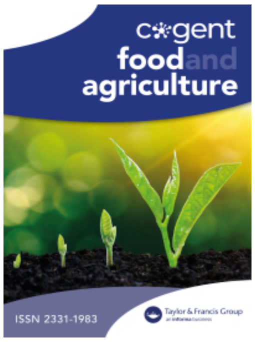

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Role of agricultural extension in learning for uptake and intensification of less-practiced dairy climate-smart practices in Kenya

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ABSTRACT

The enhanced uptake of dairy climate-smart practices (DCSPs) is important to cushion farmers against the effects of climate change. However, uptake remains low. Besides, there is limited evidence on the learning phase preceding adoption under a pluralistic extension system, while intensity is treated as a one-off process. Therefore, this study aimed to assess factors influencing learning about least adopted DCSPs through different extension providers and, evaluate determinants of adoption and intensity of adoption of least adopted DCSPs. The triple hurdle model was used to model adoption conditional on learning and intensity of adoption, using a sample of 665 dairy farmers from selected counties in Kenya. Although learning facilitated adoption, intensity of uptake was very low. Ease of accessing extension services and milk market participation influenced learning positively. Keeping dairy records, increase in knowledge about climate change, higher number of extension visits were positively associated with both adoption and intensity of adoption of least adopted DCSPs. Additionally, perception that DCSPs enhanced resilience and increased level of milk market participation were important determinants of intensity of adoption. Therefore, to foster intensified promotion and intensified uptake of the least adopted DCSPs, it is imperative to strengthen pluralistic extension system, increase extension contacts with farmers, train farmers on climate change and record keeping, facilitate market participation and ensure DCSPs contribute to improved resilience. This would contribute to the realization of sustainable development goal 13 on climate action and the country's climate change commitments and agriculture development strategy.

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1. Introduction

World over, the need for climate-smart practices in agriculture has never been more pressing as extreme weather events associated with climate change intensify and become frequent. Worse still, the effects are projected to have widespread impact (Ayanlade et al., 2022; Fagbemi et al., 2023). The effects are more pronounced in developing regions like Africa, especially sub-Saharan Africa, where the confluence of heavy dependency on agriculture and low levels of development renders the region more susceptible to climate change effects (Asfew et al., 2023; Ogisi & Begho, 2023). The repercussions of the changing climate are starkly evident in countries located in these regions including Kenya, where most agricultural production is rain-fed, and the majority of producers are resource-poor (Akinyi et al., 2022; Bukari & Aluko, 2023; IPCC, 2022). The extreme weather changes, characterized by soaring temperatures, erratic rainfall patterns and heightened climate-related catastrophes such as floods and drought, precipitates profound economic losses (Ogisi & Begho, 2023). Due to climate change effects, Kenya's dairy production zones dominant in the Rift Valley and central highlands, have seen increased incidences of tick-borne and foot and mouth diseases, alongside deterioration in both the availability and quality of feed and fodder, and water scarcity, with adverse effects on milk production potential (GoK, 2018; Nalianya et al., 2020). This has prompted the development and promotion of dairy climate-smart agriculture practices (DCSPs).

The uptake of DCSPs among farmers holds the potential to avert climate change effects and improve dairy performance (Bouchard et al., 2019; Maindi

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et al., 2020; Odari, 2011; Tadesse & Dereje, 2018). This is instrumental in meeting the rising per capita milk consumption in the country and the region. Studies have documented the contribution of implementing various DCSPs (genetic improvement, improved forage species, feed supplementation with feed blocks or concentrates, use of silage, biodigesters, covering manure heaps, treating crop residues, stocking rate adjustments, health care practices and breeding management), on enhanced dairy production resilience, milk productivity and reduction in emission of greenhouse gases (Ericksen & Crane, 2018; Escarcha et al., 2018; FAO & New Zealand Agricultural Greenhouse Gas Research Centre, 2017; Germer et al., 2023; Herrero et al., 2015; Khatri-Chhetri et al., 2017; Maindi et al., 2020; Notenbaert et al., 2017; Zhang et al., 2017). Despite these potential benefits, the uptake of DCSPs has remained low (Akinyi et al., 2022; Maindi et al., 2020), causing concerns among policymakers.

Innovation diffusion as acknowledged by Rogers (1983) is complex with information playing a pivotal role in the spread and utilization of innovations including agricultural practices (Gifford & Nilsson, 2014; Wang & Hazen, 2016; Goodarzi et al., 2021. Information helps in overcoming utilization barriers including transaction risks and costs (Goodarzi et al., 2021). To reduce uncertainty and facilitate uptake, information provided about the practices should be adequate, comprehensive and clear (Dimara & Skuras, 2003; White et al., 2019). Therefore, information provided should go beyond mere acquaintance and create deeper comprehension that can allow uptake (Adegbola & Gardebroek, 2007; Dimara & Skuras, 2003).

Agricultural extension providers play an integral role in information provision throughout innovation diffusion (Anang et al., 2020; Biswas et al., 2021; Danso-Abbeam et al., 2018; Davis et al., 2020; Dinar et al., 2007; Lipper et al., 2018; Niu & Ragasa, 2018; Olorunfemi et al., 2020; Ragasa & Mazunda, 2018; Silvestri et al., 2012; Stone, 2016; Tanti et al., 2022; Yitayew et al., 2021). Their effectiveness in information delivery as underscored by Ojijo et al. (2016) influences innovation diffusion process. The shift towards pluralistic extension system has seen private sector extension complement public extension services (Davis et al., 2020). Nonetheless, differences in institutional arrangements guiding extension service delivery by the different actors result in variations in the delivery of services (Muyanga & Jayne, 2008; Mwololo et al., 2019). Consequently, farmers develop diverse perceptions and preferences for the different extension service providers (Adegbola & Gardebroek, 2007; Bassey, 2016; Kassem et al., 2021; Lofty & Adeeb, 2016; Loki et al., 2020).

Despite the growing body of literature on the uptake of climate-smart practices (Aryal et al., 2018; Azadi et al., 2019; Bechini et al., 2020; Hyland et al., 2018; Kelebe et al., 2017; Khanal et al., 2018; Khatri-Chhetri et al., 2017; Kiggundu et al., 2021; Kurgat et al., 2020; Long et al., 2016; Maina et al., 2020; Maindi et al., 2020; Michels et al., 2019; Msuya & Wambura, 2016; Mujeyi et al., 2020; Nyasimi et al., 2017; Oyinbo et al., 2019; Pagliacci et al., 2020; Swami & Parthasarathy, 2020; Tanti et al., 2022; Thornton & Herrero, 2014), there is limited evidence on the role of learning phase preceding adoption. Existing studies that attempted to bridge the gap (Adegbola & Gardebroek, 2007; Atanu et al., 1994; Dimara & Skuras, 2003) considered the information-seeking phase as being aware or not aware, without considering extension service providers. Therefore, little is known about the learning phase before adoption in the context of pluralistic extension systems for the case of DCSPs. Further, studies examining the intensity of adoption (Aryal et al., 2018; Maindi et al., 2020) only considered either diversity or the extent of uptake of the practices. Since adoption is not a one-off process, it is important to have a holistic consideration of the intensity dimensions through the use of an adoption quotient as proposed by Pareek and Chattopadhyay (1966) and applied by Nazu et al. (2021), Mihretie et al. (2022) and Cholo et al. (2023). Therefore, intensity assessment should consider the extent of implementation, the diversity of practices promoted, the period the practice has been available for use, and consistency in use over time. This is important since optimal benefits may not be immediate and may become apparent through consistent use. Besides, the uptake of multiple practices could benefit from the complementarity of practices as well as wider application on the farm, increasing the benefits. Therefore, this study aimed to address three objectives; to assess factors influencing learning about least adopted DCSPs through different extension service providers; evaluate determinants of adoption of least adopted DCSPs conditional on learning and lastly analyze drivers of intensified uptake of least adopted DCSPs. The study findings are important for policy makers in designing and delivering extension services responsive to farmers' needs as well as designing strategies for the promotion and uptake of DCSPs for enhanced resilience of dairy production.

2. Materials and methods

2.1. Study area and sampling procedure

The study which was conducted in 2022, utilized a cross-sectional survey design and followed a multi-stage sampling procedure. Five counties namely Bomet, Nakuru, Nyamira, Nyeri, and Uasin Gishu, were purposively selected. The counties comprised of the key milk production counties in the country located in the Rift Valley region and central highlands (Wairimu et al., 2021). The selection was informed by their potential to achieve the triple win benefits of DCSPs through increased milk productivity, reduced emissions of green house gases (FAO & New Zealand Agricultural Greenhouse Gas Research Centre, 2017) and enhanced resilience. Moreover, they had been targeted for the promotion of DCSPs through interventions such as the Kenya Climate Smart Agriculture Project (KCSAP) and the Africa Milk Project (Onyango et al., 2019; Wairimu et al., 2022). The counties were also linked to three milk processors: Happy Cow Limited (HC), Wakulima Mukurueini Dairy Limited (WL), and New Kenya Cooperative Creameries factory in Sotik (NKCCS) for milk marketing to facilitate the uptake of the DCSPs. Major milk-producing sub-counties targeted for the Kenya Climate Smart Agriculture Project and Africa Milk Project interventions were identified in each county. This resulted in selection of Mathira West, Mukurwe-ini, Kieni East, and Kieni West sub-counties in Nyeri County; Njoro and Kuresoi South sub-counties in Nakuru County; Ainabkoi Sub-County in Uasin Gishu, Manga and Borabu sub-counties in Nyamira; and Chepalungu and Sotik sub-counties in Bomet County. Further, a ward from each sub-county was randomly selected using simple random sampling technique. The sampling frame comprised lists of dairy farmers from the selected wards obtained from the local administration or through the help of the agricultural extension officers.

In selecting the final respondents, the study relied on systematic random sampling. Using the lists provided by the extension officers and the local administrators, the first household was selected randomly. Thereafter, a consistent interval was used to select the subsequent household. The interval was arrived at using the sample size and the number of dairy farmers in a study ward as per the lists provided. Sample size calculation was based on Bartlett et al. (2001) formula which yielded a sample of 683 farmers. The sample size was proportionately distributed by population size across the three milksheds. The Wakulima Mukurueini Dairy Limited (WL) had the highest proportion of farmers at 45%, followed by New Kenya Cooperatives Creameries Sotik (NKCCS) milkshed at 32%. The Happy Cow Limited (HC) milkshed had the least proportion of farmers at 22%. Nonetheless, the study achieved 665 respondents due to unavailability of some respondents who were distributed as follows across the three milksheds: WL 39.8%, NKCCS 31.6% and HC 28.6%.

2.2. Data sources and sample respondents

Semi-structured questionnaires were used to collect data from the smallholder dairy farming households who were the target respondents. The tools were pretested in a county that had promoted DCSPs but was not sampled for the current study. The inclusion criteria entailed smallholder farmers practicing dairy farming and located in locations where DCSPs had been promoted. Farmers not practicing dairy farming and not located in locations where DCSPs had been promoted were excluded. Further, informed consent was obtained from target respondents before the interview could proceed. To address potential respondent selection bias, systematic random sampling was applied. The systematic random sampling ensured that every smallholder dairy farmer in the study locations had equal chances of being selected.

2.3. Selection of least adopted dairy climate-smart practices

The least adopted DCSPs were selected from a pool of 17 DCSPs (Table 1) that farmers had been exposed to through various interventions. The study used the percentage of the sampled households adopting a practice to determine the least adopted DCSPs. A threshold of 30% and below was used, such that if a DCSP was adopted by 30% or below of the sampled farming households, it was least adopted and hence included in the analysis.

Of the 17 practices, 11 were adopted by less than 30% of dairy farming households and thus categorized as the less adopted practices. These were drought tolerant fodder (DT), leguminous fodder (LF), multi-nutrient blocks (MB), treating crop residues (TCR), total mixed rations (TMR), silage (SIL), biogas (BIO), covering manure (CM), composting (COM), adaptable breeds (AB) and culling (CUL) as illustrated in Table 2.

Table 1. Description of the dairy climate-smart practices.

Practice	Description and measure
Fodder Diversification (FD)	Cultivate and use diverse high-yield fodder; 1 = yes, 0 = no
Drought Tolerant (DT)	Cultivate and use fodder crops that can withstand drought; 1 = yes, 0 = no
Leguminous Fodder (LF)	Production and use of high nitrogen fixing and high protein content leguminous fodder; 1 = yes, 0 = no
Treating Crop Residues (TCR)	Treating crop residues before feeding them to cows to enhance digestibility, unlock nutrients and improve nutrient content; 1 = yes, 0 = no
High Energy Concentrates (HEC)	Feeding milking cows with high energy concentrate; 1 = yes, 0 = no
Multi-nutrient Blocks (MB)	Feeding milking cows with nutrient-fortified blocks/feeds; 1 = yes, 0 = no
Total Mixed Rations (TMR)	Preparing dairy feeds at home that are nutrient-balanced while incorporating locally available materials; 1 = yes, 0 = no
Hay (HAY)	Baling harvested and cured fodder crops to preserve them for use during a shortage; 1 = yes, 0 = no
Silage (SIL)	Ensiling fodder crops to preserve them for use during a shortage; 1 = yes, 0 = no
Biogas (BIO)	Using cow dung to prepare biogas for household use and application of slurry to fodder crops; 1 = yes, 0 = no
Covering Manure (CM)	Heaping or putting manure in a covered manure pit or heap; 1 = yes, 0 = no
Composting (COM)	Composting manure and using it for fodder production; 1 = yes, 0 = no
Disease Prevention (DP)	Reduce disease burden through prevention techniques, including vaccination and farm biosecurity measures; 1 = yes, 0 = no
Disease Control (DC)	Manage diseases and parasites through timely treatment and appropriate use of animal drugs, and chemicals; 1 = yes, 0 = no
Artificial Insemination (AI)	Use of AI to get high-yielding breeds; 1 = yes, 0 = no
Adaptable Breeds (AB)	Rearing breeds adaptable to climatic conditions and farm characteristics; 1 = yes, 0 = no
Culling (CUL)	Replacing less productive animals; 1 = yes, 0 = no

Table 2. Adoption level of dairy climate-smart practices (Primary data, 2022).

Dairy climate-smart practice	Mean	Std. dev
Fodder Diversification (FD)	0.42	0.49
Drought Tolerant (DT)	0.17*	0.38
Leguminous Fodder (LF)	0.09*	0.29
High Energy Concentrates (HEC)	0.58	0.49
Multi-nutrient Blocks (MB)	0.09*	0.29
Treating Crop Residues (TCR)	0.08*	0.27
Total Mixed Rations (TMR)	0.02*	0.15
Hay (HAY)	0.31	0.46
Silage (SIL)	0.19*	0.40
Biogas (BIO)	0.03*	0.16
Covering Manure (CM)	0.15*	0.35
Composting (COM)	0.26*	0.44
Disease Prevention (DP)	0.55	0.50
Disease Control (DC)	0.94	0.23
Artificial Insemination (AI)	0.60	0.49
Adaptable Breeds (AB)	0.25*	0.44
Culling (CUL)	0.05*	0.21

**Represents the mean values of the DCSPs adopted by less than 30% of the respondents.

2.4. Empirical framework

The study used random utility model (RUM) to analyze dairy farmers' substitution behavior in selecting the extension provider to learn from and dairy climate-smart practices alternatives (Domencich & McFadden, 1975; McFadden, 1972). A rational dairy farmer will seek to maximize utility from the choices they make, justifying the use of RUM. In this case, the dairy farmer will select the extension service provider to learn from and DCSPs combination to adopt based on the alternatives that yield higher utility. In discrete choice analysis, an individual is believed to choose the alternative that maximizes utility. The i^{th} dairy farmer chooses j^{th} dairy extension service provider and dairy climate-smart practice (DCSP) since they derive the highest utility from the choice made such that, U_{ij} is the utility derived from alternative chosen or choice made. The utility function can be expressed as in Equation 1 (Train, 2009).

$$U_{ij} = X_{ij} + \varepsilon_{ij} \tag{1}$$

X_{ij} represents explanatory variables (farm, farmer, DCSPs and dairy extension service providers characteristics) influencing the level of utility of the chosen alternative and ε_{ij} is the random error term.

The adoption decision of dairy climate-smart practices (DCSPs) is modelled as a three-stage sequential process using the triple hurdle model as applied by Burke et al. (2015), Akrong et al. (2021) and Chen et al. (2021). The triple hurdle is desirable as it allows simultaneous estimation of the three equations providing efficient estimates since the assumption of conditional uncorrelation of the error terms can be tested (Burke et al., 2015; Sekyi et al., 2017). If such error terms are correlated, it implies that the decisions are not independent of each other. Therefore, under such circumstances, estimation of the three equations independently would yield biased estimates. Therefore, this study modelled the uptake of DCSPs conditional on learning such that learning precedes the decision to adopt. Learning involves a dairy farmer interacting with a dairy extension service provider (DESP). Through the interactions, the dairy farmer acquires different levels of information that facilitates the evaluation of the DCSPs they are presented with and subsequently informs uptake. Once the learning hurdle is passed, the dairy farmer makes the adoption decision subject to the learning process. Having adopted, the farmer then decides on the intensity of adoption of DCSPs.

The triple hurdle model integrates the three levels of decision-making: learning through different DESPs, adoption of DCSPs, and intensity of adoption of DCSPs.

2.4.1. Hurdle 1

The selection of the DESP to learn from is a binary decision since a farmer may learn from a government extension provider or otherwise depending on the utility derived. Therefore the Probit model is used to analyze the choice of DESP in line with Maddala (1992) and Wooldridge (2016) as represented by Equations 2–4.

$$Y_j^* = \beta' X_j + \varepsilon_i \tag{2}$$

$$Y_j = 1 \, if \; Y_j^* > 0 \tag{3}$$

$$Y_j = 0 \, if \; Y_j^* < 0 \tag{4}$$

Where Y_j^* is an underlying latent variable of choice of DESP. However, since Y_j^* is not observed, what is observed is the dairy farmer's choice of DESP from whom they learn about DCSP, represented by Y_j which takes the value of '1' if a farmer learned about DCSP from government and '0', otherwise (Equation 5).

$$Y_j = \beta_j X_j + \varepsilon_i > 0 \tag{5}$$

The X_j are explanatory variables (farm, farmer and DESP characteristics), β_j are the parameter estimates to be estimated and ε_i is a stochastic error term assumed to be independently and identically distributed (iid) with mean 0 and variance δ^2.

The probability that a dairy farmer learns about DCSPs from the government DESP is represented by Equation 6.

$$Prob\left(Y_j = 1 \,|\, X_j\right) = \varnothing\left(\beta_j X_j\right) \tag{6}$$

On the other hand, the probability that a dairy farmer does not learn about DCSPs from the government DESP can be represented as in Equation 7.

$$Prob\left(Y_j = 0 \,|\, X_j\right) = 1 - \varnothing\left(\beta_j X_j\right) \tag{7}$$

2.4.2. Hurdle 2

In the second stage, a dairy farmer's adoption decision of DCSPs is binary, such that a farmer decides to adopt or not to adopt any of the less adopted DCSPs given the expected utility. Therefore, a binary choice model; the probit model (Maddala, 1992; Wooldridge, 2016), is used as in Equation 8.

$$Y_i^* = \beta' X_i + \varepsilon_i \tag{8}$$

Where Y_i^* is an underlying latent variable of adoption decision, X_i explanatory variables (farm, farmer and DCSPs characteristics), β' are parameter estimates and ε_i is a stochastic error term assumed to be independently and identically distributed (iid) with mean 0 and variance δ^2. Nonetheless, Y_i^* in Equations 9 is not observed, what is observed is Y_i which is the DCSP adoption decision if Y_i^* is above the threshold.

$$Y_i = 1 \, if \; Y_{it}^* > 0 \tag{9}$$

$$Y_i = 0 \, if \; Y_{it}^* < 0 \tag{10}$$

Given the observed adoption decision, Equations 8–10 take the form of Equation 11.

$$Y_i = \beta_i X_i + \varepsilon_i > 0 \tag{11}$$

The probability that a dairy farmer adopts any of the less adopted DCSP is represented by Equation 12.

$$Prob\left(Y_i = 1 \,|\, X_i\right) = \varnothing\left(\beta_i X_i\right) \tag{12}$$

On the other hand, the probability that a dairy farmer does not adopt DCSP can be represented as in Equation 13.

$$Prob\left(Y_i = 0 \,|\, X_i\right) = 1 - \varnothing\left(\beta_i X_i\right) \tag{13}$$

2.4.3. Hurdle 3

The adoption intensity of least adopted DCSPs is measured as a quotient which is a continuous variable bound between 0 and 1 with corner solutions hence a Tobit model is used (Tobin, 1958). The latent regression model of the adoption intensity of least adopted DCSPs can be represented by Equations 14 and 15.

$$Y_l^* = \beta' X_l + e_l \tag{14}$$

Where

$$Y_l = \begin{Bmatrix} 0 \; if \; Y_l^* < 0 \\ Y_l^* \; if \; Y_l^* > 0 \\ 1 \; if \; Y_l^* > 1 \end{Bmatrix} \tag{15}$$

With 0 being the lower limit and 1 being the upper limit, Y_l^* is the latent value of the adoption quotient of least adopted DCSPs. As in other cases what is observed is Y_l which is the observed adoption quotient value. As such, Equations 14 and 15 can be represented by Equation 16.

$$Y_l = \beta_l X_l + \varepsilon_l \tag{16}$$

The Y_l is the adoption quotient, X_l explanatory variables, β_l are parameter estimates and ε_l is a random error term.

The intensity of adoption of the least adopted DCSPs is conditional on the adoption of least adopted DCSPs which in turn is conditional on learning about DCSPs from the DESPs. Therefore, Y_l is observed only if $Y_i = 1$ and Y_j=1. The error terms are distributed as a trivariate normal as in Equation 17.

$$\{\varepsilon_j, \varepsilon_i, \varepsilon_l\} \sim (0, 0, 0, \sigma^2, 1, 1, \varphi_1, \varphi_2, \rho) \tag{17}$$

$$\varphi_1 = corr(\varepsilon_j, \varepsilon_l)$$

$$\varphi_2 = corr(\varepsilon_i, \varepsilon_l)$$

$$\rho = corr(\varepsilon_i, \varepsilon_j)$$

The three-stage decision a dairy farmer is faced with (learning, adoption and intensity) has three possible outcomes. The first is not learning about DCSPs from government as a DESP $(Y_j = 0)$ or learning but not adopting least adopted DCSPs $(Y_i = 0 | Y_j = 1)$ and for those who learn and adopt, the intensity of adoption. In line with Gebremedhin et al. (2017), the probable outcomes of the three decisions that the dairy farmer is faced with can be represented by Equations 18–20.

$$Prob(Y_j = 1 | X_j) = \Phi(\beta_j X_j) \tag{18}$$

$$Prob(Y_i = 0 | Y_i = 1) = \varnothing(\beta_j X_j) - \Phi(\beta_j X_j, \beta_i X_i) \tag{19}$$

$$A(Y_l) = Adoption(Quotient) = \Phi(\beta_j X_j)\varnothing (\beta_j X_j, \beta_i X_i) * \exp(\beta_l X_l + \delta_3^2 / 2) \tag{20}$$

A likelihood function for the three possible outcomes is as in Equation 21.

$$l_i(\varnothing) = 1[Y_j = 0]\log[1 - \Phi(\beta_j X_j)] + 1[Y_j = 1]1[Y_i = 0] \{\log[\Phi(\beta_i X_i)] - log[\Phi(\beta_j X_j, \beta_i X_i]\} + 1[Y_j = 1]1[Y_i = 1] \left\{ \begin{array}{l} \log[\Phi(\beta_j X_j)] + \log[\Phi(\beta_j X_j, \beta_i X_i] + \\ \log\left(\varnothing[\dfrac{\log Y_i - X_l \beta_l}{\delta_3}]\right) - \log \delta_3 \end{array} \right\} \tag{21}$$

In Equation 21, $\varnothing(.)$ and $\Phi(.)$ represent the standard normal density and standard normal cumulative distribution functions respectively, β are parameter estimates, X are explanatory variables and δ_3 represents the error variance.

2.5. Estimation of coefficients and control of selection bias

On the assumption that only those who learn about DCSPs from government DESP adopt and only those who adopt, intensify their adoption, there is the likelihood of sample selection bias. Therefore, the empirical estimations above may yield biased estimates since they are based on the assumption that all zero observations possess the same chance of becoming adopters and intensifying least adopted DCSPs (Wooldridge, 2016). This is not the case since adoption is conditional on the learning and the intensity of adoption on adopion. Therefore, adoption and intensity of least adopted DCSPs are relevant to a non-random sample that has learned and adopted least adopted DCSP, respectively. Moreover, learning and adoption may be influenced by unobserved characteristics, which may influence adoption and adoption intensity, respectively, hence the need to jointly estimate learning, adoption, and adoption intensity, while allowing for the correlation of the error terms.

In this regard, the study used a conditional mixed-process model (CMP), which allows joint estimation of the three equations and correlation of the error terms. Besides, inverse mills ratio (IMRs) were estimated and included accordingly in line with Burke et al. (2015) to allow for selection bias correction. Wooldridge (2016) proposes using IMRs to test for the correlation of the conditional error terms in the first and second stages. The Probit was estimated for the first stage, and IMRs were predicted using CMP. The IMRs were then included in estimating the second hurdle probit equation. Subsequently, the second equation (Probit) was estimated, and IMRs were predicted and included in the third hurdle equation. The correlation of the error terms can be tested under the null hypothesis that they are uncorrelated. The null hypothesis is rejected if the IMRs from each equation are statistically significant and different from zero. If we reject the null hypothesis, it implies there is selection bias justifying the inclusion of the IMRs. If the null hypothesis is not rejected, the respective equations are estimated again, excluding the IMRs. Though not necessary, Burke et al. (2015) and Wooldridge (2016) recommend the inclusion of an exclusion restriction term when either of the stages is estimated to exclude the IMRs. In this study, ease of accessing extension services on DCSPs and risk attitude are imposed as exclusion restriction variables for the first and second hurdle equations, respectively.

2.6. Measurement of variables

2.6.1. Dairy climate-smart extension service providers

In the analysis of the dairy extension service providers (DESPs) from whom farmers learned about DCSP, the study relied on the classification provided by Davis et al. (2020). They classified extension into two broad categories: public and private sector. Which was adopted for this study. The choice of a DESP was coded as '1' if a farmer had learned about DCSPs from government before adoption and '0' otherwise (private).

2.6.2. Dairy climate-smart practices (DCSPs)

The least adopted practices analyzed are presented in Table 3. To analyze adoption, the study determined if a farmer had adopted any of the less practiced DCSPs which was coded as '1' if a farmer had adopted and '0' if a farmer had not adopted.

2.6.3. Variables hypothesized to influence learning, adoption and intensity of adoption

The study hypothesized that learning about DCSPs, adoption and intensity of adoption were influenced by socio-demographic, economic, farm, institutional and social factors as well as technology and extension provider characteristics (Table 4) in line with previous studies on uptake of climate-smart practices (Erekalo & Yadda, 2023; Kassa & Abdi, 2022; Kurgat et al., 2020; Magesa et al., 2023; Maina et al., 2020; Maindi et al., 2020; Mujeyi et al., 2020; Ogisi & Begho, 2023; Sanogo et al., 2023; Sisay et al., 2023).

2.6.4. Adoption quotient

To measure intensity of adoption of least adopted DCSPs, the study used the adoption quotient as proposed by Pareek and Chattopadhyay (1966) and applied by Nazu et al. (2021), Mihretie et al. (2022) and Cholo et al. (2023) but adapted to fit the current study. The quotient considered the diversity of practices adopted on the farm, consistency of use over time, extent of implementation and availability of the practice. These parameters were aggregated to constitute an adoption quotient. The diversity of uptake was measured as the proportion of different practices adopted amongst farmers by dividing the number of DCSPs adopted by a farmer with those promoted. Consistency was estimated as the period a farmer has been using the practice, calculated as difference in years of when data was collected (2022) and the year the technology was first used. To measure the extent of uptake, the rate of DCSP adoption by an individual farmer relative to average adoption rate of other farmers interviewed was used. Lastly, availability was calculated as the duration the technology had been available to the farmer by taking the year the data was collected (2022) subtracting the year the farmer first heard about the practice. These measures were then used to calculate the adoption quotient as in Equation 26 for a farmer adopting M number of technologies from a set of DCSPs.

$$Adoption\ quotient = diversity * \sum_{j=1}^{M}\left[\left[\frac{(consistency * extent)}{availability}\right]\right] \tag{26}$$

Table 3. Description of the less-adopted dairy climate-smart practices.

Practice	Description and measure
Drought Tolerant (DT)	Cultivate and use fodder crops that can withstand drought; 1 = yes, 0 = no
Leguminous Fodder (LF)	Production and use of high nitrogen fixing and high protein content leguminous fodder; 1 = yes, 0 = no
Treating Crop Residues (TCR)	Treating crop residues before feeding them to cows to enhance digestibility, unlock nutrients and improve nutrient content; 1 = yes, 0 = no
Multi-nutrient Blocks (MB)	Feeding milking cows with nutrient-fortified blocks/feeds; 1 = yes, 0 = no
Total Mixed Rations (TMR)	Preparing dairy feeds at home that are nutrient-balanced while incorporating locally available materials; 1 = yes, 0 = no
Silage (SIL)	Ensiling fodder crops to preserve them for use during a shortage; 1 = yes, 0 = no
Biogas (BIO)	Using cow dung to prepare biogas for household use and application of slurry to fodder crops; 1 = yes, 0 = no
Covering Manure (CM)	Heaping or putting manure in a covered manure pit or heap; 1 = yes, 0 = no
Composting (COM)	Composting manure and using it for fodder production; 1 = yes, 0 = no
Adaptable Breeds (AB)	Rearing breeds adaptable to climatic conditions and farm characteristics; 1 = yes, 0 = no
Culling (CUL)	Replacing less productive animals; 1 = yes, 0 = no

3. Results and discussions

3.1. Descriptive statistics of the sampled households

The study results showed that 79% of farmers were learning about dairy climate-smart practices (DCSPs) from private dairy extension service providers (DESPs), with only 29% learning from government. This means that farmers are more likely to access extension services on DCSPs from private extension providers relative to government. This is explained by constraints facing government extension system hence reduced outreach necessitating pluralistic extension system to address this gap (Davis et al., 2020; Tata & McNamara, 2018). Similarly, using frequency of extension visits, Ogola et al. (2023) found that majority of the farmers were never or were rarely visited by government extension provider in comparison to other providers. The findings affirm the importance of pluralistic extension system in facilitating delivery of complementary extension services through different players.

Learning resulted in 73% of dairy farmers adopting the least adopted practices. However, the level of adoption as denoted by the adoption quotient was very low at 0.1. The results show that, while farmers are adopting the least adopted DCSPs, intensification is minimal. Similarly, Maindi et al. (2020) found low intensification of dairy climate-smart practices. The low intensity of adoption could be attributed to socio-economic factors, as well as attributes of extension services and those of the practices. Moreover, some of these practices such as the multi-nutrient blocks are recent developments with majority of the farmers being at the learning phase of the adoption cycle. Therefore, despite interest demonstrated through adoption, intensification remains a major challenge.

The descriptive statistics of the explanatory variables were disaggregated between adopters and non-adopters of the least adopted DCSPs (Table 5). A higher number of adopters relative to non-adopters, indicated that DCSP enhanced resilience of dairy production, kept dairy farming records, were risk averse, considered it easy to access DCSPs services, were from male-headed households and belonged to dairy groups. Moreover, adopters exhibited greater knowledge about climate change, had frequent contacts with extension, possessed higher levels of education, had many years of experience in dairy farming, larger herd sizes, higher on-farm income and greater proportion of market participation. However, the

Table 4. Description and measurement of explanatory variables.

Variable	Variable description and measure	Expected sign		
		Learning	Adoption	Intensity
Resilience	If a farmer perceived DCSPs to enhance resilience of dairy production; 1 = yes, 0 = no		+	+
Record	If a farmer keeps dairy records; 1 = yes, 0 = no		+	+
Climate change knowledge	Level of knowledge about climate change measured as the aggregate scores of knowledge about climate change causes, effects, and extreme events divided by the total sum of scores; proportion		+	+
Extension visits	Number of visits by an extension agent; continuous		+	+
Risk attitude	Given that a farmer can afford insurance premiums, what is their insurance response to a disease anticipated in the next two years with the potential to result in the death of all their dairy cows (Risk averse – insure, and risk loving – not insure); 1 = risk averse, 0 = risk loving		+	
Ease of DCSPs extension	If a farmer perceived that it was easy to access DCSPs extension services; 1 = yes, 0 = no	+		
Household size	Number of members in a household; continuous	+	+	+
Sex	Sex of the household head; 1 = male, 0 = female	+−	+−	+−
Education	Education level of the household head as measured by the years of schooling; continuous	−	+	+
Experience	Experience in dairy farming measured as years in dairy farming; continuous	+	+	+
Agricultural group	If a farmer belongs to an agricultural group; 1 = yes, 0 = no	+	+	+
Herd size	Measured as the tropical livestock unit; continuous	+	+	+
Log on-farm income	Log household on-farm income measured as the log of aggregate on-farm income from all the enterprises practiced on the farm; continuous	+	+	+
Milk market participation	Proportion of milk produced that is sold: proportion	+	+	+
Primary occupation	If farming is the primary occupation of the household; 1 = yes, 0 = no	+	+	+
Wakulima Mukurueini Dairy Limited (WL)	Farmer being from WL milk shed; 1 = yes, 0 = no	+−	+−	+−
Happy Cow Limited (HC)	Farmer being from HC milk shed; 1 = yes, 0 = no	+−	+−	+−
New Kenya Cooperative Creameries-Sotik (NKCCS)	Farmer being from NKCCS milk shed; 1 = yes, 0 = no	+−	+−	+−

household size was the same for both adopters and non-adopters. Further, adopters were dominant in Wakulima Mukurwe-ini Dairy Limited (WL) and New Kenya Cooperative Creameries milksheds while non-adopters were dominant in Happy Cow Limited milkshed. To test if there were significant differences between adopters and non-adopters, t-test was used. The results showed that adopters were significantly different from non-adopters for all socioeconomic variables except household size, sex of household head, herd size and primary occupation of the household head. Therefore, it was apparent that adopters compared favorably than the non-adopters in terms of socio-economic well being.

3.2. Determinants of learning, adoption and intensity of adoption of the least adopted dairy climate-smart practices

The model estimating factors influencing learning, adoption, and intensity of adoption of least adopted dairy climate-smart practices (DCSPs) had strong explanatory power (Wald chi2 (47) = 170.33, Prob > chi2 = 0.000) (Table 6). The results of selection bias showed unconditional correlation of the error terms for the second and third hurdle equations. Therefore, the model was re-estimated to exclude the IMRs for the first hurdle equation in the adoption equation. Besides, the rho for the first and second, and second and third equations showed potential endogeneity. Given the unconditional correlation of the error terms, the estimation of the three equations separately without correcting for selection bias and endogeneity would have yielded biased and inconsistent estimates. The next sub-sections present and discuss the results of each of the three stages of the triple hurdle model starting with learning, then adoption and lastly intensity of adoption of the least adopted DCSPs.

3.2.1. Determinants of learning about least adopted dairy climate-smart practices from the different extension service providers

The perceived ease of accessing extension services significantly increased the likelihood of learning about DCSPs from government extension providers relative to private. This means that farmers who perceived accessing extension services as being easy were more likely to learn about the least adopted DCSPs from the government extension provider. Nonetheless, the findings are contrary to Kassem et al. (2020), who found that private extension service providers were more accessible. Therefore, though constrained, it appears that accessing government extension is easy compared to other providers. This could be explained by government extension being offered as a public good addressing access barriers. The services are open to all farmers including those that may not be reached by other extension providers due to their location or marginal status. Besides, government extension do not charge any service fee unlike private extension who may require that farmers pay to access services, restricting access to farmers who can not afford. Moreover, it could imply a shift in extension strategies and approaches towards those that enhance access, such

Table 5. Descriptive statistics of adopters and non-adopters of dairy climate-smart agriculture practices (Primary data, 2022).

Variable	Non-adopters (A)	Adopters (B)	Difference (A–B)	*t*-Value	Significance
DCSP enhance resilience	0.80 (0.40)	0.89 (0.31)	−0.09	−2.98	***
Keeping dairy records	0.25 (0.44)	0.48 (0.50)	−0.22	−5.26	***
Knowledge of climate change	0.62 (0.19)	0.69 (0.17)	−0.07	−4.42	***
Number of extension visits	2.52 (0.46)	4.57 (0.51)	−2.04	−2.29	**
Risk attitude	0.60 (0.49)	0.69 (0.46)	−0.10	−2.20	**
Ease of accessing DCSP's extension	0.61 (0.04)	0.69 (0.02)	−0.09	−2.05	**
Household size	4.50 (0.15)	4.50 (0.09)	−0.01	−0.05	
Sex	0.82 (0.03)	0.83 (0.02)	−0.01	−0.22	
Education	10.00 (3.63)	10.56 (4.10)	−0.60	−1.73	**
Experience	15.91 (12.34)	18.51 (13.39)	−2.60	−2.26	**
Agricultural group	0.74 (0.03)	0.84 (0.02)	−0.10	−2.80	***
Herd size	3.82 (2.56)	4.06 (2.76)	−0.25	−1.03	
Log on-farm income	11.75 (0.87)	11.89 (0.96)	−0.14	0.02	**
Milk market participation	0.48 (0.03)	0.54 (0.02)	−0.06	−1.97	**
Primary occupation	0.76 (0.03)	0.74 (0.02)	0.02	0.56	
Wakulima Mukurueini Dairy Limited (WL)	0.38 (0.49)	0.40 (0.49)	−0.02	−0.45	
Happy Cow Limited (HC)	0.32 (0.47)	0.28 (0.45)	0.04	1.05	
New Kenya Cooperative Creameries-Sotik (NKCCS)	0.30 (0.46)	0.32 (0.47)	−0.02	−0.55	

Notes: ** and *** indicate significance at 5% and 1% level respectively; figures in parentheses are robust standard errors.

Table 6. Marginal effect estimates of the triple hurdle model for the determinants of learning, adoption and adoption intensity of DCSPs (Primary data, 2022).

	Learning	Adoption	Intensity
	dy/dx (Probit)	dy/dx (Probit)	dy/dx (Tobit)
DCSP enhance resilience		0.210 (0.199)	0.090 (0.023)***
Keeping dairy records		0.593 (0.168)***	0.063 (0.031)**
Knowledge of climate change		1.465 (0.618)**	0.300 (0.097)***
Number of extension visits		0.047 (0.025)*	0.007 (0.003)**
Risk attitude		0.396 (0.157)**	
Ease of accessing DCSP's extension services	0.123 (0.049)**		
Household size	−0.060(0.036)*	−0.012 (0.047)	0.015 (0.006)***
Sex	0.022(0.191)	0.034 (0.208)	−0.008 (0.031)
Education	−0.023(0.019)	−0.002 (0.023)	0.009 (0.003)***
Experience	−0.013(0.005)**	0.024 (0.007)***	0.003 (0.001)***
Agricultural group	−0.036(0.176)	0.272 (0.193)	−0.026 (0.042)
Herd size	0.025(0.029)	−0.005 (0.039)	0.015 (0.006)**
Log on-farm income	−0.168(0.081)**	0.003 (0.092)	−0.002 (0.014)
Milk market participation	00.422(0.230)*	−0.129 (0.270)	0.064 (0.038)*
Primary occupation	0.000(0.163)	−0.122 (0.203)	−0.060 (0.025)**
Wakulima Mukurueini Dairy Limited milkshed	−0.084(0.177)	0.167 (0.214)	0.083 (0.032)**
Happy Cow Limited milkshed	0.505(0.190)***	−0.150 (0.209)	−0.028 (0.027)
Inverse mills ratio		−0.640 (1.177)	0.340 (0.156)**
Constant	3.012(0.876)***	−1.322 (1.015)	−0.549 (0.201)***
Number of observations	471	328	310
lnsig_3	−1.723(0.104)***		
Rho_12	−0.712 (0.978)		
Rho_13	0.026 (0.071)		
Rho_23	−0.347 (0.176)**		
Wald chi2(44)	150.17		
Prob > chi2	0.000		

Notes: *, **, *** indicate significance at 10%, 5% and 1% level respectively; figures in parentheses are robust standard errors.

as information, communication and technology (ICT)-based extension delivery (Tata & McNamara, 2018).

An increase in household size as well as years of experience in dairy farming significantly reduced the likelihood of learning from government. This suggests unique extension needs of larger households and more experienced dairy farmers beyond what government extension system can offer regarding DCSPs. Therefore, they prefer alternative extension service providers who can meet these needs. In concurrence with the study result on negative association of household size with learning from government, Adamu et al. (2023) linked large households with minimum access to municipal extension. Government extension providers face financial and human resource constraints (Ogola et al., 2023; Tata & McNamara, 2018). These limitations, coupled with capacity gaps on climate change affects service delivery as noted by Antwi-Agyei and Stringer (2021). Due to these constraints, they are unable to customize extension services on DCSPs to address the unique needs of households that are large in size and those that have more years of experience in dairy farming.

An increase in on-farm income significantly and negatively predicted learning about DCSPs from government extension providers. This shows that when farmers earn more income from farming, they are less likely to seek extension services from the government. In concurrence, Nettle et al. (2021) associated access to paid private extension services with better farm returns. Besides, the paid private extension services was considered more beneficial hence value for money. An increase in on-farm income denotes improved economic performance demonstrated by better returns. Therefore, improved farm income is likely to trigger the desire for private extension services that one has control over. With better economic returns, then such extension services can be afforded.

Milk market participation significantly and positively predicted the probability of learning from government. Therefore, as milk market participation improved, dairy farmers sought extension services from the government. This is contrary to Parven et al. (2023) who found that private extension was more likely to improve marketing skills and consequently profit. Milk market participation is mainly driven by milk yield and the farmer's commercial orientation. In the recent past, government extension providers have shifted attention towards agribusiness emphasizing market-oriented production. This shift integrates aspects of consistent quantity and quality as well as returns on investments which are associated with market participation.

3.2.2. Determinants of uptake of least adopted dairy climate-smart practices

Keeping farm records significantly increased the probability of adopting the least adopted DCSPs. This means that as dairy farmers kept records they were more likely to adopt the least adopted DCSPs. In concurrence, Okello et al. (2021) demonstrated the link between farmers knowledge about farm business records and uptake of dairy technologies. Dairy farm business records are important decision making tools associated with better strategies to farming (Benson & Smith, 2002). The farm records help monitor farming practices and their effect facilitating better decision making in planning for their implementation and resource allocations.

An increase in knowledge about climate change and contacts with extension providers, significantly increased the likelihood of adopting the least adopted DCSPs. This demonstrates that dairy farmers who had higher knowledge about climate change and were in frequent contact with an extension provider were more likely to adopt the least adopted DCSP. This aligns with results by Erekalo and Yadda (2023) who reported that climate change information and extension contacts enhanced uptake of climate-smart practices. Further, Danso-Abbeam (2022) found contact with extension to be an important driver in uptake of climate-smart practices. However, the results partly contradict those by Teklu et al. (2023) as they noted that access to extension reduced uptake of crop residue management but increased uptake of improved varieties and crop rotation. Knowledge about climate change provides a holistic picture of the climate change phenomenon, facilitating conceptualization of the role of DCSPs in enhancing resilience and mitigation. Extension services act as a conduit through which farmers access information on technologies and acquire knowledge and skills on different aspects of agriculture including climate change. The knowledge and skills gained enable dairy farmers to assess the relevance, appropriateness and effectiveness of climate-smart practices. Therefore, they are able to make informed decisions on appropriate practices that could enhance resilience of their dairy production.

Being risk-averse was significantly and positively associated with adoption of the least adopted DCSPs. Therefore, risk-averse farmers are more likely to adopt least adopted DCSPs. The findings are contrary to those by Ogisi and Begho (2023) and Musyoki et al. (2022) who reported that risk averse farmers are less likely to adopt agricultural technologies. However, the results concur with those by Jianjun et al. (2015) and Jin et al. (2016), linking risk averse attitude to uptake of adaptation practices, insurance and agricultural technologies. Risk attitude is instrumental in influencing farmers' behavior. Therefore, depending on the risk preferences towards climate change, farmers may exhibit different adoption strategies. This study demonstrates that farmers who are risk averse are keen to mitigate any potential losses that could result from climate change effects. They adopt the least adopted DCSPs as an ex-ante climate change risk management strategy for their dairy production.

The increase in years of experience in dairy farming resulted in higher likelihood of adopting the least adopted DCSPs. It could be inferred that farmers who are experienced in dairy farming are interested in adopting the least adopted DCSPs. In congruence, Aryal et al. (2018) associated experience in farming with adoption of climate-smart practices. Years of experience in a practice offers avenue to gain skills and knowledge overtime through experiential learning that involves experimentation, observations and reflection. Therefore, farmers with more years of experience in dairy farming have gained knowledge and experience on climate change and its related effects. As a result, they are able to associate uptake of DCSPs as a coping strategy to climate change. The result is an indication of experienced farmers understanding of climate change and its effects, and the ability to link DCSPs in managing those effects.

3.2.2.1. Determinants of the adoption intensity of dairy climate-smart practices. The perception that DCSPs enhance resilience of dairy production increased the intensity of adopting the least adopted practices. Therefore, favorable perception of DCSPs enhancing resilience favored intensified uptake. The result aligns to those by Michels et al. (2019) and Hyland et al. (2018) on how perceived usefulness drives uptake of dairy technologies. Yang et al. (2024) argues that perceived value is the most direct factor that influences behavior. Therefore, farmers form perceptions about the value they are likely to derive from a practice which then determines their adoption behavior. Therefore, farmers associating least adopted DCSPs with enhanced resilience intensify their uptake.

Keeping dairy records increased the intensity of uptake of the least adopted DCSPs. This denotes that keeping dairy records enhances intensity of uptake.

Dairy records are important in guiding farm decision making in terms of determining which practices are beneficial to the farm and subsequently guide their integration. Therefore, through dairy farm records farmers can effectively attribute positive performance of the dairy production amidst climate change to the DCSPs. Further, an increase in knowledge about climate change and contact with extension service providers increased the intensity of uptake of the least adopted DCSPs. This shows that knowledge about climate change and contact with extension are key drivers for intensified uptake of DCSPs. Similalrly, other studies (Gebremedhin et al., 2017; Ojo et al., 2023; Okello et al., 2021) have linked access to extension services with intensified uptake of dairy technologies. Further, Ojo et al. (2023) confirms the positive influence of access to climate information that could be considered an aspect of climate change knowledge to increased intensity of uptake of climate-smart practices. However, some studies, for instance Tilahun et al. (2023) report contrary outcome of access to extension reducing uptake of climate-smart practices. Despite divergent results, extension services play an integral role of facilitating access to climate change knowledge and skills as well as understanding the importance of climate-smart practices.

Similalrly, years of schooling significantly and positively influenced the intensity of uptake of least adopted DCSPs. This means that more educated farmers are more likely to intensify uptake. In agreement, studies by Aryal et al. (2018) and Tong et al. (2024) associated human capital variables such as education to increased levels of uptake of climate smart practices but Tilahun et al. (2023) reported contrary findings. Education is associated with exposure and capacity to understand different production aspects, including climate change and hence ability to embrace beneficial ideas. Therefore, educated dairy farmers are aware of and knowledgeable about climate change and the associated benefits of least adopted DCSPs hence likely to intensify uptake for optimal benefits.

Years of experience in dairy farming increased the likelihood of intensified uptake of the least adopted DCSPs. It could be deduced that experience facilitates intensification. However, some studies confirm the result while others negate it. For instance, Maindi et al. (2020) agreed with this study finding that age (proxy for experience) enhance intensity of uptake of dairy climate-smart practices. However, Teklu et al. (2023), associated increased years of experience with negative uptake of some climate-smart practices such as crop residue management. Overtime, farmers with many years of experience in dairy farming gain in-depth understanding of the dynamics of climate change and its effect on dairy production. Further, they are most likely to have experimented with different practices in trying to find solutions to challenges posed by climate change. As result, they are more likely to intensify least adopted DCSPs.

Larger households were more likely to intensify uptake of the least adopted DCSPs. This means that, the larger the household the higher the chances of intensifying uptake of least adopted DCSPS. Similarly, Alidu et al. (2022), Mgomezulu et al. (2023) and Mgomezulu et al. (2023) found that household size positively influenced uptake of climate change adaptation strategies. Labor has been identified as a key barrier to uptake of climate-smart practices (Antwi-Agyei et al., 2021). In smallholder farmers' setting, labor is mainly provided through family labor, linking household size to labor availability (Okello et al., 2021). Therefore, the study results provide evidence of labor demand for intensification of least adopted DCSPs with larger households being at an advantage due to labor access. This is because, when labor demands are high, larger households can leverage on their numbers to provide the needed labor.

Larger herd sizes were associated with increased rate of uptake of least adopted DCSPs. This could indicated that herd size facilitate intensified uptake of least adopted DCSPs. Maindi et al. (2020) and Okello et al. (2021) concur with this result as they found that, as the number of dairy cows increased the intensity of dairy technologies adopted increased but Gikonyo et al. (2022) reported contradictory findings with herd size reducing level of intensification. Herd size has been used as a measure of household wealth and an indicator of the economic wellbeing of a household. Since access to and acquisition of DCSPs require financial resources, possession of a larger herd size provide means for uptake and intensification. This is because, livestock asset can be monetized and used to facilitate access, acquisition and intensified use of DCSPs. The finding validate the integral role of financial resources as a driver of intensity of adoption.

Improved market participation enhanced the intensity of uptake of the least adopted DCSPs. This implies that as proportion of marketed milk increases, chances of intensifying uptake of the least adopted DCSPs also increases. In concurrence, factors relating to improved market participation have been found to enhance intensified uptake of dairy technologies (Okello et al., 2021). Market participation plays a crucial role in generating income from agricultural production. Through sales of produce, income is generated which in return is invested to improve farming practices including uptake of technologies. Therefore, when dairy farmers are able to participate in markets they are able to convert milk output into monetary value enhancing access to and intensification of least adopted DCSPs. Further, monetizing gains from increased uptake of DCSPs builds confidence and generate financial resources that can be reinvested in intensifying uptake of DCSPs.

Contrary to expectation, having farming as primary occupation of the household head reduced intensity of uptake of the least adopted DCSPs. This shows that farmers who engage in farming as their primary economic activity are less likely to intensify. This could be explained by many factors such as low returns from farming activity limiting intensification, farm diversification hence competing demand for financial and human resource where dairy is not the primary farm activity or limited external resources to support intensification. The later argument is demonstrated by Kifle et al. (2022) who found that, where farming households participated in off-farm activities, they generated additional income that supported uptake of climate-smart practices.

Being in Wakulima Mukurueini Dairy Limited milkshed increased the intensity of utilization of least adopted DCSPs. This shows that, farmers belonging to Wakulima Mukurueini Dairy Limited were more likely to intensify uptake of least adopted DCSPs than those in other milksheds. The different milkshed are characterized by different dairy production practices (Wairimu et al., 2021). As a result, the intensification of least adopted DCSPs is likely to differ by milkshed. The Wakulima milkshed is characterized by land subdivisions and reliance on external resources necessitating dairy intensification. Besides, its among the counties that has faced severe climate change effects. These characteristics increase the likelihood of intensified uptake of DCSPs due to the nature of production systems which is less resilient to climate change effects.

4. Conclusion and policy implications

The study assessed factors influencing the adoption and intensity of adoption of the least adopted dairy climate-smart practices (DCSPs) conditional on learning from dairy extension service providers (DESPs) using the triple hurdle model. The inclusion of learning as an integral phase preceding the adoption decision brings out new nuance on the diffusion of DCSPs which is overlooked yet critical in the promotion of DCSPs. The study results linked adoption of the least adopted DCSPs to learning. However, the intensity of uptake was alarmingly low. Further, the socio-economic and institutional characteristics predicted learning, adoption and intensity of adoption. Learning from government extension providers was positively and significantly predicted by ease of accessing DCSP's extension services, milk market participation and being from Happy Cow Limited milkshed. However, it was negatively predicted by household size, years of experience in dairy farming and log on-farm income. On the other hand, being risk averse and increase in years of experience in dairy farming significantly and positively increased the likelihood of adopting DCSPs. Keeping dairy records, increase in knowledge about climate change, higher number of extension visits were positively and significantly associated with both adoption and intensity of adoption of DCSPs. Further, perception that DCSPs enhanced resilience, larger household size, increase in level of education, more experience in dairy farming, bigger herd size, increase in level of milk market participation and being from Wakulima Mukurueini Dairy Limited milkshed, significantly and positively increased the likelihood of intensified uptake of the least adopted DCSPs. However, primary occupation being farming significantly and negatively predicted intensity of adoption of DCSPs.

This study concludes that learning facilitated by pluralistic extension system is integral in facilitating uptake. However, uptake does not necessarily lead to intensified uptake, hence the need to go beyond promotion for uptake and consider the intensity of adoption of dairy climate-smart practices. Further, socio-economic characteristics are important drivers of uptake and intensification of least adopted DCSPs. Therefore, to enhance uptake and intensity of adoption, it is imperative that policy makers strengthen pluralistic extension system to leverage on the strengths of the different extension providers in developing innovative extension approaches that can foster intensified uptake of least adopted DCSPs. Further, the extension should seek to increase their frequency of interaction with farmers and train farmers on climate change. Farmers should endeavor to keep dairy farm records and participate in markets. Lastly, researchers need to ensure that DCSPs developed contribute to improved resilience.

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Ethics approval

This research was approved by the Institutional Scientific and Ethical Review Committee of KALRO-Veterinary Science Research Institute, Muguga North upon compliance with provisions vetted under and coded: KALRO-VSRI/ISERC30/17052022.

Informed consent

Before commencement of the survey, a consent statement was read to the household to make them understand the purpose of the survey and get their consent to go on with the administration of the questionnaire.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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