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Does entrepreneurial orientation influence the adoption intensity of climate-smart dairy strategies? Evidence from smallholder farmers in Central Kenya

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Introduction: The dairy value chain in Kenya is important for income generation and food security, yet smallholder farmers face increasing challenges due to climate change. Climate-smart dairy strategies (CSDS), including improved breeds, feed improvement, health, and manure management, offer promising pathways to enhance productivity and environmental sustainability. While studies have focused on socio-economic factors influencing the adoption of these strategies, the role of entrepreneurial orientation remains underexplored. Entrepreneurial orientation is important in decision-making and enabling agripreneurs to capitalize on growth opportunities.

Methods: This study addresses this gap by assessing the influence of five dimensions of entrepreneurial orientation, namely risk-taking, innovativeness, proactiveness, autonomy, and competitive aggressiveness, on the adoption intensity of CSDS among 385 smallholder dairy farmers in Central Kenya. The study used a cross-sectional research design and a generalised ordered logit model.

Results and Discussion: The results reveal that autonomy and risk-taking significantly increase the likelihood of adopting CSDS (P<0.01) and that various control variables shape them. Autonomy enables farmers to make independent strategic choices, while risk-taking allows them to experiment with CSDS despite uncertainty. Policy interventions should strengthen farmers' entrepreneurial capacity by promoting training and extension programs that build confidence, decision-making autonomy, and willingness to adopt CSDS. These findings offer clear and actionable recommendations to boost CSDS uptake and support sustainable agriculture in Kenya and other Sub-Saharan African countries.

KEYWORDS

entrepreneurial orientation, climate-smart strategies, dairy, smallholder farmer, Kenya

1 Introduction

The dairy value chain is a vital source of income for many communities in Sub-Saharan countries, particularly in Kenya (Maina et al., 2020). In this country, dairy production ranks the fifth-largest agricultural sub-sector, following meat, horticulture, vegetables, and oils and fats (KIPPRA, 2020). It contributes to approximately 15% of the GDP (KNBS, 2022). Furthermore, the dairy industry, which grows at an annual rate of about 5%, sustains the livelihoods of approximately 1.8 million individuals (MOALF, 2019). With the highest milk consumption in Sub-Saharan Africa, Kenya has an estimated annual per capita consumption of 139 kg (Otieno et al., 2020). This figure is projected to increase by 35% by 2030 (Muunda et al., 2023).

However, climate change risks threaten the dairy value chain despite its importance to Kenya's economy and livelihoods. Small-scale dairy farmers face climate change-induced shocks, including rising temperatures, erratic rainfall, flash floods, and droughts (Abbas et al., 2022; Odhiambo, 2020). For instance, heat waves have been shown to reduce milk quantity and nutritional composition, lowering the quality of derived dairy products (Gauly and Ammer, 2020). By 2085, heat stress alone could contribute to annual global cattle production losses nearing $40 billion (GCA, 2022). Additionally, climate change negatively affects forage quality and quantity, water availability, disease patterns, cattle reproduction, and biodiversity (Rojas-Downing et al., 2017). Conversely, dairy production is responsible for the highest greenhouse gas emissions per product, mainly due to its low average productivity resulting from poor-quality feeds and breeds (García de Jalón et al., 2017; Rademaker et al., 2016). Therefore, it becomes imperative to reorient the dairy production system to respond to the progressive impacts of climate change effectively.

In this context, implementing CSDS has been recognised as a promising solution to mitigate the impacts of climate change. CSDS aims to boost food security and income production, strengthen resilience, and curtail greenhouse gas emissions (FAO, 2021). These strategies encompass a range of practices such as improved breeding, enhanced feeds and feeding methods, better animal health and welfare, efficient manure management, effective herd size management, grass-legume fodder intercropping, and integrated crop-livestock production systems (Gulwa et al., 2018; Hawkins et al., 2022; Maindi et al., 2020; Mujeyi et al., 2022). For example, the crop-dairy production system is a synergistic climate-smart strategy that allows dairy animals to provide manure for crops. In contrast, in return, crops supply fodder to dairy animals (Mujeyi et al., 2022). Intercropping grass and legume fodder can improve soil quality through nitrogen fixation and increase forage quantity (Ericksen and Crane, 2018; Gulwa et al., 2018). Moreover, strategies such as zero grazing, feed supplementation, enhanced breeding, and improved animal health management can boost milk production and concurrently reduce greenhouse gas emissions (FAO, 2019; Kandulu et al., 2024; Kihoro et al., 2021; Llonch et al., 2017; Richardson et al., 2022; Wilkes et al., 2020). For example, efficient feeding reduces enteric methane emissions, better breeding decreases the number of low-yield animals, and improved health minimises losses and extends productive lifespan, contributing to more sustainable and climate-resilient dairy systems (Ericksen and Crane, 2018; FAO, 2019). Despite the benefits of these strategies in mitigating feed shortages, enhancing soil fertility, and increasing milk production, their adoption remains relatively low and uneven across Sub-Saharan Africa, including Kenya (Korir et al., 2023; Maindi et al., 2020).

Over the past decade, there has been a surge in studies aimed at understanding the factors driving the adoption of CSDS. The majority of the literature has centred on the socio-economic factors (Balcha et al., 2023; Maina et al., 2020; Mokoro et al., 2021), while others have focused on institutional factors influencing adoption in dairy production (Molieleng et al., 2021; Tesfaye et al., 2016; Wodajo and Ponnusamy, 2016). These studies suggest that farm income, off-farm income, access to credit, physical assets, and human capital significantly influence the adoption intensity of CSDS due to resource availability and investment capacity (Akzar et al., 2023; de Vries, 2019; García de Jalón et al., 2017; Mokoro et al., 2021; Musafiri et al., 2022a; Zemarku et al., 2022). Off-farm income, in particular, addresses credit constraints and serves as an alternative to borrowed credit (Chelang'a et al., 2023). Additionally, socio-demographic factors such as age, gender, and education have been reported to influence adoption in diverse ways. For instance, younger and more educated farmers are often more open to adopting innovations due to better access to information and greater risk tolerance (Abegunde et al., 2019), while gender dynamics can affect decision-making power and access to resources, thereby shaping adoption outcomes (Akzar et al., 2023). There is an ongoing debate regarding the influence of large household sizes on adopting climate-smart strategies. While some empirical literature suggests that larger household sizes contribute positively to labour availability (Dhraief et al., 2018; Odhiambo, 2020; Ng'ombe et al., 2024), other studies argue that large households exert financial strain on income allocation, thereby reducing the funds available for the uptake of agricultural technologies (Elahi et al., 2021; Musafiri et al., 2022b). Similarly, access to training and agricultural extension services has been shown to increase the adoption of climate-smart strategies by improving farmers' knowledge, skills, and awareness of the benefits and application of such practices (Asule et al., 2024; Balcha et al., 2023; Kifle et al., 2022; Maina et al., 2020; Musafiri et al., 2022b). Agricultural extension services also serve as a critical link between farmers and innovations, helping to reduce uncertainty and build trust in new technologies (Dhraief et al., 2018). Group membership has also demonstrated a strong positive correlation with the adoption of climate-smart strategies, as it facilitates knowledge exchange, collective learning, and improved access to production resources such as credit and inputs (Mujeyi et al., 2022; Siraj, 2023; Yang and Wang, 2023). Recently, Rathakrishnan et al. (2022) studied the influence of socio-psychological factors on the adoption of sustainable production practices in dairy farms. They found that farmers who believed they had the ability and were equipped with the right attitude were more inclined to adopt sustainable agricultural practices.

While existing studies have shed light on the factors influencing the adoption intensity of climate-smart agricultural technologies, there is a noticeable gap in research concerning the role of entrepreneurial orientation (Kangogo et al., 2020; Andati et al., 2022), particularly in the context of dairy production. Understanding the role of entrepreneurial orientation in adoption is important because it reflects the mindset and behavioural traits that influence how farmers identify, evaluate, and act on new opportunities, particularly under conditions of risk and uncertainty, such as those caused by climate change. Moreover, there is a scarcity of studies that have examined the adoption of multiple CSDS among smallholder dairy farmers in Kenya. This study assesses the impact of smallholder farmers' entrepreneurial orientation on the adoption of CSDS in the country, considering other demographic, socio-economic, and institutional variables (control variables), to highlight policy implications and potential actionable measures.

This paper adds value to the literature by exploring the role of entrepreneurial orientation in the adoption of CSDS in the dairy

Abbreviations: KIPPRA, Kenya Institute for Public Policy Research and Analysis; FAO, Food and Agriculture Organization of the United Nations; GDP, Gross Domestic Product; KNBS, Kenya National Bureau of Statistics; MOALF, Ministry of Agriculture, Livestock and Fisheries.

sector. The study, therefore, assesses the influence of entrepreneurial orientation and other factors on the adoption of CSDS among farmers. It expands on previous studies (Kangogo et al., 2020; Andati et al., 2022; Chepng'etich et al., 2024) by evaluating all five dimensions of entrepreneurial orientation, including autonomy and competitive aggressiveness (Suvanto et al., 2020). It highlights how entrepreneurial traits influence CSDS adoption and offers insights for policymakers on enhancing productivity and reducing emissions in Kenya and beyond.

2 Materials and methods

2.1 Description of the study area

This study was carried out in Nyandarua County (Figure 1). The County is situated between latitude 0°8' North and 0°50' South and between longitude 35°13′East and 36°42' West of central Kenya. It borders Laikipia to the North, Kiambu to the South, Murang'a to the Southeast, and Nakuru to the West. The region experiences an average annual rainfall of approximately 1,700 mm during the long rains and about 700 mm during the short rains. Temperatures are generally moderate, ranging from 12 °C to 25 °C. Dairy and Irish potato production are the main farming activities practised by smallholder farmers. However, climate change has affected this area, decreasing agricultural productivity. As a result, it has become semi-arid, necessitating frequent food and water relief for households and livestock. Recognising this challenge, Nyandarua County, in collaboration with the World Bank, has developed interventions such as climate-smart agriculture to adapt to its unique circumstances. These efforts focus on improving livelihoods while reducing greenhouse gas emissions (County Government of Nyandarua, 2023).

2.2 Sampling technique and data collection

The data for this study come from a cross-sectional research design. A multistage sampling technique was employed in this study. In the first stage, we selected Kipipiri and Kinangop Sub-Counties in Nyandarua County based on milk production and climatic conditions that favour agriculture. In the second stage of our sampling technique, within the selected sub-counties, we purposively chose six wards, namely Engineer, Gathara, Njabini, Kipipiri, Wanjohi, and Githioro, due to their potential for milk production and vulnerability to climate change. Lastly, smallholder dairy farmers were randomly selected from the six wards using a systematic random sampling. Farmers were chosen after every fifth one from the list provided.

Given that the target population of the study area, comprising 9,049 smallholder dairy farmers, was known, the sample size was calculated using Yamane's (1967) formula with a 5% margin of error. Based on this formula, a representative sample size of 384 farmers was determined. Farmers were selected proportionately across wards to ensure fair representation according to the population size.

This study used secondary and primary data collected through a semi-structured questionnaire. Trained enumerators conducted face-to-face interviews with respondents to ensure accurate and consistent data collection. The survey instrument was developed based on a literature review on climate-smart agriculture and smallholder dairy systems. The final instrument covered socio-demographic characteristics, farm characteristics, adoption of climate-smart strategies, and entrepreneurial orientation. A pretest was conducted in October in Njoro Sub-County to test the reliability and validity of the instruments, followed by the main data collection, which took place between October and November 2023, utilising the ODK Collect software. The pretest aimed to determine the effectiveness, sufficiency, and suitability of the questions in obtaining the required data and played a crucial role

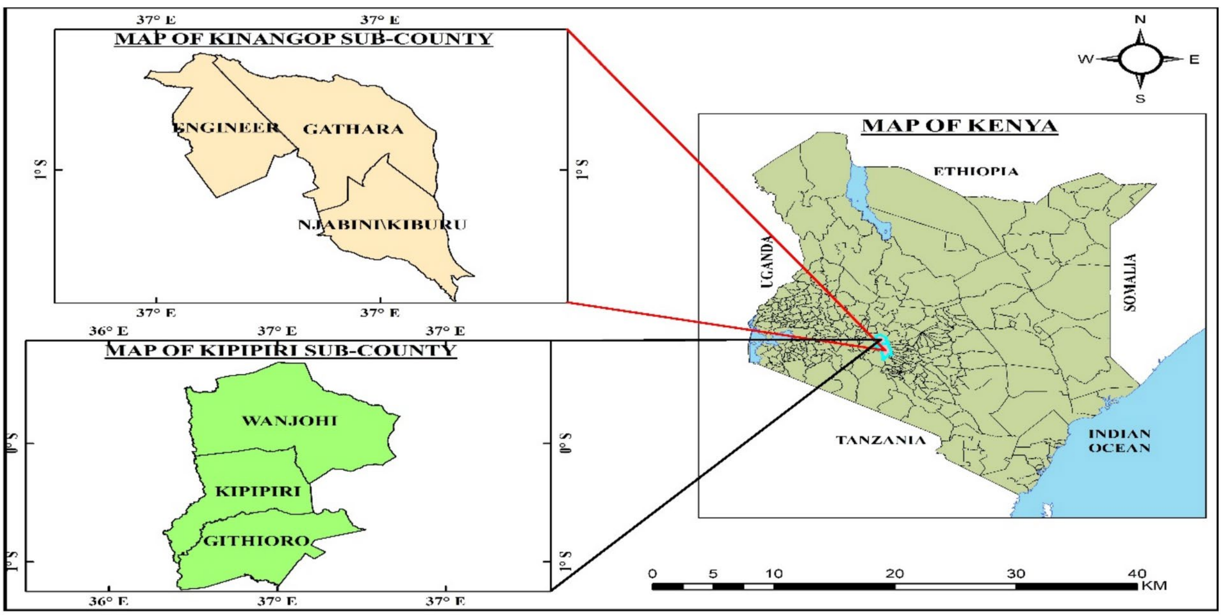

FIGURE 1
Map of the study area.

in refining the data collection tool, which involved reorganising questions for better coherence and clarity, establishing an optimal number of interviews per day, and strategically placing sensitive questions towards the end of the questionnaire. The response rate from the participants was 89%. For multi-item constructs such as entrepreneurial orientation, internal consistency was tested using Cronbach's alpha (α = 0.78), indicating acceptable reliability.

We deserved specific attention to the identification of the CSDS. In September 2023, 1 focus group discussion and one key informant interview were conducted to validate and refine the effectiveness of the selected CSDS. The focus group discussion involved eight dairy farmers, including a diverse group of participants: two youths, two women, and four men. Additionally, key informant interviews were held with eight experts, encompassing a range of stakeholders: two Sub-County dairy board members, two dairy cooperative leaders, two extension officers, and two representatives from the Kenya Climate Smart Agriculture Project.

The focus group discussion and key informant interviews were conducted by proficient enumerators fluent in the Kikuyu dialect. These discussions and interviews were instrumental in identifying new CSDS for inclusion and determining which strategies needed refinement or removal. The data collected was cleaned using Excel, and further analysis was conducted using Stata version 18.

2.3 Outcome variable

After reviewing the CSDS for the dairy subsector discussed in the literature and several documents of the Kenya Climate Smart Agriculture Project, conducting focus group discussions, key informant interviews, and consulting with researchers, we identified sustainable dairy sector practices for adoption at both farm and off-farm levels. We classified these strategies into eleven broad categories presented in Table 1.

Once strategies were identified, we collected objective responses by asking smallholder farmers to specify whether they adopted each CSDS. Subsequently, an aggregate score of CSDS (AS) was calculated by tallying all "yes" responses per household. This served as a proxy for a household's compliance with CSDS. Following Kumar et al. (2017), the aggregate score for compliance with CSDS for the k^{th} smallholder farmer is given as shown in Equation 1:

$$AS_k = \sum_{j=1}^{N} P_{jk} \tag{1}$$

where P_{jk} represents the j^{th} CSD strategy adopted by the k^{th} smallholder farmer, N is the number of available CSDS available for adoption. Based on the AS, we computed a climate-smart adoption index ($CSAI$) as shown in Equation 2. Empirically, the gologit can be specified as shown in Equation 3.

$$CSAI_k = \left(\frac{AS_k - LS}{MS - LS}\right) * 100 \tag{2}$$

where AS is the k^{th} smallholder farmer's actual score. LS is the AS minimum score, and MS is the AS maximum score among farmers that were surveyed. This index served as the adoption intensity per household. Farmers were then categorised based on their $CSAI$ as low, medium, or high adopters. Dairy farmers with a $CSAI$ of 0–50 were classified as low adopters, 50–70 as medium adopters, and 71–100 as high adopters (Kumar et al., 2017).

2.4 Entrepreneurial orientation Likert questions

The entrepreneurial orientation score was calculated based on responses to a series of survey questions administered to smallholder farmers. These questions were designed to evaluate how various dimensions of entrepreneurial orientation, such as risk-taking, proactiveness, competitive aggressiveness, innovativeness, and autonomy, affect their adoption of CSDS. Each dimension was represented by three questions, with responses measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The score for each entrepreneurial construct was derived by

TABLE 1 Climate-smart dairy strategies with their attribute levels.

Category	Strategy
Animal breeding and improvement	Sexed semen, Artificial insemination, and crossbreeding
Animal health management	Vaccination, deworming, tick control, and disease curing
Improved feeds and feeding	Planting drought-tolerant fodder varieties, intercropping legume and non-legume fodder crops, use of feed supplements, use of weaning diets, feed ration formulation, stall feeding, and fodder production under irrigation
Feed preservation	Purchase of fodder and storage, use of crop residues, growing and storage of fodder
Manure management	Collection of manure and composting, use of a biogas digester
Animal welfare	Water in the dairy parlour, shade structures, milking early morning or late evening to reduce heat stress
Herd management	Culling, calving interval adjustment
Off-farm adaptation strategies	Participation in non-farm work, use of livestock insurance, and use of private extension services
Soil and water management for fodder production and animal drinking	Soil testing, use of manure, crop rotation, roof water catchment, and run-off harvesting
Value addition	Yoghurt production, butter production, fermented milk
Diversification	Crop-livestock production, fodder diversification, livestock diversification

averaging the scores of the three corresponding Likert items. As indicated in the literature, each dimension represents a distinct aspect of how individuals approach decision-making and innovation in farming (Kirungi et al., 2023; Suvanto et al., 2020).

Risk-taking assesses a farmer's willingness to engage in uncertain or high-risk activities in the hope of potential rewards (Chepng'etich et al., 2024). In the context of climate-smart agriculture, this reflects the degree to which farmers are willing to invest in strategies that may mitigate climate change risks. The following questions were used to capture this orientation:

- "I am always ready to adopt new farming strategies"-This question gauges the farmer's openness to trying new techniques, indicating their readiness to take risks.
- "I prefer to try new farming strategies on my farm rather than stick to old ones"-This assesses a preference for innovation over traditional methods, reflecting risk-taking in uncertain situations.
- "With the current climate change shocks, I prefer to make further investments on my farm."-This question measures the willingness to take financial risks or invest despite the challenges posed by climate change.

Proactiveness refers to the tendency to anticipate future challenges or opportunities and take the initiative in addressing them (Kangogo et al., 2020). In farming, this often reflects the ability to foresee the impacts of climate change and adopt strategies proactively. This orientation was evaluated using the following questions:

- "I adopt CSDS because of the future uncertainty of climate change."-This question highlights a proactive approach where farmers prepare for future risks by adopting climate-smart strategies now.
- "Adopting CSDS will improve my dairy production in the future."-This reflects the belief that taking proactive steps today will ensure future benefits, showcasing a forward-thinking mindset.
- "I respond more quickly to changes in my environment compared to others"-This captures the individual's proactiveness in adapting to changing farming conditions, implying quick action.

Competitive Aggressiveness measures how farmers strive to outperform others and take the lead in adopting new practices or technologies, emphasising leadership in a competitive environment (Lumpkin and Dess, 1996). The following questions were used to assess this orientation:

- "I am always among the first people to adopt a practise in my village."-This question gauges the farmer's competitive drive to be ahead of others in adopting new farming practices.
- "I like having the latest information on production strategies"-This reflects a desire to stay informed and outpace competitors by accessing and applying the most current information.
- "I am constantly looking for new ways to improve my farm"-This assesses the farmer's drive for continuous improvement, highlighting their competitiveness in staying ahead.

Innovativeness reflects a farmer's creativity and willingness to experiment with new methods, products, or processes (Kirungi et al., 2023). In this context, it measures the farmer's engagement in climate-smart innovations, as indicated by the following questions:

- "I always try new strategies to increase income"-This question evaluates the farmer's inclination to innovate, linking new strategies with financial benefits.
- "I like to use the latest strategies"-This indicates a preference for up-to-date, innovative methods, reflecting the continuous pursuit of innovation.
- "I always improve my production using available resources"-This measures the farmer's ability to use innovation to optimise existing resources rather than relying on traditional methods.

Autonomy assesses the extent of a farmer's independence in decision-making, particularly regarding the adoption of new farming practices like climate-smart strategies (Shahbaz et al., 2022). This orientation was measured using the following questions:

- "I have the capacity to adopt CSDS on my own"-This question reflects the farmer's self-reliance in decision-making and ability to adopt climate-smart strategies independently.
- "I do not seek permission from my family members to make decisions on the adoption of CSDS"-This assesses the level of autonomy the farmer has in making strategic decisions without family approval.
- "I do not seek guidance from friends to make decisions about adopting CSDS"-This captures the farmer's independence from social influence, indicating strong personal autonomy in decision-making.

2.5 Other explanatory variables

In our empirical model, we include a set of explanatory variables that capture a comprehensive range of factors affecting smallholder farmers' adoption of CSDS. Demographics shape the basic capacity and willingness to adopt, asset factors representing the farm's resources, and financial resources influencing the ability to implement new practices. Geographic variables affect access to markets and resources, while psychological and behavioural factors are key to understanding farmers' motivations. Finally, institutional variables provide a framework for support and access to resources, making them crucial in enabling adoption.

2.6 Empirical strategy

We used a Gologit model to determine the influence of smallholder farmers' entrepreneurial orientations and other control factors (demographic, socio-economic, and institutional factors) on the low, medium, or high adopters of CSDS, a categorical and ordered variable. This model overcomes limitations inherent in traditional ordered logistic and probit regression models. One major limitation of conventional ordered logistic models is the assumption that relationships between outcome categories are identical, known as the proportional odds assumption (Williams, 2006). This can lead to inaccuracies when the assumption is violated. To address this issue, we used a gologit model, which relaxes the assumption by allowing coefficients to vary across categories, making it more suitable for our analysis.

Empirically, the gologit can be specified as follows:

$$P\left(Y_i > j\right) = g\left(Z\beta_j\right) = \frac{\exp\left(\alpha_j + Z_i\beta_j\right)}{1 + \left\{\exp\left(\alpha_j + Z_i\beta_j\right)\right\}}, j = 1, 2\ldots, M-1 \quad (3)$$

where M is the number of categories of the ordinal dependent variable, that is, 3, Y_i is the categorical variable for the adoption level of CSDS. α_j is the intercept, β_j is the coefficient to be estimated and Z_i is a vector of independent variables.

This model calculates the probabilities for each adoption category as follows:

$$\left(Y_i = 1\right) = 1 - g\left(Z_i\beta_1\right) \quad (4)$$

$$\left(Y_i = 2\right) = 1 - g\left(Z_i\beta_1\right) - g\left(Z_i\beta_2\right) \quad (5)$$

$$\left(Y_i = 3\right) = g\left(Z_i\beta_2\right) \quad (6)$$

$$Y_i = \beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \ldots \beta_n Z_n + \mu_i \quad (7)$$

Equation 4 gives the probability of the ordinal outcome. $Y_i$is in the first category (category 1 = lower adopter). It states that the probability of Y_i being equal to 1 is 1 minus the cumulative probability up to a certain threshold, which is a function of the linear predictor $Z_i\beta_1$. Z_i represents the set of independent variables for observation i; β_1 is a vector of coefficients corresponding to the first threshold, and $g(\cdot)$ is the logistic cumulative distribution function. Similarly, Equations 5, 6 give the probability that the ordinal outcome Y_i is in the second category (category 2 = medium adopter) and third category (category 3 = high adopter), respectively. Equation 7 represents the observed ordinal outcomes Y_i. β_0 is the intercept term, $Z_1, Z_1 \ldots Z_n$ are the independent variables, $B_1, B_1 \ldots B_n$ are the corresponding coefficients, and μ_i is the error term, typically assumed to follow a standard logistic distribution.

The gologit is equivalent to a series of binary logistic regressions where categories of the dependent variables are combined (Williams, 2006). The model can be thought of as conducting a series of binary logistic regressions, each one contrasting a different grouping of the ordinal categories. For an ordinal outcome variable with M categories, there are $M-1$ binary logistic regressions. We used the gologit2 command in Stata, which estimates this model by fitting a series of binary logistic regressions that compare combined outcome categories. Specifically, for M = 3, the first regression contrasts category 1 (low adopters) vs. categories 2 and 3 combined (medium and high adopters). The second regression contrasts categories 1 and 2 combined vs. category 3 (high adopters).

This approach allows the coefficients to vary across these contrasts, relaxing the proportional odds assumption required in the standard ordered logit model. We tested the proportional odds assumption using the Brant test, which indicated significant violations for some predictors, justifying the use of the generalised ordered logit model. Table 2 presents the variables used in the study and explains their relevance in influencing the adoption of climate-smart strategies among smallholder farmers.

2.7 Data analysis

Data were analysed using Stata software (version 18). Descriptive statistics such as frequencies, means, and standard deviations were used to summarize the farmer and farmer characteristics. The Chi-square test was employed to examine associations between categorical variables. Additionally, the F-test was used to compare means across the adoption groups.

3 Results and discussion

3.1 Descriptive analysis

3.1.1 Adoption of CSDS among farmers

Tables 3–5 provide the results for the adoption of CSDS.

The average adoption level among farmers stood at 56%. The 385 smallholder dairy farmers in our sample consisted of 27% low adopters, 45% medium adopters, and 28% high adopters. Overall, adoption of animal welfare, which includes the presence of a dairy shade, full water access, and milking early and late evening during the hot weather season, recorded the highest score (76%). Similarly, farmers were keen on adopting improved breeds through artificial insemination and sexed semen and had an adoption rate of 72%. Soil and water management strategies, improved feeds, and feeding and animal health management were moderately adopted at about 59, 59 and 44%, respectively. However, value addition, manure management (use of biogas and manure collection, covering, and composting), and culling were poorly adopted, each reporting an adoption level of about 9, 11, and 13%, respectively. Additionally, feed conservation measures, including silage making, hay making, and treatment of crop residue, and off-farm adaptation strategies, such as livestock insurance and participation in non-agricultural activities, reported a low adoption rate of 33 and 30%, respectively.

Regarding individual CSDS attribute uptake levels, Table 6 shows that deworming (96%) and use of minerals (91%) were the most adopted CSDS among farmers. Dairy producers consider deworming a key practise in maintaining good animal health and enhancing production. This finding conforms to the results of García de Jalón et al. (2017), which revealed that deworming had the highest adoption rate among dairy farmers.

The adoption rate for sexed semen was 9%. The low adoption level of this strategy could be attributed to the high cost of establishing or servicing. The utilization of sexed semen technology holds the potential to yield a herd where approximately 90% of newborn calves are females. This outcome reduces the production of lower-value male offspring within the breeding program (Henchion et al., 2022). Additionally, livestock insurance, fodder production under irrigation, and the use of biogas reported a low adoption rate (below 5%). Farmers considered fodder

TABLE 2 Explanatory variables used in the study and the related literature.

Category	Variables	Importance and citation(s)
Demographic variables	Age	Age influences the willingness and ability to adopt new strategies. Younger farmers may be more open to innovation, while older farmers may have more experience (Abegunde et al., 2019; Akzar et al., 2023).
	Education	Education affects the ability to understand and implement climate-smart technologies. Higher education generally leads to better access to information and adoption (Abegunde et al., 2019; Farid et al., 2015).
	Household size	Larger households provide more labour but may lead to risk aversion. Household size can influence willingness to adopt labour-intensive climate-smart strategies (Maindi et al., 2020; Balcha et al., 2023).
	Gender	Gender shapes access to resources and decision-making authority. Male farmers may have more access to resources, while female farmers may face barriers (Balcha et al., 2023).
Assets and experience	Land size	Farmers with larger landholdings may have more to gain from adopting climate-smart strategies, particularly in terms of productivity and sustainability (Arakelyan, 2017; Maindi et al., 2020).
	Herd size	Larger herd sizes incentivise the adoption of climate-smart strategies to improve resilience and productivity in dairy farming (Balcha et al., 2023; Maindi et al., 2020).
	Farming experience	Experience enhances awareness of climate risks and the benefits of adopting climate-smart strategies. More experienced farmers may be more inclined to adopt (Kassa and Abdi, 2022; Khatri-Chhetri et al., 2017).
Financial variables	Credit access (in KES)	Access to credit enables farmers to invest in climate-smart technologies and strategies, which often require upfront financial outlays (García de Jalón et al., 2017).
	Off-farm income	Off-farm income provides financial stability, encouraging the adoption of new practices by reducing the perceived risk of failure (Dhraief et al., 2018).
Geographical variables	Distance to the market	Proximity to markets influences access to inputs, information, and resources. Closer proximity generally increases the likelihood of adoption (Kassa and Abdi, 2022; Mujeyi et al., 2022).
Psychological/ Behavioural variables	Behavioural intention	Behavioural intention reflects the motivation to adopt climate-smart strategies. Farmers with positive intentions are more likely to follow through with adoption (Kirungi et al., 2023).
	Climate change risk perception	Perception about the negative effects of climate change on dairy production, such as increased incidence of ticks and diseases, is likely to increase adoption (Abegunde et al., 2019)
Institutional variables	Awareness	Information about the importance of CSDS is likely to increase adoption (Mujeyi et al., 2022; Rohila et al., 2018)
	Number of training	Training increases awareness and understanding of climate-smart practices. The more training a farmer has, the better equipped they are to adopt these strategies (Abegunde et al., 2019; Dhraief et al., 2018).
	Extension access	Access to extension services provides knowledge, technical support, and advice, which are critical for the informed adoption of climate-smart practices (Dlamini and Botha, 2023; Maina et al., 2020).
	Group membership	Group membership enhances access to social support, knowledge sharing, and collective resources, encouraging the adoption of climate-smart strategies (Mujeyi et al., 2022; Yang and Wang, 2023).

TABLE 3 Category of users of climate-smart dairy strategies.

Adoption levels	%
Overall (*N* = 385)	55.91
Low (105)	27.27
Medium (174)	45.19
High (106)	27.53

rotation and intercropping important in maintaining soil quality for increased forage and had an adoption rate of 76.36 and 77.14%, respectively.

3.1.2 Descriptive statistics of farmers and their farms

Tables 6, 7 present descriptive statistics of entrepreneurial orientation constructs and demographic, socio-economic, institutional, and Psychological factors disaggregated by adoption level.

TABLE 4 Share of farmers by category of CSDS adopted.

Variables	Overall (*N* = 385)
	%
Animal health management	43.8
Improved breeding	72.6
Improved feeds and feeding	59.4
Feed preservation	33.3
Manure management	10.6
Herd management	12.4
Animal welfare	77.1
Value addition	8.7
Off-farm adaptation	30.0
Soil and water management	59.9
Diversification	76.6

TABLE 5 Adoption of climate-smart dairy strategies among farmers (N = 385).

Category	Parameters of CSDs	Mean adoption (%)
Animal health	Deworming after every 3 months	95.5
	Weekly tick control	74.8
	Vaccination against trypanosomiasis	20.0
	Vaccination against East Coast Fever	34.9
	Vaccination against Rift Valley Fever	17.4
	Vaccination against foot and mouth disease	43.1
Improved breeding	Improved breed through AI	78.9
	Improved breed through sexed semen	9.3
	Calving intervals adjustment	65.9
Improved feeds and feeding	Intercropping a grass and a legume	77.1
	Zero grazing	39.7
	Feed formulation	40.5
	Production of improved fodder varieties	41.0
	Full water access	74.0
	Low forage-to-concentrate ratio	55.8
	Use of feed additives	50.3
	Use of minerals	91.9
	Use of weaning diets	49.8
Feed preservation	Use of crop residues	91.4
	Treatment of crop residue	12.9
	Hay making	22.6
	Silage making	45.1
	Storage of feeds for the dry season	52.7
Manure management	Use of biogas	2.33
	Collection, covering, and composting for at least 3 months before use	18.8
Soil and water conservation	Fodder rotation	76.3
	Produce fodder under irrigation	4.68
	Water harvesting	72.2
Herd management	Sale of weak animals/replacement of unproductive animals	11.6
	Sale of animals due to feed unavailability	13.5
Animal welfare	Milk early or late evening	76.4
	Evidence of shade for dairy animals	77.1
Off-farm adaptation	Participation in non-agricultural activities	55.8
	Livestock insurance	1.8
	Use of private extension services	32.4
Value addition	Produce cheese	1.8
	Fermented milk	24.4
Diversification	Fodder diversification	84.4
	Livestock diversification	58.7
	Mixed crop livestock production	87.5

The standard deviation indicates variations in the overall sample and the adoption categories for the continuous variables. Additionally, the F-test of the three adoption categories rejected the null hypothesis, meaning that these categories had significant differences for most of the continuous variables. For all the categorical variables, the Chi-Square test with a significance level below 0.05 indicated a significant difference across categories.

TABLE 6 Descriptive statistics of categorical variables across three levels of adoption, as well as the overall group.

Variables	Description	Overall	Low	Medium	High	χ^2
		%	%	%	%	
Demographic variables						
Gender	Male	56.6	22.9	62.1	81.1	76.8***
	Female	43.4	77.1	37.9	18.8	
Financial variables						
Off-farm income	Yes	43.6	38.1	36.9	60.3	16.7***
	No	56.3	61.9	63.2	39.6	
Institutional variables						
Extension access	Yes	43.1	22.9	37.4	72.6	57.6***
	No	56.9	77.1	62.6	27.4	
Group membership	Yes	61.8	48.6	59.8	78.3	20.3***
	No	38.2	51.4	40.2	21.7	

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

TABLE 7 Descriptive statistics of continuous variables across the three levels of adoption, as well as the overall group.

Variables	Overall (*N* = 385)	Low (L) (*N* = 105)	Medium (M) (*N* = 174)	High (H) (*N* = 106)	F-value
	Mean	Mean	Mean	Mean	
Entrepreneurial orientation					
Risk-taking	3.7 (0.8)	2.8 (0.7)	4.0 (0.6)	4.4 (0.5)	201.5***
Innovativeness	3.8 (0.9)	4.0 (0.9)	3.6 (0.9)	3.8 (0.8)	3.0*
Proactiveness	3.7 (0.9)	3.1 (0.8)	3.6 (0.8)	4.3 (0.6)	74.1***
Aggressiveness	3.5 (1.0)	3.7 (1.0)	3.5 (1.1)	3.6 (0.9)	1.7
Autonomy	3.5 (1.1)	2.3 (1.0)	3.6 (0.7)	4.5 (0.5)	220.8***
Demographic variables					
Age	51.0 (12.5)	53.2 (13.7)	50.3 (12.1)	50.2 (11.2)	2.2
Education	9.3 (3.9)	5.3 (2.4)	9.0 (2.8)	13.4 (1.9)	294.6***
Household size	4.6 (2.1)	4.5 (1.8)	4.5 (1.9)	5.7 (2.5)	2.9*
Assets and experience					
Land size	1.3 (1.5)	1.1 (1.3)	1.31 (1.5)	1.7 (1.3)	4.9***
Herd size	2.0 (0.9)	1.7 (0.9)	2.0 (0.91)	2.2 (1.0)	9.8***
Farming experience	15.1 (10.4)	14.4 (11.4)	14.6 (9.4)	16.6 (10.8)	1.5
Financial variables					
Credit access	15,496 (44370)	6,600 (20218)	12,293 (31534)	29,566 (69717)	8.1***
Geographical variables					
Distance to market	2.4 (1.8)	2.6 (1.9)	2.5 (1.9)	2.3 (1.4)	0.9
Psychological/behavioural variables					
Behavioural intention	3.9 (0.8)	4.1 (0.7)	3.9 (0.9)	3.7 (0.7)	4.4***
Climate change risk perception	3.6 (0.6)	3.2 (0.7)	3.6 (0.6)	4.0 (0.6)	45.3***
Institutional variables					
Number of trainings	1.6 (1.9)	1.3 (6.1)	1.2 (1.8)	2.4 (2.4)	14.9***
Awareness	2.8 (0.9)	2.7 (0.8)	3.0 (0.8)	2.8 (0.9)	3.4**

***, **, * denotes statistical significance at 1, 5 and 10%, respectively.
N means the number of observations.
Figures in parentheses are standard deviations associated with the means of the variables indicated.

The results show statistically significant differences across adoption categories for most entrepreneurial orientation constructs. High adopters scored highest in risk-taking (4), proactiveness (4), and autonomy (5), with significant *F*-values, indicating that entrepreneurial traits are positively associated with higher adoption levels (Table 7). Similarly, adoption increased significantly with education, from 5 years for low adopters to 13 years for high adopters. Similarly, access to resources such as land, herd size, and credit improves adoption intensity, suggesting that resource endowments and financial access facilitate greater uptake of CSDS. Notably, high adopters accessed more training sessions (2 times on average) and had higher climate change risk perception (4), further underlining the role of institutional support and awareness in influencing adoption.

A significantly higher proportion of high adopters were male (81%) compared to only 22% among low adopters, indicating a gender disparity in adoption (Table 6). Off-farm income was also more prevalent among high adopters (60%), suggesting that additional income sources may support CSDS adoption. Institutional variables such as access to extension services and group membership were positively associated with adoption, with 73% of high adopters having extension access and 78% belonging to a farmer group. These findings emphasise that demographic characteristics, financial capacity, and institutional engagement are key drivers of CSDS adoption among farmers.

TABLE 8 Test of parallel lines assumption using a 0.05 significance level.

Variables	*p* value
Risk-taking	0.009***
Proactiveness	0.219
Aggressiveness	0.113
Innovativeness	0.814
Autonomy	0.001***
Age	0.939
Gender	0.274
Education	0.165
Household size	0.482
Land size	0.233
Off-farm income	0.701
Experience	0.198
Group membership	0.019**
Extension access	0.278
Awareness	0.221
Training	0.832
Risk perception	0.991
Behavioural intention	0.652
Distance	0.368
Credit access	0.986

***, **denote statistical significance at 1 and 5% levels, respectively.
Significant variables do not meet the parallel lines assumption, while the insignificant test statistic indicates that the variable does not violate the parallel lines assumption.

3.2 Results on factors influencing the adoption of CSDS

3.2.1 Diagnostic tests

Several pre-estimation diagnostic tests were conducted before the analysis. Based on these results, the gologit2 model was chosen due to violations of the proportional odds assumption for some variables (Table 8). At the same time, diagnostic tests confirmed no issues with heteroscedasticity, multicollinearity, or non-normal residuals. This model offers a robust framework for analysing the relationships between the independent and categorised dependent variables.

3.2.2 Results of the gologit regression

Table 9 presents the results on the determinants of CSDS adoption, while Table 10 shows the marginal effects of the gologit model. Table 11 gives an autonomy disaggregated analysis. In Table 10, the likelihood ratio test for proportionality of odds is highly significant. This suggests that the relationships between the independent and dependent variables differ across categories. Additionally, the significant Wald chi-square test for overall goodness of fit indicates that the independent variables included in the model provide satisfactory explanatory power. The dependent variable was categorised into three groups: low, medium, and high user categories, with the high user category serving as the reference group.

The results suggest that autonomy and risk-taking are the most significant constructs influencing the intensity of adopting climate-smart strategies, with autonomy showing a particularly strong effect on high-intensity adoption. Other factors such as education, gender, off-farm income, and climate change risk perception are crucial in driving high-intensity adoption. In contrast, factors such as age and household size seem to favour lower-intensity adoption. Our findings suggest that addressing risk perceptions, providing risk-mitigating interventions, and empowering farmers through increased autonomy may be crucial in promoting the adoption of climate-smart practices in Kenya's dairy sector.

The analysis findings show that risk-taking is statistically significant in explaining adoption intensity. Individual farmers' ability to assign resources to activities whose outcome is uncertain increases the likelihood of being in the higher user category by 4 times and reduces the likelihood of being in the lower user category by about 8 times. This evidence aligns with findings from previous studies examining the role of risk-taking in adopting climate-smart agricultural practices (Aryal et al., 2021; Zakaria et al., 2020). For instance, research on adopting drought-tolerant maize varieties in Africa has shown that risk-averse farmers are less likely to adopt these technologies. Similarly, a study on smallholder farmers' adaptation strategies to mitigate the effects of drought on maize production in South Africa found that farmers who were more willing to take on risks were more likely to adopt strategies such as changing farming practices and sustainable land management (Muroyiwa et al., 2022). Kangogo et al. (2020) pointed out that risk-taking increased the probability of adopting climate-smart practices that required high financial resources and skilled labour. Our study's findings are also consistent with other studies highlighting the importance of personal resources and risk-taking in driving the adoption of green technologies and innovative practices in agriculture (Ali et al., 2020). As agriculture becomes increasingly technology-intensive, farmers' ability and willingness to adapt quickly to exogenous changes like climate change will be key to productivity growth and poverty

TABLE 9 Determinants of adoption using the gologit model.

Adoption status	Coeff.	Std.	Coeff.	Std.
Low	Low		Medium	
Entrepreneurial orientation				
Risk-taking	3.644***	0.679	1.374**	0.636
Proactiveness	0.575	0.382	0.575	0.382
Innovativeness	−0.635	0.482	−0.635	0.482
Aggressiveness	0.038	0.393	0.038	0.393
Autonomy	2.217***	0.506	4.847***	0.827
Demographic factors				
Age	−0.042**	0.027	−0.042**	0.027
Gender	1.467**	0.625	1.467**	0.625
Education	1.032***	0.158	1.032***	0.158
Household size	−0.166	0.103	−0.166	0.103
Assets and experience				
Land size	0.189***	0.068	0.189***	0.068
Herd size	−0.294	0.307	−0.294	0.307
Farming experience	0.067**	0.032	0.067**	0.032
Institutional variables				
Extension access	0.312	0.565	0.312	0.565
Group membership	0.458	0.766	3.086***	0.874
Number of trainings	0.308***	0.116	0.308***	0.116
Awareness	−0.903***	0.344	−0.903***	0.344
Geographical variables				
Distance to market	0.171***	0.059	0.171***	0.059
Financial variables				
Credit access	−0.000	0.000	−0.000	0.000
Off-farm income	1.621***	0.557	1.621***	0.557
Psychological/behavioural variables				
Climate change risk perception	−1.786***	0.481	1.786***	0.481
Behavioural intention	−0.938***	0.354	−0.938***	0.354
_cons	−29.042***	4.845	−45.757***	7.123

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

reduction. In this context, a farmer's risk-taking propensity can be an important determinant of their adoption of climate-smart practices (Barzola Iza et al., 2019; Bukchin and Kerret, 2018). This suggests that addressing risk perceptions and providing risk-mitigating interventions may be crucial in promoting the adoption of climate-smart practices.

It should also be noted that the heterogeneity in farmer preferences for risk often correlates with their resource endowments and access to services. Better-off farmers with more assets and information are more willing to invest in high-input agriculture. In contrast, resource-constrained farmers are more sensitive to yield variability and prefer low-risk options (Oyinbo et al., 2019).

Improving the design of extension services to provide information on the riskiness of expected outcomes and flexibility in switching between low-risk and high-risk recommendations can help farmers make more informed decisions and improve the uptake of new technologies (Ali et al., 2020; Li et al., 2023).

Our findings revealed that autonomy is positively and statistically significant among high adopters of CSDS, while it is negatively associated with low adopters. A possible explanation for this scenario is that autonomous farmers have the discretion to allocate resources to adoption independently. This finding aligns with previous research on the relationship between autonomy and the adoption of agricultural technologies (Zakaria et al., 2020). For instance, a study on adopting improved rice varieties in Ghana found that farmers with more autonomy in decision-making were more likely to adopt these technologies. Furthermore, the positive relationship between autonomy and the intensity of adoption of CSDS suggests that farmers with more control over their farming decisions are more likely to invest in and implement climate-smart practices. This finding

TABLE 10 Marginal effects of the generalised ordered logit model.

Variables	dy/dx	std.	dy/dx	std.	dy/dx	std.
	Low		Medium		High	
Entrepreneurial orientation						
Risk-taking	−0.075***	0.009	0.035	0.022	0.040**	0.019
Innovativeness	0.013	0.010	0.006	0.005	−0.019	0.014
Proactiveness	−0.012	0.008	−0.005	0.004	0.017	0.011
Aggressiveness	−0.001	0.008	−0.000	0.003	0.001	0.012
Autonomy	−0.046***	0.010	−0.097***	0.016	0.143***	0.014
Demographic variables						
Age	0.001*	0.001	0.000	0.000	−0.001**	0.001
Gender	−0.030**	0.012	−0.013	0.009	0.043**	0.019
Education	−0.021***	0.004	−0.009**	0.004	0.030***	0.003
Household size	0.003	0.002	0.001	0.001	−0.005*	0.003
Assets and experience						
Land size	−0.004***	0.001	−0.002*	0.001	0.006***	0.002
Herd size	0.006	0.006	0.003	0.003	−0.009	0.009
Farming experience	−0.001**	0.001	−0.001	0.000	0.002**	0.001
Institutional variables						
Extension access	−0.006	0.012	−0.003	0.005	0.009	0.016
Group membership	−0.009	0.016	−0.081***	0.028	0.091***	0.023
Number of trainings	−0.006**	0.003	−0.003**	0.001	0.009***	0.003
Awareness	0.019**	0.007	0.008**	0.004	−0.027***	0.009
Geographical variables						
Distance to market	−0.004***	0.001	−0.001*	0.001	0.005***	0.002
Financial variables						
Credit access	0.000	0.000	0.000	0.000	−0.000	0.000
Off-farm income	−0.034***	0.012	−0.014**	0.007	0.048***	0.015
Psychological/behavioural variables						
Climate change risk perception	−0.037***	0.010	−0.016**	0.007	0.053***	0.012
Behavioural intention	0.019***	0.007	0.008*	0.005	−0.028***	0 0.010

Number of observations = 385.
LR χ^2 (24) = 693.75.
Prob > χ^2 = 0.0000.
Log likelihood = −64.459219; Pseudo R^2 = 0.8433.
***, **, * denote statistical significance at 1, 5 and 10% level.

emphasises the importance of empowering farmers, particularly in the context of climate change adaptation, to make informed decisions that align with their needs and priorities. In this regard, the literature highlights that farmers who perceive themselves as having more control over their farming decisions are more likely to adopt CSDS (Li et al., 2023). Providing farmers with more autonomy and decision-making power can, therefore, be an effective strategy for promoting the adoption of CSDS (Ali et al., 2020).

The analysis further shows that autonomy significantly increases the likelihood of being in the high CSDS adoption category when interacting with gender, education, land size, off-farm income, and access to training. This suggests that autonomy alone is not uniformly influential; rather, its effect is conditional on enabling demographic and socio-economic contexts. For instance, more educated farmers will likely leverage their autonomy more effectively due to better information processing and decision-making capabilities (Musafiri et al., 2022a). Similarly, male farmers may face fewer social constraints in implementing autonomous decisions since they have rights and control over production resources (Ngetich et al., 2022). Farmers with larger landholdings and access to off-farm income are better positioned to manage the risks and investments associated with adopting new technologies. Likewise, training enhances knowledge and confidence, enabling autonomous individuals to act decisively (Asule et al., 2024). These interaction effects highlight that autonomy becomes more practically meaningful when supported by favourable structural and institutional factors.

TABLE 11 Gologit estimates with some variables interacted with autonomy.

Variables	dy/dx	std.	dy/dx	std.	dy/dx	std.
	Low		Medium		High	
Entrepreneurial orientation variables						
Risktaking	−0.043***	0.007	−0.010	0.008	0.053***	0.012
Proactiveness	−0.016**	0.008	−0.004	0.004	0.020**	0.011
Innovativeness	0.013	0.010	0.003	0.003	−0.016	0.012
Aggressiveness	0.001	0.008	0.000	0.002	−0.001	0.010
Demographic variables						
Age	0.001*	0.001	0.000	0.000	−0.001*	0.001
Gender	−0.009**	0.004	−0.002	0.002	0.011**	0.005
Education	−0.006***	0.001	−0.001	0.001	0.008***	0.001
Household size	0.005**	0.002	0.001	0.001	−0.006**	0.003
Assets and experience						
Land size	−0.001**	0.000	−0.000	0.000	0.001**	0.000
Off-farm income	−0.009***	0.003	−0.002	0.001	0.011***	0.003
Experience	−0.001**	0.001	−0.000	0.000	0.002**	0.001
Extension access	−0.002	0.003	−0.001	0.001	0.003	0.004
Herdsize	0.003	0.006	0.001	0.002	−0.004	0.007
Institutional variables						
Group membership	−0.011	0.016	−0.069**	0.029	0.080***	0.024
Training	−0.002***	0.001	−0.000	0.000	0.002***	0.001
Awareness	0.032***	0.009	0.008	0.005	−0.040***	0.009
Geographical factors						
Distance	−0.003**	0.001	−0.001	0.001	0.004**	0.001
Psychological/behavioural variables						
Risk perception	−0.029***	0.010	−0.007	0.005	0.036***	0.012
Credit access	0.000	0.000	0.000	0.000	−0.000	0.000
Behavioural intention	0.035***	0.001	0.008	0.005	−0.044***	0.010

Number of observations = 385.
LR χ^2 (22) = 699.37.
Prob > χ^2 = 0.0000.
Log likelihood = −61.650035; Pseudo = 0.8501.
***, **, * denote statistical significance at 1, 5 and 10% level.
Gender, education, off-farm income, land size, and training were interacted with autonomy.

In Table 10, proactiveness was not statistically significant. However, once autonomy was interacted with other variables, proactiveness became significant. This suggests that the simpler model may have masked the actual effect of proactiveness due to omitted variable bias or overlapping variance with autonomy. By including relevant interaction terms, the model better captured the complex structure of the data, allowing the independent contribution of proactiveness to emerge.

We also found that innovativeness and aggressiveness do not significantly influence the independent adoption of CSDS. This contradicts existing literature that has generally reported a positive association between leadership characteristics such as idealised influence and innovative behaviour (Kangogo et al., 2020; Sethibe and Steyn, 2017). However, our findings are consistent with those of Zakaria et al. (2020), who found no significant relationship between these traits and the adoption of climate-smart agricultural practices among smallholder rice farmers in Sri Lanka. Similarly, Chepng'etich et al. (2024) reported that innovativeness had no significant effect on the adaptive capacity of livestock farmers. One possible explanation is that, while entrepreneurial traits are often expected to drive early adoption, their influence may be muted in contexts where external barriers such as limited access to CSDS-relevant information, credit, or extension services constrain action. Farmers may possess entrepreneurial attributes in Central Kenya's smallholder dairy sector, but lack the enabling environment to translate them into adoption behaviour. This suggests that the adoption of CSDS is shaped more by institutional and structural factors than by individual entrepreneurial orientation. Consistent with this, Bukchin and Kerret (2018) and Kaua (2020) also found that systemic constraints often outweigh behavioural traits influencing technology adoption. Thus, while entrepreneurial capacity remains relevant, it must be supported by targeted interventions that address underlying structural limitations to enhance CSDS uptake.

Foguesatto et al. (2020) and Zakaria et al. (2020) emphasised the importance of research exploring the complex interactions between personality traits, socio-economic factors, and institutional support in shaping the adoption of climate-smart agricultural practices. Our findings confirm that the influence of entrepreneurial orientation on adopting these practices is a multifaceted process shaped by various demographic, asset-related, experiential, geographical, psychological, and institutional factors.

In Kenya, institutional collaboration is central to the adoption of CSDS. Government agencies such as the Kenya Dairy Board and county agricultural departments provide policy, regulation, and public extension. At the same time, research institutions like KALRO and ILRI generate improved technologies, breeds, and feeding practices. Cooperatives aggregate farmers, making accessing inputs, extension, and credit easier, often in partnership with financial institutions (Maindi et al., 2020). NGOs and development projects complement these efforts by piloting innovations, training farmers, and bridging gaps in extension and service delivery, while private actors supply inputs and advisory services. These interactions help overcome key barriers by expanding access to extension, easing credit constraints, improving input supply chains, and closing knowledge gaps through training and farmer-to-farmer learning (Mujeyi et al., 2022). However, challenges remain, including limited public extension capacity, difficulties in accessing formal credit, and weak institutional capacity in some cooperatives (Asule et al., 2024; Mokoro et al., 2021; Ngetich et al., 2022).

Several notable patterns emerged from our analysis. For instance, older farmers are more likely to adopt climate-smart strategies at lower intensities and are less inclined to embrace them at higher intensities. This may reflect a preference for lower-risk or more gradual adjustments, which is often associated with age (Mango et al., 2018; Martey et al., 2020; Oyinbo et al., 2019). Recent research has also highlighted the importance of targeted interventions to empower young women and men in the dairy sector (Bullock and Crane, 2021). However, Asule et al. (2024) found that older age was associated with adopting climate-resilient practices due to experience accumulated over time. While Kenya's dairy sector is transforming toward more intensive production practices and a greater commercial focus, which presents opportunities and challenges for youth engagement, our study indicates that attention must also be directed toward older farmers. Older people comprised a significant portion of our sample.

On the other hand, male farmers are less likely to adopt climate-smart practices at lower intensities but are more inclined to embrace them at higher intensities. This suggests a tendency toward comprehensive adoption or non-adoption, which may be influenced by differing risk perceptions or decision-making processes between genders (Fahad et al., 2020). More educated farmers are similarly less likely to engage in low- or medium-intensity adoption but exhibit a significantly higher propensity for high-intensity adoption. This pattern likely reflects greater awareness and a deeper understanding of the benefits associated with climate-smart practices among more educated individuals (Fahad et al., 2020). Previous studies have also documented a positive relationship between formal education and adopting agricultural technologies in Africa (Abegunde et al., 2019; Farid et al., 2015).

Larger households may prefer incremental, lower-risk adoption of climate-smart strategies, possibly due to resource constraints or the dynamics of collective decision-making (Kaua, 2020). These households might prioritise strategies that can be implemented gradually rather than more comprehensive but riskier approaches. Conversely, access to off-farm income provides financial security, enabling more extensive adoption of climate-smart strategies by reducing the perceived financial risks associated with higher-intensity adoption.

Perception of climate change risks and behavioural intention are significant drivers of high-intensity adoption, while they negatively influence low-intensity adoption. This observation aligns with the findings of Arakelyan (2017) and Abegunde et al. (2019), suggesting that farmers who perceive greater risks from climate change and exhibit a stronger intention to act are more likely to adopt climate-smart practices comprehensively.

Our results also indicate that increased awareness and proximity to markets significantly enhance the likelihood of high-intensity adoption while reducing the probability of low-intensity adoption. This underscores the critical role of access to information and market opportunities in fostering deeper engagement with climate-smart practices, as supported by previous literature (Alonso et al., 2018).

4 Conclusion

This study provides several targeted policy recommendations to enhance the adoption of CSDS among smallholder farmers in Kenya. First, the results highlight that farmers with high-risk perceptions are more likely to adopt CSDS, suggesting that perceived climate and production-related risks may motivate adoption as a coping or adaptation strategy. To further strengthen this behaviour, policymakers should reinforce climate and market information availability and promote access to CSDS as a credible risk-mitigation option through demonstration farms, success stories, and tailored extension messaging.

Second, the finding that farmer autonomy, when combined with factors like education, gender, land size, off-farm income, and training access, significantly increases the likelihood of high adoption underscores the need for differentiated support policies. Capacity-building programs should equip farmers with technical skills and foster decision-making autonomy through tailored training, peer learning platforms, and digital extension services that provide real-time market and climate information. Extension agents must be trained to recognize socio-economic and gender-based dynamics influencing autonomy and respond with context-sensitive support.

Third, our findings show that access to training and education, particularly when interacted with autonomy, positively influences adoption. Thus, policies should scale up inclusive agricultural education initiatives, focusing on women and youth, and improve the quality and accessibility of training modules on CSDS. These should be embedded within existing cooperative and group structures, which our findings also suggest enhance adoption.

Additionally, access to markets was identified as a key enabler of CSDS adoption. Investments in infrastructure development, such as rural roads, milk cooling facilities, and storage infrastructure, can reduce transaction costs and post-harvest losses, making adoption more economically viable. Further, strengthening farmer linkages to value chains and expanding cooperative marketing models can improve price stability and market access, reinforcing the incentive to adopt sustainable practices.

Lastly, this study affirms that demographic and socio-economic diversity, including differences in gender, landholding size, income sources, and education, shapes farmers' adoption pathways. Therefore, policies should adopt an equity lens, designing targeted interventions that reflect these variations to avoid leaving vulnerable groups behind in the transition toward climate-smart agriculture.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by National Commission for Science, Technology and Innovation. 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.

Author contributions

NC'a: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. MM: Conceptualization, Supervision, Writing – review & editing. DO: Conceptualization, Supervision, Writing – review & editing. MS: Conceptualization, Supervision, Writing – original draft, Writing – review & editing.

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