Global Agricultural GDP in developing countries. The use of technologies in the livestock sector enhances productivity, reduces threats of diseases and ensures environmental sustainability in productive areas (Kimunya, 2014)

The dairy industry plays an imperative role in improving the livelihood status of small dairy farmers. The presence of reliable markets for dairy products in developed and semi-developed countries creates an opportunity for dairy producers to allocate more resources for improved productivity and higher incomes. However, the level of dairy productivity in Sub-Saharan Africa remains low because of weak regulatory institutions, undesirable cultural practices and financial constraints. Bayei and Nache (2014) revealed that an average cow in Africa produces only 454 liters of milk per year compared to 5,630 liters for top dairy producers in the European Union. According to Ogola et al (2015), the principal constraints affecting dairy production in Sub Saharan Africa include: feed and nutrition, genetic structure, animal health problems and availability of appropriate technologies.

The dairy industry offers a pathway out of poverty for millions of small dairy farmers in Rwanda as well as service providers who engage in value addition throughout the supply chain (MINAGRI, 2013). The respective sub-sector contributes 15% to Agricultural Gross Domestic Product (AGDP) and 6% to Gross Domestic Product (GDP). According to Eugene (2017), the cattle population in Rwanda is dominated by the indigenous long horned Ankole cattle which have poor genetic potential and thus low productive capacity. Data from the Ministry of Agriculture and Animal Resources show that the country has 1.3 million cattle of which 28% are improved cattle producing 82% of total milk production (MINAGRI, 2013). This implies that the dominance of the indigenous Ankole cattle in the country lowers dairy productivity and thus negatively affects the wellbeing of

producers and other stakeholders in the respective industry. Having recognized the strategic importance of the dairy industry, the Government has made significant investments in order to increase productivity and tap into market opportunities within and outside the country. One of the strategies to modernize the dairy industry is the introduction of Artificial Insemination Technology (AIT). The dissemination of AIT involves different stakeholders namely; the Rwanda Agricultural Board (RAB), Local Government Authorities as well as private organizations that collaborate in different aspects with the aim of modernizing the dairy industry which employs millions of small dairy farmers in the countryside.

Artificial Insemination is the process by which sperms are collected from a male, processed, stored and artificially introduced into the female reproductive tract for the purpose of conception (Shehu et al, 2010). Foote (2002) postulates that AI supports maximum extension of the males' desired traits over a vast number of females. This process creates results that would be unachievable naturally. Galloway and Perera (2003) highlighted the point that infectious genital diseases in cattle spread through sexual contact. Therefore, through Artificial Insemination Technology, the risks of such diseases are minimized since the procedure itself is performed without physical contact. In addition, Eklundh (2013) articulated that with AI, cattle become healthier and their capacity to produce is increased resulting in improved livelihood status among dairy farmers.

The Rwanda Agricultural Board is the main regulatory authority responsible for allocating resources for procuring essential equipment for AI services. This intervention goes hand in hand with the improvement of livestock infrastructure in productive areas and recruitment of inseminators who provide AI services to small dairy farmers. Principally, the presence of AI technology in the country enables small dairy farmers to revolutionize the dairy industry by improving reproductive performance and thereby increasing productivity. Kangale (2017) revealed that, access to AI technology is a relevant factor contributing to high productivity in the dairy industry. The average output of milk per day for AI users in the country reaches 9 liters compared to 3 liters for their counterparts using natural mating.

Despite the dominance of the government's effort to disseminate AI technology in the country, the rate of adoption varies widely across different agro-ecologies and also within the same agro-ecology due to some socio-economic and institutional factors. Statistics from the Department of Agriculture and Natural Resources in Rwamagana District (2017) revealed that the rate of AI adoption in the respective district is 38% implying that 62% of the small dairy farmers in the study area continue using natural mating practices. Based on the indicated statistics, it is evident that the rate of AI adoption in Rwamagana district is still low. This study therefore focused on assessing factors affecting adoption of Artificial Insemination Technology among small dairy farmers in the respective district. Specifically, the study focused on exploring the attitude of small dairy farmers towards AI services and identifying socio-economic and institutional factors affecting adoption of AI technology in the study area.

2. Materials and Methods

2.1 Description of the study area

The study was conducted in Rwamagana District (1°57'S, 30° 26'E) situated in the Eastern Province of Rwanda with an area of 691.6 km^2. According to the National Population Census conducted in 2012, the total population of Rwamagana District is estimated to be 313,461.The district consists of 14 sectors namely; Fumbwe, Gahengeri, Kishari, Karenge, Kigabiro, Muhazi, Munyaga, Munyiginya, Musha, Mwunyumbu, Mwulire, Nyakariro,Nzige and Rubona. Agriculture and livestock rearing are the main economic activities employing the majority of people in the district.

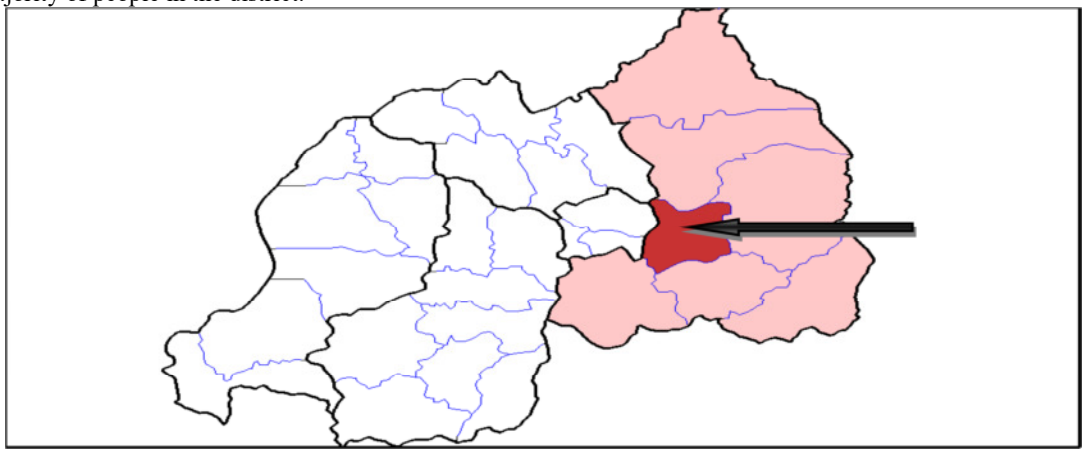

Figure 1: A Map of Rwanda (An arrow indicates the study area – Rwamagana District)

Rwamagana district accommodates approximately 8,311 small dairy farmers (38%) who adopted AI

technology for the sake of increasing productivity and improving their livelihood status. Therefore, data on AI practices were gathered from the appropriate respondents who possessed sufficient knowledge and skills on the essence of the respective technology and its operations in the study area.

2.2 Research Design

The study adopted a cross sectional design where by data were collected at a single point in time. According to Babies (1973), the design provides quick results and allows collection of data from groups with different characteristics. In addition, Masunga (2014) argues that this design has the highest degree of accuracy and precision as it saves time and resources. Principally, the study employed this design in order to minimize biasness and maximize reliability of the data collected from the respondents.

2.3 Sampling and Data Collection procedure

Both probability and non-probability sampling techniques were used to select the appropriate population sample. Rwamagana district was selected purposively, because it was one of the districts benefiting from the implementation of the AI programme. In addition, the same sampling technique was employed to select key informants such as inseminators, District Agricultural and Natural Resource Officer of the Rwamagana District and Senior Agricultural and Livestock Officials from MINAGRI because of having expertise in the area being researched. Through simple random sampling, two sectors namely; Kigabiro and Nzige were selected as well as 90 AI users and 30 non-users from the respective sectors. In addition, semantic differential scale was employed to explore the attitude of small dairy farmers towards Artificial Insemination Technology.

Semi-structured questionnaires were used to collect raw data from small dairy farmers (both AI users and non-users) while in-depth interviews were employed for the key informants. Secondary data were collected from the Ministry of Agriculture and Animal Resources (MINAGRI), Rwanda Agricultural Board (RAB) and the Department of Agriculture and Natural Resources of Rwamagana District.

2.4 Data analysis

Raw data were coded and analyzed using Statistical Package for Social Science (SPSS) computer software. Content analysis was used to analyze qualitative information whereas descriptive and inferential statistics were carried out for analyzing quantitative data. Descriptive statistics including frequency, percentages and mean were used to examine socio-economic characteristics of the respondents. Binary regression model was employed to estimate factors affecting adoption of AI technology by small dairy farmers. Etymologically, binary logistic regression is a form of regression which is used when the dependent variable is dichotomy (dummy) and the independent variables are of three types: nominal, ordinal and scale. The independent variables (predictors) relate directly with the dependent variable, either positively or negatively (Garson, 2008).

The empirical form of binary logistic regression model is given:-

$$\ln \{P/(1-P)\} = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + b_{10}X_{10} + \varepsilon_i$$

Where:

$\ln \{P/(1-P)\}$=Dependent variable (1= Adopter of AI technology; 0= Otherwise)

b_0 = Intercept term of the model.

b_1, b_2, b_3, b_4, b_5, b_6, b_7 and b_8 are the parameters need to be estimated.

Table 1: Definition of explanatory variables for logistic regression model

Variables	Type	Descriptions
Age	Continuous	Number of years for small dairy farmers
Gender	Dummy	(1= male;0= female)
Education status	Continuous	Number of years in schooling
Farming experience	Continuous	Number of years in dairy production
Land size	Continuous	Acres of land being accessed for dairy production (in numbers)
Household Income	Continuous	Amount of money earned from farm and non-farm activities
Extension services	Dummy	Technical services for dairy production (1= accessible;0= otherwise)
Marketing services	Dummy	(1=accessible; 0=otherwise)
Distance from AI centers	Continuous	Physical length between farmers' households and technological centers
Access to credit	Dummy	Amount of money accessed from financial institutions for improving dairy production (1= accessible;0=otherwise)

3. Results and Discussions

3.1 Respondents socio-demographic characteristics

According to Table 2, the age of AI users and non-users between 20-40 years were ranked the highest while

those greater than 60 years were the least. This indicates that most of the small dairy farmers in the study area are within the productive age and thus capable of boosting dairy production for improving their well being. Similarly, Quddus (2013) reports that small dairy farmers who are within the productive age can adopt and use new technologies more efficiently than aged farmers and thus manage to increase the level of productivity.

Table 2: Respondents' socio-demographic characteristics (n=120)

Characteristics		AI users **(n=90)**		Non-AI users **(n_s=30)**	
		No	**%**	**No**	**%**
Respondent's Age (Years)	20- 40	47	52.3	15	50.0
	41-60	35	38.8	11	36.7
	> 60	8	8.9	4	13.3
Respondent's sex	Male	50	55.6	16	53.3
	Female	40	44.4	14	46.7
Educational attainment	Primary Education	65	72.2	24	80.0
	Secondary Education	20	22.3	4	13.3
	Tertiary Education	5	5.5	2	6.7
Household members	1-4	48	53.2	14	46.7
	5-9	32	35.5	10	33.3
	> 9	20	22.3	6	20.0
Herd Size	1-5	52	57.8	8	23.3
	6-10	28	31.1	7	31.4
	> 10	10	11.1	15	50.0
Farmers' Experience (Years)	1-5	33	36.7	16	53.3
	6-10	38	42.2	10	33.3
	> 10	19	21.1	4	13.4
Dairy cattle breed	Ankole	12	13.3	20	66.7
	Cross breed	60	66.7	6	20.0
	Friesian/Jersey	18	20.0	4	13.3
Feeding system	Fodder	23	25.6	16	53.3
	Fodder and minerals	67	74.4	14	46.7

The findings revealed that 55.6% of AI users were males while 44.4% of the respondents were females. More results from the same variable indicated that 55.3% of non-users were males whereas 46.7% of the respondents were females. These findings imply that more males participate in dairy production than females.

Results in Table 2 show that the majority of small dairy farmers in the study area had attained primary education while the minority had post-secondary education. About 22.3% of AI users had secondary education compared to 13.3% for their counterparts using natural mating. Based on the indicated findings, it is evident that AI users are more educated than their counterparts using natural mating. Key informants reported that, educational attainment remains the underlying attribute for increasing the rate technological adoption among small dairy farmers in the study area.

Moreover, the results depicted that the highest percentages (53.2% of AI users and 46.7% of non-users) had less than five household members. Only 22.3% of AI adopters and 20% of non-adopters had more than nine household members. This implies that household size can determine the number of laborers in the dairy industry. Households with a large number of family members have sufficient workers to work in the respective industry compared to households with a small number of family members. Dihinenet et al (2014) noted that household size has a positive relationship with dairy production and income generation among small dairy farmers.

The findings indicated that non-users possessed more dairy cows than their counterparts accessing AI services. Differences in possession of dairy cows prevailed because natural mating users intended to maintain high levels of productivity in their households. However, reports from the Department of Agriculture and Natural Resources of Rwamagana District revealed that the level of productivity among small dairy farmers using natural mating continues to be low because of improper farm management practices and inaccessibility to dairy technology.

With regards to farmers' experience, the study identified that most AI users had between 6-10 years' experience in dairy farming whereas the minority had more than 10 years' experience in the respective production role. In contrast, the findings reported that the majority of non-users had between 1- 4 years' experience whereas the minority (13.4%) spent more than 10 years in the same productive role. This infers that farmers' experience has a positive impact on adoption of Artificial Insemination Technology in the study area.

The study findings revealed that small dairy farmers in Rwamagana district kept different types of dairy cattle breeds. The majority of AI users kept cross breeds while 20% of them had exotic breeds. Results in Table 2 indicated that 13.3% of non-AI users kept cross breeds whereas 76.7% of them had the indigenous cattle

(*Ankole*). According to key informants, most AI users' prefer improved cattle breeds as they have a greater capacity to produce large quantities of milk compared to the traditional ones. However, some respondents argued that they prefer Ankole breeds because of easier management and higher tolerance towards tropical diseases. Eugene (2017) and Kugonza et al (2001) revealed that, Ankole cattle have an advantage of being highly adaptable to adverse environmental conditions and are believed to be high producers of quality milk and beef.

The results indicated that 74.4% of small dairy farmers accessing AI services fed their cattle with fodder and minerals while 25.6% of them fed their cattle with fodder only. Similarly, the findings revealed that 53.3% of farmers using natural mating fed their cattle with fodder only whereas 46.7% of them fed their cattle with fodder and minerals. This suggests that, the majority of small dairy farmers grow improved fodder grasses which contain a high percentage of protein and ultimately meets dietary requirements of the dairy cattle.

3.2 Attitude of small dairy farmers towards Artificial Insemination Technology

Results in Table 3 revealed that 105 respondents (87.5%) affirmed the statement that "AI services improve the reproductive performance among indigenous cattle and make them more productive" whereas 15 respondents (12.5%) opposed this statement. According to key informants, AI services enable small dairy farmers to access higher producing cattle through genetic improvement. This indicates that the respective breeding technology remains one of the essential attributes for enhancing productivity in the dairy industry.

The findings also indicated that 98 small dairy farmers (81.7%) agreed with the statement that "AI technology minimizes the risk of diseases transmission between/among dairy cows" while 22 small dairy farmers denied this statement. The results are in line with Boa-Amposem and Minozzi (2006) who concluded that proper utilization of AI technology enhances the efficiency in genetic selection and thus reduces the danger of spreading infectious genital diseases between/among the dairy cows.

Table 3: Respondents' attitude towards AI Technology (n=120)

Attitudinal statement	Agree	Disagree
Artificial Insemination services improve the reproductive performance among the indigenous cattle and make them more productive	105(**87.5**)	15 (**12.5**)
AI Technology minimizes the risk of diseases transmission between/among dairy cows	98 (**81.7**)	22 (**18.3**)
AI Technology is simple, quick and affordable	109 (**90.8**)	11 (**9.2**)
Proper use of AIT leads to high dairy productivity at the household level	104 (**86.7**)	16 (**13.3**)
Adoption of AIT is essential for the development of dairy industry	101 (**84.2**)	19 (**15.8**)

NB: Numbers in Brackets indicate percentages

About 109 respondents (90.8) perceived AI as simple, quick and affordable technology while 11 respondents (9.2%) denied the statement by pointing out the complexity of this technology to the beneficiaries. This implies that AI technology is simple to use and that small dairy farmers can access the service at affordable prices. Yohannes (2014) argues that, AI technology can be adopted rapidly because it does not require the adopter to develop new skills and understanding.

Table 3 further shows that 104 respondents (86.7%) agreed with the statement that "proper use of Artificial Insemination Technology can lead to high productivity in the dairy industry" while 16 respondents (13.3%) opposed this statement. According to key informants, the presence of AI services together with other agricultural services such as extension services, marketing facilities and micro-credit enable AI users to produce an average of 9 liters of milk per day compared to their counterparts whose maximum level of milk productivity cannot exceed 4 liters per day. This implies that adoption of AI technology is one of the attributes contributing to high productivity in the dairy industry.

According to Table 3, most of the respondents (84.2%) perceived AI technology as an essential attribute for development of the dairy industry in the country whereas the minority opposed this statement. Key informants affirmed that provision of AI services enables the adopters to access technical and institutional support such as financial services, marketing and entrepreneurship training from other actors in order to stimulate production and improve their livelihood status.

Based on the indicated findings from Table 3, it is evident that the majority of AI users and non-users have a positive attitude towards the AI technology. Therefore, it is obligatory for the responsible authorities to create a conducive environment for small dairy farmers living in the peripheral to join the programme and become active stakeholders in the whole process of modernizing the dairy industry in the country.

3.3 Socio-economic and Institutional factors affecting adoption of AI technology

The study employed the binary logistic regression model to assess socio-economic and institutional factors affecting adoption of AI technology in Rwamagana district. Considering the summary in Table 4, Cox and Snell R^2 suggests that 64.2% of the variation in the dependent variable was explained by the logistic regression model. The Nagelkerke R^2 value was 74.6% implying that the independent variables used in the model explained the

indicated percentage of variance in the dependent variable.

In Table 4, the Wald statistic value of education status (52.421) was the highest and statistically significant at 1% (p=0.000). The implication of this finding is that, small dairy farmers with higher education status are more likely to adopt AI technology compared to their counterparts with lower education status. According to Ogola et al (2015), small dairy farmers with higher education status can adopt new technologies in order to improve production practices and enhance productivity. In addition, Oyo et al (2007) pointed out that higher education propels small dairy farmers to adopt new innovations and technologies which are vital for enhancing productivity and improving farmers' household income.

Table 4: Socio-economic and Institutional factors influencing the rate of AI adoption

Variables	B	S.E	Wald	Sign	Exp
Age	-2.013	0.122	14.421	0.004*	1.013
Gender	2.032	0.021	15.703	0.004*	0.969
Education status	6.472	0.431	52.664	0.001***	0.604
Farming experience	-0.012	1.019	2.351	0.457 NS	1.022
Land size	-0.031	1.218	1.204	0.214 NS	0.971
Household Income	4.019	0.426	38.892	0.001***	0.119
Extension services	5.041	0.018	45.239	0.001***	1.042
Marketing services	0.022	2.021	3.062	0.348 NS	1.022
Distance from AI centers	5.091	0.235	46.089	0.000 ***	0.914
Access to credit	3.302	0.016	18.768	0.000 ***	2.011
Constant	1.884	3.781	1.385	0.536 NS	0.154
Cox & Snell R Square=0.642					
Nagelkerke R Square=0.746					
-2 Log likelihood =82.774					
Chi-square=35.675					

Note: NS represents non significant while *, **, ***, represents level of significance of parameter at 10, 5 and 1 percent.

Extension service was highly significant at 1% with Wald statistic value of 45.239. This indicates that small dairy farmers who access extension services regularly are more likely to adopt AI technology compared to their counterparts who rarely access the respective services. According to Namwata et al (2010), regular contacts with extension agents enable small dairy farmers to access information about new dairy technologies and ultimately, use them for enhancing productivity and ensuring food security at the household level. Likewise, Idrisa et al (2012) pointed out that extension contact determines the information that farmers obtain on production activities and the procedures of cattle breeding using Artificial Insemination.

Distance from AI centers was positively signed and highly significant at 1% level of probability. This implies that small dairy farmers who live closer to AI centers are more likely to adopt and use the technology compared to their counterparts who live farther away from the respective centers. Similarly, Quddus (2012) postulates that distance from technological centers can determine the level of adoption among small dairy farmers. As the distance from technological centers increases, the rate of adoption to dairy technologies decreases because of the costs incurred in the whole process of obtaining technological information from the agricultural experts.

The Wald statistic value of Household income (38,892) was highly significant at 1% (p=0.001), suggesting that small dairy farmers with higher income have the capacity to procure and ultimately adopt AI technology earlier than those with lower income status whose economic base remains weak in accessing such services. According to Temba (2011), wealthier farmers can incur the costs of adopting new technologies and thus improve productivity in the dairy industry. In addition, Tefera et al (2014) stated that a strong financial base enables farmers with high income to adopt new dairy technologies earlier than their counterparts with low income. Wealthier dairy farmers can procure new technologies and improve agricultural practices for enhancing productivity and ensuring food security.

Access to credit was the fifth predictor of dependent variable with Wald statistic 18,768, which was also highly statistically significant at 1% (p=0.001). This implies that small dairy farmers who access credit from the financial institutions are more likely to adopt AI technology compared to those who cannot access credit. Similar findings are reported by Mohamed and Temu (2008) in which they found that access to credit stimulates dairy technology adoption. Likewise, Sintowe and Zeller (2006) articulated that access to credit promotes the adoption of risky dairy technologies through relaxation of the liquidity constraint as well as through the boosting of household's risk bearing ability.

Gender was also statistically significant at 5% implying its positive contribution to AI adoption in the study area. The findings signify that the rate of AI adoption is more likely to be higher in households which involve both men and men in dairy production compared to the households which involve one sex in the respective

productive role. However, Chi and Yamada (2002) have a different opinion arguing that low level of education among women is one of the key bottlenecks of AI technology adoption in rural communities. In addition, Chelkeba et al (2016) found that progress in rural women participation towards improved technologies is not satisfactory and needs emphasis as they are characterized by dependency and resource constraints.

The Wald statistic value of age (14.421) was the least and statistically significant at 5%. This suggests that the rate of AI adoption decreases as small dairy farmers get older. Thus, the young dairy farmers are more likely to adopt AI technology compared to the older dairy farmers. This situation prevails because the majority of young dairy farmers in the study area perceive AI technology as one of the attributes for increasing the level of productivity in the study area. Their positive attitude contributes positively to the adoption of AI technology in the study area. According to Adekoya and Ajayi (2000), the aged dairy farmers rely on old and traditional production practices which do not have any significant impact on productivity. They tend to stick to what they are used to and hardly venture into new ways of doing things. Likewise, Onazi (1978) postulates that the rate of technology adoption among the older farmers is low because of their tendency of relying on outdated practices.

However, the findings depicted that farming experience, land size and marketing services were insignificant to the existing dependent variable implying that their operations do not have any positive influence on adoption of AI technology in the study area. This signifies that adoption of AI technology by small dairy farmers is influenced with education status, extension services, household income, distance from AI centers, age of respondents and gender.

4. Conclusion and Recommendations

The dairy industry plays an indispensable role in improving the livelihoods of people in rural Rwanda. The use of Artificial Insemination ensures enormous socio-economic benefits among the small dairy farmers and other actors involved in the value chain system. Based on the empirical findings, it is evident that the majority of small dairy farmers in Rwamagana district have shown a positive attitude towards AI technology by exploring its necessity in increasing productivity through the genetic improvement of their stock. Similarly, the study found a positive relationship between educational attainment, farming experience, extension services, distance from AI centers and household income and adoption of AI technology by small dairy farmers.

Therefore, the study recommends that the responsible authorities such as the Rwanda Agricultural Board (RAB) and Local Government Authorities should continue to allocate more resources for capacity building programmes in productive areas. This intervention would enhance farmers' knowledge and skills on the respective technology and dramatically increase the rate of AI adoption. Also, the Local Government Authorities should strengthen semi-formal financial institutions such as Umurenge SACCOS in order to create favorable environment for small dairy farmers in rural areas to access financial services namely; savings, credit and remittances. The presence of financial resources at the household level would enable dairy farmers to adopt new dairy technologies and hence improve productivity.

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