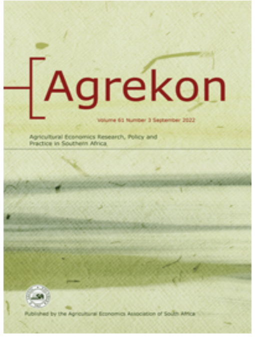

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Factors affecting adoption of technical, organisational and institutional dairy innovations in selected milksheds in Kenya

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ABSTRACT

Technical dairy innovations (TDI), such as improved cow feeding, health management and genetic improvement, could boost milk production. At the same time, organisational and institutional dairy innovations (OIDI), including group milk sales, feed and credit access, could boost dairy supply chain efficiency. This study examined the TDI adoption determinants and the OIDI adoption intensity. Data were collected from 1146 farmers (410, 382 and 354 in the milksheds of Mukurweini Wakulima Dairy Limited [MWDL], Happy Cow Limited [HCL] and New Kenya Co-operative Creameries [NKCC], respectively) and analysed using a double hurdle model. Access to credit positively influenced the TDI adoption in the three milksheds. Adoption of TDI was influenced by hired employees, dairy records, total dairy cows and household head education. The empirical evidence from the study supports the observation that OIDI adoption intensity is influenced by income, farm size, dairy records, and dairy information access. To boost TDI adoption, the dairy development partners should link cooperative society members with agricultural credit lenders. Additionally, the dissemination of dairy information to farmers by the dairy stakeholders could spur TDI adoption, while providing dairy information and training farmers on dairy record keeping should be promoted to boost TDI and OIDI adoption.

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Adoption of innovations; dairy farming; dairy innovations; adoption intensity; milk shed

1. Introduction

Dairy farming in Kenya is among its key economic enterprises, supporting an estimated 1.5 million smallholder farmers (KDB 2016). In addition, the dairy value chain supports milk transporters, informal milk sellers and processors as their source of livelihood. The sub-sector contributes more than 4% of Gross Domestic Product (GDP) and 12% of agricultural GDP (KNBS 2019).

While the country's total milk consumption is growing at a rate of 4% per year (MoALF 2019), the per capita consumption of milk (110 litres) remains the highest in Sub Saharan Africa (KDB 2015). Milk production is often insufficient to meet growing demand, especially during dry periods. To cushion consumers against milk shortages, the government opens import windows for powdered and fresh milk. For instance, the value of milk from Uganda increased from KES (Kenya Shillings) 19.3 billion in 2016, to KES 42.0 billion in 2017 and KES 49.4 billion in 2018 (KNBS 2018, 2019).

The decrease in milk quantity has been attributed to several constraints faced by farmers, including a limited quantity of feeds and poor-quality feeds. Farmers are also discouraged from improving

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their dairy breeds because of the high cost of adopting Artificial Insemination (AI) and low success rates, while dairy cow diseases such as mastitis are becoming prevalent and a lack of access to credit affects milk productivity (Omunyin et al. 2014; Kibiego, Lagat, and Bebe 2015).

In response to farmers' constraints, the Kenyan government and its development partners have been supporting the sub-sector through TDI and OIDI. TDI are adopted at the farm level and aim to increase milk production. Mainly, they include feeding dairy cows, reproduction, animal health, milk hygiene, breeding and cow management (i.e., housing). ODI, on the other hand, include optimisation of collection routes, implementation of collection centres and introduction of cooling systems that could consist of more producers and reduce milk losses (Odero-Waitituh 2017).

Changes in the formal and informal rules that govern milk collection schemes and milk marketing channels, such as quality and seasonality-based payments and feed credit schemes, are examples of institutional dairy innovations (IDI) that are expected to encourage dairy farmers to improve their practices (Holloway et al. 2000; Ndambi et al. 2019). Among TDI that the national and county governments have been supporting include developing disease-resistant fodder, on-farm feed production, silage making and dairy infrastructure. Regarding ODI, the two levels of government (national and county) have been operationalising strategic milk reserves, procurement of milk coolers for counties, and encouraging milk sales through cooperatives (KDB 2016; Rademaker et al. 2016).

The promotion of dairy innovations (DIs), including TDI and OIDI (ODI and IDI), collectively, has the potential to increase the quantity of milk sold by dairy farmers and improve efficiency in the dairy value chain. TDI activities like local animal feed sourcing, improved cow nutrition, better health management and hygienic milking, reproduction management, and genetic enhancement have been shown to increase milk output quantity, minimise seasonality and improve the microbiological quality of milk (Wambugu, Place, and Franzel 2011).

Despite the potential of DIs for increasing milk quantity and the dairy stakeholders' support of farmers, adoption of the promoted DIs remains low (Omondi et al. 2017). To enhance the success of DI adoption by farmers, increase milk quantity and enhance quality, there is a need to understand the factors influencing their adoption. This is because farmers are the primary milk producers in the dairy value chain. Their adoption and continued use of DIs could positively impact the dairy value chain through increased milk supply and enhanced quality.

Past studies have revealed DI adoption and intensity of use determinants to include farm and farmer characteristics, as well as institutional and dairy innovation attributes. For example, Tebug, Chikagwa, and Wiedemann (2012) evaluated the adoption of common dairy practices in Malawi, including stall feeding, milking practices, stable farm sanitation, farm record keeping, breeding methods, milk sales, protein supplements and mineral supplements. On-farm visits by dairy extension workers were positively associated with the adoption of dairy practices. Mugisha et al. (2014) studied breeding services and the factors influencing their use on smallholder dairy farms in Central Uganda and indicated that the use of AI was positively influenced by the size of grazing land, record keeping and access to extension services, among others. Aksoy, Külekçi, and Yavuz (2011), while evaluating determinants of innovation adoption in dairy farms in Turkey, focused on six innovations, including stable techniques, keeping farm records, milking techniques, silage making, cooling tanks and artificial insemination (AI). The study indicated that younger farmers had higher levels of adoption of innovation than older farmers. Education status, animal breed and probability of benefiting from government support policies had a statistically significant positive influence on innovation adoption.

Still on TDI, specifically breeding, Mwanga et al. (2019) focused on determinants of farmers' breeding decisions in Ethiopia, Kenya, Tanzania and Uganda. The study revealed that a farmer's experience, record-keeping by farmers, water and feed availability were significantly and positively associated with AI adoption among dairy farmers with a small herd. On the contrary, farmers with a large herd and large farm acreage were not likely to use AI services. Further, the cost of AI services and the distance covered by the service provider reduced the probability of the use of AI as a breeding option.

Contrary to past studies that focused on adoption determinants of one or several TDIs, this study determined both TDI adoption determinants and the adoption intensity of OIDI together. This is because the dairy value chain is complex, and while determining factors affect TDI adoption, it is also important to consider OIDI, which compliments the adoption of TDI. Additionally, understanding the factors that influence the adoption of the three types of DIs is important in coming up with relevant evidence-based policies enhancing their uptake by farmers. Further, enhancing milk quantity and quality is important, especially in Kenya, where dairy farming contributes greatly to the economy. Moreover, the study focused on MWDL, HCL and NKCC Sotik, representing processors that are farmer-owned, privately owned and state-owned, respectively. The three processors are located in areas where farmers practise three distinct production systems. Most farmers in MWDL practise the cut and carry system (zero-grazing); farmers in HCL use semi-zero grazing, a system whereby cows are grazed during the day and are enclosed and offered supplementary feed at night; and farmers in NKCC Sotik practise a free range grazing system whereby cows graze on natural and/or improved pastures using a paddocking or strip grazing approach, and are also supplemented with fodder, respectively. Given the different processor types and production systems in these milksheds, dairy innovation adoption could be influenced by different factors.

In recognition that farmers are main actors and primary producers in the dairy value chain, understanding DI adoption determinants on the farm and in the milkshed is important because they can increase milk quantity and enhance quality along the dairy value chain. In addition, few studies have sequentially analysed different DI adoption determinants. Therefore, this study contributes to the literature by sequentially modelling the adoption of DIs at two levels, namely farm and milkshed, by fitting a double hurdle model. The model results give a broad measure of determinants and intensity of use of the selected dairy innovations by dairy farmers practising different production systems.

The objective of this study was to determine TDI adoption determinants as well as the intensity of use of OIDI. The postulated hypothesis of the study was that socio-economic and demographic factors do not influence TDI adoption and the adoption intensity of OIDI.

2. Materials and methods

2.1 Study area

The study area of three milksheds (Mukurweini Wakulima Dairy Limited, Happy Cow Limited and NKCC Sotik) and a total of 1146 farmers were the ones involved in a study that took place between July and December 2019 (Wairimu et al. 2021).

2.2 Sampling procedure and data collection

The study used data based on a household survey of 1146 dairy households from three milksheds supplying milk to MWDL, HCL and NKCC Sotik, representing farmer-owned, privately owned and state-owned processors respectively. The sampling technique and sample size was arrived at as described in Wairimu et al. (2021). Data was collected using a structured questionnaire designed with the Open Data Kit (ODK) software. Before actual data collection, the questionnaire was pretested and amended to ensure that all required data was collected for the analysis.

2.3 Description of variables used in the TDI adoption determinants and OIDI intensity of use analysis

The dependent variable, *TECHINNOVAT* (TDI adoption status of a household head at the farm) took values of 1 if a household had adopted at least 50% of TDI or 0 if otherwise. Fifteen TDI were considered: keeping pure breeds; feeding cows with concentrates; use of AI; store fodder; housing of cows; use of aluminium milk cans to store and deliver milk to collection centre; preparing homemade rations; growing fodder; observing a withdrawal period after treating cows with antibiotics; deworming cows frequently after two weeks; cleaning cow teats before and after milking; detecting cows infected by mastitis; use of pre-milking products; use of post-milking products; and cleaning milking containers with water and soap.

The dependent variable, ORGINNO/INSTIT (the ratio of the number of OIDI adopted by a farmer to the total number of possible OIDI available for adoption at the milkshed), was used to denote the OIDI intensity of use. Six OIDI (three ODI and three IDI) were considered. The ODI included milk sales through a cooperative, a cooperative having a chilling plant and a milk collection centre equipped with a cooling system, while IDI was made up of access to long term loans, contractual arrangements in milk supply and cooperative society shareholding. The explanatory variables chosen for analysis and presented in Table 1 were based on literature review findings.

2.4 Analytical framework

Dairy farmers are assumed to adopt a dairy innovation (DI) when the utility of DI (P_k) surpasses the utility of a traditional technology (P_w). The utility gained from a DI is assumed to be a function of the vector of observed socio-economic factors, perceived DI characteristics (X_i) and a random disturbance term. This arises from unobserved variation in preferences, attributes of the alternatives and errors in optimisation. According to Adesina and Zinnah (1993), a farmer weighs the utility derived from adopting different technologies and chooses the one that is expected to provide higher utility than the traditional technology. If a farmer's utility of adopting a DI in the case of this study TDI and OIDI is denoted by $P_k(X)$ and the preference of adopting the traditional technology as $P_w(X)$, then adoption Equations of a DI and traditional technology are as indicated in Equation 1 and 2 respectively:

$$P_k(X) = X\beta_k + \varepsilon_k \tag{1}$$

$$P_w(X) = X\beta_w + \varepsilon_w \tag{2}$$

where βk, and ε_k, in Equation 1 of the adoption of DIs are coefficient and a random disturbance in adoption of DIs and β_w and ε_w in Equation 2 adoption of traditional technology are the coefficients and random disturbances associated with the adoption of traditional technologies. The probability of adopting a DI could be denoted by a dichotomous variable Y, value 1 for farmers willing to adopt a DI and zero otherwise. The function of X in Equation 3 indicates the probability that a given dairy farmer will adopt the DI:

$$\begin{aligned} P(Y = 1) &= P(P_k > P_w) \\ &= P(X\beta_k + \varepsilon_k > X\beta_w + \varepsilon_w) \\ &= P[(X(\beta_k - \beta_w) > \varepsilon_k - \varepsilon_w] \\ &= P(X\beta > \varepsilon) \\ &= F(X\beta) \end{aligned} \tag{3}$$

where P is the probability function, $\beta = \beta_k - \beta_w$ is a vector of unknown parameters and represents the net influence on the vector of independent variables on adoption of DIs and $\varepsilon = \varepsilon_k - \varepsilon_w$ is a random disturbance term and $F(X\beta)$ is cumulative distribution function F evaluated at $X\beta$ (Rahm and Huffman 1984). The difference between the expected utility production with the adoption of DI and without the DI is the potential factors determining the farmers' decision to adopt Dis, including TDI and OIDI. These factors include socio-economic factors, physical capital, financial capital, milk price, access to information and village level factors.

2.5 Empirical model

This study estimated a double hurdle model (DH) using STATA 14 econometric software to establish TDI adoption determinants and the intensity of use of OIDI. The maximum likelihood parameter

Table 1. Description, measurement and hypothesised effects of the variables in the model.

SOCIO-ECONOMIC CHARACTERISTICS	Variable description and measure	Sign	Hypothesised effect
AGEHED	Household head age in years	+/-	Older farmers were expected to be more experienced in farming activities, and hence adopt DIs. On the contrary, due to more experience in farming with older farmers, they could be risk averse and therefore less likely to adopt new technologies (Adesina and Baidu-Forson 1995; Rahelizatovo and Gillespie 2004).
EXPERIENCE	Years in dairying	+/-	More experience in farming activities help in understanding the attributes of innovations and hence adoption. On the contrary, adoption of DIs could decrease with farm experience due to the risk averse nature of older farmers (Kassie et al. 2013).
INCOME	Total annual household income in KES	+	High income is associated with adoption of innovations. Income from other sources such as crop production may enable farmers to access resources to invest in the dairy enterprise, such as acquiring dairy cows of high genetic potential.
GEDRHED	Household head gender: 1=Male; 2=Female	-	Females are expected to be risk averse to innovations, hence negative influence. Their risk averse nature could be associated with their limited access to resources and information compared to their male counterparts (Yesuf and Bluffstone 2009).
HHEDUC	Complete years in formal education	+	More educated farmers are likely to be more confident in adapting to innovations (Rao and Qaim 2011; Abdulai and Huffman 2014).
HHSIZE	Household size	+/-	Large family size, a proxy of family labour provision, can have a positive effect on adoption of TDI, unlike hired labour that poses a moral hazard (Asfaw et al. 2012). On the contrary, large household size is likely to result in a family becoming financially constrained from engaging in innovations that may result in increased costs and time, such as growing fodder.
TDCOWS	Total dairy cattle 2018	+	Large herd size is expected to affect DI adoption positively, particularly TDI like feed conservation technologies (Birhanu, Girma, and Puskur 2017).
DAIRYINGINFOR	Access to dairying information: 1=Yes; 0=No	+	Access to information can improve farmers' adoption capacity by creating effective demand for innovations (Ayele et al. 2012).
FARMSIZE	Total farm area in acres	+/-	Large farms are likely to support many cows (Kabunga, Ghosh, and Webb 2017), hence positively influencing TDI, such as the growing of fodder. On the contrary, farmers with small farms may adopt intensive farming resulting in high productivity on their farms compared to farmers with large pieces of land (Chen, Huffman, and Rozelle 2011), and hence opt to sell milk through cooperatives due to the advantage of the economies of scale, particularly transportation costs and market information search costs. (Rao and Qaim 2011).
EMPLOYEES	Number of employees	+	A large number of employees is positively associated with adoption of TDI and OIDI, such as growing improved fodder and milk sales through cooperative respectively. Hired labour could result in efficient use of resources and consequently more milk production sold through cooperatives (Mburu, Wakhungu, and Gitu 2007).
RECORDS	Keep records: 1=Yes; 0=No	+	Keeping dairy records is expected to positively influence adoption of TDI and OIDI, such as AI and access to credit respectively.
MILKPRICE	Milk price per litre in KES	+	As milk prices increase, farmers get resources to adopt OIDI such as milk sales through collective action like cooperative societies (Hernández-Espallardo, Arcas-Lario, and Marcos-Matás 2013).
YRCROSSBRED	Years household kept cross breed(s)	+	Rearing of cross-breeds has the potential to enhance milk productivity (Wong and Kibirige 2009; Wambugu, Place, and Franzel 2011).

(*Continued*)

Table 1. Continued.

SOCIO-ECONOMIC CHARACTERISTICS	Variable description and measure	Sign	Hypothesised effect
CREDIT_ACCESS	Access to credit: 1=Yes; 0=No	+	Access to credit can positively influence adoption of agricultural technologies (Abdulai and Huffman 2014). Dairy technologies that can be boosted by credit access include adoption of cross-breed cows (Abdulai and Huffman 2005).

estimates, the unconditional average partial effects (APE) and bootstrapping replications on each observation were performed using the Craggit command in Stata (Burke 2009). According to the author, this process helps in estimating the observed coefficient, standard errors and the *P*-values showing the significance levels. A multicollinearity test was conducted using Variance Inflation Factor (VIF) (Gujarati 2004). The DH model was justified because the dependent variable, particularly the adoption of TDI and the decision to adopt OIDI, are made sequential conditions on adoption of TDI. Furthermore, the study assumed that productivity on the farm relies on both TDI adoption and intensity of OIDI use in the milkshed, and therefore it is imperative to consider determinants of both adoption and the adoption intensity of DIs.

According to the DH model, adoption determinants and adoption intensity are allowed to differ. In the context of the adoption of OIDI analysis, those farmers who perceive low production due to seasonality in production, exclusion from the value chain and low milk quality decide to either adopt TDI and OIDI or not. This study assumed that a farmer could only adopt OIDI after adopting TDI. The first hurdle of the DH model modelled the discrete choice of whether the farmer has adopted 50% of the TDI or not, with a specification similar to that of the probit model. The adoption options (first hurdle) under TDI included innovations on the farm, while the second hurdle concerned the adoption intensity of OIDI in the milkshed.

Each hurdle was conditioned by household socio-economic characteristics (e.g., household head age, education, household size and farm size) and innovation attributes (distance to collection centres). The first equation in the DH model represents the decision to adopt TDI (y) and is expressed as indicated in Equation 4,

$$\begin{aligned} y_i &= 1 \text{ if } y_i^* > 0 \text{ and } 0 \text{ if } y_i^* \leq 0 \\ y_i^* &= X_i^* \alpha + \varepsilon_i \end{aligned} \qquad (4)$$

where y^* is a latent adoption variable that takes the value of 1 if a household adopted at least half of the TDIs and 0 otherwise. Coefficient X is a vector of socio-economic characteristics and α is a vector of parameters. The second hurdle representing the adoption intensity of OIDI is expressed in Equation 5,

$$\begin{aligned} z_i &= z_i^* \text{ if } z_i^* > 0 \text{ and } 0 \text{ if } y_i^* \leq 0 \\ z_i &= 0 \text{ otherwise} \\ z_i^* &= Z'_i \beta + \nu_i \end{aligned} \qquad (5)$$

where z_i represents the proportion of OIDI adopted expressed as a proportion of total OIDI adopted by the farmer. The $Z_i^{'}$ is a vector of the farmer's characteristics and β is a vector of parameters. The errors indicated by vi and ε_i are assumed to be independent and normally distributed. For both TDI and OIDI, multiple innovations were considered. Empirically, the first hurdle (probit model) was estimated as shown in Equation 6 and the second hurdle (Tobit) Equation 7.

$$\begin{aligned} TECHINNOVAT = {} & B_0 + \beta_1 AGEHED + \beta_2 EXPERENCE + \beta_3 INCOME \\ & + \beta_4 GEDRHED + \beta_5 HHEDUC + \beta_6 HHSIZE + \beta_7 TDCOWS \\ & + \beta_8 DAIRYINGINFOR + \beta_9 FARMSIZE + \beta_{10} EMPLOYEES \\ & + \beta_{11} RECORDS + \beta_{12} ROADTYPE + \beta_{13} MILKPRICE \\ & + \beta_{14} YRCROSSBRED + \varepsilon_1 \end{aligned} \tag{6}$$

$$\begin{aligned} ORGINNO/INSTIT = {} & B_0 + \beta_1 AGEHED + \beta_2 EXPERENCE + \beta_3 INCOME \\ & + \beta_4 GEDRHED + \beta_5 HHEDUC + \beta_6 HHSIZE + \beta_7 TDCOWS \\ & + \beta_8 DAIRYINGINFOR + \beta_9 FARMSIZE + \beta_{10} EMPLOYEES \\ & + \beta_{11} RECORDS + \beta_{12} ROADTYPE + \beta_{13} MILKPRICE \\ & + \beta_{14} YRCROSSBRED + \varepsilon_2 \end{aligned} \tag{7}$$

3. Results

3.1 Descriptive statistics of variables

Table 2 presents the summary statistics of variables used in this study.

Farmers in the MWDL milkshed were older and more experienced in dairy farming than farmers in the other milksheds, while farmers in NKCC Sotik had the highest mean household size (Table 1). Farmers' mean yearly total income was KES 187,236.00. There was a significant difference in total earnings between farmers in NKCC Sotik and MWDL and farmers in NKCC Sotik and HCL, all at the 5% level. Farmers in the milkshed of HCL had the highest mean, KES 202,604.91. Most household heads (76.20%) were male and comparative analysis across the milksheds indicated a significant difference at a 1% level of gender distribution, with most respondents being male across the three milksheds. Overall, farmers had on average 10.47 years of formal education. Farmers owned an average of 1.81 dairy cows in 2018. About one third of farmers accessed dairy information and there was a significant difference in access to information, with the MWDL milkshed having the largest proportion at 46.30%. Farmers owned a mean of 3.34 acres of land, and farm sizes were larger in HCL (4.05 acres) compared to the other two milksheds. The average farm size in MWDL was smaller and significantly different to that of farmers in NKCC Sotik. However, there was no significant difference in farm size in HCL and NKCC Sotik. Only one third and slightly more than a quarter of the sample respectively employed labourers in 2018 and kept dairy records.

The dairy records kept by farmers included breeding, production, sale and purchase of cows and veterinary (treatment). Overall, the mean milk price was KES 32.28, with farmers in NKCC Sotik receiving the lowest mean price (KES 30.77) and farmers in HCL the highest (KES 33.34). On average, farmers had mean of 18.40 years of experience in keeping cross-breeds with farmers in MWDL having the highest mean of 20.46 and farmers in NKCC Sotik having the lowest mean (16.01 years).

3.2 Tests of association between independent variables and dependent variables

Correlation analysis was also conducted on variables used in the double hurdle regression model, using Pearson correlations of numeric variables on adoption intensity and Pearson chi-square for nominal independent variable with adoption. The results of these analyses are presented in Table 3.

In MWDL, household head education, total dairy cows owned and employed labourers had a weak positive statistically significant correlation, while experience in keeping cross-breed cows had a weak negative correlation with intensity of innovation adoption (Table 3). Household income, education, total dairy cows owned and farm size had a weak positive correlation with adoption intensity while milk price had a weak negative correlation with innovation adoption intensity in

Table 2. The descriptive statistics of factors used in the DH model in the study areas.

Variable	Full sample	MWDL	HCL	NKCC Sotik	χ^2	Kruskal-Wallis
AGEHED (Mean)	56.12 (14.25)	60.88 (12.75)	56.79 (14.31)	49.87 (13.55)		117.30***
EXPRNCE (Mean)	20.02 (14.63)	22.89 (14.75)	20.10 (14.16)	16.62 (14.29)		42.19***
INCOME (Mean)	187,236.44 (179,090.5)	186,372.47 (162,921.04)	202,604.91 (191,521.91)	172,230.74 (182,349.18)		12.08***
GEDRHED (%)	76.2	69.8	76.7	83.1	18.59***	
HHEDUC (mean)	10.47 (4.09)	10.24 (3.91)	10.58 (4.31)	10.64 (4.08)		2.58
HHSIZE (Mean)	4.22 (2.13)	3.20 (1.62)	4.57 (2.24)	5.01 (2.06)		163.87***
TDCOWS (Mean)	1.81 (1.59)	1.57 (1.7)	1.79 (1.3)	2.09 (1.7)		55.72***
DAIRYINGINFOR (%)	36	46.3	33.5	26.8	32.95***	
FARMSIZE (Mean)	3.34 (3.017)	2.336 (2.085)	4.052 (3.345)	3.735 (3.257)		*89.68****
EMPLOYEES (Mean)	1.59 (1.14)	1.51 (0.96)	1.66 (1.34)	1.64 (1.10)		876
RECORDS (%)	25.8	27.8	24.6	24.9	1.31	
MILK_PRICE	32.28 (5.30)	32.60 (3.62)	33.34 (6.54)	30.77 (5.14)		76.69***
YRCROSSBRED	18.40 (14.34)	20.46 (14.71)	18.33 (13.72)	16.01 (14.23)		30.23***
ACESS_CREDIT (%)	60.82	68.27	60.73	52.26	20.49***	

Note: Figures in the parentheses are the standard deviations associated with the means for the variables indicated. ***$P < 0.01$, mean significant at 1% probability levels.
Source: Survey data, 2019.

Table 3. Correlation analysis of independent variables and the dependent variables.

Milkshed Variable	MWDL Correlation coefficient	MWDL *P*-value	HCL Correlation coefficient	HCL *P*-value	NKCC Correlation coefficient	NKCC *P*-value
EXPRNCE	−0.0882	0.0746	0.0694	0.1759	**0.1125***	0.0343
INCOME	0.0031	0.9505	**0.2097***	0.000	**0.2755***	0.000
AGEHED	−0.0132	0.7905	−0.0143	0.7799	**0.1385***	0.0091
HHEDUC	**0.1556***	0.0016	**0.1781***	0.0005	0.0859	0.1066
HHSIZE	−0.0259	0.601	−0.0042	0.9349	0.078	0.1432
TDCOWS	**0.1098***	0.0262	**0.1683***	0.001	**0.2453***	0.000
YRCROSSBRED	**−0.2116***	0.000	0.0637	0.2138	0.0745	0.1618
FARMSIZE	−0.0054	0.9137	**0.2371***	0.000	**0.2243***	0.000
EMPLOYEES	**0.1574***	0.0014	0.0768	0.1342	**0.2244***	0.000
Milk_PRICE	−0.0865	0.0802	**−0.3172***	0.000	**−0.2424***	0.000
Variable	Pearson Chi-square	*P*-value	Pearson Chi-square	*P*-value	Pearson Chi-square	*P*-value
GEDRHED	0.7978	0.372	0.4486	0.503	**4.0786***	0.043
DAIRYINGINFOR	**5.1240***	0.024	**20.1609***	0.000	**13.3254***	0.000
RECORDS	0.1414	0.707	11.1238	0.001	**21.6263 ***	0.000
CREDIT_ACCESS	**12.4018***	0.000	37.8560*	0.000	**39.7687***	0.000

HCL. The variables experience, income, age of household head, total dairy cows, farm size and employees had a weak positive correlation with innovation adoption intensity, while milk price had a weak negative correlation with adoption intensity in NKCC Sotik. The results of Pearson chi-square results showed that, except the access to dairy information variable, which had a positive correlation with innovation adoption across the three milksheds, household head gender and keeping records had a significant positive correlation with adoption only in NKCC Sotik.

3.3 Factors influencing TDI adoption and OIDI adoption intensity across the milksheds

The VIF results ranged between 1.05 and 2.14 for MWDL, 1.06–7.15 for HCL and 1.03 and 8.64 for NKCC Sotik, an indication that multicollinearity was not a problem among the continuous variables. Adoption of TDI and intensity of OIDI use decisions were influenced by different factors across the three milksheds and presented in Table 4.

3.3.1 Factors influencing TDI adoption across the three milksheds

Total number of dairy cattle, dairy information access and access to credit positively influenced TDI adoption, while farm size negatively influenced the adoption of TDI in MWDL. In HCL, access to dairy information, number of employees, dairy records and credit access positively and significantly influenced TDI adoption, while milk price was significant and had a negative influence. Moreover, the variables access to dairy information, total land, number of employees, dairying records and access to credit positively influenced adoption of TDI, while milk price was significant and had a negative influence in NKCC Sotik.

3.3.2 Factors influencing adoption intensity of OIDI

Household head education positively influenced intensity of OIDI use in MWDL, and intensity was negatively influenced by household size, income and number of years that the household kept cross-breeds. The APEs of total number of dairy cattle, dairy information, milk price and number of years the household kept cross-breed cows were significant. In HCL, income, farm size and access to credit were significant and positively influenced OIDI intensity of adoption, while the number of employees on the farm and milk price had a negative influence. The APEs of gender, dairy record and access to credit were positive and significant, while milk price APE was negative. Whereas age of household head, income and access to dairy information were significant and positively influenced adoption of OIDI in NKCC Sotik, dairy records and milk price were significant and had a negative influence. The APEs of age, total income, dairy

Table 4. Adoption and intensity of adoption of TDI and OIDI by milkshed.

	MWDL			HCL			NKCC		
	TDI	ORG/INST	APE	TDI	ORG/INST	APE	TDI	ORG/INST	APE
AGEHED	0.0030 (0.0075)	0.0010 (0.0013)	0.0009 (0.0012)	−0.0016 (0.0066)	0.0004 (0.0013)	−2.54e-05 (0.0011)	0.0091 (0.0077)	**0.0021*** (0.0013)	**0.0021**** (0.0010)
EXPRNCE	0.0001 (0.0075)	0.0018 (0.0014)	0.0011 (0.0013)	−0.0062 (0.0129)	0.0006 (0.0024)	−0.0004	0.0055 (0.0155)	0.0030 (0.0020)	0.0021 (0.0025)
INCOME	1.86e-07 (3.04e-07)	**−8.89e-08**** (4.38e-08)	−3.70e-08 (4.95e-08)	5.24e-08 (2.12e-07)	**6.64e-08**** (3.38e-08)	3.76e-08 (3.10e-08)	2.90e-07(4.71e-07)	2.07e-07*** (6.83e-08)	**1.30e-07**** (6.01e-08)
GEDRHED	−0.1691 (0.1703)	0.0269 (0.0289)	0.0003 (0.0259)	0.2622 (0.1874)	0.0480 (0.0359)	0.0545 (0.0277)	−0.0246 (0.2231)	−0.0235 (0.0354)	−0.0138 (0.0314)
HHEDUC	−0.0135 (0.0215)	**0.0064*** (0.0035)	0.0026 (0.0030)	−0.0107 (0.0175)	0.0010 (0.0032)	**−0.0008**** (0.0030)	−0.0175 (0.0217)	0.0031 (0.0031)	−0.0007 (0.0028)
HHSIZE	0.0515 (0.0503)	**−0.0179**** (0.0091)	−0.0061 (0.0086)	−0.0453 (0.0339)	−0.0007 (0.0067)	−0.0059 (0.0053)	0.0517 (0.0375)	0.0016 (0.0064)	0.0069 (0.0048)
TDCOWS	**0.4133***** (0.1300)	−0.0104 (0.0155)	**0.0336**** (0.0163)	0.0935 (0.0683)	0.0062 (0.0139)	0.0143 (0.0120)	0.0414 (0.0742)	−0.0021 (0.0100)	0.0040 (0.0091)
DAIRYINGINFOR	**0.4271***** (0.1593)	0.0293 (0.0270)	**0.0595**** (0.0233)	0.2716 (0.1668)	0.0023 (0.0299)	0.0342 (0.0225)	**0.3263*** (0.1884)	**0.0701**** (0.0300)	**0.0714***** (0.0269)
FARMSIZE	**−0.0634***** (0.0230)	0.0048 (0.0052)	−0.0032 (0.0041)	−0.0074 (0.0178)	**0.0091***** (0.0032)	0.0034 (0.0028)	**0.0453*** (0.0251)	−0.0040 (0.0027)	0.0036 (0.0036)
EMPLOYEES	0.0800 (0.0903)	0.0212 (0.0129)	0.0208 (0.0142)	**0.1992***** (0.0669)	**−0.0339***** (0.0119)	0.0129 (0.0123)	**0.2172**** (0.0922)	0.0036 (0.0131)	**0.0277**** (0.0130)
RECORDS	0.2252 (0.1876)	0.0256 (0.0300)	0.0377 (0.0243)	**0.3151*** (0.1836)	0.0457 (0.0315)	**0.0772**** (0.0272)	**0.4295**** (0.1966)	**−0.0700**** (0.0305)	0.0240 (0.0298)
MILK_PRICE	−0.0233 (0.0199)	−0.0044 (0.0042)	**−0.0050*** (0.0028)	**−0.0624***** (0.0122)	**−0.0132***** (0.0032)	**−0.0143***** (0.0031)	**−0.0860***** (0.0182)	**−0.0085**** (0.0035)	**−0.0139***** (0.0022)
YRCROSSBRED	−0.0119 (0.0076)	**−0.0047**** (0.0014)	**−0.0040***** (0.0011)	0.0070 (0.0125)	0.0005 (0.0023)	0.0011 (0.0018)	−0.0070 (0.0158)	−0.0033 (0.0021)	−0.0024 (0.0025)
CREDIT_ACCESS	**0.3058**** (0.1557)	−0.0138 (0.0298)	0.0211 (0.0242)	**0.4469***** (0.1552)	**0.1029***** (0.0326)	**0.1028***** (0.0251)	**0.3859**** (0.1670)	−0.0492 (0.0301)	0.0234 (0.0229)
_cons	−0.2496 (0.9094)	**0.4108**** (0.1828)		0.6118 (0.6475)	0.4155*** (0.1371)		0.1651 (0.7587)	**0.5541***** (0.1352)	
Sigma _cons		0.1996101			**0.1739***** (0.0102)			**0.1559***** (0.0094)	
Observations	410			382			354		
Log likelihood	−95.422452			−140.07215			−116.27777		
Waldchi2(14)	41.26			61.7			68.07		
Prob> chi2	0.0002			0			0		

Note: Figures in the parentheses are the standard errors associated with the coefficients and marginal effects.
***$P < 0.01$, **$P < 0.05$ and *$P < 0.10$ mean significant at 1%, 5% and 10% probability levels, respectively.
Source: Survey data, 2019.

information, and number of employees were positive and significant while APE of milk prices was negative and significant.

4. Discussion

4.1 Factors influencing TDI adoption across the three milksheds

In the three milksheds, access to credit positively and significantly influenced TDI adoption, an indication that farmers who accessed credit were more likely to adopt TDI than those who did not. This variable's probability marginal effect (APE) was statistically significant only in HCL and indicated that TDI adoption in HCL increased by 10.28% with access to credit. This finding agrees with Abdulai and Huffman (2005) in Tanzania, who revealed a positive effect of access to credit and the adoption of cross-breed cows. Access to dairy information positively and significantly influenced adoption of TDI in MWDL and NKCC Sotik, an indication that farmers who accessed dairy information were more likely to adopt TDI than those who did not. The APE of this variable was statistically significant in the two milksheds with a higher significance level in MWDL than in NKCC Sotik. This variable's higher significance level in MWDL than in NKCC Sotik could be because most farmers in MWDL belong to cooperative societies and groups where they are likely to access dairy information. As revealed by APEs, adoption of TDI increased by 5.95% and 7.14% with access to dairy information in MWDL and NKCC Sotik respectively. The finding agrees with those of other studies on adoption determinants of different agricultural technologies (Lapar and Ehui 2003; Uaiene 2011).

Farm size significantly and negatively influenced adoption of TDI in MWDL and had a positive influence in NKCC Sotik. The negative sign of farm size on TDI adoption in MWDL could imply that farmers in this milkshed could opt to use AI, one of the TDIs, instead of keeping bulls due to limited land, unlike farmers in NKCC Sotik who, because of relatively large pieces of land, could keep bulls and use them for reproduction. The finding in MWDL is consistent with Mwanga et al.'s (2019) findings, which reported a negative influence of land size on the adoption of AI.

Number of employees was significant and positively influenced TDI adoption in HCL, implying that as farmers engage more employees, TDI adoption, such as the growing of fodder or improved feeds, also increases. The APE of the variable for NKCC was positive and indicated that adoption of TDI increased by 2.77% as the number of employees increased by one person.

Keeping of dairy records such as reproduction, feed formulation and health records positively influenced adoption of TDI in HCL and NKCC Sotik. The APE of this coefficient in HCL indicated that adoption of TDI increased by 7.72% for farmers who kept records compared to those who did not. This finding corroborates Mugisha et al. (2014) in Uganda, which indicated a positive influence of record keeping on the use of AI.

Milk price negatively and significantly influenced TDI adoption in HCL and NKCC Sotik. This implies a farmer's decreased adoption of TDI as milk prices increase. The APE of this variable indicated that adoption of TDI dropped by 1.43% and 1.39% in HCL and NKCC Sotik respectively, when milk price increased by one Kenya shilling. The opposite influence of the adoption of TDI and milk prices can be explained by seasonal variability in milk production in the two milksheds. When prices are high, milk production is also low due to limited feed, and therefore farmers are unlikely to adopt TDI.

Total dairy cattle owned positively influenced TDI adoption in MWDL. The APE of the variable revealed a probable increase of 3.11% TDI adoption, resulting from an increase of one dairy cow. An explanation could be that as the number of dairy cattle increases, TDI such as use of AI, health services, housing and feeding also increases. Other studies (Asfaw et al. 2011; Shikur and Beshah 2013) have also found a positive and significant relationship between technology adoption and herd size measured by total livestock units.

4.2 Factors influencing OIDI adoption intensity across the milksheds

Total income negatively influenced adoption of OIDI in MWDL, while the variable had a positive influence on OIDI adoption in HCL and NKCC Sotik. The finding implied that as income increased, farmers in MWDL were unlikely to join a cooperative society, while in HCL and NKCC Sotik, high income increased farmers' probability of joining cooperative societies. The reason could be that the extra income gained by the farmer from off-farm activity could be used to purchase dairy cows and engage employees to take care of them, and hence prefer to sell through a cooperative which already has a determined payment schedule at the end of the month. The finding agrees with Mburu, Wakhungu, and Gitu (2007) in Kenya, which revealed that the probability of milk marketing through cooperative societies in Kenyan highlands increased if the household head engaged in off-farm work.

Household head education level positively influenced adoption of OIDI only in MWDL. An explanation is that farmers in MWDL who were more educated joined cooperative societies where they could adopt IDI such as credit access than those who were less educated. The reason could be more educated farmers are more likely to be more confident in adjusting to new innovations (Rao and Qaim 2011; Abdulai and Huffman 2014). This finding corresponds with that of Ngeno (2018), who reported education level had a positive influence on participation in a dairy hub by farmers in Kenya.

Household size negatively influenced adoption of OIDI in MWDL. This implies that as the number of persons in the household increased, the probability of the household adopting OIDI decreased. An explanation could be that as household size increases, the available land decreases, resulting in decreased milk production to be marketed through cooperative societies – although this finding coincides with that of Ngeno (2018) in Kenya, who reported a significant negative effect of household on dairy hub participation and contradicts those of other studies, which found a positive and significant relationship between household size and market participation (Demissie, Komicha, and Kedir 2014; Chamboko, Mwakiwa, and Mugabe 2017).

The number of employees negatively influenced adoption of OIDI in HCL. The APE of this variable was positive and significant at the 5% level in NKCC Sotik, indicating that as the number of employees increases by one person, the probability of adoption of OIDI increases 2.8%. The finding agrees with that of Mburu, Wakhungu, and Gitu (2007) in Kenya, which reported a positive relationship between hired permanent labour and marketing milk through dairy cooperatives in Kenyan highlands. In HCL, only a few farmers had joined cooperatives and groups engaged in milk selling, hence the negative effect.

Contrary to the expectation, farmers with more years with cross-breeds were unlikely to adopt OIDI in MWDL. Results indicate that despite the farmers keeping cross-breed cows, there could be other factors, such as inadequate feeding, that could lead to low milk production, hindering farmers from selling milk through groups or a cooperative society. The negative influence of farmers' experience on the adoption of OIDI, such as milk sales through cooperatives, is in line with the findings of Kuma et al. (2014) in Ethiopia.

Farm size positively influenced adoption of OIDI in HCL. The implication is that household heads with large pieces of land can keep a large number of cows, resulting in increased milk production. The farmer may decide to sell the large volume of milk through cooperative societies, therefore adopting ODI and access credit (IDI) than those with small pieces of land. These results contrast those of Kuma et al. (2014) in Ethiopia, who found a negative and significant effect of farm size on household milk market participation.

Keeping dairying records had a negative effect in NKCC Sotik. The implication could be that since most of the dairy records kept were on the use of AI, a majority of farmers in NKCC Sotik used bulls for reproduction. Farmers who used AI produced more milk, and therefore they could sell it through cooperative societies. This possibility corresponds to Yeamkong et al.'s (2010) finding, which established that farms that kept records had higher milk yields per farm than those without records.

Milk price negatively influenced OIDI adoption in HCL and NKCC Sotik. This implies that due to low prices offered by cooperative societies in these two milksheds compared to prices offered by milk agents, farmers were unlikely to sell their milk through cooperatives or groups. The results corroborate with those of Mburu, Wakhungu, and Gitu (2007) in Kenya, which revealed a negative relationship between average milk price (KES/kg) and milk marketing through dairy cooperative channels in the Kenyan highlands. Similarly, other studies noted that cooperative dairy societies offered low prices compared to other milk marketing channels (Chagwiza, Roldan Muradian, and Ruben 2016; Laishram and Chauhan 2019).

Access to dairy information positively influenced OIDI adoption in NKCC Sotik, an indication that farmers who accessed dairy information were more likely to sell their milk through cooperative societies than those who did not. Similar findings were reported by Mburu, Wakhungu, and Gitu (2007) in Kenya, who reported a positive influence of dairy cooperatives as a source of animal production information and availability of credit services on milk sales through cooperative dairy channels.

Credit access positively influenced the adoption of OIDI in HCL, and APE results revealed 10.28% adoption of OIDI with access to credit. Since access to finance could enhance access to dairy production support services like breeding, feeds and extension services resulting in increased milk production and income, farmers could be willing to sell their milk through cooperative societies, one of the OIDI.

5. Conclusion and policy implications

This study assessed the TDI adoption determinants, as well as the intensity of the use of OIDI, in three milksheds in Kenya. The study contributes to existing dairy technology adoption literature by revealing dairy innovations adopted by farmers practising different production systems and selling milk to farmers privately, as well as to state-owned processors. The study further considered dairy innovations and practices adopted at two levels: farm and milkshed. A low adoption of OIDI compared to TDI in the three milksheds was noted. Regarding the TDI adoption determinants, the study revealed that credit access is an important factor in the adoption of TDI in the three milksheds. Further, TDI adoption and the intensity of use of OIDI were influenced by different factors, which differed in magnitude and significance level across the three milksheds. The study, therefore, revealed varied interventions required to promote dairy innovations across the three milksheds. To promote the adoption of TDI in MWDL, focus should be made on the provision of dairy information. The county government and dairy innovation promoters should develop extension approaches that would go toward disseminating dairy information. Regarding OIDI, promoters of these innovations should target the large households, the less educated and those with higher income levels.

In HCL, adoption of TDI can be boosted by the county government together with TDI and OIDI promoters training farmers on dairy record keeping. The training should be tailored to reach young dairy farmers. In addition, farmers should be encouraged to join groups dealing with milk sales because they can enhance information, knowledge sharing and access to credit at affordable interest rates to buy improved cow breeds and animal feeds. Group membership can therefore promote adoption of TDI and OIDI. In NKCC Sotik, the county government should enhance access to dairy information and train farmers on how to keep dairy records to enhance TDI and OIDI adoption. Efforts should target farmers with large farms and many employees.

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