# Knowledge Roles in Agricultural Information Networks: Evidence from Dairy Information Networks in Nakuru County, Kenya

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## Abstract

With social networks increasingly becoming important in the determination of critical social and economic outcomes, this paper interrogates knowledge roles in dairy information networks in Nakuru County, Kenya. Multi-stage sampling is used to select 390 dairy farmers operating in formal and informal dairy networks. Multinomial logit regression is used to evaluate the determinants of knowledge roles for smallholder farmers. Farmers' gender, access to extension services, and group leadership increase the likelihood of a dairy farmer being a knowledge sharer, rather than a seeker, of dairy information. With men dairy farmers being likely knowledge seekers and women dairy farmers being likely knowledge sharers, there is need for dairy trainings to be geared towards attendance by men dairy farmers. Men dairy farmers are likely knowledge brokers relative to women dairy farmers, implying higher incomes accruing to men dairy farmers. Group leaders are likely knowledge sharers, implying the extant dairy information network structure predisposes them towards better knowledge diffusion opportunities. Better educated dairy farmers are likely knowledge seekers, implying high opportunity costs for them in the procurement of dairy information. Knowledge diffusion policies should thus be geared towards the less educated dairy farmers.

**Key words:** Dairy information networks , Knowledge seeker, Knowledge sharer, Knowledge broker , Multinomial logistic regression.

## Introduction

One of the most potent ideas in the social sciences is the notion that individuals are embedded in the web of social relations and interactions (Borgatti, 2009). According to Qiao *et al*.(2019), knowledge diffusion is increasingly being recognized as a major driver of innovation, the foundation of firms' competitive advantage, and the key anchor of growth in firms. Reviewed literature (Qiao *et al*., 2019; Havhakor, 2018; Kane & Alvin, 2007) suggests knowledge gaps existing in the understanding of the emergent, highly intricate network-level dynamics. The literature further suggests that future research consider unpacking how knowledge spreads across networks. The justification for this lies in the fact that there currently is no directly deducible connection between emergent global patterns of knowledge diffusion and individual-level behavior.

Qiao *et al*. (2019) attempt to redress this through the interrogation of the nexus between specific network attributes and knowledge diffusion. Specifically, Qiao *et al*. discuss the distribution of distinct knowledge roles and the design of selection rules. The knowledge roles outlined are knowledge seekers and knowledge sharers. The percentage of knowledge seekers and knowledge

sharers has a negative and significant correlation with the extent of knowledge diffusion. This has the key implication that the extent of knowledge diffusion decreases in instances where knowledge brokers are replaced either by knowledge seekers or knowledge sharers. Qiao *et al*. additionally found that replacing knowledge brokers with knowledge seekers has less effect than if the same knowledge brokers are replaced by knowledge sharers.

This paper contributes to the growing body of literature on knowledge diffusion by identifying the factors that determine the likelihood of dairy farmers playing varied knowledge diffusion roles in agricultural information networks in Nakuru County, Kenya. A multinomial regression model is employed to disaggregate the factors that determine the likelihood of dairy farmers occupying three distinct knowledge diffusion roles: broker, seeker, and sharer. The next section gives a background of dairy production in Kenya, while section 3 presents the data and description of variables. Section 4 describes the multinomial regression model, whereas section 5 presents the empirical results. Section 6 provides the study conclusion and policy implications arising therefrom.

**Background of Dairy Production in Kenya**

Globally, between 65% and 79% of farms are classified as smallholder (Lowder, 2016; Rapsomanikis, 2015). The livestock sector is broad and covers diverse agro-ecological, social, and political dimensions across continents, regions, and countries (Kingori, 2022). Milk production employs approximately 1.3 billion people worldwide, with smallholder dairy farmers accounting for more than 150 million farms (Chawala *et al*., 2019). The Kenya dairy industry contributes between 4% and 8% of the country's Gross Domestic Product (Bonilla *et al*., 2018; Kenya Dairy Board [KDB], 2016). About 80% of total milk output is produced by smallholder dairy farmers (Mawa *et al*., 2014 About 80% of total milk output is produced by smallholder dairy farmers (Mawa *et al*., 2014). About 1.2 million Kenyans are directly engaged in dairy production. In addition to contributing to economic growth, the dairy industry is identified as a significant enabler of household food security and income. It provides livelihoods to 25% of Kenyan households (GoK, 2019).

As a high-value enterprise, dairy farming in Kenya is recognized by the Nakuru County government as presenting profitable opportunities to increase demand for milk and dairy products through sustainable intensification and commercialization of smallholders and medium-scale producers (DFEP, 2018; DFEP, 2013). some of the challenges faced by smallholder dairy farmers in Kenya include; low economies of scale, low productivity, seasonal fluctuations, low dairy intensification, high costs of production, instability in milk supply, poor milk quality and safety, and the risk of unfair competition from oligopolies in milk processing (Odero-Waitituh, 2017; Bebe *et al*., 2016; Rademaker, 2016; Kibiego *et al*., 2015). Dairy productivity in Kenya is still significantly lower than the 6,000kg/cow/year potential yield of exotic dairy breeds (Kebebe *et al*., 2017; Njarui *et al*., 2016; Muasya *et al*., 2014; Njubi *et al*., 2009). We therefore seek to contribute to the existing body of knowledge by interrogating the knowledge diffusion roles played by dairy farmers in agricultural information network.

**3.**

*3.1 Multinomial regression model*

This study employs a multinomial logit regression model to evaluate the determinants of knowledge roles in dairy information networks. We employ the generic model as conceptualized by Greene (2020).

Let $\pi(x) = p(Y = 1|X = x) = 1 - p(Y = 0|X = x)$

The binary logistic regression model becomes;

$$Logit\ [\pi(x)] = log\left(\frac{\pi(x)}{1-\pi(x)}\right) = \alpha + \beta x$$

With the odds expressed as

$$\left(\frac{\pi(x)}{1-\pi(x)}\right)$$

The binary model is thus expressed as;

$$Logit\ [\pi(x)] = log\left(\frac{\pi(x)}{1-\pi(x)}\right) = \log[\exp(\alpha + \beta x)] = \alpha + \beta x \quad (1)$$

Equation (1) may be extended to models with multiple explanatory variables.

Let $k$ denote the number of predictors for a binary response, $Y$ by $x_1, x_2,\ldots, x_k$. The model of the log odds thus becomes;

$$logit[P(Y = 1)] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \quad (2)$$

The alternative formula, specifying $\pi(x)$ is expressed as;

$$\pi(x) = \frac{\exp(\alpha + \beta x)}{1 + \exp(\alpha + \beta x)} \quad (3)$$

To construct the logits in the multinomial case, one of the categories is treated as the base level, and all the logits are constructed relative to it. We assume $n$ independent observations with $p$ explanatory variables, with the qualitative response variable having $k$ categories.

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Let $\pi_j$ denote the multinomial likelihood of an observation falling in the $j^{th}$ category. To find the relationship between this probability and the $p$ explanatory variables $x_1, x_2,\ldots, x_p$, the multinomial regression model is expressed thus;

$$log\left[\frac{\pi_j(x_i)}{\pi_k(x_i)}\right] = \alpha_{01} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \cdots + \beta_{pj}x_{pi} \quad (4)$$

where $j = 1,2,\ldots,(k-1);\ i = 1,2,\ldots,n$

Since all $\pi_s$ add to unity, equation (4) is further reduced to;

$$log\left(\pi_j(x_i)\right) = \frac{\exp\left(\alpha_{01} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \cdots + \beta_{pj}x_{pi}\right)}{1 + \exp\left(\alpha_{01} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \cdots + \beta_{pj}x_{pi}\right)} \quad (5)$$

For $j = 1,2,\ldots,(k-1)$, the model parameters are estimated by the method of maximum likelihood.

As earlier stated, for the multinomial linear regression model, the estimate for the parameter can be identified compared to a baseline category. Let $\pi_j(\mathbf{x}) = p(Y = j|\mathbf{x})$ at a fixed setting $\mathbf{x}$ for explanatory variables. With $\sum_j \pi_j(\mathbf{x}) = 1$ for observations of that setting. We treat the counts at $J$ categories of Y as multinomial with probabilities $\{\pi_1(\mathbf{x}),\ldots,\pi_j(\mathbf{x})\}$; the baseline category is thus expressed as;

$$log\frac{\pi_j(\mathbf{x})}{\pi_k(\mathbf{x})} = \alpha_j + \beta_j'\mathbf{x} \quad (6)$$

where $j = 1, \ldots, (J-1)$;$k = 1, \ldots, (K-1)$ simultaneously describe the effects of $\mathbf{x}$ on these $(J-1)$ logits.

## 4. Data, and Description of Variables

### *4.1 Study Area*

The study was conducted in Nakuru County in Kenya. Nakuru County is located in the middle of the Rift Valley region of Kenya (GoK, 2015). Nakuru County lies between latitude $0° 10' \; and \; 0° 20'$ South and longitude $36° 0' \; and \; 36° 10'$ East. Administratively, Nakuru County is further divided into the following sub-counties: Gilgil, Kuresoi North, Kuresoi South, Molo, Naivasha, Nakuru East, Nakuru West, and Nakuru North, and Njoro (GoK, 2018). The county receives between 700 mm and 1,200 mm of rainfall annually, with an average annual rainfall of approximately 800mm. Nakuru has two rainy seasons: April, May and August (long rains) and October and December (short rains).

### *4.2 Sampling scheme*

Our data is derived from a survey of 390 households in four of the six sub-counties in Nakuru County. Table 1 shows the sample distribution per Sub-County. The sampling ratios are derived from the Kenya Housing and Population Census data of 2019.

**Table 13**: Sampling distribution per Subcounty

| Sub-county | Population | Sample size | Sample ratio |
|---|---|---|---|
| Gilgil | 185,209 | 97 | 24.87% |
| Rongai | 199,906 | 96 | 24.62% |
| Molo | 156,732 | 85 | 21.79% |
| Njoro | 238,773 | 112 | 28.72% |
| | | $n = 390$ | 100.00% |

Source: KNHPC Report Vol.II (2020)

the study employs a multi-stage sampling procedure. Firstly, Nakuru County was purposively selected due to its dairy farming potential, as indicated by current reviewed literature on dairy production, and as seen by the significant number of smallholder dairy farmers (MoALFI, 2019; MoALFI, 2013). Secondly, four sub-counties-Njoro, Molo, Rongai and Gilgil- were purposively selected to represent high and medium potential agro-climatic zones in Nakuru County. Two wards per Sub County selected were then chosen purposively. Finally, snowball sampling is used to select smallholder dairy farmers to be interviewed. The interviews were administered by use of semi-structured questionnaires. In line with COVID-19 protocols, the questionnaire was administered by use of digital equipment such as smart phones and tablets. *KoboKollekt* software was employed as a digital research instrument for the study.

### *5.2 Multinomial Logistic Regression Results for Composite, Formal and Informal Networks*

Tables 3 presents the multinomial logistic regression results for formal, informal and for the composite network. As outlined in the conceptual framework, three knowledge roles were contemplated for the dairy farmer: knowledge seeker, knowledge sharer, and knowledge broker.

In modelling the same, knowledge seeker was picked as the base case. The coefficients and the relative risk ratios (RRRs) thus generated are interpreted with respect to the base case aforementioned. Women dairy farmers are more likely to be knowledge sharers relative to being knowledge seekers to men dairy farmers at the 1% level of significance. The relative risk ratio of 0.4571 implies that men dairy farmers are less likely to be knowledge sharers relative to being knowledge seekers. Moreover, though not statistically significant, results show that men farmers are more likely to be knowledge brokers within the formal and informal networks. Indeed, the RRR suggests they are almost twice as likely (1.895) to be brokers than knowledge seekers.

Regarding dairy farmers' number of informational links, with RRR of 1.0669, knowledge sharers are equally as likely to have the same amount, or number of informational links-as indicated by their respective edge weights-as knowledge seekers at the 5% level of significance. Additionally, at the same level of significance (5%), knowledge sharers are less likely to access extension services compared to knowledge seekers. Farmers accessing extension services are 0.5738 times less likely to be knowledge sharers than knowledge seekers.

At the 5% level of significance, dairy farmers who identify as group leaders are almost twice as likely (1.8954) to be knowledge sharers than knowledge seekers in both formal and informal networks. Though not significant, group leaders are 2.39 times more likely to be knowledge brokers relative to being knowledge seekers. Regarding the highest level of education attained by a dairy farmer, results show that farmers with comparatively higher levels of education are less likely to be knowledge brokers or seekers. These results are however not significant.

Regarding formal dairy networks in Nakuru County, farmers' age and farmer group leadership returned significant results in the comparison of knowledge brokers and knowledge seekers. Farmers' gender, access to extension services, farmer having relatives in group leadership and farmer group leadership returned significant results in comparison of knowledge sharers and knowledge seekers. Older farmers were 0.891 times less likely to be knowledge brokers relative to them being knowledge seekers. A typical dairy farmer occupying a leadership position in a group makes them less likely to be knowledge brokers relative to them being knowledge seekers. Comparing knowledge sharers with the base case, men farmers are less likely to be knowledge sharers, and are more likely to be knowledge seekers at the 1% level of significance. At the same level of significance, results show that access to extension services predisposes dairy farmers to be 0.3243 times less likely to be knowledge shares relative to the said farmers be knowledge seekers. Having kin in group leadership position had the largest marginal effect, with results showing that such dairy farmers were 27.8 times more likely to be knowledge sharers, and less likely to be knowledge seekers.

For formal networks, and at the 1% level of significance, only farmers' level of education returned significant results in the comparison of knowledge brokers and knowledge seekers. A comparatively higher level of educational attainment predisposes dairy farmers to be less likely to be knowledge brokers relative to being knowledge seekers. Though not significant, results for farmers' gender, educational attainment, node weights, edge weights, extension access, kin in group leadership, and farmer in group leadership mirror those for formal and all networks.

**Table 3**: Multinomial regression results for composite, formal and informal dairy information networks in Nakuru County, Kenya

| | Composite network | | | | Formal network | | | | Informal network | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Base case: Knowledge seeker* | Knowledge Broker | | Knowledge sharer | | Knowledge Broker | | Knowledge sharer | | Knowledge Broker | | Knowledge sharer | |
| | beta | RRR[3] | beta | RRR | beta | RRR | beta | RRR | beta | RRR | beta | RRR |
| Age (years) | -0.031 | 0.969 | 0.015 | 1.015 | -0.116** | 0.891 | -0.005 | 0.995 | 0.022 | 1.022 | 0.027 | 1.027 |
| Gender (*1=male*) | 0.64 | 1.9 | -0.783*** | 0.457 | 0.931 | 2.536 | -1.331*** | 0.264 | 0.314 | 1.369 | -0.42 | 0.657 |
| education level | -0.587 | 0.556 | -0.012 | 0.988 | -0.083 | 0.921 | -0.040 | 0.961 | -0.808*** | 0.446 | -0.082 | 0.921 |
| node weight | 0.104 | 0.901 | 0.027 | 1.027 | 0.792 | 2.208 | 0.036 | 1.036 | -0.561 | 0.571 | 0.203 | 1.225 |
| edge weight | 0.09 | 1.094 | 0.065** | 1.067 | -0.158 | 0.854 | 0.049 | 1.05 | 0.235 | 1.265 | 0.038 | 1.039 |
| extension access | -0.048 | 0.953 | -0.556** | 0.574 | -0.462 | 0.629 | -1.126*** | 0.324 | -0.267 | 0.765 | -0.132 | 0.877 |
| kin in group leadership (*1=yes*) | 0.077 | 1.079 | 0.228 | 1.256 | 1.364 | 3.911 | 17.141*** | 27.8 | 0.106 | 1.112 | 0.052 | 1.053 |
| group leadership (*1=yes*) | 0.871 | 2.39 | 0.639** | 1.895 | -13.085*** | 0 | 0.966** | 2.63 | 1.023 | 0.006 | 0.264 | 1.303 |
| Intercept | -2.73 | 0.065 | -0.746 | 0.474 | 1.353 | 0.0652 | 1.5839 | 4.874 | -5.182** | 0.065 | -1.90* | 0.149 |

[3] Relative Risk Ratio

## 6. Conclusions and Implications

*6.1 Conclusions*

With the role of interpersonal networks in facilitating knowledge diffusion having been demonstrated in a number of studies, this paper contributes to the growing body of literature on by identifying factors that determine likelihoods of dairy farmers playing varied knowledge diffusion roles in agricultural information networks in Nakuru County, Kenya. A multinomial regression model is employed to disaggregate factors determining the likelihood of dairy farmers occupying three knowledge diffusion roles. The knowledge seeking role is employed as the base case in the multinomial regression model.

Women dairy farmers are more likely to be knowledge sharers than knowledge seekers, whereas men farmers are likely to be knowledge seekers than knowledge sharers. With respect to knowledge brokerage, men farmers are twice as likely to be knowledge brokers relative to women farmers. Farmers accessing extension services are more likely to be knowledge seekers than knowledge sharers. Dairy farmers who double as group leaders are twice as likely to be knowledge sharers as knowledge seekers in both formal and informal networks.

Though not significant, group leaders are more likely to be knowledge brokers than knowledge seekers. Farmers with comparatively higher levels of education are less likely to be knowledge brokers or seekers. For formal dairy information networks, older dairy farmers are more likely to be knowledge seekers than knowledge brokers. A dairy farmer occupying a leadership position is more likely to be a knowledge seeker than a knowledge broker. A comparatively higher level of educational attainment predisposes dairy farmers to be more likely to be knowledge seekers than knowledge brokers.

*6.2 Policy implications*

Results showing likelihood of women dairy farmers being knowledge sharers than knowledge seekers may point to the fact that women dairy farmers have over time attended and been successfully trained on current dairy best practices compared to their men counterparts. This may in turn suggest a need for men dairy farmers to be encouraged to attend dairy trainings as and when available. This point is further strengthened by the significant results showing men dairy farmers to more likely be knowledge seekers than knowledge sharers within the dairy information network. The significant gender differentials observed in the results also provides further scope for future research on knowledge diffusion roles. It may be that cultures embedded in these networks see dairy farming as a woman's responsibility, rather than a man's.

The significant results showing likelihood of men dairy farmers being twice as likely to be knowledge brokers than women farmers may point to an observed advantage for men dairy farmers over women dairy farmers. Men dairy farmers are in a better position to leverage on their dairy knowledge for some income. Results further suggest that farmers with access to extension services are likely to be knowledge seekers than knowledge sharers. This may point to a willingness of men dairy farmers to actively seek, and pay, for information on current best dairy practices within dairy information networks. Further, it may be argued that a latent demand exists for the provision of extension services within the dairy networks, and thus the state may consider encouraging both public and private extension providers to participate in dairy information networks.

Results showing group leaders as knowledge sharers may point to the fact that central farmers are more trusted with leadership positions in dairy farmer groups; this allowing them to leverage on their centrality to share information on current best dairy practices with other dairy farmers. Strategies that promote the sharing of dairy expertise between leaders of dairy groups

and group members are recommended from a policy standpoint. Additionally, group leaders and members should be considered for platforming by extension platforms that are already a part of dairy information networks. When compared to traditional extension approaches, social networking sites like Facebook, WhatsApp, Telegram, and others may offer inexpensive and quick means of exchanging information, especially in the context of the expanding knowledge economy space in less developed economies.

The fact that better educated farmers are more likely to be knowledge seekers than brokers may point to high opportunity costs existing in the procurement of dairy information in dairy information networks for such farmers. Better educated dairy farmers, *ceteris paribus*, prefer to dedicate more of their temporal resources towards non-dairy economic activities whereas less educated dairy farmers prefer to dedicate more of their temporal resources towards dairy economic activities. Additionally, less educated dairy farmers are better able to leverage their dairy knowledge to earn income through brokerage of the same compared to better educated dairy farmers.

For both composite and formal networks, older dairy farmers are likely to be knowledge seekers than brokers. It may thus be argued that younger dairy farmers are better able to leverage on dairy knowledge to earn income through knowledge brokerage compared to older dairy farmers. For formal networks, group leaders are likely to be knowledge seekers than brokers. This is indicative of possible high opportunity costs existing for group leaders, while simultaneously predisposing the same to existing dairy training opportunities. Lastly, for informal networks, only dairy farmers educational level returned significant results in the multinomial regression model, with the results mirroring the composite and formal networks earlier discussed.

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