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Promoting sustainable dairy production amid climate change: adoption of climate-smart dairy strategies and welfare effects on farmers in Central Kenya

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Introduction: In Kenya, smallholder dairy farming is a livelihood and a cornerstone of the national economy, accounting for 80% of the country's milk supply and a significant portion of its GDP. Yet, this sector grapples with sustainability challenges, marked by high methane emissions and a downturn in milk yields. To combat these issues, climate-smart dairy strategies, including improved breeding, feeds and feeding, animal health management, manure management, and zero grazing, are being championed. These strategies aim to boost production sustainably, fortify resilience against climate variability, and curtail emissions. Despite their potential, the uptake of these strategies is sporadic and uneven. This study delves into the effects of climate-smart dairy strategies on milk productivity and gross margins in Kenya.

Methodology: This study employed a multinomial endogenous switching regression model on 385 respondents in Nyandarua County. The data sheds light on the determinants of adopting climate-smart dairy strategies and their effects on milk productivity and gross margin.

Results and discussion: According to the findings, age, education, cooperative membership, group duration, entrepreneurial orientation, distance to input market, and risk perception significantly influenced the uptake of climate-smart dairy strategies. Further, the adoption of improved breeding, improved feeds and feeding, and animal health management significantly increased milk productivity (ATT = 547 litres) and gross margin (ATT = KES 18649) for adopters, indicating that adopting multiple strategies is effective. The study offers robust support for implementing holistic and cohesive climate-smart dairy strategies. These strategies are pivotal in optimising productivity and enhancing the dairy sector's economic viability. The study underscores the need for targeted policies to improve the adoption of sustainable dairy practices, offering comprehensive insights into balancing economic and environmental goals in smallholder dairy farming.

KEYWORDS

climate-smart dairy strategies, dairy production, smallholder farmers, multinomial endogenous, Kenya

1 Introduction

Globally, urbanization, economic growth, and higher incomes are increasing demand for animal products, particularly dairy and beef. As a result, there is a strong emphasis on commercializing and expanding the production of these products. However, this drive to boost dairy production has negative environmental and climate impacts, leading to increased Greenhouse gas (GHG) emissions (Giro and Kumar, 2022). This trend, coupled with emissions from other sectors, intensifies climate change.

According to a study by Vernooij et al. (2024), the GHG emission intensity of cow milk in sub-Saharan Africa is the highest globally, at 9 kg of CO2 equivalent per kilogram of fat and protein-corrected milk. This is four times higher than the global average, and estimates from other parts of sub-Saharan Africa are likely to be similar (Pressman et al., 2018). Although developed countries contribute significantly to climate change, the effects are dire in developing countries, where agriculture is a primary source of livelihood (Abbas et al., 2023; Ntinyari and Gweyi-Onyango, 2020). In Africa, over 70% of GHG emissions attributable to agriculture stem from the livestock sector (Balehegn et al., 2020). The reliance on rainfed agriculture in sub-Saharan African countries exacerbates the impact of climate change, highlighting the need for disseminating climate-smart strategies as one of the possible solutions (Mburu et al., 2024).

The global demand for dairy products, driven by urbanization and economic growth, is mirrored in Kenya, where smallholder dairy farming plays a vital role in the economy but grapples with sustainability and environmental challenges. Kenya's dairy industry is notable within Sub-Saharan Africa, producing 3% of the region's milk (Odero-Waitituh, 2017), with each cow producing about 4,000 kg of milk annually (Kirui et al., 2021). Smallholder dairy farmers in Kenya contribute 80% of the nation's milk, typically managing three dairy animals per household (Ngeno, 2018). The dairy sector significantly contributes to Kenya's GDP, accounting for about 8% of the economic output and growing at an annual rate of 4.1%, surpassing other agricultural sectors (Odero-Waitituh, 2017; Vernooij et al., 2024).

Kenya's agriculture accounts for 63% of the country's total GHG emissions. Of these emissions, 55% are attributed to enteric fermentation from livestock, while 37% are estimated to originate from manure (Vernooij et al., 2024). Consequently, dairy production contributes to approximately 15% of total GHG emissions in the country (Government of Kenya, 2017; Wilkes et al., 2020). The dominant GHG emissions in the sector are methane, accounting for 96%, followed by nitrous oxide at 3%, and carbon dioxide at 1%. The amount of methane emitted is influenced by the breed type, feed quality and quantity, and environmental conditions (Pinto et al., 2020). If no action is taken, this emission is projected to increase as annual milk consumption is expected to rise from 110 kg to 220 kg per person by 2030 (Vernooij et al., 2024). With cattle production contributing over 80% of the livestock emissions, addressing emissions from dairy production is critical (Martius et al., 2023). This has implications for Kenya's climate policy, particularly its commitment to the United Nations Framework Convention on Climate Change, the Paris Climate Agreement, and the Nationally Determined Contributions, which target a 7% annual reduction in GHG emissions by 2030 (Chelang'a et al., 2025; Martius et al., 2023). Furthermore, the Kenya Climate Smart Agriculture Strategy (2017–2026) identifies dairy production as a priority for emission reduction and resilience building through improved feeds and manure management (Wilkes et al., 2020).

Although the dairy sector contributes to climate change, smallholder dairy farming has been severely affected by climate change effects, including prolonged drought, temperatures, and frequent floods, in the recent decade (Intergovernmental Panel on Climate Change, 2022; Maindi et al., 2020).

In recognition of this dual challenge, climate-smart dairy strategies (CSDS) have been promoted to cushion smallholder dairy farmers from climate change risks. CSDS is based on three pillars: sustainably increase production for income and food security; adapt and build resilience for agri-food systems and people; and reduce GHG emissions (Food Agriculture Organisation, 2021; Rodríguez-Barillas et al., 2024). However, the adoption of CSDS has remained low and uneven (Maindi et al., 2020; Mburu et al., 2024). Existing literature has centered on factors influencing the adoption of CSDS, such as improved breeding, fodder varieties, feed supplementation with concentrates, treating crop residues with urea, feed conservation, health management, herd size management, composting, and use of biogas (Korir et al., 2023; Mujeyi et al., 2022; Mburu et al., 2024; Shikuku et al., 2017). Adoption of CSDS, such as biogas production, appropriate manure composting, use of leguminous fodder, feed formulation, and treatment of crop residues remain low, with less than 10% of farmers implementing these strategies (Maindi et al., 2020; Mburu et al., 2024).

Research studies have pointed out that demographic, socioeconomic, and institutional factors such as gender, human capital, household size, land ownership rights, off-farm income, credit, and access to extension services are strongly tied to the adoption of CSDS (Korir et al., 2023; Maindi et al., 2020; Mburu et al., 2024; Musafiri et al., 2022a). For instance, education level increases the ability to comprehend information (Abegunde et al., 2019); large household size indicates available labor for adoption (Mujeyi et al., 2022); off-farm income reduces the need for borrowed credit (Chelang'a et al., 2025); physical assets provide resources for adoption (Akzar et al., 2023); while extension services are key for knowledge and skills development (Maina et al., 2020; Musafiri et al., 2022a).

Other studies have explored the effects of adoption on productivity (Akzar et al., 2023), income (Shikuku et al., 2017), food security (Mujeyi et al., 2021; Teklu et al., 2024), poverty reduction (Zegeye et al., 2022), and reduction of GHG emissions (Ericksen and Crane, 2018; Kihoro et al., 2021; Vernooij et al., 2024). However, these studies assessed the outcomes separately. Bridging this gap is essential for aligning agricultural development with national climate commitments, particularly in enhancing adoption, reducing emissions, and improving the welfare of farmers.

Therefore, the present study adds significant value to the literature by comprehensively investigating the double effect of CSDS on milk productivity and gross margin. Increasing milk production through improved feeds reduces GHG emissions (O'Hara, 2023). We assume that strategies that enhance milk production will also reduce GHG emissions. Further, we include farmer entrepreneurial orientation variables to complement the socioeconomic and institutional factors affecting productivity and gross margin. According to our knowledge, literature on the effect of entrepreneurial orientation on milk productivity (Daneluz et al., 2021; Kimaru et al., 2020) and gross margin in smallholder farms is scarce.

We found two main approaches in the literature for studying the impact of climate-smart strategies. The first approach involves using the propensity score matching technique to determine the effect of CSDS on productivity, income, and food security. Studies conducted by Abbas et al. (2023), Belay et al. (2023), and Radeny et al. (2022) have used this method. However, one limitation of the propensity score matching model is that it does not account for unobserved heterogeneity, which can result in biased estimates, as noted by Ngeno (2018). The second approach involves using an endogenous switching regression model to estimate the effects of CSDS on food security. A study conducted by Teklu et al. (2024) employed this method. It is worth noting that endogenous switching regression and propensity score matching models are limited when the outcome variables are more than two. Considering these drawbacks and having two outcome variables, our study employed a multinomial endogenous switching regression model (MESR) to account for selection bias arising from unobserved and observed heterogeneity. Additionally, the model allows the estimation of individual and combined effects of CSDS on milk productivity and gross margin. The present study used primary data collected from 385 smallholder dairy farmers from Nyandarua County between October and November 2023.

This paper contributes twofold to the literature. First, we assess the factors influencing the adoption of single and multiple CSDS. Second, we estimate the individual and combined effects of CSDS on milk productivity and gross margin. The study's implications apply to many Sub-Saharan countries that face common challenges, including low uptake of dairy technologies (Akzar et al., 2023; Mburu et al., 2024; Korir et al., 2023).

The rest of this paper is organized as follows: Sections 2 and 3 provide details on the methodology and empirical strategy, respectively. Section 4 presents the data. Section 5 discusses the empirical findings. Section 6 draws conclusions based on the results along with potential policy implications.

2 Materials and methods

2.1 Research design and sample selection

The study employed a cross-sectional research design, offering numerous advantages for effectively achieving the research objectives. It ensures efficient data collection from diverse respondents at one time, providing timely results and cost-effectiveness (Sedgwick, 2014). Additionally, it captures a broad spectrum of population characteristics, enabling further investigation while laying the foundation for future research endeavors.

Primary data was collected in Kinangop and Kipipiri Sub-Counties in Nyandarua County, a crucial region for milk production in central Kenya, between Mount Kenya and the Aberdare areas (Figure 1).

The unit of analysis was smallholder dairy producers. The respondents included males and females who are key decision-makers in a household. We employed a multistage sampling technique to select them. In the first stage, Nyandarua County was chosen purposively since cow milk is one of the County's three priority value chains for quality and quantity enhancement. It is also the second-largest milk producer in Kenya. The second stage involved the purposive selection of two out of five Sub-Counties based on milk production and climatic conditions favoring agriculture. These Sub-Counties are Kinangop and Kipipiri. In the third stage, six wards, namely Gathara, Engineer, Njabini, Kipipiri, Wanjohi, and Githiori, were selected from the two Sub-Counties based on milk production and their vulnerability to climate change. In the last stage, smallholder producers were randomly selected from the six wards using a systematic random sampling at intervals of five from the list of dairy producers. The list of dairy producers was obtained from the Ministry of Agriculture, Livestock and Fisheries in Nyandarua County. We applied the Yamane formula (Yamane, 1973) to compute a sample size of 384 farmers. This choice is justified using a finite population. The dairy farmers were proportionately selected at the Ward level since the population in each ward is not equal in size.

2.2 Data collection method

This study gathered primary data using a semi-structured questionnaire, which included a mix of open and closed-ended questions. Data was collected through face-to-face interviews with participants. To ensure the questionnaire's effectiveness and appropriateness, a pre-test was conducted, evaluating the relevance and clarity of the questions. Additionally, a pilot study was carried out to measure the time needed to complete the questionnaire and gauge respondents' reactions to the questions. Following Abegunde et al. (2019), we conducted the pilot study with 10% of the intended sample size. Specifically, forty dairy producers from Njoro Sub-County were selected for the pre-test due to their similar characteristics to those in Kipipiri and Kinangop Sub-Counties. The pre-test allowed us to test for the reliability and validity of the questionnaire. As a result of this phase, we refined the questionnaire, which included in refining the questionnaire, which included rephrasing questions for enhanced coherence, determining the ideal number of daily interviews, and positioning sensitive questions toward the questionnaire's conclusion for strategic purposes.

During this process, we devoted specific attention to validating and enhancing the effectiveness of the selected CSDS by organizing focus group discussions and conducting key informant interviews. Altogether, 8 dairy farmers engaged in the focus group discussions, encompassing 2 youths, 2 females, and 4 males. Likewise, 8 experts were interviewed for the key informant interviews, representing a diverse range of perspectives: 2 Sub-County dairy board members, 2 dairy cooperative leaders, 2 extension officers, and 2 officers from the Kenya Climate Smart Agriculture Project.

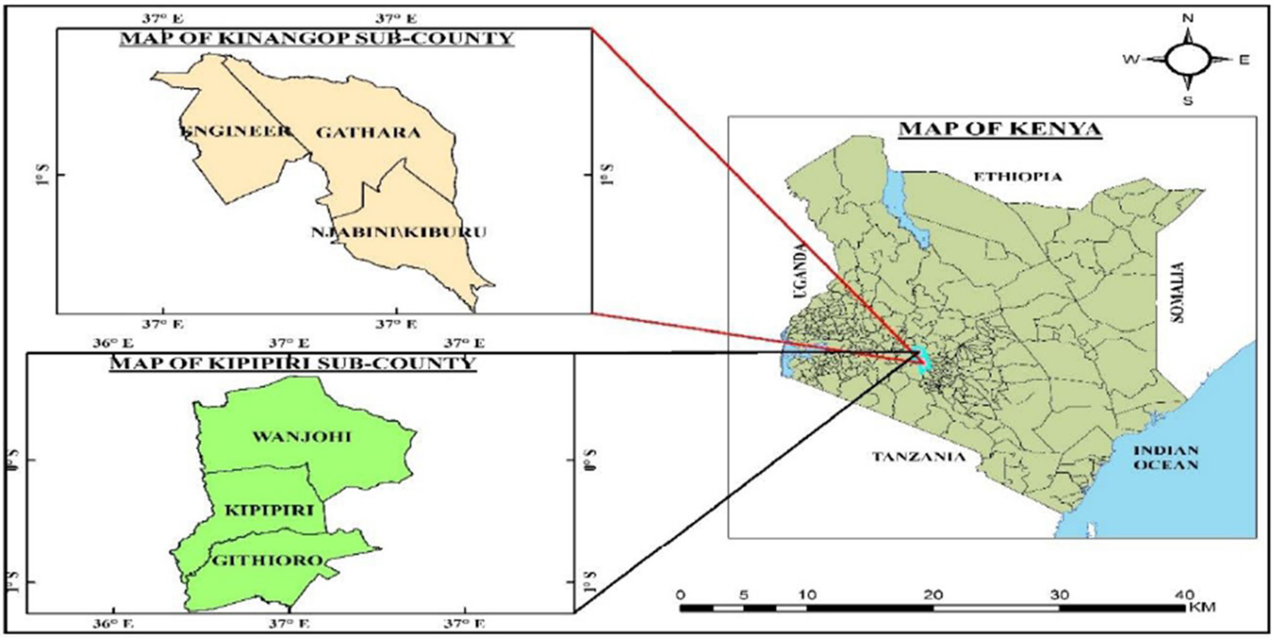

FIGURE 1
Map of Nyandarua County.

The participants were purposely selected to ensure a comprehensive understanding of the CSDS from various stakeholders, including farmers, local authorities, and project personnel. By including different demographics and expertise, we aimed to gather insights that are both inclusive and representative of the community's needs and challenges.

Proficient enumerators fluent in the Kikuyu dialect, the predominant language in the selected geographic area, facilitated both the focus group discussions and key informant interview sessions. This choice ensured effective communication and rapport-building with participants, maximizing the quality and depth of collected data. We aimed to foster a conducive environment for open dialogue and nuanced understanding during the research process by utilizing enumerators familiar with the local language and cultural nuances. These discussions and interviews were instrumental in identifying new CSDS for inclusion and determining which strategies needed refinement or removal.

The study gathered data on household and farmer demographic factors, socioeconomic characteristics, social capital and institutional factors, and entrepreneurial and behavioral factors. Additionally, we obtained information on the adoption status of CSDS through structured yes-and-no questions.

Prior to data collection, 10 enumerators who were experienced in using digital software underwent a thorough 3-day training session focusing on ethical conduct guidelines for surveys and effective probing techniques to ensure accurate data acquisition.

The survey was conducted between October and November 2023. Participants were briefed on the study's objectives and guaranteed that the information they provided would remain confidential. Further, they were not required to disclose personal identifiers on the questionnaires. The researcher reassured participants that the data collected would be used solely for research purposes and treated with the utmost confidentiality. Data collection occurred during the daytime, with regular evening meetings between the researcher and enumerators to assess progress and address emerging issues. The researcher reviewed the data daily to ensure its consistency and promptly identify and correct any errors that arose during data collection. Additionally, enumerators were required to record the respondents' GPS coordinates as part of the quality control measures. The data collection process utilized ODK software, while subsequent cleaning and analysis were done using Excel and STATA version 18 software.

2.3 Selection of the treatment and outcome variables

Variable selection was pivotal in this study, enabling us to build more accurate, interpretable, and efficient models. We deserved specific attention to identifying the subset of predictors that were most relevant to the phenomenon under investigation.

This study has two outcome variables: productivity and gross margin. The CSDS considered treatment variables for the present study are indicators of GHG emissions reduction and those related to increased milk productivity and gross margin. The selected CSDS was based on the literature review and validated using focus group discussion. The five treatment variables include manure management, improved breed, improved feeding and feeds, animal health management, and zero grazing.

For accurate estimates, milk production was classified into three seasons: high, average, and low. Dairy farmers were required to specify the amount of milk produced per cow per day during

TABLE 1 Level used as an indicator of adoption by climate-smart dairy strategy and reference literature.

CSDS	Level used to indicate adoption	Reference literature
Improved breed	Use of artificial insemination	(Ericksen and Crane, 2018; Maindi et al., 2020)
Improved feeds and feeding	Use of concentrates/cultivation of high energy-protein fodder	(Food and Agriculture Organisation, 2019; Giro and Kumar, 2022; Mburu et al., 2024)
Animal health management	Deworming every 3 months and weekly tick control	(Kihoro et al., 2021; ood and Agriculture Organisation, 2017; Ericksen and Crane, 2018)
Manure management	Manure collection, covering and composting	(Niles et al., 2022; Vernooij et al., 2024)
Zero grazing	Zero grazing unit	(Kihoro et al., 2021; Wilkes et al., 2020)

months characterized by high, medium, and low production. The mean of these three seasons was then calculated as the daily milk production per cow, which was subsequently multiplied by the average number of days milked per month to determine the average milk production per month. This average monthly milk production was further multiplied by the number of months milked and the total number of milking cows to obtain the average annual milk production per household. Finally, productivity was computed by dividing the total milk yield per year by the number of milked cows.

On the other hand, the gross margin from milk was calculated as the difference between the total milk yield per cow per year multiplied by the average price and the total variable cost incurred. The variable costs include deworming, vaccination, spraying, disease treatment, feed purchase, and fodder production costs, such as seeds, fertilizer, fungicides, pesticides, and labor incurred during the last production year.

2.4 Empirical strategy

We estimated two separate models using a two-step multinomial MESR model. One model has productivity as the outcome variable, while the other has gross margin as the outcome variable. We used MESR to compare the effect of adopting and non-adopting CSDS on these outcome variables. A major advantage of MESR models is that they estimate individual and combined effects of the treatment variables on the outcome. Unlike the propensity score matching technique, they also account for both observed and unobserved factors that may influence decisions on CSDS adoption and outcome equations. This approach helps to account for both endogeneity and self-selection bias. The MESR treatment effect model was utilized following McFadden (1974) and Bourguignon et al. (2007) to correct selection bias.

In the first stage, a multinomial logit (MNL) model determined producers' individual and combined CSDS decisions. The MNL model helps account for the interrelationships among the CSDS decisions. In the second stage, the effects of each alternative and combined CSDS on productivity/gross margin were estimated using ordinary least squares regressions (OLS) with selectivity corrections terms from the first step. The CSDS considered are improved breeds (j_1), improved feeding and feeds (j_2), animal health management (j_3), zero grazing (j_4) and manure management (j_5). As each attribute has multiple attribute levels, this study used a single attribute level to distinguish between adoption and non-adoption. We used the literature to select the reference level (Table 1).

The adoption of each strategy was treated as binary, with a value of one assigned if the household adopted the strategy and zero otherwise. Producers were assumed to use a single or multiple CSDS to maximize expected utility, (T_i), by comparing the productivity and gross margin given by K alternative CSDS. The condition for the producer i to adopt j over other alternatives is that $T_{ij} > T_{iK}$ $K \neq j$ that is, j gives the highest productivity/gross margin compared to any other $K \neq j$ alternatives. The expected gross productivity/gross margin associated with each CSD strategy cannot be directly observed but can be described as a function of observable factors in a latent variable as follows:

$$T_{ij}^{*} = \beta_j Z_i + \varepsilon_{ij} \tag{1}$$

where T_{ij}^{*} is a latent variable explaining the outcome, Z_i is a vector of independent variables while ε_{ij} is the error term. The Z_i covariates are assumed to be uncorrelated with the error term ε_{ij} that is, $E\left(\varepsilon_{ij}\middle| Z_i\right) = 0$. The assumption implies that ε_{ij} is independent and identically Gumbel distributed.

The probability (Pr) that producer i will adopt CSDS j can be expressed by a MNL model (McFadden, 1974) as follows:

$$P_{ij} = \Pr\left(\varepsilon_{ij} < 0\middle| Z_i\right) = \frac{\exp(Z_i\,\beta_j)}{\sum_{K=1}^{j}\exp(Z_i\,\beta_K)} \tag{2}$$

The outcome equations for each possible regime j can be expressed in binary terms as follows, based on the framework of five CSDS' adoption and non-adoption status. We used the Hausman test to assess the independence of the assumption of irrelevant alternatives in the MNL model (Freese and Long, 2000). The test was insignificant, indicating our analysis did not violate the assumption. The expected outcomes for choosing any combination of CSDS are given as follows:

$$\begin{cases} E\left(T_{i1}|A_i = 1\right) Q_i\beta_1 + \mu_{i1} \\ E\left(T_{i0}|A_i = 0\right) Q_i\beta_0 + \mu_{i0} \\ \quad\vdots \\ E\left(T_{ij}|A_i = j\right) Q_i\beta_j + \mu_{ij} \end{cases} \tag{3}$$

where T_{ij} is the expected productivity/gross margin of household i in regime j ($j = 1, 2, 3, 4, 5$), (A_i) is the adoption status, with $(A_i) = 1$ being adopters while $(A_i) = 0$ being non-adopters, Q_i is a vector of explanatory variables, β_i is a vector of coefficients to be estimated, while the error terms μ_i is normally distributed, which satisfies $E\left(\mu_{ij}\middle|Q_{ij},\ Z_{ij}\right) = 0$ and variance $\left(\mu_{ij}\middle|Q_{ij},\ Z_{ij}\right) = \sigma_j^2$.

OLS estimates in the second step will be biased if the error terms in the selection and regime equations are not independent. Consistent estimation necessitates including the alternative selection correction components in Equation 5 to account for unobserved factors (producers' intuitive abilities and motivation).

The actual and counterfactual scenarios for adopters and non-adopters can be presented in four cases as follows:

Adopters, if they adopt (actual)

$$E\left(T_{i1}|A_i=1\right)=\beta_a Q_{ia}+\sigma_a\lambda_a \tag{4}$$

Adopters, if they do not adopt (counterfactual)

$$E\left(T_{i0}|A_i=1\right)=\beta_{na} Q_{ia}+\sigma_{na}\lambda_a \tag{5}$$

Non-adopters, if they do not adopt (actual)

$$E\left(T_{i0}|A_i=0\right)=\beta_{na} Q_{ina}+\sigma_{na}\lambda_{na} \tag{6}$$

Non-adopters, if they adopt (Counterfactual)

$$E\left(T_{i1}|A_i=0\right)=\beta_a Q_{ina}+\sigma_a\lambda_{na} \tag{7}$$

where $\sigma_j$is the covariance between the ε_{ij} of selection and the μ_{ij} of the regime equations, $\lambda_j$is the inverse mills ratios computed from the estimated probabilities in the regime equations. The standard errors in the regime equations were bootstrapped to account for possible heteroscedasticity arising from the generated regressor λ_j. The actual and counterfactual productivity/gross margin expected from adopters and non-adopters was calculated based on the parameters to be estimated β_a and β_{na}. To estimate the average treatment on the treated (ATT) for adopters, the observed productivity/gross margin and its counterfactual were differentiated as follows:

$$ATT=E\left(T_{i1}|A_i=1\right)-E(T_{i0}|A_i=1) \tag{8}$$

Similarly, the average treatment on untreated (ATU) for non-adopters was computed as the difference between the actual and the counterfactual productivity/gross margin, according to the following equation:

$$ATU=E\left(T_{i0}|A_i=0\right)-E(T_{i1}|A_i=0) \tag{9}$$

2.5 Selection of the instrumental variable

As Asante et al. (2024) proposed, estimating a MESR model must include at least one instrumental variable for model identification. The admissibility of possible variables as instruments can be established by performing a simple falsification test (Asante et al., 2024; Khonje et al., 2018). While the MESR model helps address selection bias by accounting for both observed and unobserved heterogeneity, it does not, on its own, ensure causal inference. To strengthen identification, we employed group membership duration as an instrumental variable for adoption. We conducted a simple falsification test, which supported the instrument's validity, indicating that group duration is correlated with adoption but not directly associated with the outcome productivity and gross margin, thus satisfying the exclusion restriction (Table A2). The distance to the input market was a weak instrument and, hence, was not included in the analysis. Despite this, causal interpretation still depends on the validity of underlying assumptions that cannot be empirically verified. Therefore, we interpreted the results as indicative of causal relationships, but we maintain a degree of caution and acknowledge that the findings remain subject to the limits of observational data.

2.6 Measuring of entrepreneurial orientation

Entrepreneurial orientation was measured using a multi-item index adapted from the validated scales of Lumpkin and Dess (1996) and Sambrumo et al. (2022), which have been widely used in agricultural and rural entrepreneurship studies. The index captured five key dimensions of entrepreneurial orientation: innovativeness, which is the ability of farmers to try new innovations before others; risk-taking, which is the ability of farmers to invest their resources to unpredictable outcomes; proactiveness, which is the farmers' ability act in anticipation of future changes in dairy farming; autonomy which is the ability of farmers to make independent decisions on dairy farm investments, and competitiveness aggressiveness is the ability of farmers to strive to outperform other farmers in dairy production. Each dimension was measured using three items on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

2.7 Diagnostic tests

To address potential econometric issues, heteroskedasticity and multicollinearity were tested using the Breusch-Pagan and Variance Inflation Factor (VIF). Table 1 shows the level used as an indicator of adoption of climate-smart dairy strategy and reference literature. Table A1 provides results for multicollinearity test using Variance Inflation Factor. Table A1 presents VIF results discussed under diagnostic tests. There was evidence of heteroskedasticity ($p < 0.05$), and robust standard errors were applied to ensure consistent and efficient parameter estimates. All variables included in the model had VIF values (Mean VIF = 1.29) below the threshold of 5, indicating no multicollinearity problem. Furthermore, an inverse probability weighting regression adjustment (IPWRA) was used to check the robustness of MESR results (Tables A3, A4). The results of the MESR model had lower standard errors than IPWRA, making it a better model for this study.

3 Results

3.1 Descriptive statistics

Table 2 provides the combinations of CSDS adopted by dairy farmers, while Table 3 presents summary statistics for various variables of the farmers' demographic factors, socioeconomic characteristics, social capital and institutional

TABLE 2 Alternative combination of CSDS adopted by smallholder dairy producers.

Alternative	CSDS	Frequency	Percentage
One	Single strategy or none	36	9.35
Two	Two combinations	70	18.18
Three	$B_1F_1H_1$	50	12.99
Four	$B_1F_1H_1M_1$	110	28.57
Five	$B_1F_1H_1M_1Z_1$	119	30.91

One means adoption of a single climate-smart dairy (CSD) strategy or none such as [improved breed (B_1) or improved feed (F_1) or manure management (M_1) or adoption of none (N_o)], non-adoption and adoption of single strategy were merged together due to low frequencies; Two means adoption of two CSDS [improved breed, and health management (B_1H_1) or improved health and manure management (H_1M_1)]; $B_1F_1H_1$ denotes improved breed, feed, and health management; $B_1F_1H_1M_1$ denotes improved breed, feed, health management and manure management; and $B_1F_1H_1M_1Z_1$ denotes improved breed, feed, health management, manure management and zero grazing.

factors, entrepreneurial and behavioral factors, and dairy milk productivity and income factors. The overall statistics are also provided.

Results reveal several tendencies regarding the adoption of CSDS. In summary, higher adoption of CSDS is associated with older age, male-headed households, higher education, larger farm, and herd sizes, greater off-farm income, stronger group and cooperative memberships, better access to extension services, closer training distances, higher entrepreneurial orientation, greater risk perception, and awareness. These farmers also tend to access more credit, produce more milk, and achieve higher revenues and margins, indicating better overall profitability. The evidence from the present paper shows no statistical difference between the averages of age, household size, farming experience, and total variable costs. Education, extension access, entrepreneurial orientation, risk perception, milk yield, and financial metrics show significant differences across adoption categories, denoted by high statistically significant F-values and chi-squared values.

The literature on Africa and Kenya supports some of these tendencies. For example, other studies have shown that participation in dairy cooperatives significantly improves the adoption of climate-smart strategies (Balchax et al., 2023; Maindi et al., 2020). According to Candemir et al. (2021), dairy cooperatives in developing countries assist farmers in adopting innovations to increase productivity and reduce transaction costs. However, the authors argue that some innovations, such as fertilizer use, may harm the environment.

Another notable result concerns the total variable costs for milk production per year. On average, they were KES 23,895. However, we noticed notable differences when breaking down these costs based on different CSDS categories.

On the one side, farmers who used improved breeds, better feeds, and enhanced animal health management ($B_1F_1H_1$) faced the highest average variable costs (KES 29,986). This suggests that while these strategies might lead to better milk production or quality, they also come with higher expenses. Conversely, farmers who adopted a more comprehensive approach, incorporating improved breeds, feeds, health management, manure management, and zero grazing ($B_1F_1H_1M_1Z_1$), incurred the lowest average variable costs (KES 21,089). This indicates that while this method is more extensive, it is more cost-efficient overall.

An important factor in these cost differences is the expenditure on feed. Feed concentrates and fodder production alone constituted about 79% of the total variable costs in dairy production. Therefore, the high costs observed with the $B_1F_1H_1$ combination can likely be attributed to the significant expenses associated with feed. Adopting improved breeds and better feeds and health management leads to higher costs, primarily due to feed expenses. However, adding manure management and zero grazing to these practices can reduce overall costs, highlighting the efficiency of a more integrated farming approach, as Kihoro et al. (2021) suggested.

The annual individual variable costs per cow indicate that labor costs were higher (KES 15,512) than other non-feed costs for all CSDS. This finding aligns with the results of Maina et al. (2020), which emphasized that dairy production is labor-intensive.

The findings of this paper are also consistent with existing literature suggesting that adopting agricultural technologies can lead to improved productivity and income in Africa and Kenya (Khonje et al., 2018; Musafiri et al., 2023; Ngeno, 2018). In our sample, the average milk production per cow was 2,724 liters per year. However, farmers who adopted all five CSDS experienced a significant increase in production, reaching 3,319 liters per cow annually. This comprehensive adoption also resulted in the highest gross margin for smallholder dairy farmers, amounting to KES 99,518 annually.

3.2 Drivers of CSDS adoption among farmers

Table 4 shows the effect of different factors on the adoption of various combinations of CSDS using MNL model and the ($B_1F_1H_1M_1Z_1$) as the base category. Interpreting the marginal effects on individual probabilities is more convenient as they are expressed in the same unit as a probability (Khonje et al., 2018). The columns of the table display the marginal effects for each combination, while the rows represent different factors influencing adoption, along with their estimated parameters, statistical significance, and standard errors.

The statistical analysis of the model's fit and performance shows that it is statistically significant and explains a relatively large portion of the variation in the outcome, indicating a good fit to the data. The Likelihood Ratio Chi-Square of 266.26 with 76 degrees of freedom suggests that the model is statistically significant, with a probability of 0.0000. This means that the independent variables collectively significantly affect the dependent variable. The Pseudo R^2 suggests that 37.94% of the variability in the adoption of CSDS is explained by the model.

The adoption of CSDS can be influenced by various factors, which can be grouped into three categories. Factors such as age, gender, education, herd size, access to extension services, and membership in cooperatives positively affect the adoption of different CSDS. On the other hand, factors like risk perception, level of education, entrepreneurial orientation, and distance to resources generally lower the adoption of fewer strategies. Additionally, off-farm income, group membership, and training have insignificant

TABLE 3 Summary statistics and adoption of multiple climate-smart dairy strategies among smallholder farmers.

Variables	One	Two	$B_1F_1H_1$	$B_1F_1H_1M_1$	$B_1F_1H_1M_1Z_1$	Overall	f-value/χ^2
Demographic factors							
Age	53.81 (11.32)	53.74 (15.33)	49.46 (12.39)	50.7 (11.90)	49.62 (10.71)	51.04 (12.33)	1.93
Male headed households	27.78	30.00	52.00	63.64	76.47	56.62	54.12***
Household size	4.67 (1.60)	4.44 (2.18)	4.64 (2.37)	4.96 (2.34)	4.67 (2.10)	4.71 (2.17)	0.66
Socioeconomic factors							
Education	6.06 (2.12)	5.29 (2.69)	7.32 (2.82)	10.16 (2.90)	12.61 (2.71)	9.28 (3.93)	103.7***
Farm size	1.53 (2.22)	0.75 (0.70)	1.40 (1.74)	1.38 (1.39)	1.56 (1.32)	1.34 (1.45)	3.87***
Herd size	1.67 (0.68)	1.71 (1.00)	1.8 (0.76)	2.09 (0.87)	2.19 (1.07)	1.97 (0.95)	4.71***
Farmers with off-farm income (%)	36.11	37.14	44.00	39.09	53.78	43.64	7.94*
Farming experience	13.78 (7.95)	16.67 (13.31)	12.94 (8.50)	16.38 (10.03)	14.35 (10.0)	15.11 (10.39)	1.67
Social capital and institutional factors							
Farmers in group (%)	41.67	44.29	60.00	68.18	73.11	61.82	23.70***
Cooperative member (%)	8.33	5.71	12.00	49.09	57.14	35.06	84.44***
Extension access (%)	25.00	28.57	26.00	50.91	57.14	43.12	29.10***
Amount of credit	7,500 (23,068.22)	5,800 (17,739.34)	10,760 (28,668.09)	11,945.46 (30,896.94)	28,890.76 (67,558.99)	15,496.10 (44,370.07)	4.30***
Distance	2.15 (1.25)	2.96 (2.14)	2.34 (1.64)	2.68 (1.95)	2.18 (1.40)	2.48 (1.75)	3.02**
Training	0.83 (0.91)	1.24 (1.21)	1.62 (2.18)	1.55 (2.08)	2.0 (2.22)	1.57 (1.95)	3.30**
Entrepreneurial and behavioral factors							
Entrepreneurial orientation	58.81 (58.81)	53.70 (16.36)	59.24 (19.90)	67.26 (19.72)	72.12 (13.50)	64.47 (18.89)	14.78***
Risk perception	3.39 (0.57)	3.20 (0.67)	3.49 (0.60)	3.77 (0.64)	3.88 (0.63)	3.63 (.68)	16.16***
Awareness	2.5 (0.82)	2.73 (0.91)	3.03 (0.90)	2.94 (0.86)	2.88 (0.97)	2.86 (0.91)	2.44**
Behavioral intention	4.08 (0.76)	4.1 (0.64)	4.09 (0.70)	3.80 (0.84)	3.80 (0.79)	3.91 (0.78)	3.33**
Dairy milk productivity and income							
Milk yield/cow/ year	1,168.25 (594.3)	1,882.21 (1,245.4)	2,798.9 (1,761.2)	3,091.43 (1,450.5)	3,318.91 (1,587.3)	2,724.06 (1,607.3)	23.09***
Milk price/liter	44.64 (2.0)	44.89 (2.48)	45.36 (2.29)	45.45 (1.66)	46.11 (1.91)	45.46 (2.12)	5.72***
Total revenue/cow/ year	52,053.58 (26,084.42)	84,094.5 (54,526.96)	127,919 (83,499.20)	140,462.89 (67,551.83)	150,478.82 (72,988.93)	123,414 (74,097.41)	23.05***
Total variable cost/cow/ year	22,985.90 (16,935.54)	25,602.43 (23,106.71)	29,985.77 (24,318.21)	23,374.48 (18,097.41)	21,089.08 (17,611.71)	23,895.44 (19,843.88)	1.96
Gross margin/cow/ year	29,067.68 (58,492)	58,492.07 (43,983)	97,933.23 (77,011)	117,088.41 (58,037.9)	129,389.74 (68,543.2)	99,518.57 (68,496.8)	30.40***

***, **, * denotes statistical significance at 1%, 5%, and 10% level. The gross margin and total revenue are in Kenya shillings currency.
Standard deviation is given in parentheses; categorical variables are in percentages.

effects across most combination strategies. Insignificant and significant positive and negative estimated marginal effects highlight the relationship between demographic, socioeconomic, and institutional factors in determining the likelihood of adopting specific combinations of CSDS and the nuanced nature of adoption decisions among farmers.

TABLE 4 Determinants of adoption of CSDS using MNL model.

Variables	One	Two	$B_1F_1H_1$	$B_1F_1H_1M_1$	$B_1F_1H_1M_1Z_1$
	Marginal effects	Marginal effects	Marginal effects	Marginal effects	Marginal effects
Demographic factors					
Age	0.003** (0.001)	−0.002 (0.002)	0.000 (0.002)	−0.002 (0.002)	0.001 (0.002)
Gender	−0.020 (0.027)	−0.047 (0.035)	0.058* (0.033)	−0.012 (0.045)	0.021 (0.041)
Household size	−0.001 (0.006)	0.004 (0.007)	0.006 (0.010)	0.008 (0.011)	−0.017** (0.008)
Socioeconomic factors					
Education	−0.003 (0.004)	−0.028*** (0.006)	−0.015*** (0.006)	−0.008 (0.007)	0.054*** (0.007)
Land size	0.020 (0.011)	−0.054* (0.029)	0.021 (0.014)	−0.002 (0.015)	0.014 (0.013)
Off-farm income	0.021 (0.028)	−0.009 (0.034)	0.038 (0.031)	−0.055 (0.046)	0.006 (0.042)
Farming experience	−0.002 (0.001)	0.005** (0.002)	−0.002 (0.002)	0.004 (0.003)	−0.004 (0.003)
Herd size	−0.014 (0.014)	0.034* (0.019)	−0.020 (0.018)	0.016 (0.024)	−0.017 (0.022)
Social capital and institutional factors					
Group membership	0.019 (0.035)	−0.010 (0.041)	−0.022 (0.041)	−0.018 (0.047)	0.030 (0.043)
Cooperative membership	−0.030 (0.037)	−0.072 (0.056)	−0.078* (0.046)	0.141*** (0.043)	0.040 (0.039)
Group membership duration	−0.017*** (0.006)	0.001*** (0.006)	0.007*** (0.005)	0.011** (0.005)	−0.002 (0.004)
Extension access	0.012 (0.032)	−0.032 (0.039)	−0.061 (0.039)	0.073* (0.043)	0.007 (0.039)
Training	−0.017** (0.009)	0.003 (0.009)	0.012 (0.008)	−0.004 (0.011)	0.007 (0.009)
Distance	−0.021*** (0.007)	0.019*** (0.007)	−0.006 (0.010)	0.024** (0.011)	−0.017 (0.010)
Amount of credit	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000* (0.000)
Entrepreneurial and behavioral factors					
Entrepreneurial orientation	−0.066*** (0.025)	−0.017 (0.032)	0.010 (0.034)	0.039 (0.046)	0.035 (0.043)
Risk perception	0.017 (0.020)	−0.072*** (0.027)	0.002 (0.028)	0.020 (0.035)	0.033 (0.030)
Awareness	−0.031* (0.016)	−0.015 (0.021)	0.024 (0.019)	0.020 (0.024)	0.002 (0.024)
Behavioral intention	0.027 (0.021)	0.042* (0.022)	0.014 (0.023)	−0.065** (0.026)	−0.018 (0.023)
Number of observations = 385					
LRχ2 (76) = 266.26					
Prob > χ2 = 0.0000					
Log likelihood = −362.56359					
Pseudo = 0.3794					

***, **, * denotes statistical significance at 1%, 5% and 10% level.

3.2.1 Demographic factors

The results reveal that age has a negative effect on the adoption of CSDS. Older farmers prefer simpler strategies, as supported by Gemtou et al. (2024) and Maindi et al. (2020), who found a negative correlation between age and the use of multiple climate-smart strategies due to aging-related physical limitations. However, Akzar et al. (2023) reported that older farmers' experience leads to a positive correlation with the adoption of multiple dairy technologies.

Gender influences CSDS adoption, with males more likely to adopt improved breeds, feeds, and health management ($B_1F_1H_1$), possibly due to their control over resources and understanding of CSDS, aligning with Maindi et al. (2020)'s findings. The finding contradicts those of Musafiri et al. (2022a), which suggested that female-headed households had a higher propensity to adopt climate-smart practices than their male counterparts.

Household size has an inverse relationship with adopting comprehensive CSDS ($B_1F_1H_1M_1Z_1$), where larger households have fewer resources for such strategies. Household size is an important variable as it signifies labor to adopt labor-intensive CSDS. However, larger families could be constrained with resources to adopt capital-intensive CSDS, such as biogas plant and feed supplementation, which aligns with the findings of Musafiri et al. (2022a). This contradicts Asante et al. (2024) and Balchax et al. (2023), who argued that larger households' labor resources lead to broader adoption of climate-smart strategies.

3.2.2 Socioeconomic characteristics

Farmers with higher levels of education are less likely to adopt the simpler combinations ($B_1F_1H_1$), yet more inclined to embrace the comprehensive suite ($B_1F_1H_1M_1Z_1$). This trend suggests that each additional year of formal education equates to a broader adoption of CSDS. Educated farmers are better equipped to understand the synergies between different strategies, leading to a more holistic implementation. These observations are consistent with the research conducted by Asante et al. (2024), Korir et al. (2023) and Musafiri et al. (2022a).

Land size presents a contrasting effect, with a larger land area negatively impacting the adoption of two CSDS combinations. Land serves as a source of wealth, which may drive the adoption of CSDS that require farmland, such as improved fodder varieties. A large land size implies a larger herd, which may limit the time available for adopting labor-intensive CSDS, like improved fodder production and manure management. This finding echoes Okello et al. (2021), who noted that large land size was linked to low intensification. However, Meraner and Finger (2019) argued that large farms were associated with the adoption of on-farm risk management strategies due to greater wealth.

Regarding herd size, a positive correlation exists with the adoption of two CSDS. As the number of dairy animals rises, competition for resources like land and labor also escalates. Consequently, this diminishes the available time and resources for adopting capital and labor-intensive CSDS. This finding stands in contrast to Korir et al. (2023), which reported that expanding herd size was associated with the adoption of multiple dairy technologies in Ethiopia. Larger herd sizes necessitate more feed, thereby encouraging farmers to adopt manure management and multiple feed sources, as supported by Balchax et al. (2023) and Maina et al. (2020).

Additionally, there is a positive correlation between a farmer's experience and the likelihood of adopting a combination of two CSDS. This relationship is nuanced by age; with increased experience, farmers are more inclined to implement multiple CSDS. However, this trend may reverse as physical capabilities decline with age. Over time, the initial appeal of new technologies can wane, leading to reduced usage, as noted by Schukat and Heise (2021).

3.2.3 Social capital and institutional factors

Our findings reveal that the duration of a farmer's membership in agricultural groups has a dual effect on the adoption of CSDS. While a longer membership negatively affects the adoption of a single CSD strategy, it positively influences the adoption of combinations involving two, three, and four strategies. Agricultural groups play a pivotal role in knowledge dissemination and extended participation in these groups equips farmers with a deeper understanding of the advantages of integrating multiple CSDS. This pattern is supported by literature, such as Ng'ang'a et al. (2020), who found that robust social capital promotes the adoption of key climate-smart strategies, including improved breeds, fodder production, irrigation, and livestock manure management, in Laikipia.

Similarly, dairy cooperative membership exhibits a contrasting effect on CSDS adoption. It appears to hinder the adoption of the basic combination ($B_1F_1H_1$) while fostering the uptake of a more multiple CSDS ($B_1F_1H_1M_1$). This could be attributed to the role of social networks in enhancing information exchange and learning opportunities. In our study region, dairy cooperatives are instrumental in providing resources such as feed concentrates, feed formulation guidelines, and ingredients, thereby facilitating the adoption of improved feeding practices among farmers. This observation aligns with Akzar (2021), which emphasized the significance of cooperative membership in embracing complementary dairy feed technologies.

Furthermore, access to extension services is positively correlated with the adoption of the $B_1F_1H_1M_1$ combination. Extension services, both governmental and non-governmental, are crucial in disseminating information and educating farmers on the multifaceted benefits of adopting an array of CSDS, potentially leading to enhanced milk production and lower production costs. Extension provides farmers practical skills to implement agricultural technologies (Musafiri et al., 2022a). Supporting this, Korir et al. (2023) noted that Ethiopian farmers who trusted government extension officers were more inclined to adopt a broader spectrum of dairy technologies.

Access to credit positively influences the adoption of the ($B_1F_1H_1M_1Z_1$) combination. This suggests that financial access is a key enabler for households, particularly those with limited resources, to implement capital-intensive CSDS. The significance of financial support is corroborated by studies such as Mburu et al. (2024), Mujeyi et al. (2021), and Yang and Sharp (2017). However, this contrasts the findings of Zemarku et al. (2022) and Okello et al. (2021), who reported a negative correlation between credit access and the adoption of dairy technologies. The present study underscores the importance of financial resources in facilitating the uptake of advanced CSDS.

TABLE 5 ATT and ATU estimates of MESR model (Milk productivity per year).

CSDS	Scenario	Productivity of actual (a)	Productivity of counterfactual (b)	Treatment effects: ATT/ATU (a–b)	SE
No or Single CSDS	Adopter	1,168.25	2,459.895	ATT = −1,291.645***	92.964
	Non-adopter	1,155.934	2,884.549	ATU = −1,728.615***	45.025
Two CSDS	Adopter	1,882.214	2,113.508	ATT = −231.2936**	51.384
	Non-adopter	2,929.856	2,911.141	ATU = 18.7152	41.204
$B_1F_1H_1$	Adopter	2,798.9	2,251.711	ATT = 547.1888***	99.676
	Non-adopter	2,989.261	2,712.894	ATU = 276.3669***	49.396
$B_1F_1H_1M_1$	Adopter	3,091.432	2,741.538	ATT = 349.8941***	33.444
	Non-adopter	3,288.262	2,577.116	ATU = 711.1455***	30.684
$B_1F_1H_1M_1Z_1$	Adopter	3,318.908	3,026.97	ATT = 291.9371***	42.187
	Non-adopter	3,338.292	2,457.949	ATU = 880.3426***	35.473

***, ** denotes statistical significance at 1% and 5% level. SE is the standard error.

Contrary to initial assumptions, the distance to input markets has a negative relationship with CSDS adoption. While one might expect proximity to the market to be a facilitator, the study reveals that greater distances do not deter farmers from adopting two or three ($B_1F_1H_1$) CSDS combinations. This is attributed to the critical role of improved breeds, feeds, and health management in dairy productivity, which may outweigh the transaction costs incurred from longer distances. This finding is at odds with Zemarku et al. (2022), who suggested that closer market access boosts the likelihood of technology adoption in dairy farming.

Our study reveals a statistically significant negative relationship between training and adopting a single CSD strategy or none. Specifically, as farmers attend more training sessions, they are less likely to adopt a single CSD strategy or none, favoring the adoption of multiple strategies instead. This trend suggests that training broadens farmers' understanding of the synergistic benefits of employing various strategies concurrently. This is consistent with Yang and Sharp (2017), who observed that training positively impacts the adoption of multiple best management practices among dairy farmers. Training is crucial for increasing awareness and encouraging behavioral shifts toward adopting integrated climate-smart strategies, as Gemtou et al. (2024) support.

3.2.4 Entrepreneurial and behavioral factors

The entrepreneurial mindset of farmers significantly influences their adoption of CSDS. Those with a strong entrepreneurial orientation are more inclined to invest in multiple CSDS, which has been shown to enhance milk production, rather than limiting themselves to a single CSD strategy or none. This trend is supported by research emphasizing the role of entrepreneurial spirit in embracing sustainable agricultural technologies, as documented by Barzola Iza et al. (2019); Daneluz et al. (2021), and Wang et al. (2023).

Furthermore, farmers' awareness of CSDS appears to decrease the likelihood of adopting a single CSD strategy or none over multiple strategies. Empirical evidence suggests that a comprehensive understanding of CSDS encourages adopting various practices, particularly when farmers recognize the potential for increased production and resilience against climate change. This behavior aligns with findings from Li et al. (2023), Maina et al. (2020), and Mburu et al. (2024).

Perceived risks of climate change also play a critical role. Farmers' perception of the risks associated with climate change on dairy production is negatively related to the adoption of two specific combinations of CSDS. When farmers perceive climate change as a threat to dairy production, they are less likely to adopt a few CSDS than multiple CSDS. This finding is consistent with Amamou et al. (2018), who discovered that climate change risks such as new diseases, reduced animal fertility, decreased milk production, reduced longevity, and feed unavailability increased the likelihood of adopting multiple mitigation measures. Similarly, Mburu et al. (2024) reported that past drought conditions encouraged farmers in Kenya to adopt feed concentrates.

Lastly, behavioral intention is positively correlated with adopting two CSDS combinations and negatively associated with adopting ($B_1F_1H_1M_1$). Behavioral intention is assessed through self-reporting. Self-reported intentions may not always translate into action, often hindered by the substantial financial commitments required for multiple CSDS, which may be beyond the reach of smallholder farmers. This observation diverges from Schukat and Heise (2021), who reported a positive correlation between the intent and actual adoption of smart farming technologies in Germany.

3.3 Effects of adopting climate-smart dairy strategies on milk yield and gross margin

Tables 5, 6 present the results of the analysis of the effects of CSDS on milk productivity and gross margin per cow per year, respectively. These tables evaluate how effective CSDS are in improving milk productivity/gross margin by comparing actual outcomes (column 3) with estimated outcomes (column 4) if the strategies had not been adopted. The difference between the treatment (ATT) and the counterfactual (ATU) effects, presented in column 5, indicates the productivity/gross margin gains attributable to these strategies, and the standard error (column 6) provides information on the reliability of these estimates, ensuring the validity of our findings.

The data presented in the tables for each category of CSDS can be interpreted through two distinct scenarios. In the first scenario, farmers have implemented the particular strategy under analysis, while in the second, they have not. This comparative approach allows for a clearer understanding of the effects of adopting specific CSDS. MESR provides estimates associated with actual and counterfactual scenarios.

The Average Treatment Effect on the Treated (ATT) and Average Treatment Effect on the Untreated (ATU) values across different strategies and farmer groups show varying degrees of statistical significance, with most being highly significant (at 1%). This robustness indicates reliable findings.

Our research findings indicate that the impact of implementing CSDS on milk productivity per cow per day varies significantly depending on the type and number of strategies used. As farmers adopt multiple CSDS, such as moving from implementing two strategies to the most comprehensive set ($B_1F_1H_1M_1Z_1$), the positive effect on productivity generally improves, especially for adopter farmers. This suggests that a more integrated approach to CSDS can lead to better results.

The $B_1F_1H_1M_1Z_1$ strategy is the most beneficial for non-adopters, suggesting that a more integrated approach to CSDS could result in higher productivity gains. Among adopters, the $B_1F_1H_1$ strategy demonstrates the greatest increase in productivity, indicating that multiple CSDS may be the most effective for current adopters. This finding supports empirical literature emphasizing the importance of improved breed, feed, and animal health management in increasing milk production (Akzar et al., 2023; Balehegn et al., 2020; Kihoro et al., 2021). This finding reinforces the results of Musafiri et al. (2023), which indicated that input combinations such as organic fertilizer and climate-resilient crops enhance farmers' livelihoods through improved soil health and crop yields.

Moreover, the analysis suggests that broader CSDS not only improve milk productivity but also have a favorable effect on the gross margin per cow: more comprehensive CSDS ($B_1F_1H_1$, $B_1F_1H_1M_1$, $B_1F_1H_1M_1Z_1$) tend to have positive economic impacts for both adopters and non-adopters, whereas the single and two option CSDS may not be as beneficial. The significant positive ATU values for non-adopters suggest that there may be barriers to adoption that are not economic, such as lack of access to technology, knowledge, or other resources. The findings emphasize the significance of selecting the appropriate CSDS to maximize economic returns and promote climate-smart agriculture practices. Strategies that offer multiple options ($B_1F_1H_1$, $B_1F_1H_1M_1$, $B_1F_1H_1M_1Z_1$) seem more economically advantageous for adopters, suggesting that a comprehensive approach to CSDS may be more beneficial. The finding supports the validity of counterfactual modeling for estimating yield gains under climate-smart agriculture (Musafiri et al., 2022b).

3.3.1 Robustness check using the IPWRA

When treatment is multivalued, a treatment effects model could be appropriate (Akzar et al., 2023). The study employed the IPWRA model to conduct a comparative analysis between the MESR model results and determine the best model between the two. The IPWRA model has a double robust property and thus offers consistent estimates even when one of the models (outcome or treatment) is misspecified (Caldera, 2019). It also accepts various outcomes such as count, continuous, fractional, or nonnegative variables. Moreover, it can handle both binary and multivalued treatment variables. The findings indicate that the direction of the average treatment on treated was the same for both models. However, the MESR model had more significant outcomes and lower standard errors than IPWRA (Tables 5, 6; Tables A3, A4). Although both results indicate that adopting multiple CSDS positively influenced milk production and gross margin, IPWRA estimates were less precise. Additionally, the IPWRA model does not account for unobserved heterogeneity, such as individuals' motivation and skills (Zegeye et al., 2022).

4 Conclusions and policy implications

This study on the effects of adopting CSDS yields several insights into how these strategies affect productivity and economic returns in Nyandarua County, Kenya. The study's findings underscore the importance of adopting comprehensive and multifaceted CSDS to maximize economic benefits and promote sustainable agricultural practices. Implementing a single CSD strategy or none significantly reduces productivity for adopters and non-adopters, indicating that minimal adoption is ineffective. In contrast, a holistic approach encompassing multiple strategies leads to better economic outcomes. This is evident as the number of CSDS increases, and there is a corresponding improvement in productivity, particularly for adopter farmers. This trend suggests that more integrated approaches to CSDS yield better results and can transform the dairy sector by enhancing productivity and sustainability.

The study highlights the significant economic advantages of adopting a more comprehensive CSDS. Specifically, strategies like $B_1F_1H_1M_1Z_1$ show the highest benefits for non-adopters, while the $B_1F_1H_1$ strategy is most beneficial for adopters. These findings suggest that while specific strategies are universally effective, others may need to be tailored based on whether a farmer is an adopter or non-adopter of CSDS. This differentiation is crucial for maximizing the economic benefits and ensuring that all farmers benefit from CSDS.

Furthermore, the statistically significant ATT and ATU values across different strategies affirm the reliability of the findings. These metrics demonstrate that the positive impacts of CSDS are not random but statistically robust, giving policymakers and stakeholders confidence in their efficacy.

While productivity is a crucial factor, the study emphasizes the importance of considering other aspects, such as environmental impact, cost, and feasibility, in evaluating the overall effectiveness of CSDS. This broader perspective ensures that CSDS not only enhances economic outcomes but also contributes to environmental sustainability and the long-term viability of the dairy sector.

Various farmers' demographic factors, socioeconomic characteristics, social capital and institutional factors, and entrepreneurial and behavioral factors influence the adoption

TABLE 6 ATT and ATU estimates of MESR model (Gross margin per year).

CSDS	Scenario	Gross margin of actual (a)	Gross margin of counterfactual (b)	Treatment effects: ATT/ATU (a−b)	SE
No or Single option CSD	Adopter	29,067.68	85,294.69	ATT = −56,227.01***	4,018.275
	Non-adopter	26,528.11	106,785.7	ATU = 80,257.59***	1,995.988
Two option CSD	Adopter	58,492.07	64,247.66	ATT = −5,755.589	2,369.204
	Non-adopter	81,092.45	108,635.6	ATU = −27,543.11***	1,448.303
$B_1F_1H_1$	Adopter	97,933.23	79,283.98	ATT = 18,649.25**	4,453.917
	Non-adopter	108,782.1	99,755.18	ATU = 9,026.934**	2,380.734
$B_1F_1H_1M_1$	Adopter	117,088.4	100,314.9	ATT = 16,773.48***	1,553.471
	Non-adopter	120,628.1	92,490.63	ATU = 28,137.51***	1,313.303
$B_1F_1H_1M_1Z_1$	Adopter	129,389.7	115,265.3	ATT = 14,124.49***	1,939.901
	Non-adopter	128,384.7	86,155.14	ATU = 42,229.57***	1,642.285

***, **denotes statistical significance at 1%, 5% and 10% level.

of multiple CSDS. This highlights the relationship of human, physical, and financial resources in successfully adopting CSDS. Understanding these influences can help in designing targeted interventions that address the specific needs and challenges faced by different groups of farmers.

For example, the findings from our MNL model suggest that policies should support strengthening agricultural groups and cooperatives and expanding extension services. These institutions are vital for fostering the adoption of CSDS, leading to more sustainable and productive dairy farming practices. Encouraging long-term engagement in agricultural groups and cooperative membership can significantly enhance farmers' propensity to implement comprehensive CSDS. Additionally, trust-building initiatives within extension services can further promote the adoption of beneficial dairy technologies.

The findings of this study underscore the need for integrated policy interventions that address the multiple barriers to CSDS adoption. Policymakers should consider bundled support packages that combine access to training, credit, and extension services to improve uptake. Training programs should go beyond introducing individual CSDS to demonstrate the synergistic benefits of adopting multiple complementary strategies. Such an approach would help farmers understand how integrating strategies such as improved feeding, manure, and animal health management can enhance productivity, profitability, and environmental sustainability.

Moreover, targeted support should be directed toward aging farmers, who may face physical limitations in adopting labor-intensive technologies. Interventions such as labor-saving devices, youth engagement in farm labor, and simplified technologies could reduce physical strain and improve adoption among older demographics. In addition, policies should support farmer groups and cooperatives as channels for disseminating CSDS knowledge and offering collective access to inputs and finance. These actionable insights provide a pathway for scaling CSDS adoption while ensuring inclusivity and long-term sustainability.

A holistic approach, combining financial, educational, and entrepreneurial support, is essential for the widespread adoption of CSDS and the sustainability of dairy farming in the face of climate change. Policies should focus on providing financial support, improving infrastructure, offering targeted education, and encouraging research to understand local adoption barriers. Customized approaches and behavioral interventions are recommended to ensure farmers' intentions to adopt CSDS translate into actual practice, promoting sustainable and resilient dairy farming.

The present study provides compelling evidence for adopting multiple and integrated CSDS to maximize productivity and economic benefits in the dairy sector. While the analysis is grounded in the Kenyan context, the findings have broader relevance for livestock systems across Sub-Saharan Africa, where smallholder dairy farming faces similar challenges such as climate variability, low productivity, limited access to extension, and aging farmer populations.

Although the study provides valuable insights, it is important to acknowledge some of its limitations. First, the study was limited by financial resources, which restricted it to four out of eight sub-counties in Nyandarua County. Secondly, the focus on Nyandarua County may not represent all dairy producers in Kenya. Thirdly, the effects of CSDS on milk productivity and gross margin may not be fully captured due to the unavailability of longitudinal data. Finally, the study relied on farmers' capacity to recall production input and output information. This may contribute to inconsistencies in the reported data, as most farmers do not keep farm records.

Given the reliance on self-reported data for variables such as milk yield, input costs, and milk price, potential recall bias was addressed through multiple measures. Enumerators used short recall periods, specifically asking farmers to report on daily milk yields and input costs based on monthly expenditures. To aid memory, enumerators guided probing. Where possible, farmers were encouraged to refer to existing records or receipts. Despite these efforts, we acknowledge that some recall errors may persist.

Future research endeavors might expand their scope to overcome these limitations, facilitating the generalization of findings to broader populations and enabling comparisons between rural and urban settings. Further, future studies could consider panel data for robust impact evaluation. Future research could also enhance data reliability by triangulating self-reported figures with farm records or integrating digital record-keeping tools like mobile apps.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Ethics statement

The studies involving humans were approved by National Commission for Science, Technology and Innovation (NACOSTI). The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

NC: Writing – original draft, Formal analysis, Resources, Writing – review & editing, Project administration, Methodology, Validation, Investigation, Conceptualization, Data curation, Software. MM: Supervision, Writing – review & editing, Conceptualization, Methodology. DO: Supervision, Conceptualization, Writing – review & editing, Methodology, Validation. MS: Supervision, Conceptualization, Writing – review & editing, Methodology, Writing – original draft, Resources, Formal analysis.

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The author(s) declare that no Gen AI was used in the creation of this manuscript.

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References

Abbas, Q., Han, J., Bakhsh, K., and Kousar, R. (2023). Estimating impact of climate change adaptation on productivity and earnings of dairy farmers: evidence from Pakistani Punjab. *Environ. Dev. Sustain.* 26, 13017–13029. doi: 10.1007/s10668-023-04068-1

Abegunde, V. O., Sibanda, M., and Obi, A. (2019). Determinants of the adoption of climate-smart agricultural practices by small-scale farming households in King Cetshwayo District Municipality, South Africa. *Sustainability* 12:195. doi: 10.3390/su12010195

Akzar, R. Y. (2021). *Adoption of Multiple Dairy Farming Technologies Issues and Opportunities for Smallholder Dairy Farmers in West Java, Indonesia*. Dissertation, Adelaide: University of Adelaide.

Akzar, R. Y., Peralta, A., and Umberger, W. (2023). Adoption of dairy feed technology bundles improves smallholder dairy farmers' milk production. *J. Agribus. Dev. Emerg. Econ.* 15, 269–287. doi: 10.1108/JADEE-12-2022-0267

Amamou, H., Sassi, M. B., Aouadi, H., Khemiri, H., Mahouachi, M., Beckers, Y., et al. (2018). Climate change related risks and adaptation strategies as perceived in dairy cattle farming systems in Tunisia. *Clim. Risk Manag.* 20, 38–49. doi: 10.1016/j.crm.2018.03.004

Asante, B. O., Ma, W., Prah, S., and Temoso, O. (2024). Farmers' adoption of multiple climate-smart agricultural technologies in Ghana: determinants and impacts on maize yields and net farm income. *Mitig. Adapt. Strateg. Glob. Change* 29:1. doi: 10.1007/s11027-024-10114-8

Balchax, E., Menghistu, H. T., Zenebe, A., Teferi, T., and Hadush, B. (2023). Climate-smart agricultural practices: a case of dairy cooperative farmers in Agula and Maychew, Northern Ethiopia. *Carbon Manag.* 14:2271880. doi: 10.1080/17583004.2023.2271880

Balehegn, M., Duncan, A., Tolera, A., Ayantunde, A. A., Issa, S., Karimou, M., et al. (2020). Improving adoption of technologies and interventions for increasing supply of quality livestock feed in low- and middle-income countries. *Glob. Food Secur.* 26:100372. doi: 10.1016/j.gfs.2020.100372

Barzola Iza, C. L., Dentoni, D., Mordini, M., Subikalu, P., Auma Oduol, J. B., and Omta, O. (2019). "The role of farmers' entrepreneurial orientation on agricultural innovations in Ugandan multi-stakeholder platform," in *The Climate-Smart Agriculture Papers: Investigating the Business of a Productive, Resilient and Low Emission Future* (Cham: Springer), 201–213.

Belay, A., Mirzabaev, A., Recha, J. W., Oludhe, C., Osano, P. M., Berhane, Z., et al. (2023). Does climate-smart agriculture improve household income and food security? Evidence from Southern Ethiopia. *Environ. Dev. Sustain.* 26, 16711–16738. doi: 10.1007/s10668-023-03307-9

Bourguignon, F., Fournier, M., and Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *J. Econ. Surv.* 21, 174–205. doi: 10.1111/j.1467-6419.2007.00503.x

Caldera, S. (2019). *Techniques for Robustness and Threats to Inference: Inverse Probability Weighted Regression Adjustment.*

Candemir, A., Duvaleix, S., and Latruffe, L. (2021). Agricultural cooperatives and farm sustainability – a literature review. *J. Econ. Surv.* 35, 1118–1144. doi: 10.1111/joes.12417

Chelang'a, N. C., Mathenge, M., Otieno, D. O., and Sassi, M. (2025). The determinants of greenhouse gas reduction levels among smallholder farmers: insights from the adoption of climate-smart dairy strategies in Central Kenya. *Front. Clim.* 7:1593584. doi: 10.3389/fclim.2025.1593584

Daneluz, M., Canever, M. D., Lima, H. G. D., Bermudes, R. F., and Menezes, G. R. (2021). Linking entrepreneurial orientation and managerial capacity to performance in dairy farms. *Rev. Econ. Sociol. Rural* 60:e229910. doi: 10.1590/18069479.2021.229910

Ericksen, P. J., and Crane, T. A. (2018). *The Feasibility of Low Emissions Development Interventions for the East African Livestock Sector: Lessons From Kenya and Ethiopia*. Nairobi: ILRI Research Report. Available online at: https://ccafs.cgiar.org/donors (accessed June 2023).

Food and Agriculture Organisation (2017). *Livestock Solutions for Climate Change*. Rome, Italy. Available online at: https://www.fao.org/3/i8098e/i8098e.pdf (accessed March 17, 2025)

Food and Agriculture Organisation (2019). *Options for Low Emission Development in the Tanzania Dairy Sector: Reducing Enteric Methane for Food Security and Livelihoods*. Rome, Italy. Available online at: https://www.fao.org/documents/card/ru/c/CA3215EN (accessed January 6, 2023).

Food and Agriculture Organisation (2021). *Climate-Smart Agriculture Case Studies 2020: Projects From Around the World*. Rome, Italy. doi: 10.4060/cb5359en

Freese, J., and Long, J. S. (2000). Tests for the multinomial logit model. *Stata Tech. Bull.* 10, 1–10.

Gemtou, M., Kakkavou, K., Anastasiou, E., Fountas, S., Pedersen, S. M., Isakhanyan, G., et al. (2024). Farmers' transition to climate smart agriculture: a systematic review of the decision-making factors affecting adoption. *Sustainability* 16:2828. doi: 10.3390/su16072828

Giro, A., and Kumar, N. (2022). Climate smart livestock system: a review. *J. Agric. Res. Pestic. Biofert.* 3:1.1045. doi: 10.2022/1.1045

Government of Kenya (2017). *Kenya Climate Smart Agriculture Strategy 2017-2026*. Nairobi, Kenya.

Intergovernmental Panel on Climate Change (2022). *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge; New York, NY: Cambridge University Press. Available online at: https://www.ipcc.ch/report/ar6/wg2/ (accessed October 30, 2023)

Khonje, M. G., Manda, J., Mkandawire, P., Tufa, A. H., and Alene, A. D. (2018). Adoption and welfare impacts of multiple agricultural technologies: evidence from Eastern Zambia. *Agric. Econ.* 49, 599–609. doi: 10.1111/agec.12445

Kihoro, E. M., Schoneveld, G. C., and Crane, T. A. (2021). Pathways toward inclusive low-emission dairy development in Tanzania: producer heterogeneity and implications for intervention design. *Agric. Syst.* 190:103073. doi: 10.1016/j.agsy.2021.103073

Kimaru, G. G., Bwisa, H. M., and Go, O. (2020). The relationship between innovativeness and performance of commercial small scale dairy enterprises in Kenya. *Int. J. Bus. Manag. Econ. Res.* 11:1839–1850. Available online at: https://www.ijbmer.com/docs/volumes/vol11issue4/ijbmer2020110403.pdf

Kirui, J. W., Muthama, N. J., Gachuiri, C. K., and Ngaina, J. N. (2021). Adaptation and mitigation strategies to climate change by smallholder dairy farmers: a case of Nandi County in Kenya. *J. Sustain. Environ. Peace* 4, 39–47. doi: 10.53537/jsep.2021.09.005

Korir, L., Manning, L., Moore, H. L., Lindahl, J. F., Gemechu, G., Mihret, A., et al. (2023). Adoption of dairy technologies in smallholder dairy farms in Ethiopia. *Front. Sustain. Food Syst.* 7:1070349. doi: 10.3389/fsufs.2023.1070349

Li, J., Liu, G., Chen, Y., and Li, R. (2023). Study on the influence mechanism of adoption of smart agriculture technology behavior. *Sci. Rep.* 13:8554. doi: 10.1038/s41598-023-35091-x

Lumpkin, G. T., and Dess, G. G. (1996). Clarifying the entrepreneurial orientation construct and linking it to performance. *Acad. Manag. Rev.* 21, 135–172. doi: 10.5465/amr.1996.9602161568

Maina, K. W., Ritho, C. N., Lukuyu, B. A., and Rao, E. J. O. (2020). Socioeconomic determinants and impact of adopting climate smart Brachiaria grass among dairy farmers in Eastern and Western regions of Kenya. *Heliyon* 6:e04335. doi: 10.1016/j.heliyon.2020.e04335

Maindi, N. C., Osuga, I. M., and Gicheha, M. G. (2020). Advancing climate smart agriculture: adoption potential of multiple on-farm dairy production strategies among farmers in Murang'a County, Kenya. *Livest. Res. Rural Dev.* 32:63.

Martius, C., Guérin, L., Pingault, N., Mwambo, F., Wassmann, R., Cramer, L., et al. (2023). *Food Systems Emissions in Kenya and Their Reduction Potential: A Country Profile*. Bogor: CIFOR. Available online at: https://www.cifor-icraf.org/publications/pdf_files/OccPapers/CIFOR-ICRAF-OP-7.pdf (Accessed February 11, 2025).

Mburu, M., Mburu, J., Nyikal, R., Mugera, A., and Ndambi, A. (2024). Role of agricultural extension in learning for uptake and intensification of less practiced dairy climate smart practices in Kenya. *Cogent Food Agric.* 10:2330182. doi: 10.1080/23311932.2024.2330182

McFadden, D. (1974). The measurement of urban travel demand. *J. Public Econ.* 3, 303–328. doi: 10.1016/0047-2727(74)90003-6

Meraner, M., and Finger, R. (2019). Risk perceptions, preferences, and management strategies: evidence from a case study using German livestock farmers. *J. Risk Res.* 22, 110–135. doi: 10.1080/13669877.2017.1351476

Mujeyi, A., Mudhara, M., and Mutenje, M. J. (2021). The impact of climate smart agriculture on household welfare in smallholder integrated crop livestock farming systems: evidence from Zimbabwe. *Agric. Food Secur.* 10:4. doi: 10.1186/s40066-020-00277-3

Mujeyi, A., Mudhara, M., and Mutenje, M. J. (2022). Adoption patterns of climate-smart agriculture in integrated crop-livestock smallholder farming systems of Zimbabwe. *Clim. Dev.* 14, 399–408. doi: 10.1080/17565529.2021.1930507

Musafiri, C. M., Kiboi, M., Macharia, J., Ng'etich, O. K., Kosgei, D. K., Mulianga, B., et al. (2022a). Adoption of climate-smart agricultural practices among smallholder farmers in Western Kenya: do socioeconomic, institutional, and biophysical factors matter? *Heliyon* 8:e08677. doi: 10.1016/j.heliyon.2021.e08677

Musafiri, C. M., Kiboi, M., Macharia, J., Ng'etich, O. K., Okoti, M., Mulianga, B., et al. (2022b). Does the adoption of minimum tillage improve sorghum yield among smallholders in Kenya? a counterfactual analysis. *Soil Tillage Res.* 223:105473. doi: 10.1016/j.still.2022.105473

Musafiri, C. M., Kiboi, M., Macharia, J., Ng'etich, O. K., Okoti, M., Mulianga, B., et al. (2023). Use of inorganic fertiliser on climate-smart crops improves smallholder farmers' livelihoods: evidence from Western Kenya. *Soc. Sci. Humanit. Open* 8:100537. doi: 10.1016/j.ssaho.2023.100537

Ng'ang'a, T. W., Coulibaly, J. Y., Crane, T. A., Gachene, C. K., and Kironchi, G. (2020). Propensity to adapt to climate change: insights from pastoralist and agro-pastoralist households of Laikipia County, Kenya. *Clim. Change* 161, 393–413. doi: 10.1007/s10584-020-02696-4

Ngeno, V. (2018). Impact of dairy hubs on smallholder welfare: empirical evidence from Kenya. *Agric. Food Econ.* 6:11. doi: 10.1186/s40100-018-0107-3

Niles, M. T., Wiltshire, S., Lombard, J., Branan, M., Vuolo, M., Chintala, R., et al. (2022). Manure management strategies are interconnected with complexity across US dairy farms. *PLoS One* 17:e0267731. doi: 10.1371/journal.pone.0267731

Ntinyari, W., and Gweyi-Onyango, J. P. (2020). "Greenhouse gases emissions in agricultural systems and climate change effects in Sub-Saharan Africa," in *African Handbook of Climate Change Adaptation* (Cham: Springer), 1–25.

Odero-Waitituh, J. A. (2017). Smallholder dairy production in Kenya; a review. *Livest. Res. Rural Dev.* 29:139.

O'Hara, J. K. (2023). State-level trends in the greenhouse gas emission intensity of US milk production. *J. Dairy Sci.* 106, 5474–5484. doi: 10.3168/jds.2022-22741

Okello, D., Owuor, G., Larochelle, C., Gathungu, E., and Mshenga, P. (2021). Determinants of utilisation of agricultural technologies among smallholder dairy farmers in Kenya. *J. Agric. Food Res.* 6:100213. doi: 10.1016/j.jafr.2021.100213

Pinto, A., Yin, T., and Reichenbach, M. (2020). Enteric methane emissions of dairy cattle considering breed composition, pasture management, housing conditions and feeding characteristics along a rural-urban gradient in a rising megacity. *Agriculture* 10:628. doi: 10.3390/agriculture10120628

Pressman, E., Schaefer, J. M., and Kebreab, E. (2018). *Mitigation of Enteric Methane Emissions From Dairy Cattle in East Africa Through Urea Treatment of Crop Residue Feeds*. AGU Fall Meet. Abstr.

Radeny, M., Rao, E. J., Ogada, M. J., Recha, J. W., and Solomon, D. (2022). Impacts of climate-smart crop varieties and livestock breeds on the food security of smallholder farmers in Kenya. *Food Secur.* 14, 1511–1535. doi: 10.1007/s12571-022-01307-7

Rodríguez-Barillas, M., Poortvliet, P. M., and Klerkx, L. (2024). Unraveling farmers' interrelated adaptation and mitigation adoption decisions under perceived climate change risks. *J. Rural Stud.* 109:103329. doi: 10.1016/j.jrurstud.2024.103329

Sambrumo, G. M., Ngigi, M. W., and Mutai, B. K. (2022). Influence of agripreneurial orientation constructs on growth of cassava-based small and medium enterprises in Migori County, Kenya. *Asian Res. J. Agric.* 15, 45–55. doi: 10.9734/ARJA/2022/v15i4353

Schukat, S., and Heise, H. (2021). Towards an understanding of the behavioral intentions and actual use of smart products among German farmers. *Sustainability* 13:6666. doi: 10.3390/su13126666

Sedgwick, P. (2014). Cross sectional studies: advantages and disadvantages. *BMJ* 348:g2979. doi: 10.1136/bmj.g2979

Shikuku, K. M., Valdivia, R. O., Paul, B. K., Mwongera, C., Winowiecki, L., Läderach, P., et al. (2017). Prioritising climate-smart livestock technologies in rural Tanzania: a minimum data approach. *Agric. Syst.* 151, 204–216. doi: 10.1016/j.agsy.2016.06.004

Teklu, A., Simane, B., and Bezabih, M. (2024). Climate smart agriculture impact on food and nutrition security in Ethiopia. *Front. Sustain. Food Syst.* 7:1079426. doi: 10.3389/fsufs.2023.1079426

Vernooij, V., Schoneveld, G., Vellema, S., Crane, T., and Kihoro, E. (2024). From fix to fitting: connecting low-emission development with multilevel smallholder dairy practices in Kenya. *NJAS Impact Agric. Life Sci.* 96:2334965. doi: 10.1080/27685241.2024.2334965

Wang, S., Höhler, J., Ang, F., and Lansink, A. O. (2023). Dutch dairy farmers' adoption of climate mitigation measures – the role of socio-psychological and socio-demographical factors. *J. Clean. Prod.* 427:139187. doi: 10.1016/j.jclepro.2023.139187

Wilkes, A., Wassie, S., Fraval, S., and van Dijk, S. (2020). Variation in the carbon footprint of milk production on smallholder dairy farms in central Kenya. *J. Clean. Prod.* 265:121780. doi: 10.1016/j.jclepro.2020.121780

Yamane, T. (1973). *Statistics: An Introductory Analysis, 2nd Ed.* New York, NY: Harper and Row.

Yang, W., and Sharp, B. (2017). Spatial dependence and determinants of dairy farmers' adoption of best management practices for water protection in New Zealand. *Environ. Manag.* 59, 594–603. doi: 10.1007/s00267-017-0823-6

Zegeye, M. B., Fikrie, A. H., and Asefa, A. B. (2022). Impact of agricultural technology adoption on wheat productivity: evidence from North Shewa Zone, Amhara Region, Ethiopia. *Cogent Econ. Finance* 10:2101223. doi: 10.1080/23322039.2022.2101223

Zemarku, Z., Senapathy, M., and Bojago, E. (2022). Determinants of adoption of improved dairy technologies: the case of Offa Woreda, Wolaita Zone, Southern Ethiopia. *Adv. Agric.* 2022:3947794. doi: 10.1155/2022/3947794

Appendix

Pre estimation tests

Table A1 Variance inflation factor.

Variables	VIF	1/VIF
Education	1.854	0.539
Age	1.823	0.549
Experience	1.75	0.572
Entrepreneurial orientation	1.516	0.659
Coopmember	1.335	0.749
Land size	1.254	0.798
Herd size	1.252	0.799
Risk perception	1.237	0.808
Gender	1.229	0.814
Awareness	1.199	0.834
Off Income	1.154	0.867
Extenesion access	1.147	0.872
Behavioral intention	1.139	0.878
Credit amount	1.093	0.915
Group membership	1.073	0.932
Training	1.065	0.939
Household size	1.061	0.943
Distance to input market	1.049	0.954
Mean VIF	1.29	

Table A2 Simple falsification test of the excluded instrument (group duration).

Outcome variable	CSD	F-statistic	*P*-value
Milk production	One or none	0.02	0.9022
	Two	0.97	0.3303
	$B_1F_1H_1$	0.04	0.8398
	$B_1F_1H_1M_1$	0.8398	0.2587
	$B_1F_1H_1M_1Z_1$	0.2587	0.9029
Gross margin	One or none	0.12	0.7346
	Two	0.7346	0.1951
	$B_1F_1H_1$	0.16	0.6891
	$B_1F_1H_1M_1$	0.60	0.4398
	$B_1F_1H_1M_1Z_1$	0.4398	0.9268

Insignificant P-values indicate that the instrument does not affect the outcome variables; thus, a good instrument.

Robustness check results

Table A3 Inverse probability weighting regression adjustment estimates for productivity.

CSDS	Milk yield of actual adoption (a)	Milk yield of counterfactual adoption (b)	ATET a−b	SE
One or none CSDS	1,168.25	2,732.124	−1,563.874***	288.6449
Two CSDS	1,882.214	2,348.952	−466.7381*	251.3508
$B_1F_1H_1$	2,798.900	2,297.654	501.2464*	266.7496
$B_1F_1H_1M_1$	3,102.965	2,804.388	287.0435	175.9219
$B_1F_1H_1M_1Z_1$	3,318.908	3,025.588	293.3196	224.594

***, * denotes statistical significance at a 1%, and 10% levels, respectively.

Table A4 Inverse probability weighting regression adjustment estimates for gross margin.

CSDS	Gross margin of actual adoption (a)	Gross margin of counterfactual adoption (b)	ATET a−b	SE
One or none CSDS	29,067.69	98,648.32	−69,580.63***	15,474.67
Two CSDS	58,492.07	71,073.18	−12,581.11	11,614.29
$B_1F_1H_1$	92,882.75	81,320.22	16,613.01	11,562.53
$B_1F_1H_1M_1$	117,079.42	103,798.3	13,290.12*	7,393.479
$B_1F_1H_1M_1Z_1$	129,389.71	115,893	13,496.71	8,674.357

***, * denotes statistical significance at a 1%, and 10% levels, respectively.