Characterization and Determinants of Smallholder Dairy Farmers in Rwanda

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DOI: https://dx.doi.org/10.47772/IJRISS.2025.90300207

Received: 21 February 2025; Accepted: 28 February 2025; Published: 08 April 2025

ABSTRACT

Dairy farming enhances food security and drives economic growth in Rwanda. While existing literature on dairy farming has primarily examined its production factors and the challenges associated with it, there is a gap in the literature in understanding the characteristics of dairy farmers and the factors that determine dairy farming in Nyabihu District. Using cross section data of 205 dairy farmers in Nyabihu District, Rwanda, we employed Principal Component Analysis and Cluster Analysis to characterize dairy farmers and identify determinants of dairy farming. Results show that dairy farmers are grouped in two clusters low resource endowed and low production and high resource endowed and high production categories. Clusters of dairy farmers are shaped by experience in dairying, age, monthly farming cost, milk produced per month, Herd size, Land size, and the number of dairy trainings received. The study suggests the need to train best practices in dairy farming to increase their efficiency and returns. Through training, well informed farmers make better decisions along all factors of production. Also, more investment in herd management and farm land allocation potentially increases productivity.

Keywords: Dairy farming, dairy farmer's characteristics, Rwanda, cluster analysis, principal component analysis.

INTRODUCTION

Dairy farming plays a crucial role in global food security by providing essential nutrients and supporting economic livelihoods and rural development (FAO, 2018). Global milk production in 2023 was estimated at 965.2 million tonnes, with 84.7 million tonnes traded internationally (FAO, 2024a). In Africa, milk production reached 53.8 million tonnes in 2023, indicating stable production (FAO, 2024b). Rwanda has seen a steady increase in milk production, rising from over 121,400 tonnes in 2005 to over 891,326 tonnes in 2020, and reaching 1,061,301 tonnes in 2023 (MINAGRI, 2023).

Dairy products like milk, cheese, and yogurt supply crucial nutrients such as protein, calcium, and vitamins (Shah *et al*., 2023). Technological advancements and innovative practices, including precision agriculture and automated milking systems, have enhanced efficiency, sustainability, and animal welfare in dairy farming (Kaur *et al*., 2023). As consumer demands and sustainability needs evolve, dairy farming continues to play a significant role in global food systems and agricultural economies.

While existing studies have examined the improvement of dairy farming systems (Ojango *et al*., 2017) and dairy marketing (Erato *et al.,* 2024), there is limited empirical research on the characteristics of dairy farmers and the factors influencing dairy farming in Rwanda , a case study of Nyabihu District. Previous research in Rwanda has mainly focused on production systems (Mazimpaka, 2017) and milk processing (Hirata, 2018), highlighting the need to understand the current status of dairy farming in Nyabihu to further develop this strategic subsector for increasing district revenue and farmers' income.

The present study aims to characterize dairy farmers in Rwanda, a case study of Nyabihu District and to analyze determinants of dairy farming. The study thus complements the study of Mazimpaka (2017) on the characterization of cattle production systems in Eastern Province of Rwanda which was recommended to adopt effective supplementation and improved pastures. Karege *et al*. (2021) analyzed livestock production systems and showed that improved feeding are key potential for enhancing productivity in Nyanza District, Rwanda. The study further complements the study of Mikhail *et al*. (2017) who analyzed the producers characteristics in the dairy value chain analysis by doing the analysis of farmers' markets characteristics and recommended to increase the interventions that focus on increasing the market for raw milk. Overall, the study aims to provide insights on characterization and determinants of dairy farming in order to inform appropriate policies for the sub-sector.

LITERATURE REVIEW

This paper reviews the available literature linking to the characterization and determinants of smallholder dairy farmers in Rwanda. Smallholder dairy farming in Rwanda operates within a complex socioeconomic landscape, influencing both farm characteristics and farmer decision-making. The Socioeconomic Model of Agricultural Marketing provides a framework for understanding how factors like farm size, resource access, education, infrastructure, and household demographics shape farm productivity and market participation. These factors influence the scale of operations, the adoption of improved technologies, and the ability to access and benefit from market opportunities. As researchers have found (Abate, 2020; Ma, Abdulai, & Goetz, 2020), this model is instrumental in analyzing the diverse characteristics of smallholder farms and their varied levels of engagement in the market.

Furthermore, Transaction Cost Economics (TCE) plays a crucial role in explaining farmers' choices regarding market participation. The costs associated with searching for buyers, negotiating prices, and ensuring contract enforcement, especially given the perishable nature of milk and often limited access to formal markets, significantly influence farmers' decisions. Researchers have demonstrated (Brown & Potoski, 2005; Key et al., 2000; Pingali et al., 2005) how TCE helps illuminate the challenges smallholders face in minimizing these transaction costs and the strategies they employ to navigate market imperfections. Complementing this, Behavioral Economics offers insights into the non-rational aspects of farmer behavior, including the role of trust in established buyers, risk aversion towards new technologies or market approaches, and the influence of social norms and community practices. Studies have used these behavioral insights (Thaler & Sunstein, 2008) to explain why some farmers may be slow to adopt innovations or prefer traditional methods, even when presented with potentially more profitable alternatives. Collectively, these theoretical lenses, as explored by various researchers, provide a robust framework for understanding the multifaceted nature of smallholder dairy farming in Rwanda.

Several studies have employed farm typology analysis to understand the diverse characteristics of smallholder farming systems and inform targeted interventions. Goswami et al. (2014) used principal component analysis (PCA) and cluster analysis (CA) to categorize 144 households in West Bengal, India, based on income sources. Their findings revealed distinct farm clusters with varying levels of gross returns, cultivation costs, and cost-benefit ratios, highlighting the need for tailored advisory services and improved access to inputs and credit. Similarly, Kuivanen et al. (2016) applied PCA and CA to characterize 70 smallholder farms in Northern Ghana, identifying farm types based on land use, labor, income, and livestock ownership. This approach allowed them to understand the resource constraints and opportunities for innovation within different farm typologies. Woomer et al. (2016) investigated small-scale farming systems in West Kenya, using a survey of 291 households to describe farming operations and conditions. Their research revealed significant gender disparities in land ownership, income, and resource utilization, emphasizing the importance of considering such differences in agricultural interventions. These studies collectively demonstrate the value of farm

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue III March 2025

typology analysis in understanding the heterogeneity of smallholder farming systems and developing targeted support strategies.

MATERIALS AND METHODS

This study employed a mixed-methods approach with a cross-sectional survey design to analyze the characteristics of dairy farmers and the factors that determine dairy farming in Rwanda, A case of Nyabihu District. Quantitative data on socioeconomic characteristics, and farm attributes were collected using structured questionnaires. Qualitative data exploring perceptions and rationales were gathered through focus group discussions.

The study was carried out in Nyabihu District, Western Province in Rwanda, focusing on areas known for their high milk production.

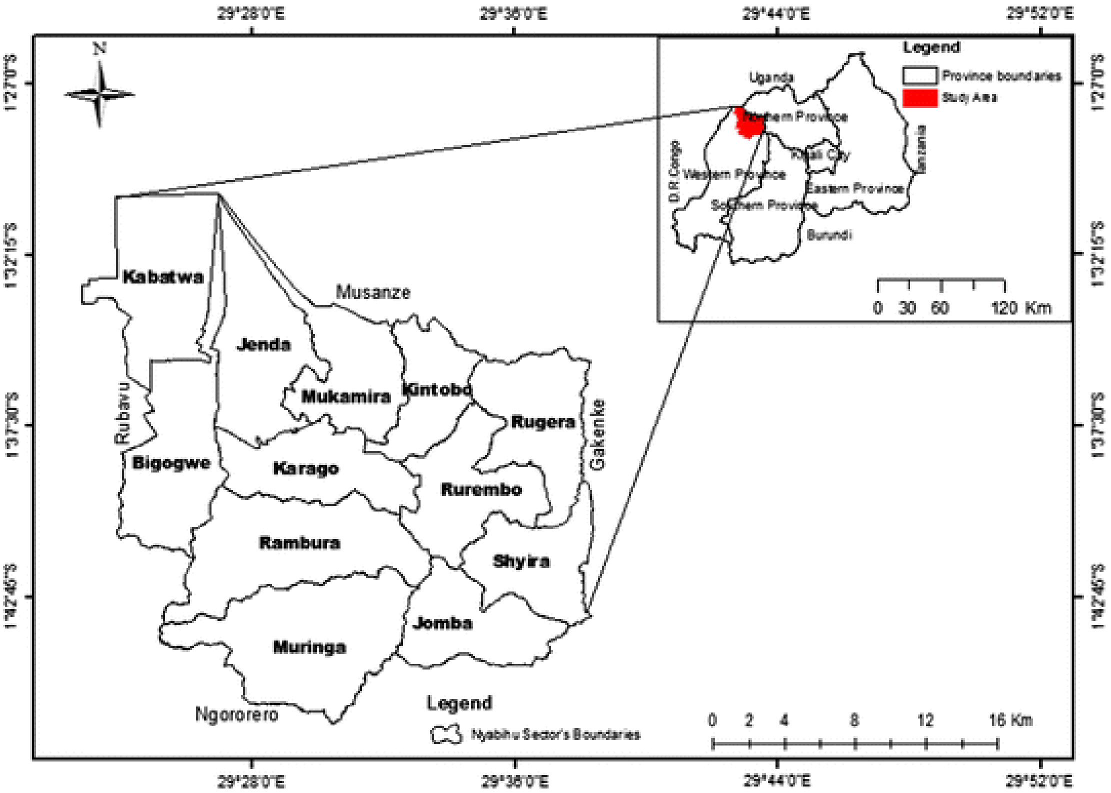

Figure 1. Map of Nyabihu District Source: Nahayo *et al.*, (2017)

The study used multistage sampling stages, among others, which are purposive sampling and simple random sampling. In the first stage, we used purposive sampling by choosing three (3) sectors over twelve (12) sectors based on criteria of high milk production and the availability of various marketing channels in the area. The three sectors that were selected are Mulinga, Bigogwe and Rambura. Finally, simple random sampling was used which means every dairy farmer had an equal chance of selection. The list of total household heads in the selected sectors was obtained from the sector office.

According to Glenn (2013) when calculating a sample for large populations is advisable to use $\mathbf{n} = \frac{z^2pq}{e^2}$ Equation 3.1 the formula developed by Cochran 1963 to yield a representative sample for proportions. Which is valid where n_0 is the sample size, Z^2 is the abscissa of the normal curve that cuts off an area α at the tails (1 - α equals the desired confidence level, e.g., 95%)1, **e** is the desired level of precision, p is the estimated proportion of an attribute that is present in the population, and q is 1-p. The value for Z is found in statistical tables which contain the area under the normal curve. As we do not know the variability in the proportion to choose one marketing channel to another; therefore, assume p=0.5 (maximum variability) with 95%

confidence level. The migratory nature of the population under study makes it difficult to find the precise sample size in the time allocated for fieldwork. In order to address this, the precision/accuracy level was increased from the typical +5% to +7%.

The resulting sample size is demonstrated in Equation 3.1

$\mathbf{n} = \frac{z^2pq}{e^2}$ where **n** represent sample size

$\mathbf{n} = \frac{(1.96)^2 * 0.5 * 0.5}{0.7^2}$ **= 205 farmers**

Data collected used structured questionnaires between October and December 2023 and was analyzed using descriptive statistics and a two stage multivariate statistical technique was applied, involving Principal Component Analysis (PCA) and Cluster Analysis (CA), to categorize dairy farmers in Nyabihu. PCA was utilized to condense the original interdependent variables into a smaller set of independent variables, thereby reducing the dimensionality while preserving the essential information. These new independent variables, known as components, were then used in CA to identify distinct typologies of dairy farmers. By employing PCA, the correlated variables were effectively transformed into smaller sets of uncorrelated variables, as described by Soni (2018). PCA relies on the assumptions of data interdependence normality, matrix factorability, and sampling adequacy, which were validated using the Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity (BTS). Eleven socioeconomic variables were analyzed using PCA, which condensed them into principal components; these components were then rotated using the varimax method, grouping highly correlated variables under each factor. VARIMAX was chosen for its ability to simplify interpretation by maximizing variance within each factor, creating uncorrelated, easily interpretable components. It groups highly correlated variables distinctly, ensuring clear, independent factors, ideal for reducing data complexity.

Factors with an eigenvalue above one were retained, following the Kaiser criterion, which is suitable for datasets with fewer than 30 variables (Soni, 2018). The retained factors from PCA were used in CA to classify dairy farmers based on their attributes. A two-step clustering method of hierarchical and partitioning clustering was employed to determine the number of clusters. Hierarchical agglomerative clustering using Ward's method defined the initial categories, which were then refined using partitioning. A dendrogram helped identify meaningful clusters. Finally, ANOVA was conducted to assess variance differences between clusters, testing the hypothesis that dairy farmers do not differ in characteristics.

RESULTS AND DISCUSSIONS

The summary descriptive characteristics of the respondents in Nyabihu District, Rwanda include the socioeconomic and market characteristics of the dairy farmers. Table 1 shows the socio-economic traits of dairy farmers, revealing notable divergences among Bigogwe, Mulinga, and Rambura, underscoring distinct profiles within these segments.

Table 1 : Socioeconomic Characteristic of Dairy farmers

Description	**Bigogwe (%)**	**Mulinga (%)**	**Rambura (%)**
Household Size (Mean)	4.5	6.6	5.4
Experience years in dairying (Mean)	16.4	9.7	10.5
Herd size (Mean)	7.3	10.5	4.8
Land owned in Hectares (Mean)	1.2	1.4	0.1
Number of dairy trainings received(Mean)	1.2	2.2	0.5

Source: Author's computation based on 2023 survey data.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue III March 2025

Table 1 compares household size, dairying experience, herd size, land ownership, and dairy training across three regions: Bigogwe, Mulinga, and Rambura.

Mulinga households are the largest, with an average size of 6.6 members, followed by Rambura (5.4) and Bigogwe (4.5). Bigogwe farmers have the most dairying experience, with an average of 16.4 years, compared to 10.5 years in Rambura and 9.7 years in Mulinga. Mulinga leads in herd size, averaging 10.5 cows, while Bigogwe and Rambura trail with 7.3 and 4.8 cows, respectively. Regarding land ownership, Mulinga farmers own the most land (1.4 hectares), followed by Bigogwe (1.2 hectares), while Rambura farmers own very little land (0.1 hectares). Mulinga also leads in dairy training, with an average of 2.2 training sessions received per household, compared to 1.2 in Bigogwe and only 0.5 in Rambura, indicating higher capacity-building efforts in Mulinga.

The Kaiser-Meyer-Oklin (KMO) and Bartlett's Test of Sphericity were conducted before conducting PCA, and the results are presented in Table 2.

Table 2 : Kaiser-Meyer-Olkin and Bartlett's Test of Principal Components

Measure	Value
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.734
Bartlett's Test of Sphericity	
Approx. Chi-Square	1631
Degrees of Freedom	66
P-value	0

Source: Author's computation based on 2023 survey data.

The data has adequate properties for principal component analysis based on the Kaiser-Meyer-Olkin measure of 0.734 and Bartlett's test of sphericity value of 1.631E3 with p=0.00. Principal components with eigenvalues above 1 are retained according to Kaiser's rule. Table 3 indicates that out of the various resulting components, four had eigenvalues exceeding the threshold value.

Table 3: Components and Total Variance Explained

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	4.483	37.356	37.356
2	1.581	13.177	50.533
3	1.194	9.948	60.481
4	1.049	8.744	69.225
5	0.862	7.18	76.405
6	0.798	6.652	83.057
7	0.611	5.092	88.149
8	0.545	4.545	92.693
9	0.441	3.674	96.368
10	0.339	2.825	99.193
11	0.086	0.719	99.912
12	0.011	0.088	100
Extraction Method: Principal Component Analysis.			

Source: Author's computation based on 2023 survey data.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue III March 2025

The PCA results show that the first four components have eigenvalues greater than 1, explaining 69.225% of the total variance, indicating they capture the most significant patterns in the data. The first component alone accounts for 37.356% of the variance, while the next three components contribute 13.177%, 9.948%, and 8.744%, respectively, cumulatively explaining the majority of the variance in the dataset.

Figure 1. shows the scree plots for the retained eigenvalues. In this analysis, 4 components met this criterion and were retained.

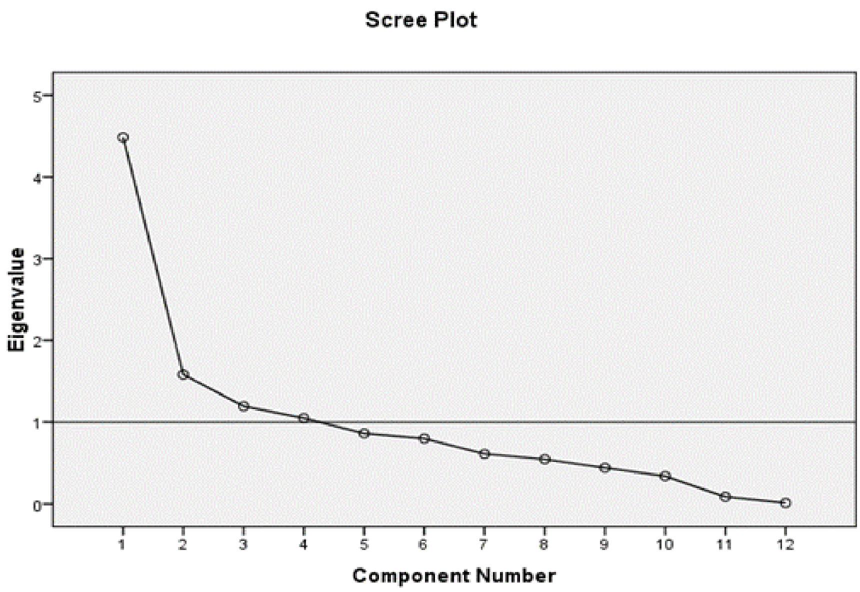

Figure 1 : Scree Plot for Eigenvalues

Source: Author’s computation based on 2023 survey data.

Table 4: Principal Components Factor Loading

Factor and Item description	Factor Loadings	% Variance Explained
Factor 1: Milk output		37.356
Monthly milk produced	0.803	
Monthly milk sold	0.808	
Monthly cost	0.682	
Factor 2: Input and Services		13.177
Membership in cooperative	0.702	
Number of dairy trainings received	0.803	
Herd size	0.557	
Factor 3: Socio demographics		9.948
Age	0.781	
Household size	0.705	
Experience in dairying	0.588	
Factor 4 : Resource Capital		8.744
Monthly income from Non-Dairying	0.764	
Educational Level	0.717	

Source: Author’s computation based on 2023 survey data.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue III March 2025

The first principal component, which accounted for 37.3% of variance, is the milk output factor comprising monthly milk quantity, milk sales, and milk costs. The second component is the milk input factor (13.1%), including herd size and elements of training and cooperative participation. The third component, the socio-demographic factor (9.948%), consists of farmer age, household size, and dairying experience. Finally, the fourth component (8.7%) is the household human and financial capital factor made up of off-farm income and education levels. In summary, the PCA highlights that milk output and input technical factors along with socio-demographic and income attributes emerge as important dimensions for characterizing differences across this dairy farming population using these principal components.

The four principal components from the PCA were utilized in a subsequent cluster analysis to segment the dairy farming population based on those factors. Table 5 demonstrates, the cluster analysis revealed heterogeneity across two distinct dairy farmer groups that emerged. The households were classified into clusters that differ in terms of socioeconomic traits and PCA-based characteristics. The results from ANOVA indicated that two distinct types of dairy farmers exist as shown.

Table 5 : Characteristics of the Clusters Based on the Means.

Socio-economic characteristics	Cluster 1	Cluster 2	F value	P Value
Age	43.48	48.3	5.678	0.018
Experience in dairying (years)	10.08	19.7	42.623	0
Household Size	5.53	5.47	0.022	0.883
Herd size	5.73	13.94	32.512	0
Milk produced per Month (Liters)	517.22	1429.47	45.257	0
Land owned (hectares)	0.6878	1.644	8.085	0.005
Milk sold per Month (Liters)	395.89	1215.32	43.465	0
Monthly farming cost (Rwandan francs)	37002	98342	278.4	0
Number of dairy trainings received	1.2215	1.7021	4.434	0.036
Cluster frequency	158	47		
Cluster distribution (%)	77%	23%		

Note: 1$=1290 Frw.

Source: Author’s computation based on 2023 survey data.

The significant variance across the clusters in traits like herd size, monthly milk output, sales volumes and costs suggests Cluster 2 as a more specialized commercial activity compared to Cluster 1 operating at a small scale.

Typology 1 (Cluster 1): Low resource endowed and low production

This cluster comprises 158 households, representing 77% of the study sample. Households in this group are characterized by limited resources and low milk production. The average milk production per household in this group was 517.22 liters per month, significantly lower than the other cluster. Despite their low production, respondents had an average of 8 years of education, indicating a moderate level of schooling. Their land ownership was also limited, with an average of 0.68 hectares per household, restricting their potential for larger-scale farming operations. Milk sales were modest, with households selling an average of 395 liters per month, which reflects the group's lower production capacity. Additionally, these households had lower incomes from other sources, suggesting they rely more heavily on subsistence farming than commercial activities. Overall, this group is less commercialized and operates with fewer resources, which limits both their production and income generation compared to other clusters.

Typology 2 ((Cluster 2): High resource endowed and high production

This cluster appears to represent individuals with a higher average age, larger herd and land size, substantial milk production and sales, and a higher level of income from non-dairying activities. These individuals may be more involved in commercial dairy farming, focusing on higher productivity and diversification. This group was made up of 47 households who represented approximately 24% of the study sample. The respondents in this cluster had a mean of 19 years of dairy farming; hence they were more experienced. In terms of land ownership, farmers in this group, owned land with an average size of 1.6 hectares, which was the highest among the 2 groups. The production volume of this group was far higher than cluster 1 with a monthly average of 1429.47 litres. They are more commercialized than cluster 1 with HCI of 80%.

Factors influencing clusters variations in dairy farming

The results of PCA and CA as detailed in Table 4 and Table 5 revealed the factors contributing to variations among dairy farmers including experience in dairying, age, monthly farming cost, milk produced per month, Herd size, Land size and number of dairy trainings received.

The age of the household head varies among the two clusters. Farm families in cluster 1 are seen to have 5 years younger to the Cluster 2. Some studies thus find the age of a household head to positively influence food production (Kansiime, 2021). The finding also agrees with the study of Adegun *et al.,* 2023 and Oke *et al.*, 2021 as household head age advances, it's likely that output increases, possibly due to the accumulation of knowledge and experience gained through years of observing and experimenting with different production methods.

Experience in dairying significantly varies among the clusters. The study finds a substantial difference in dairy farming experience between Cluster 1 (10.08 years) and Cluster 2 (19.70 years) ($F = 42.623$, $p = 0.000$), indicating that accumulated knowledge and skills acquired over many years significantly contribute to the observed clustering patterns (Barua *et al.,* 2018). Greater experience enables farmers to utilize superior strategies and practices related to management, feeding, housing, calf rearing, fertility control, record keeping, etc. that enhance the productivity and profitability of dairy operations. The study thus emphasizes that variations in hands-on dairy farming experience result in typological differences between farmer clusters and highlights the multifaceted impact of experience on smallholder dairies.

Monthly farming cost significantly varies among the clusters. The study found a major difference in monthly costs between Cluster 1 (37,002 Rwandan Francs) and Cluster 2 (98,342 Rwandan Francs) ($F = 278.334$, $p = 0.000$). This suggests Cluster 2 is investing more in resources, technology, or herd management, potentially increasing productivity or quality. Operational costs play a role in shaping smallholder farming types, with market dynamics and food safety influencing costs. The study underscores understanding production costs for sustainable milk production, aligning with Viira *et al.* (2015). Variations are attributed to location, production intensity, feed quality and pricing. Labor costs also contribute to farming typology, emphasizing labor management's importance for optimization, as Panda and Samanta (2018) noted.

Milk Produced per Month (Liters) significantly varies among the clusters. The study found a substantial difference in monthly milk production between Cluster 1 (517 liters) and Cluster 2 (1,429 liters) ($F = 45.257$, $p = 0.000$). Cluster 2's significantly higher output highlights a key productivity factor. According to Zijlstra *et al., (*2015) the difference was due to better breeding, herd management or technology access, showcasing efficiency's pivotal role in distinguishing the clusters and this emphasizes productivity and efficiency factors that set apart smallholder dairy farming approaches.

Land Owned (Hectares) significantly varies among the clusters. Differences in land ownership (0.6878 hectares in Cluster 1 and 1.6440 hectares in Cluster 2, $F = 8.085$, $p = 0.005$) influence clustering, indicating that larger land holdings in Cluster 2 facilitate expanded grazing and support extensive dairy infrastructure, potentially increasing production capacities (Hyland *et al.,* 2018). Land is crucial in dairy farming, determining farming types and impacting factors like stock, feed availability, and workload. Limited land access or dependence on leased land constrains dairy enterprise decisions, while rented land may prioritize short-term profit but limits infrastructure development. The study of Brandt *et al.,*(2018) supports findings that small land holdings compromise fodder productivity, increase costs, and pose a threat to dairy farmers. Land also serves as collateral, influencing financial capacity in dairy farming.

Number of dairy trainings received significantly varies among the clusters. Type 2 had more access to training compared to type 1. Training is an important factor in dairy farming. Training empowers dairy farmers with information on best animal husbandry practices, milk handling and marketing skills and regulations. Well informed farmers make better decision on where to sell to. These findings are in agreement with the study by Adeyonu *et al*. (2016) who found out that training promoted sweet potato value addition in Nigeria.

CONCLUSION AND RECOMENDATIONS

This study investigated the dairy farmers characterization and determinants of dairy farming using a sample of 205 dairy farmers from Nyabihu District. Descriptive, principal component, and cluster analysis techniques were used in the analysis. From the study findings, it can be concluded that the majority of dairy farmers were male. Dairy farmers would generally be categorized into 2 clusters namely low resource endowed and low production and High resource endowed and high production. The factors that caused variations in dairy farming were age, experience in dairying (years), number of dairy trainings received, monthly cost, milk produced per month (liters) and land size.

In line with the above conclusion, the study suggests the following recommendations. First, it is important to empower farmers through training to increase their knowledge of best animal husbandry and marketing practices which improves their returns. As dairy farming needs a slightly higher production cost, there is a need for the government, NGO partners, community partners and other stakeholders to support dairy farmers in groups or cooperatives for easy access to subsidies and credit.

Finally, future research could investigate the effects of targeted interventions, such as training and participation in collective action initiatives, on dairy farm outcomes (productivity, profitability), focusing on differentiated typology needs. The study has some limitations including the geographically constrained sample, which may limit the transferability of findings to other regions with different agro-ecological and socio-economic contexts.

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ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue III March 2025

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