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The determinants of greenhouse gas reduction levels among smallholder farmers: insights from the adoption of climate-smart dairy strategies in Central Kenya

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In Kenya's dairy sector, climate change mitigation focuses on sustainable milk production. However, dairy producers often overlook emission reduction, creating a gap between national policies and local practices. This paper aims to identify the factors, including smallholder entrepreneurial orientation, socio-economic characteristics, and institutional influences, that drive the adoption and uptake intensity of on-farm greenhouse gas reduction measures in the dairy sector, particularly among smallholder producers in Nyandarua County, Kenya. The study uses a fractional response model to examine factors influencing greenhouse gas reduction at the farm level based on survey data from 385 dairy farmers. Greenhouse gas reduction was measured using a composite index, with proxies drawn from the literature. Key factors influencing greenhouse gas reduction include education, social capital, entrepreneurial orientation, awareness, and risk perception. The study recommends that the national and county governments promote and support the adoption of climate-smart dairy strategies that increase milk production while simultaneously reducing greenhouse gas emissions. This support could include technical assistance, financial support and educational programs to encourage complementary adoption by dairy farmers.

KEYWORDS

smallholder farmers, adoption, climate-smart dairy strategies, greenhouse gas reduction, Kenya

1 Introduction

Dairy production faces a critical challenge: balancing the need to increase output to meet rising milk demand with the imperative to reduce greenhouse gas (GHG) emissions (O'Hara, 2023). Meeting this growing demand has advantages and drawbacks (Graham et al., 2022). On the positive side, increasing production ensures an adequate supply of dairy products, supporting food security and contributing to economic growth for dairy farmers. However, it also risks exacerbating climate change through higher GHG emissions (Vernooij et al., 2024). Globally, agriculture contributes approximately 17% of total greenhouse gas emissions, with the livestock sector responsible for nearly two-thirds of these emissions. The dominant greenhouse gas emissions in the dairy sector are methane, accounting for 96%, nitrous oxide at 3%, and carbon dioxide at 1% (FAO, 2017). A significant portion of these emissions, particularly in African agriculture, arises from enteric fermentation, which accounts for half of the sector's GHG emissions (Ntinyari and Gweyi-Onyango, 2020). This issue has prompted a growing body of literature on low-emission development strategies in developing countries (Kihoro et al., 2021; Vernooij et al., 2024). Factors such as breed composition, poor-quality feeds, and inadequate manure management significantly influence the amount of GHG emissions (Rotz, 2018; Pinto et al., 2020a, 2020b). However, discrepancies remain in the reported emissions by smallholder farmers. While some studies argue that smallholding agricultural production is a major contributor to climate change (Vernooij et al., 2024), others contend that their emissions per capita are negligible (Mwaura et al., 2024).

Despite the dairy sector's contribution to GHG emissions, it is also heavily affected by climate change. Challenges such as rising temperatures, water scarcity, declining feed quality and quantity, and the emergence of new pests and diseases threaten its sustainability (Graham et al., 2022).

Recognising this twofold challenge, numerous Sub-Saharan African nations have incorporated climate change policies into their national frameworks by participating in the United Nations Framework Convention on Climate Change and the Paris Climate Agreement (Mwaura et al., 2024). Many countries mention livestock in their Nationally Determined Contributions and/or Adaptation Plans or outline large-scale low-emissions development initiatives (Graham et al., 2022).

The literature focused on the dairy sector suggests that changes should be made to production practices at the farm level to reduce GHG emissions. These changes include implementing improved feeding strategies, better management of manure and herds, conserving feed, and treating crop residues (Maindi et al., 2020; Kihoro et al., 2021). Studies have used life cycle assessment to measure GHG reduction at the farm level (Zhao et al., 2017; Xu et al., 2023). However, using this approach is complicated, resource-intensive, and time-consuming, with limitations that can affect its feasibility and effectiveness. To this purpose, Mwaura et al. (2024) recommend simpler and easily monitored techniques to tackle the current emission trend among smallholder farmers. Collectively, these studies have provided insights into how various climate-smart dairy strategies (CSDS) reduce GHG emissions. The available literature lacks an empirical model to assess how farm and farmer characteristics influence the uptake intensity of GHG emissions reduction strategies. Addressing this gap is crucial because this information provides critical insights for designing targeted, effective interventions.

The present paper addresses these aspects using the Fractional Response Model (FRM) to assess the factors influencing the adoption of on-farm GHG reduction measures in the dairy sector. Employing a different approach to studying the determinants of GHG emissions reduction contributes to enhancing the depth, breadth, and robustness of the analysis conducted in the literature. This information is essential for tailoring policies, programs, and technologies to specific contexts, thereby increasing the feasibility and scalability of GHG reduction initiatives. Furthermore, such a model could help bridge the gap between high-level theoretical frameworks and on-the-ground implementation, ensuring that proposed solutions are practical and impactful.

Building on the work of Kihoro et al. (2021) and Vernooij et al. (2024), this study introduces a novel approach by utilising proxies as indicators of GHG reduction to compute a comprehensive index. The selected CSDS are grounded in robust evidence from the literature, which demonstrates their effectiveness in reducing GHG emissions (Ericksen and Crane, 2018; Wilkes et al., 2020; Kihoro et al., 2021; Mburu et al., 2024; Vernooij et al., 2024).

What sets this study apart is the integration of smallholder entrepreneurial orientation alongside socio-economic and institutional factors to investigate the drivers of adopting various GHG reduction measures among farmers. This multidimensional approach provides added value by offering a more comprehensive and nuanced understanding of the decision-making processes and constraints at the farm level. Unlike previous studies, which primarily focus on the technical efficacy of CSDS, this research delves into the interplay of individual, economic, and institutional influences, shedding light on the conditions necessary for successful adoption.

This research is particularly important for informing policies and interventions tailored to regions facing similar climate-related challenges, ensuring that agricultural practices are both productive and environmentally sustainable. This study, therefore, assesses the factors that influence the reduction of greenhouse gas emissions at the farm level. The study hypothesised that farmer demographic, socio-economic, institutional, entrepreneurial, and behavioral factors significantly influence the level of greenhouse gas emissions reduction.

2 Methodology

2.1 Description of the study area

This study was conducted in Nyandarua County, located between Mount Kenya and Aberdare areas in Central Kenya. The County between latitude 0°8' North and 0°50' South and between longitude 35°13' East and 36°42' West (Figure 1). The area receives long rains in March and May, with an annual rainfall of 1700 mm. Short rains are recorded from September to December, with an annual rainfall of 700 mm. The temperatures are considered moderate, ranging between 120\u00B0C and 250\u00B0C. Agriculture is the primary economic activity in the region, contributing approximately 3.9% to the national gross domestic product. The major agricultural produce includes dairy, poultry, Irish potatoes, floriculture, cabbages, carrots, peas, pyrethrum, sugar beet, and cereals. However, the county has experienced decreased agricultural productivity due to its increasingly semi-arid conditions, which have led to frequent food and water shortages for both households and livestock. In response, the County, in collaboration with the World Bank, has implemented climate-smart agriculture interventions to improve livelihoods while simultaneously reducing GHG emissions (County Government of Nyandarua, 2023).

The proposed study in this area is crucial as it addresses the dual challenge of adapting to climate change while promoting sustainable agricultural practices. Focusing on Nyandarua County provides valuable insights into how smallholder farmers can adopt climate-smart strategies to mitigate the impacts of climate change and reduce emissions.

2.2 Data and sampling procedure

The study employed a cross-sectional research design, utilizing a multi-stage sampling technique to select Kipipiri and Kinangop

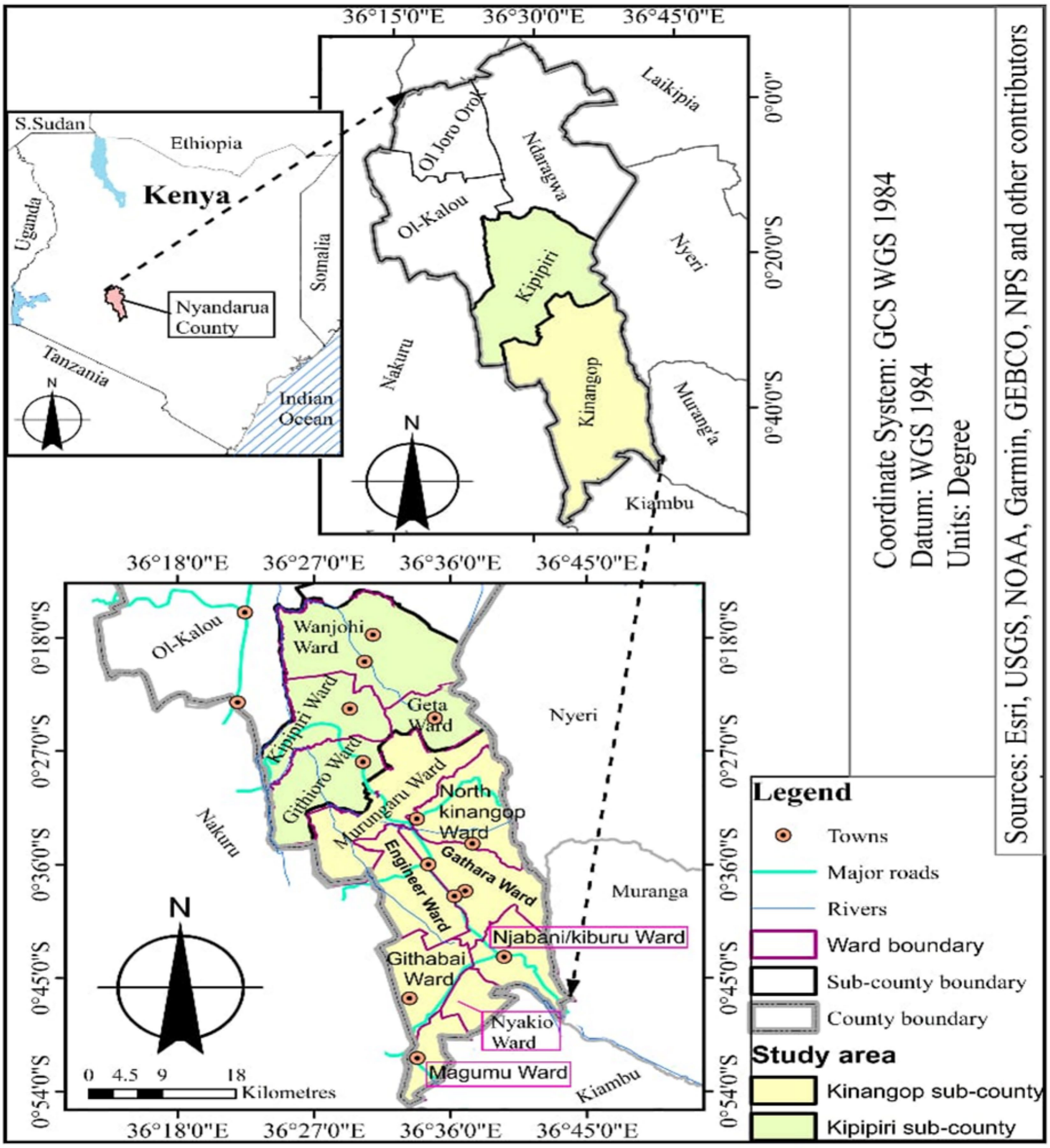

FIGURE 1
Map of the study area.

Sub-Counties of Nyandarua County based on their favourable conditions for milk production and climatic conditions that favour agriculture. In this area, six wards namely Engineer, Gathara, Njabini, Kipipiri, Wanjohi, and Githioro, were selected because their relevance to the dairy sector and their vulnerability to climate impacts make them ideal for investigating the adoption of CSDS. In Kenya, a ward is a smaller administrative unit within a sub-county, typically representing a community or village. Given the known target population size of the study area, it used the Yamane (1967) formula to estimate a minimum sample size of 384 dairy farmers from a population of 9,049 to achieve a 5% margin of error. Smallholder dairy farmers were randomly selected from the six wards considered using a systematic random sampling at intervals of five from the list of dairy producers. To distribute the sample across the wards, the study used the target population data at the ward level provided by the Ministry of Agriculture Livestock and Fisheries, County Government of Nyandarua (2023). The proportion of the target population was calculated in each ward relative to the total target population and then used these proportions to allocate the sample accordingly (Table 1).

This study used primary data collected through a semi-structured questionnaire with a mix of open and closed-ended questions chosen based on relevant literature and validated through focus group discussion and key informant interviews. Altogether, 8 dairy farmers engaged in the focus group discussion, 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

TABLE 1 Sample size distribution in each ward.

Sub-county	Ward	Sample	Share of the target population
Kinangop	Gathara	69	0.18
	Engineer	77	0.2
	Njabini	75	0.19
Kipipiri	Githioro	48	0.13
	Wanjohi	54	0.14
	Kipipiri	61	0.16
Total		384	1.00

Sub-County dairy board members, 2 dairy cooperative leaders, 2 extension officers, and 2 officers from the Kenya Climate Smart Agriculture Project with each interview taking about forty minutes. In addition, a questionnaire pre-test was carried out to assess the questions' effectiveness, sufficiency, and suitability in obtaining the necessary data. The pilot study also evaluated the time needed to complete the questionnaire and the respondents' sensitivity to the questions. The pilot study involved respondents representing 10% of the actual sample size (Abegunde et al., 2020). Data was collected through face-to-face interviews conducted by a team of properly trained enumerators chosen for their data collection skills and knowledge of the local language.

2.3 Outcome variable selection

The outcome variable in this study is the Composite Greenhouse Gas Reduction Index (CGHGRI), which was developed using the following steps:

i Identification of GHG reduction strategies: Based on a review of relevant literature, the study identified strategies that reduce GHG emissions (methane, nitrous oxide and carbon dioxide) to form the basis of the index.
ii Data collection using yes/no questions: the study designed a series of yes/no questions to assess whether smallholder dairy producers in our sample implemented these strategies.
iii Scoring and aggregation: The responses to these questions were aggregated to calculate a score for each CGHG reduction indicator, contributing to the final CGHG reduction index.

The GHG reduction strategies considered are listed in Table 2 with the supporting literature.

Given each indicator's varying number of attribute levels, the study normalised them to ensure comparability. The literature suggests normalising variables within a range of 0 to 1 (Kumar et al., 2016; Sendhil et al., 2018; Balaganesh et al., 2020). Accordingly, the study employed minimum-maximum normalisation, a straightforward method commonly used to standardise various indicators before amalgamating them into a single index (Shahbaz et al., 2023).

After getting the normalised values for each indicator, the next step was to assign weights to indicators. There are various ways of assigning weights to indicators, including equal weights, expert opinion, and principal component analysis. The equal weights method removes the influence of certain variables but may oversimplify the index, while expert opinion can be subjective depending on the expert's knowledge (Kumar et al., 2016; Dabkiene et al., 2021). Principal Component Analysis (PCA) assumes a linear relationship among variables and uses their correlations, but it may assign low weights to important indicators with weak correlations, leading to potentially invalid results. Additionally, PCA requires a sufficient number of indicators with a moderate correlation to be effective (Greco et al., 2019).

To avoid the above biases, the following formula was employed to assign weights to indicators as suggested by Shahbaz et al. (2023). First, the study normalised each indicator of the GHG emissions reduction as shown in Equation 1:

$$J_{ik} = \frac{AS - LS}{MS - LS} \tag{1}$$

where J_{ik} represents the normalised value of the indicator i for household k, AS represents its actual score, LS is the lowest score in the sample and MS the maximum score. The weights were computed as shown in Equation 2:

$$W_i = \frac{J_{ik}}{\sum J_{ik}}; i = 1\ldots 4; k = 1\ldots 385 \tag{2}$$

where W_i represents the weight of the i^{th} indicator; $\sum J_{ik}$ denotes the sum of normalised values of four indicators for household k. This weight estimation formula offers the advantage of distributing weight to each indicator according to its contributing share. According to the results, animal health management, improved breeding, feeding and manure management received the highest weights, respectively.

Finally, a combined GHG emissions reduction index was computed using indicators and their respective weights as per Shahbaz et al. (2023). For each of the $N = 4$ indicators in Table 2, the study computed the weighted index (*Index*) as follows:

$$Index = \sum_1^N W_i * J_{ik} \tag{3}$$

Afterwards, the study computed the *GHGRI* as a sum of the indices computed with Equation 3 as shown in Equation 4:

$$CGHGRI = \sum Index\left(1+2+3+4\right) \tag{4}$$

Where $CGHGRI$ denotes composite greenhouse gas emissions reduction index for the four indicators. Higher values of $CGHGRI$ indicate a reduction of GHG emissions by a household. As suggested by the literature, the study utilised a set of characteristics of farms and farmers to explain the dependent variable.

This study uses a FRM to assess the factors influencing the adoption of GHG emission reduction levels. Since the FRM effectively captures nonlinear relationships, it is particularly suitable for our analysis where the dependent variable, the CGHGRI, is an index ranging between 0 and 1. As noted by Wamuyu et al. (2023), FRM provides reliable estimates of regression coefficients regardless of the dependent variable's distribution. Additionally, it accounts for

TABLE 2 GHG emissions reduction indicators.

GHG reduction indicators	Strategy	Reference
Animal health management	Deworming after every three months, weekly tick control, vaccination and treatment of East Coast Fever control, Rift Valley Fever, foot and mouth disease and trypanosomiasis which were used as a proxy for animal health management	FAO (2017), Ericksen and Crane (2018), FAO (2019), and Kihoro et al. (2021)
Improved breeding	Calving interval below 14 months, use of improved bulls, artificial insemination, and sexed semen	FAO (2016), Kihoro et al. (2021), Aguirre-Villegas et al. (2022), and Hawkins et al. (2022)
Improved feeds and feeding	Concentrates or dairy meal, feed additives, weaning diets, sweet potato vines, sweet lupin seeds, Desmodium, production of improved fodder varieties, use of treated crop residue, hay and silage making, intercropping legume with grass fodder and full water access, zero grazing and use of stall feeding	FAO (2016), FAO (2017), Ericksen and Crane (2018), FAO (2019), Ibidhi and Calsamiglia (2020), Wilkes et al. (2020), Kihoro et al. (2021), and Aguirre-Villegas et al. (2022)
Manure management	At least 3 months of composting before manure use, and use of biogas	Chand et al. (2015), Herrero et al. (2016), Ericksen and Crane (2018), and Kandulu et al. (2024)

nonlinearity arising from data censoring without the need for transformations or corrections for observations at the data's upper or lower bounds. Under the assumptions of a Generalized Linear Model, FRM is both robust and efficient (Wamuyu et al., 2023). The specification equation is as follows:

$$E\left(GHGRI\right)=g^{-1}\left(X_i\beta\right) \tag{5}$$

where:

- $GHGRI$: The dependent variable and $E\left(GHGRI\right)$ is its expected value given the independent variables $(X_i\beta)$
- X_i: A set of independent variables
- β: A vector of coefficients that measure the effect of each independent variable.
- g^{-1}: The inverse of a link function $g(\ )$, which ensures the predicted $GHGRI$ stays between 0 and 1.

3 Results

3.1 Farm and farm producers' characteristics

Table 3 presents the descriptive statistics of the variables used in the analysis. The average age of the farmers was 51 years. A majority (56.6%) of the households were male-headed. The mean household size was about 5 members, indicating moderate household sizes among the sampled farmers.

In terms of socio-economic characteristics, respondents had an average of 9 years of formal education, suggesting that most had completed at least primary schooling, with others progressing to secondary level. The average farm size allocated to dairy production was 1.3 acres, and the mean herd size was about 2 cows. The land allocated to dairy emphasizes the significance of dairy farming as a primary income source for a majority of households, considering smallholder dairy production. Approximately 44% of the respondents reported having off-farm income sources.

Regarding social capital and institutional factors, the survey findings indicated that the sampled farmers had extensive experience in dairy production, with many having more than 15 years of experience in the field. Group membership was relatively common, with 62% of farmers participating in groups and 35% being members of cooperatives. Access to extension services was reported by 43% of

TABLE 3 Summary statistics of the variables used in the study.

Variables	Mean	Standard deviation
Demographic factors		
Age	51.04	12.33
Gender of the household head (male = 1)	56.62	
Household size	4.71	2.18
Socio-economic factors		
Education	9.23	3.92
Farm size	1.34	1.45
Herd size	1.97	0.95
Farmers with Off-farm income (%) (Yes = 1)	43.64	
Social capital and institutional factors		
Farming experience	15.11	10.39
Farmers in groups (%) (yes = 1)	61.82	
Cooperative Member (%) (yes = 1)	35.06	
Extension access (%) (yes = 1)	43.12	
Amount of credit	15496.10	44370.07
Distance to market	2.48	1.76
Training	1.57	1.95
Entrepreneurial and behavioral factors		
Entrepreneurial orientation	64.48	18.90
Risk perception	3.63	0.68
Awareness	2.85	0.91
Behavioral intention	3.92	0.77
Perceived behavioral control	2.86	1.10
Milk yield/cow/year	2724.06	1607.2
GHG reduction index	0.682	0.15

The overall farmer entrepreneurial orientation index was used to measure respondents' entrepreneurial orientation (Sambrumo et al., 2022).

respondents. On average, farmers accessed KES 15,496.1 in credit and lived 2.5 km from the nearest market. The average number of training sessions attended was 1.6.

In terms of entrepreneurial and behavioral factors, the average entrepreneurial orientation score was 64.5. Risk perception had a mean score of 3.6, while awareness and perceived behavioral control had average scores of 2.9 and 2.8, respectively. The average behavioral intention score was 3.9. On average, milk yield per cow per year was 2,724.1 litres. The mean greenhouse gas (GHG) reduction index was 0.7, reflecting moderate adoption of GHG-reducing practices among dairy producers.

3.2 Diagnostic tests

Before estimating the probit model, diagnostic states were conducted to determine multicollinearity in the explanatory variables, heteroscedasticity, and normality of the residuals. The results indicated that the Variance Inflation Factor (VIF) was 1.31, below the recommended threshold of 5 (Table 4). The Breusch-Pagan test (p-value = 0.000) showed that the variance of the error terms is not constant across the observations thus heteroscedasticity was a problem. This study accounted for heteroscedasticity by running robust standard errors. Finally, the Shapiro–Wilk test (p-value = 0.037) depicted that the residuals were normally distributed.

When choosing between the logit and probit models for the fractional response model, the study evaluated key model fit statistics, including Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and log-likelihood (Table 5). The logit model had a slightly higher log-likelihood compared to the probit model, which suggested that the logit model fitted the data reasonably well. Additionally, the logit model exhibited lower AIC and BIC values compared to the probit model's AIC and BIC values. Since lower AIC and BIC values indicate a better model, the logit model emerged as the most suitable model for this analysis.

3.3 Determinants of greenhouse gas emissions reduction level among smallholder dairy farmers

Table 6 shows the factors influencing the GHG reduction level among smallholder farmers. A total of 19 explanatory variables were included in the model. The model's strong statistical significance (Prob>$\chi 2$ = 0.0000) and the pseudolikelihood value (269.3741) indicate robust model performance, implying that at least a subset of the explanatory variables has non-zero effects. The results highlight several key determinants across demographic, socio-economic, social capital, institutional, entrepreneurial, and behavioral factors. Specifically, nine variables (education, off-farm income, proportion of cows milked, farmer group and cooperative membership, entrepreneurial orientation, perceived behavioral control, awareness, behavioral intention and risk perception) were statistically significant in explaining GHG reduction levels among farmers. Specifically, education level, proportion of cows milked, group and cooperative membership, and perceived behavioral control were positive and statistically significant at the 1% level, indicating a strong association with GHG reduction levels. Entrepreneurial orientation, awareness, and risk perception were all significant at the 5% level, while behavioral control was negative and statistically significant at the 10% level.

TABLE 4 Multicollinearity test for explanatory variables.

Variable	VIF	1/VIF
Education	2.279	0.439
Cooperative membership	1.325	0.754
Herd size	1.233	0.811
Gender	1.23	0.813
Land size	1.229	0.814
Awareness	1.161	0.861
Behavioral intention	1.15	0.869
Extension access	1.123	0.891
Group membership	1.088	0.919
Age	1.069	0.936
Training	1.056	0.947
Household size	1.049	0.953
Distance	1.048	0.954
Mean VIF	1.308	.

TABLE 5 Tests for the choice between logit and probit model in FRM model.

Fractional response model	AIC	BIC	Pseudo-likelihood
Logit	−496.748	−413.730	269.374
Probit	−496.559	−413.541	269.280

4 Discussion

Among the socio-economic factors, education exhibited a positive and highly statistically significant effect, indicating that higher educational attainment is strongly associated with increased GHG reduction levels. The knowledge gained through education increases the likelihood of adopting climate CSDS since individual farmers can fully understand the benefits of the specific strategies. This finding aligns with the conclusions drawn by Brody and Ryu (2006), Ongare et al. (2016), Alsayed and Malik (2020) and Bohvalovs et al. (2023). Additionally, higher levels of education may enhance farmers' ability to comprehend the synergies between various mitigation strategies, thereby facilitating the adoption of multiple GHG-reducing practices, as supported by Gebre et al. (2023), Korir et al. (2023) and Asante et al. (2024).

The proportion of dairy animals milked was positively associated with reduced GHG emissions, confirming the studies by Zehetmeier et al. (2012) and Kashangaki and Ericksen (2018). Milking a higher proportion of dairy animals is associated with lowering GHG emissions due to several climate-smart strategies. These include improved feed efficiency, where lactating cows are provided with nutrient-dense feed, resulting in higher milk production (Ericksen and Crane, 2018). Further, there might be an element of efficiency

TABLE 6 Analytical results for the drivers of GHG emissions reduction using fractional response model.

GHG reduction level	dy/dx	Standard errors
Demographic factors		
Age	0.000	0.001
Gender	0.013	0.014
Household size	0.001	0.003
Socio-economic factors		
Education	0.011***	0.002
Land size	0.003	0.004
Off-farm income	0.003	0.013
Proportion of cows milked	0.195***	0.065
Social capital and institutional factors		
Experience	0.001	0.001
Extension access	0.001	0.014
Group membership	0.051***	0.013
Cooperative membership	0.042***	0.013
Training	0.002	0.003
Distance to input market	0.004	0.004
Credit access	0.000	0.000
Entrepreneurial and behavioral factors		
Entrepreneurial orientation	0.031**	0.013
Perceived behavioral control	0.016***	0.006
Awareness	0.014**	0.007
Behavioral intention	−0.016*	0.009
Risk perception	−0.023**	0.010
Constant	−1.386***	0.386
Number of observations 385		
Prob > $\chi2$ = 0.0000		
Pseudolikelihood = 269.3741		

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

where if a larger proportion of the herd is productive, the overall emissions per unit of milk produced could be lower (Vernooij et al., 2024). These results suggest conducting further studies to determine whether this relationship holds in other regions or with different livestock types. Selective breeding and enhanced animal health contribute to fewer emissions, as healthier, more productive animals emit less methane per unit of milk (Kihoro et al., 2021). Additionally, proper manure management and the adoption of renewable energy, such as bio-digesters, reduce methane and nitrous oxide emissions (Kandulu et al., 2024).

Cooperative and other farmers' group membership had a significant positive effect on the GHG reduction level. Agricultural groups play a crucial role in disseminating knowledge, and by actively engaging in these groups, smallholder farmers gain a better understanding of the benefits of adopting multiple GHG-reducing strategies. Participation in social and institutional networks, such as group and cooperative memberships, has been shown to enhance the adoption of climate-smart practices (Nganga et al., 2019). This observation aligns with Akzar et al. (2023), who emphasised the importance of cooperative membership in embracing complementary dairy feed technologies. This pattern is also consistent with the findings of Bacon et al. (2012), Pinto et al. (2020a, 2020b), Chong et al. (2023), and Guo et al. (2023), who discovered that substantial social capital promotes the adoption of key climate-smart strategies, including improved breeds, fodder production, irrigation, and livestock manure management. The literature also suggests that agricultural cooperatives can play a significant role in promoting the adoption of green technologies among farmers. Cooperatives can facilitate the diffusion of green technologies through technical training, breaking down the knowledge barriers that may hinder farmers from adopting these practices (Chong et al., 2023). Additionally, cooperatives can help establish market-based incentives for the adoption of green technologies, as the social benefits generated by their use can be transformed into tangible benefits for the adopters through market transactions (Guo et al., 2023).

Entrepreneurial orientation was positively and significantly associated with GHG reduction, highlighting the importance of proactive and informed decision-making. This finding implies that farmers with higher entrepreneurial orientation were slightly more likely to adopt GHG-reducing strategies. This tendency is supported by research emphasizing the role of entrepreneurial spirit in embracing sustainable agricultural technologies, as reported by Barzola Iza and Dentoni (2020), Daneluz et al. (2021), and Wang et al. (2023). Entrepreneurial orientation constructs such as risk-taking, innovativeness, and proactiveness enable farmers to implement innovative climate-smart practices (Kangogo et al., 2021).

Perceived behavioral control was positively associated with a reduction in GHG emissions. Perceived behavioral control reflects farmers' confidence in their ability to perform specific behaviors. When farmers believe they have the necessary skills and resources, they are more likely to adopt GHG-reducing practices. This sense of control can stem from access to information, extension services, and supportive networks. According to Ngigi et al. (2018) and Kirungi et al. (2023), farmers require support such as technical training and resources from the government and other actors to implement climate-smart agricultural technologies. This finding also aligns with Li et al. (2020) and Elahi et al. (2021), who demonstrated a correlation between farmers who perceive themselves as possessing adequate skills and their increased propensity to adopt sustainable production practices in cattle production.

Awareness of CSDS was another significant factor in explaining the uptake of GHG reduction strategies. Access to information on the benefits of CSDS such as increased milk production, and reduced cost of production increased the uptake of GHG reduction measures. Maina et al. (2020), Li et al. (2023), and Mburu et al. (2024) suggest that a comprehensive understanding of CSDS encourages the adoption of a wide range of practices, particularly when farmers recognise the potential for increased production and reducing GHG emissions.

Behavioral intention and risk perception negatively affected GHG reduction supporting studies such as (Gebre et al., 2023). Although farmers recognise the risks of climate change, factors like uncertainty about the effectiveness of new practices, fear of potential losses, and lack of immediate benefits can lead to inaction (Wossen et al., 2019). This finding potentially reflects hesitation or aversion to adopting mitigation practices due to perceived risks or uncertainties. A possible explanation for this evidence is that farmers tend to prioritise strategies that enhance milk production, often overlooking those that do not contribute directly to increased output (Kogo et al., 2022). This finding appears to contradict Amamou et al. (2018), who found that climate change risks such as new diseases, reduced animal fertility, decreased milk production, reduced longevity, and feed unavailability increased the likelihood of adopting climate-smart practices (Gebre et al., 2023). Likewise, the intention to adopt GHG reduction measures was negatively related to GHG emissions reduction. A possible explanation could be that factors such as limited resources, lack of immediate benefits, and socio-cultural barriers can impede the realisation of intentions. For instance, a study by Gikunda et al. (2022) reported that communication barriers with extension agents reduced the intentions to adopt climate-smart practices. Similar findings were reported by Kashangaki and Ericksen (2018). This study's finding contradicts the result of Kirungi et al. (2023), who found that intention to adopt significantly influenced the uptake of climate-smart technologies among farmers. These results highlight the complexity of the decision-making process in adopting sustainable dairy practices.

This study relied on the self-reported adoption status of the surveyed households. The self-reporting method may introduce response bias, as respondents may try to present certain images of themselves to the researcher. Literature indicates that self-reported data can be prone to misclassification, leading to biased estimates of adoption rates and associated outcomes (Wossen et al., 2019). To overcome response distortion, this study explained to the respondents the importance of the exercise and its contents in informing policy decisions. Future studies could consider cross-validating self-reported data with observational methods to address measurement errors in the self-reported adoption status. Moreover, a detailed analysis of external factors influencing adoption beyond farmers' characteristics would enhance the understanding of the drivers of GHG reduction measures.

5 Conclusion

This study reveals several critical determinants of GHG reduction practices among farmers, encompassing demographic, socio-economic, social capital, institutional, entrepreneurial, and behavioral factors. These findings offer significant insights into areas where targeted policies and interventions could promote climate-smart agricultural practices. Policies should prioritise enhancing farmers' knowledge through educational initiatives, as higher educational attainment strongly correlates with adopting GHG-reducing strategies. Promoting advanced livestock management practices can also play a significant role in climate change mitigation. Strengthening social capital by supporting agricultural groups and networks is essential for facilitating knowledge sharing, peer learning, and resource access, as well as encouraging sustainable practices. Addressing behavioral barriers such as risk aversion and resource constraints through targeted interventions, including risk mitigation strategies and financial support, is critical for the broader adoption of climate-smart agriculture.

To translate these insights into action, several stakeholders must play a role. Agricultural extension officers should focus on delivering localized training on GHG-reducing practices, particularly those tied to improved livestock feeding, manure management, and animal health management. Regular on-farm demonstrations and follow-up visits can enhance practical adoption and confidence among farmers, especially those with limited formal education.

Dairy cooperatives are well-positioned to drive peer learning by facilitating farmer field schools and incentivizing members who adopt GHG-reducing practices through preferential access to markets and feed subsidies. Cooperatives can also partner with service providers to offer bundled climate advisory services alongside input delivery.

Local governments should integrate climate-smart agriculture into county-level agricultural extension plans and budgets. This includes financing training programs for extension staff on climate resilience, creating ward-level climate response plans, and supporting the establishment of innovation platforms that bring together farmers, researchers, and private sector actors. Local governments can also provide targeted subsidies, or financial support to smallholder farmers adopting GHG-reducing technologies.

An integrated policy approach combining education, social capital enhancement, technical training, and financial incentives is necessary to drive the implementation of GHG-reducing practices. However, the potential impact of these policy interventions requires careful evaluation to ensure their effectiveness and adaptability to diverse agricultural contexts, such as wards. Additionally, further research is needed to understand the nuanced relationship between risk perception, resource availability, and adoption behavior, enabling the design of more effective and evidence-based interventions.

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 below: https://github.com/Naomi-Chebi/Naomi-Chebiwot-Chelang-a/commit/4f7798ff7fa6c0306a8f77a5d6490484ef3fb6b9.

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. 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, Visualization, Writing – review & editing, Project administration, Methodology, Validation, Investigation, Conceptualization, Data curation, Software. MM: Supervision, Writing – review & editing, Investigation, Conceptualization, Methodology. DO: Writing – review & editing, Conceptualization, Supervision. MS:

Writing – review & editing, Supervision, Writing – original draft, Conceptualization.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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

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