Check for updates

OPEN ACCESS

EDITED BY Valerien Pede, International Rice Research Institute (IRRI), Philippines

REVIEWED BY

Aminou Arouna, Africa Rice Center (CGIAR), Côte d'Ivoire Ebenezer Toyin Megbowon, University of Fort Hare, South Africa Ashok Mishra, Arizona State University, United States

*CORRESPONDENCE Lilian Korir Ikorir@lincoln.ac.uk Simon Nyokabi I ndungukabi@gmail.com

[†]These authors have contributed equally to this work and share first authorship

⁺These authors have contributed equally to this work and share senior authorship

[§]These authors have contributed equally to this work and share last authorship

RECEIVED 14 October 2022 ACCEPTED 17 April 2023 PUBLISHED 12 May 2023

CITATION

Korir L, Manning L, Moore HL, Lindahl JF, Gimechu G, Mihret A, Berg S, Wood JLN and Nyokabi NS (2023) Adoption of dairy technologies in smallholder dairy farms in Ethiopia. *Front. Sustain. Food Syst.* 7:1070349. doi: 10.3389/fsufs.2023.1070349

COPYRIGHT

© 2023 Korir, Manning, Moore, Lindahl, Gimechu, Mihret, Berg, Wood and Nyokabi. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Adoption of dairy technologies in smallholder dairy farms in Ethiopia

Lilian Korir^{1*†§}, Louise Manning^{1‡§}, Henrietta L. Moore^{2‡§}, Johanna F. Lindahl^{3§}, Gizachew Gemechu^{4§}, Adane Mihret^{4§}, Stefan Berg^{5§}, James L. N. Wood^{6‡§} and Ndungu S. Nyokabi^{2*†§}

¹Lincoln Institute for Agri-Food Technology, University of Lincoln, Lincoln, United Kingdom, ²Institute for Global Prosperity, University College London, London, United Kingdom, ³International Livestock Research Institute (ILRI), Nairobi, Kenya, ⁴Armauer Hansen Research Institute (AHRI), Addis Ababa, Ethiopia, ⁵Bernhard Nocht Institute for Tropical Medicine, Hamburg, Germany, ⁶Department of Veterinary Medicine, University of Cambridge, Cambridge, United Kingdom

The adoption of modern agricultural technologies in Ethiopia's dairy production system remains underutilized and under-researched yet it is a promising sector to aid in reducing poverty, improving the food security situation and the welfare of rural households, and in ensuring environmental sustainability. This paper uses the Negative Binomial regression model to examine determinants of multiple agricultural technology adoption in the Addis Ababa and Oromia regions of Ethiopia. Data was collected from 159 smallholder dairy farms in Ethiopia's Addis Ababa and Oromia regions exploring 19 technologies used by the farmers during the study period. The findings show that farm location and herd size impact adoption decisions. Increasing herd size is associated with increased uptake of multiple technologies. Further, as farmer education level increases the more likely farmers are to adopt multiple technologies. The increase in the number of female workers is positively associated with the adoption of multiple dairy technologies. In terms of farmers'/workers' years of experience, those with no years of work experience are less likely to have adopted multiple technologies than those with more than 5years of experience. However, this could be due to a number of factors where experience stands as a proxy value. Trust in information from government agencies was associated with a higher propensity to adopt multiple dairy technology as was farmer perception of fellow farmers as peers compared to those who perceive them as competitors. This is an important finding as it may help policymakers or institutions explore knowledge exchange and diffusion of innovation strategies tailored to specific farming and community situations. Studies have shown that farmers within a social group learn from each other more fully about the benefits and usage of new technology. These findings are of value in future technology adoption studies, particularly which factors influence the intensity of adoption of multiple technologies by smallscale producers.

KEYWORDS

milk hygiene, animal health, food safety, biosecurity measures/adoption, constraints, dairy technologies, smallholder, Ethiopia

1. Introduction

Globally, livestock production contributes 40% to global agricultural Gross Domestic Product (GDP) and to an estimated 30% of agricultural GDP within the developing world (Abbasi and Nawab, 2021). Dairy production, a sub-sector of livestock production, is important for the livelihood of many smallholder farmers in the developing world (Janssen and Swinnen,

2019; Abbasi and Nawab, 2021). Smallholder dairy production systems in Sub-Saharan African (SSA) countries are characterized by low productivity and a slow rate of technology adoption (Mekonnen et al., 2010). This is equally the case in Ethiopia where adoption of dairy technologies and practices has been slow, despite numerous efforts to disseminate the technologies in the past.

Several factors contribute to this low productivity and slow rate of adoption; among them animal disease, livestock nutrition, poor management, lack of infrastructure, and veterinary service provision (Kebebe, 2017; Tschopp et al., 2021). The adoption of modern dairy technologies such as use of improved breeds, improve forage, promoting animal health and hygiene is important to drive productivity, farmer's profits, welfare of poor farmers and is promising as a driver of rural development and poverty reduction (Janssen and Swinnen, 2019). There is thus a need for policies that increase technology adoption and agricultural productivity which can significantly reduce poverty (Zegeye et al., 2022). To realize significant productivity gains multiple adoption of advanced agricultural technologies and better production practices by small holder farmers should be a priority (Ojango et al., 2017), as a pathway out of poverty and food insecurity (Mekonnen et al., 2010; Kebebe, 2019).

Ethiopia has the largest cattle population in Africa and dairy production is dominated by smallholder farming systems with cattle managed in traditional ways. The cattle have multiple uses such as wealth storage, draft power and milk production (Mekonnen et al., 2010; Chagwiza et al., 2016). Dairy production is an important pillar of the Ethiopian economy creating employment and livelihood opportunities (Mekonnen et al., 2010; Chagwiza et al., 2016). Increasing population, urbanization, and the rise in consumers' incomes are expected to increase the demand for dairy products in Ethiopia (Mekonnen et al., 2010; Chagwiza et al., 2016). Therefore, smallholder dairy production will increasingly become important for the improvement of the livelihoods of poor rural communities while contributing to food security (Mekonnen et al., 2010). The adoption of modern agricultural technologies in smallholder farming is a promising strategy in Ethiopia for improving the welfare of rural households, reducing poverty, improving food security and ensuring environmental sustainability (Zegeye et al., 2022).

Ethiopia has many endemic cattle diseases, some being zoonotic, that can harm smallholder dairy farmers and consumers. Growing consumer awareness of food safety risks, food safety legislation and increasing standards of milk quality being demanded by dairy processors has led smallholder farmers to adopt hygienic milking, milk handling and storage practices, biosecurity and animal health technologies to ensure improved milk quality (Kumar et al., 2016; Burkitbayeva et al., 2019). It is therefore important that farmers adopt multiple technologies including biosecurity, animal health and hygiene technologies and practices that reduce the risk of disease introduction and spread within cattle herds, reducing zoonoses risks and helping to address antibiotics resistance associated with the overuse of veterinary drugs (Sarrazin et al., 2014; Ritter et al., 2016). There is however, a limited number of studies that have investigated the multiple adoption of biosecurity, animal health and hygiene technologies and practices in smallholder dairy farms in Ethiopia. Thus the significance and need for this paper. While extant literature has explored the adoption of technologies in Ethiopia (Mekonnen et al., 2010; Dehinenet et al., 2014; Kebebe et al., 2015; Kebebe, 2017; Kebebe, 2019) they have mostly explored a narrower range of the available technologies for dairy production, with limited studies considering the intensity of multiple adoption. Extant literature suggests that despite increased dissemination efforts (Kebebe, 2017), the adoption rate of technologies in the dairy sector has been slow (Russell and Bewley, 2013; Barrios et al., 2020).

We investigated the adoption of 19 dairy technologies in Addis Ababa and Oromia regions of Ethiopia, concentrating on the importance and the influence of the socio-economic factors described herein as adoption intensity. Measuring adoption intensity requires several assumptions (Rahelizatovo and Gillespie, 2004) such as the adoption of any one of the 19 technologies would not preclude the use of any of the other 18 dairy technologies. However, the implementation of one technology may not be independent of the implementation of another technology, because many of them may be complementary. Also, the use of more dairy technologies may be preferential in terms of productivity gains compared to the adoption of fewer technologies (Rahelizatovo and Gillespie, 2004; Akzar et al., 2019).

Our study differs from more commonly used approaches, which focused on each specific technology; we view adoption in terms of the total number of technologies implemented over a period of time. The study used a count data analysis, the Negative Binomial regression model, similar to that used by Rahelizatovo and Gillespie (2004), Kumar et al. (2020), Nonvide (2021), and Yang et al. (2021) in the analysis of the adoption of technologies in agricultural production. This type of analysis is advantageous in situations where there are large numbers of technologies that might be adopted, and the researcher(s) wish to examine the intensity of technology adoption. Other analyses that have examined the adoption of multiple technologies have used multinomial probit or logit or multivariate probit (see Kebebe, 2017) and a latent class analysis (see Akzar et al., 2019) frameworks. Such models, however, provide significant computational difficulties when the number of technologies being adopted by farmers becomes greater than two, in the case of multinomial logit, or four or five, in the case of multivariate probit. And even more difficult when all the studied farmers were able to adopt more than four or five technologies. The obvious disadvantages of count data analyses compared with other approaches are that they provide little information as to the type of producer who would adopt a specific technology. The advantage of this finding is that it can be useful for policymakers as interventions can be formulated to target the less intensive adopters.

Data was collected from 159 smallholder dairy farms in Ethiopia's Addis Ababa and Oromia regions exploring 19 technologies that could be potentially used by the farmers during the study period. The findings show that farm location and herd size impact adoption decisions. Increasing herd size is associated with increased uptake of multiple technologies. Further, as farmer education level increases the more likely farmers are to adopt additional dairy technologies. The increase in the number of female workers is positively associated with the adoption of multiple dairy technologies. In terms of farmers'/ workers' years of experience, those with no years of work experience are less likely to adopt more technologies than those with more years of experience. However, this could be due to a number of factors where experience stands as a proxy value. Trust in information from government agencies was associated with a higher propensity to adopt dairy technologies as was farmer perception of fellow farmers as peers compared to those who perceive them as competitors. This is an important finding as it may help policymakers or institutions explore knowledge exchange and diffusion of innovation strategies tailored to specific farming and community situations. Studies have shown that farmers within a social group learn from each other more fully about the benefits and usage of new technology. These findings are of value in future technology adoption studies, particularly considering the less intensive adopters.

The rest of the paper is organized as follows: section 2 outlines the factors influencing dairy farmers decisions to adopt multiple dairy technologies; section 3 describes the data and methods; section 4 describes and discusses the empirical results; and section concludes the paper.

Factors influencing dairy farmers' decisions to adopt multiple dairy technologies

The adoption of dairy technologies by farmers varies widely across different agro-ecologies and within the same agro-ecology based on various technical and non-technical factors (Dehinenet et al., 2014). Researchers have studied numerous motivating factors and constraints to adoption by observing the different behaviors between adopters and non-adopters of technology (Ruzzante et al., 2021). They found that the influence of many factors can be explained by; the level of diffusion of the specific technology, the economic constraints of the adopters and the perception of adopters to the technology (Ruzzante et al., 2021). Technological, economic, institutional, and human specific factors have been found to be key determinants of technological adoption (Mwangi and Kariuki, 2015) coupled with unobserved cultural, contextual, and policy factors (Ruzzante et al., 2021). Some of those factors are family size, farming experience, availability of dairy production extension services, availability of cross breed cows, accessibility of saving institutions, total income from milk and milk products, availability of training on livestock, age of household head and off-farm activity participation played significant roles on both the probability of dairy technology adoption and its level of adoption (Dehinenet et al., 2014). Higher levels of technology adoption are associated with better milk yield regardless of the breed of cattle (local or crossbred) owned by smallholder dairy farmers (Mekonnen et al., 2010). Adoption of new practices and technologies is however limited by various factors such as affordability, and limited access to information and training (Akzar et al., 2019; Janssen and Swinnen, 2019), which is a major constraint to quality, and higher milk yields.

Two properties determine the adoption of agricultural technologies namely the key aspects of decision-making and diffusion theory. The first is the change in the production function. That is, with the same level of inputs, the level of output may increase due to technology adoption. In other words, the same output level can be produced with fewer inputs which can lead to improved efficiency of agricultural production (Nonvide, 2021). The second attribute of the adoption of new agricultural technologies is the increase in profitability. Farmers base their adoption decision on the expected utility. In this case, and in line with neoclassical microeconomic theory, the farmer may decide to adopt a technology when it provides him a utility greater than non-adoption (Nonvide, 2021; Ruzzante et al., 2021). In this case, farmers may be more likely to adopt multiple technologies as being complementary or substitutes for current practice, specifically to maximize their expected benefit from their adoption decisions despite being constrained by their limited budget

and access to information (Akzar et al., 2019). In this study, adoption theory is used to contextualize and interpret the causal (or contributory) relationship affecting the number of technologies adopted by farmers in this context.

3. Data and methods

3.1. Description of the study area

This research was undertaken within a bovine tuberculosis control project in the wider Addis Ababa and Oromia milk shade in Ethiopia. The study area comprised urban and peri-urban and intermediate rural areas within a 60 km radius of Addis Ababa, the capital city of Ethiopia. The urban areas consisted of Bole, Kolfe, Ketema and Kaliti sub-cities of Addis Ababa while Sendafa, Sebata, Debre-Zeit, and Holeta made up the peri-urban areas located in the Oromia region. This study area was selected based on several factors. First, dairy production in the area is an important economic activity for dairy farmers (Deneke et al., 2022). The region is undergoing rapid urbanization which creates new dairy production constraints such as reduced land availability and lack of forage due to the loss of grazing areas (Alemayehu et al., 2021; Deneke et al., 2022). The high prevalence of endemic zoonoses is a major public health problem for both farmers and consumers of animal source products (Amenu et al., 2019; Gizaw et al., 2020). Finally, climate change is creating new production challenges for smallholder farmers including heat stress, limited access to feed resources and new pests and diseases (Yengoh and Ardö, 2020).

This study had ethical clearance from ALERT hospital AHRI/ ALERT Ethics Review Committee (AAERC) approval (Protocol number PO-(46/14)) and the University College London Research Ethics Committee (UCL-REC) approval number 19867/001.

The questionnaire used to collect the data was based on the identified research gap following a structured literature review on dairy production and technology adoption in the Ethiopian context. The questionnaire covered topics such as farmer socio-economic characteristics, dairy technology adopted and possible drivers and constraints to technology adoption. The dairy technologies explored in this study focused on breed improvement, animal health, biosecurity and feeding technologies. Breed improvement technologies considered included animal purchasing and breed improvement included AI, breed upgrading, and testing new animals (Mekonnen et al., 2010; Burkitbayeva et al., 2019). Biosecurity and hygiene practices and technologies explored in the questionnaire included visits by a veterinarian, presence of biosecurity plans, fencing, disinfection baths, improved housing and use of improved containers meant to prevent diseases being introduced to a farm (Sarrazin et al., 2014; Ritter et al., 2016). Feeding technologies considered included zero grazing, purchase of feeds/forage and growing own feeds/forage which are meant to improve livestock performance (Mekonnen et al., 2010). Animal health technologies explored included ectoparasite control, endoparasite control, animal health records, vaccination, teat disinfection and dry cow therapy which are meant to reduce disease burden and improve animal welfare (Mekonnen et al., 2010; Kumar et al., 2015).

The questionnaire was administered to a total of 159 farmers selected through convenience and purposive sampling methods. The selected

farmers had previously participated in the Ethiopia Control of Bovine Tuberculosis Strategies (ETHICOBOTS) project work. The inclusion criteria were willingness to freely participate in the study and experience of around 5 years in farming. In cases where a farmer declined to participate, or the farm had ceased to operate, an alternative farm within the study areas with similar characteristics was selected as a replacement.

3.2. Empirical strategy: the negative binomial regression model

The study investigates the likelihood of a farmer adopting the 19 improved technologies/practices iteratively derived from the extant literature. The methodology determines how many technologies or practices are adopted (multiple adoption) and how the adoption of multiple technologies/practices is affected by different factors. The events of adopting the various dairy technologies were assumed to occur at a constant rate within each farm but were allowed to vary across farms. The events can, therefore, be considered as generated by a Poisson process. The density function associated with the Poisson model is expressed in Equation (1):

$$f(y_i|x_i) = \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!} Y;=0,1,2,...,$$
 (1)

where x_i are variables that affect the adoption of the technologies. The mean parameter μ ; represents the expected number of events and is expressed as in Equation (2):

$$\mu_i = E[y_i | x_i] = \exp(x'_i \beta)$$
(2)

If we assume the independence of the observations, one can express the log-likelihood function associated with the estimation as in Equation (3):

$$\ln L(\beta) = \sum_{i=1}^{n} \left[y_i x_i' \beta - \exp(x_i' \beta) - \ln y_i'! \right]$$
(3)

Properties of the Poisson regression model require the mean and variance of v, to be equal. However, the assumption of a constant rate of adoption may not be realistic in practice. The variance of v, can be greater (lower) than its mean value, indicating the presence of over-(under-) dispersion in the count data. In such a case, the Poisson regression would not be fully efficient, and the estimated standard errors would be biased and inconsistent. The negative binomial analysis allows for an adjustment for the presence of overdispersion and permits a flexible modeling of the variance. The variance function for the negative binomial model is presented in Equation (4), in which a is the dispersion parameter to be estimated:

$$\operatorname{var}(y_i)^n = \mu_i + \alpha \mu_i^2 \tag{4}$$

The Poisson regression is a special case of the negative binomial with $\alpha = 0$. Under the assumption that the specification of the mean

is the same as that in the Poisson regression model, the log-likelihood function associated with the negative binomial formulation is expressed in Equation (5):

$$\ln L(\alpha,\beta) = \sum_{i=1}^{n} \left\{ \sum_{j=0}^{y_i-1} \ln\left(j+\alpha^{-1}\right) - \ln\left(y_i!\right) - \left(y_i+\alpha^{-1}\right) \ln[1+\alpha\exp\left(x_i'\beta\right] + y_i\ln\alpha + y_ix_i'\beta \right\}$$
(5)

In summary, the Poisson model is not particularly appropriate if the probability of an event is more balanced, which is the case in our study. As the underlying assumption in this study is that all events (adoption of a technology) have the same probability of occurrence is violated as the probability of adopting the first technology could differ from the probability of adopting a second or third practice, given that in the latter case the farmer has already gained some experience with adoption of a given technology, and/or there is an aggregated enhanced benefit of adopting multiple technologies, or having adopted one technology this may limit farmers ability to fund further adoption. Therefore, the number of technologies adopted by farmers is considered as an ordinal variable and therefore a negative binomial (NB) regression analysis was employed, and we obtain similar findings as those of the Poisson. The advantage with NB is that it loosens the restrictive assumption with the Poisson Regression that the variance should be equal to the mean. And hence it is an appropriate estimation strategy for this case.

3.3. Descriptive statistics

The majority of the dairy farmers in this study had adopted several of the 19 technologies (Table 1), namely, breed improvement, purchases of commercial feeds and minerals, vaccinations control of endoparasites (i.e., worms and flukes), fencing, use of AI for breeding, teats disinfections, zero-grazing feeding system, control for ectoparasites (i.e., ticks), keeping of records, having a biosecurity plan, keeping records of cattle deaths that occur in the farm, growing of feeds in the farm, use of disinfection footbath to be used before entering the shed, vet visits, improved housing, containers used for milking and storage, dry cow therapy, and testing new cattle before introducing them to the herd as shown in Table 1.

In the survey, dairy producers were asked which of the 19 dairy technologies and practices they had adopted. Table 2 summarizes each technologies and which have been grouped into four categories: (1) animal purchasing and breed improvement including AI use, breed upgrading, and testing new animals, (2) Biosecurity and hygiene, for example, visits by a veterinarian, farm having a biosecurity plan, fencing, disinfection baths, improved housing and use of improved milking and storage containers, (3) Feeding such as the adoption of zero grading, purchase of feeds, growing own feeds, and (4) Animal health related ectoparasite control, endoparasite control, animal health records, vaccination, teat disinfection and dry cow therapy. The farmers response regarding his or her current adoption of each of the technology was considered as an event. Count numbers of technologies and practices adopted on the farm constituted the dependent variable in the study. Furthermore, the expected number of events E(Y) and the hypothesized independent variables were assumed to have a log-linear relationship, as in Equation (2).

TABLE 1 Summary of the number of technologies adopted and the percentage of adopters.

Number of technologies adopted by dairy farmers (count)	Number of adopters (count)	Adopters in percentage
4	1	0.63
5	1	0.63
6	2	1.26
7	6	3.77
8	18	11.32
9	27	16.98
10	19	11.95
11	24	15.09
12	23	14.47
13	7	4.4
14	11	6.92
15	6	3.77
16	6	3.77
17	3	1.89
18	2	1.26
19	3	1.89
Total	159	100

TABLE 2 Thematic grouping of the dairy technologies explored in this study.

Groups	Description
Animal purchasing and breed improvement	AI use, breed upgrading, and testing new animals
Biosecurity and hygiene	Visits by a veterinarian, farm having a biosecurity plan, fencing, disinfection baths, improved housing and use of improved milking and storage containers
Feeding	Adoption of zero grading, purchase of feeds, growing own feeds
Animal health	Ectoparasite control, endoparasite control, animal health records, vaccination, teat disinfection and dry cow therapy

Table 3 shows the rate of adoption of individual technologies by the farmers in the sample group. They are listed from the most frequently adopted technologies, breed improvement and purchase of commercial feeds and minerals (96%), vaccination (94%), control for endoparasites, i.e., worms and flukes (94%), fencing (91%), using AI for breeding (86%), disinfection of teats (79%), use of zero-grazing (78%), control for ectoparasites, i.e., ticks (76%), and health records (51%) to the least commonly adopted (testing new cattle before introducing to the herd, 14%).

Least adopted technologies were a biosecurity plan (44%), record keeping of cattle mortality on farm (44%), growing feed/forage on farm (30%), disinfection footbath use on entry to cattle sheds (28%), veterinary visits (27%), improved housing (25%), containers used for milking and storage (17%), dry cow therapy (16%), and testing new cattle before introducing them to the herd (14%). This demonstrates that the majority of the farms adopt more animal purchasing and breed improvement related technologies, followed by those for biosecurity and hygiene, then animal feeding, then lastly animal health related biosecurity measures.

In addition, Table 4 provides a correlation matrix showing significance level and the magnitude and direction of the associations for the technologies adopted. Table 4 shows that there is a positive and weak association between breed improvements and records of deaths, health records, and zero grazing, while strong positive correlations were observed for improved housing and biosecurity plan, disease testing, disinfect teats and disinfection using footbaths and a negative moderately strong correlation between improved housing and disinfecting teats. Table 5 shows the means of the key socio-economic variables used in this paper for farmers and their farms, i.e., farm location, herd size, age of farmer, the highest level of education of the farmer, number of male and female workers, years of experience, trust in information from government, government agencies or from other farmers and whether they perceived their fellow farmers as peers or competitors and some institutional variables, such as membership of farmer organizations/groups.

The mean of the technologies adopted were 11.5 (SD = 2.88). The average age of farmers in the study was 41.65 (SD = 21.73), while the average herd size was 16.53 (SD = 17.89), showing that there is a wide dispersion of herd size across the sample population. In terms of the farm locations, farms were sited in the following areas Holeta (21%), Bole (19%), Sebeta (17%), Bishoftu (14%), Sendafa (11%). Kaliti (9%), Ketema and Kolfe (both 4%). With regard to education the sample population with no education was (6%), primary education (31%), secondary education (38%) and tertiary education (25%). The mean of the number of female workers use were 1.31 (SD = 2.60), 68 farms did not exploy any female workers while another farmers had up to 19 female workers showing there is a wide dispersion in the number of female workers across the study farms. The mean for male workers was 3.11 (SD = 5.66), 18 farms did not employ any male workers, while another farmer has 35 male workers on the dairy farm. This show there is a wide dispersion in the number of male workers used on the dairy farms. In terms of years of dairy farming experience, those who had no experience were 23%, 1-5 years (24%), 6-7 years (14%) and more than 10 years (38%). Trust was reported in government information (91%,) government agencies (93%) and other farmers (82%) with the majority of farmers (72%) perceiving fellow farmers as peers. Nearly one quarter of the farmers (23%) were members of farmers organizations/group, while 21% of the dairy farmers had additional income. These variables deduced from the literature review were positioned as being to the adoption of agricultural technologies in Ethiopia.

4. Results

4.1. Factors influencing dairy farmer's adoption of multiple dairy technologies

The results of the Negative Binomial Regression are presented in Table 6 and estimates associated with the marginal effects are computed at the mean values of the Xs. Comparison of the values of the mean and variance of the dependent variable technologies showed

TABLE 3	Rate of individual	technologies	adoption	by farmers.
---------	--------------------	--------------	----------	-------------

Technologies	Adopters (percentage of study population)
Breed improvement	96%
Purchased commercial feeds and minerals	96%
Vaccinate	94%
control for endoparasites (i.e., worms and flukes)	94%
Fencing	91%
Using AI for breeding	86%
Disinfect teats	79%
Animals feeding in a zero-grazing	78%
control for ectoparasites (i.e., ticks)	76%
Health records	51%
Biosecurity plan	44%
Record keeping of cattle deaths that occur on the farm	44%
Grow feeds for your cattle on your farm	30%
Use disinfection footbath to step through before entering the cattle shed	28%
Vet visit	27%
Improved housing	25%
Containers used for milking and storage	17%
Dry Cow Therapy	16%
Testing new cattle before introducing them to the herd	14%

a variance (2.88) compared with the mean (11.04). This would suggest the inappropriateness of using the Poisson model, because the equality property of the mean and variance was not fulfilled. Tests for overdispersion indicate that one should consider a variance functiontype negative binomial. The Negative Binomial Regression model yielded a log-likelihood value of (-365.28), similar to that of the Poisson. The Poisson was estimated for robustness. The results from the two regressions were very similar.

The results suggested that, for the two regions Oromia and Addis Ababa those dairy producers' having a larger herd size, reside in Kolfe and Sendafa, having no education, employing female workers, having limited experience, trusting in information from government agencies and perceiving fellow farmers as peers were significantly more likely to adopt multiple dairy technologies.

Furthermore, being from Kolfe yielded the greatest marginal effects compared with other explanatory dummy variables. Such results show the importance of efforts to stimulate regional reach in inducing technology adoption. A farmer who is from Kolfe (which is a location in Addis Ababa) is more likely to be willing to adopt technology than those in other regions. While a farmer from Sendafa (which is a location the Oromia region) is more reticent to adopt technology compared to other regions. Both regions are known for their high dairy production sector and have varying agroecological characteristics. The study shows a differing effect on willingness to adopt multiple technologies. This is a valuable finding while exploring interventions for uptake of the dairy technologies, Adoption of technology is not a linear process, it is often dynamic requiring an understanding of the decisions made by individual farm households (Ruzzante et al., 2021). The findings in this study show variations by context, such as farm location, as well as factors such as level of education, herd size and number of female workers. These factors, both individually and in a concerted manner, influence decisionmaking at the farm level. Further examples of non-linearity are that due to the different risk appetites of farmers some may wish to see the benefits of technology adoption over a longer period of time, or may wish to see other peer farmers experiment before they are willing to engage in the adoption process.

The positive effect of farmers having trust in information from government agencies, such as extension officers, is associated with the adoption of a greater number of dairy technologies. This may suggest that having an institutional trust will stimulate multiple adoptions of technologies. Similarly, the positive effect associated with how they perceive their fellow farmers as 'peers' suggests that farmers who perceived their fellow farmers as peers are more likely to engage in multiple technology adoption. Thus, peer to peer involvement may stimulate greater adoption of dairy technologies. Thus, the use of farmer-to-farmer approaches to enhance communication about various technologies, their specific needs and the benefits the technologies may have on dairy production efficiency would be good to study in further research work.

Lack of education and lack of work experience both have a negative association with multiple technology adoption, similar, to having limited or no work experience in dairy farming. This may suggest that with no education the farmer is less likely to be aware of the potential adverse effects less use of technologies may have on dairy production, i.e., milk yield, herd health and overall dairy production. While no to less working experience farmers are less likely to be aware of existing technologies, may have their level of literacy as a barrier or have not had enough time to obtain information from sources (informal and formal) on various technologies that may be beneficial. Access to female workers has a positive association with the adoption of a greater number of dairy technologies. Hiring or using more female workers is associated with an increase in the adoption of multiple dairy technologies. The larger the herd size the more dairy technologies were adopted, and the farmers with greater resources were better able to afford the technology and fully utilize it. This result is consistent with previous findings.

5. Discussion

Dairy production in Ethiopia comprises mainly smallholder farming systems managing cattle in traditional ways and research on these systems offers an opportunity for developing recommendations that can lead to livelihood improvement at household, community and national scales (Mekonnen et al., 2010). The adoption of multiple technologies in smallholder dairy farming remains a promising strategy in Ethiopia to improve farm productivity, farm incomes and reduce poverty improving food security and ensuring environmental sustainability (Zegeye et al., 2022). Dairy production technologies such as breed improvement, milking, forage and feed conservation, biosecurity, and animal health and food safety interventions have the potential to improve milk yields and quality of production, reduce disease prevalence and improve food safety (Mekonnen et al., 2010;

TABLE 4 Pairwise correlation of the 19 technologies explored in this study.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) Breed	1.000																		
improvement	0.027	1.000																	
(2) Improved housing	-0.037	1.000																	
(3) Biosecurity	-0.024	0.508***	1.000																
(4) Veterinary visit	0.046	0.495***	0.487***	1.000															
(5) Fencing	0.055	0.027	-0.037	-0.011	1.000														
(6) Disease test	-0.012	0.503***	0.320***	0.474***	0.002	1.000													
(7) AI breeding	0.112	0.106	0.025	0.039	0.004	0.165**	1.000												
(8) Recording deaths	0.176**	0.187**	0.209***	0.145*	-0.082	0.140*	0.025	1.000											
(9) Using home grown feeds	-0.014	0.124	0.052	0.186**	0.011	0.041	-0.094	0.107	1.000										
(10) Using commercial feeds	0.118	0.054	0.005	0.062	0.042	0.088	0.180**	0.129*	0.074	1.000									
(11) Using milking containers	0.090	0.201**	0.071	0.366***	0.022	0.147*	-0.110	0.308***	0.177**	0.015	1.000								
(12) Disinfecting teats	-0.020	-0.525***	-0.358***	-0.491***	0.115	-0.539***	-0.115	-0.077	-0.035	-0.110	-0.099	1.000							
(13) DCT	-0.005	0.307***	0.348***	0.282***	0.012	0.314***	0.023	0.139*	0.130*	0.093	0.127	-0.290***	1.000						
(14) Vaccination	0.094	-0.109	-0.002	0.027	0.020	-0.209***	-0.098	0.053	0.043	-0.053	0.111	0.210***	-0.118	1.000					
(15) Keeping health records	0.136*	0.279***	0.262***	0.201**	-0.172**	0.189**	0.008	0.617***	0.179**	0.157**	0.276***	-0.099	0.251***	0.032	1.000				
(16) Using disinfection footbaths	0.051	0.633***	0.399***	0.372***	0.097	0.456***	0.211***	0.202**	0.104	0.135*	0.125	-0.470***	0.266***	-0.148*	0.253***	1.000			
(17) Control of worms	0.094	-0.046	0.053	-0.035	-0.076	0.101	-0.019	-0.002	-0.076	-0.053	0.038	0.009	0.031	0.058	-0.077	-0.088	1.000		
(18) Control of ticks	0.044	0.121	0.111	0.042	0.138*	0.147*	0.032	0.051	0.272***	-0.048	0.136*	0.004	0.161**	0.118	-0.019	0.156*	0.118	1.000	
(19) Use of zero grazing	0.213***	-0.007	-0.110	-0.121	-0.058	-0.040	0.227***	0.165**	-0.180**	0.182**	-0.002	0.065	-0.062	0.001	0.116	0.031	0.001	-0.013	1.000

p < 0.05, p < 0.01, p < 0.001, p < 0.001.

TABLE 5 Summary statistics of the variables used in the regressi	on.
--	-----

Variable	Mean	Standard deviation	Min	Max
Technologies	11.04	2.88	4	19
Age	41.65	12.73	20	89
Age squared	1896.09	1198.64	400	7,921
Number of cows	16.53	17.89	0	99
Bishoftu farm location	0.14	0.35	0	1
Bole farm location	0.19	0.39	0	1
Kaliti farm location	0.09	0.29	0	1
Ketema farm location	0.04	0.19	0	1
Kolfe farm location	0.04	0.21	0	1
Holeta farm location	0.21	0.41	0	1
Sebeta farm location	0.17	0.38	0	1
Sendafa farm location	0.11	0.32	0	1
No education	0.06	0.23	0	1
Primary education	0.31	0.47	0	1
Secondary education	0.38	0.49	0	1
Tertiary education	0.25	0.43	0	1
Number of female workers	1.31	2.60	0	19
Number of male workers	3.11	5.66	0	35
No years of experience	0.23	0.42	0	0
1–5 years of experience	0.24	0.43	0	1
6–7 years of experience	0.14	0.35	0	1
More than 10 years of experience	0.38	0.49	0	1
Trust government information	0.91	0.28	0	1
Trust information from government agencies	0.93	0.25	0	1
Trust information from other farmers	0.82	0.38	0	1
Perceived fellow farmers as peers	0.72	0.45	0	1
Membership to farmer organizations/groups	0.23	0.42	0	1
Additional income	0.21	0.41	0	1

Kumar et al., 2016; Burkitbayeva et al., 2019; Janssen and Swinnen, 2019). While extant literature has explored the adoption of technologies in Ethiopia, this has mostly focused on crop production systems, with limited studies considering dairy production systems, and specifically the intensity of adopting multiple technologies simultaneously. There are different technologies available for dairy farmers such as those considered in this research namely animal housing, mechanisms to improve milking hygiene and storage, and use of emergent technologies at the farm level in SSA such as animal electronic identification (EID) for farm management, artificial insemination (AI) and embryo transfer, cattle surveillance, welfare qualitative behavioral assessment, anaerobic digestion, pedometers or activity monitors to detect oestrus and increase fertility/conception, and webcams, smartphones/tablets for animal husbandry (Kumar et al., 2011, 2017; Liu et al., 2019). Animal health technologies including improved housing, veterinary visits and biosecurity measures could reduce disease pressures in smallholder dairy farming systems, reduce the reliance on antibiotics, reduce zoonotic risk and have the potential for anti-microbial resistance. Indeed, the adoption of animal health technologies such as preventive and curative measures including vaccine technology, internal and external parasitic remedies technology, disinfectants technology and veterinarian's services have been shown to have positive farm-level outcomes (Sarrazin et al., 2014; Ritter et al., 2016). The adoption of technologies related to food safety measures could improve milk quality and reduce the public health risks associated with milk-borne illnesses (Kumar et al., 2011, 2017). There is a paucity of research on the adoption of food safety measures at the farm level in developing countries (Mekonnen et al., 2010; Kumar et al., 2017), so further research is needed.

The aim of this study was to examine the degree of adoption of 19 different dairy technologies/practices singularly and together. The objectives of the study are to identify the factors that influence multiple adoption, described herein as adoption intensity, as well as seeking insight into the types of farmers most likely to adopt multiple dairy technologies simultaneously. The adoption of improved technology promises to improve dairy production, animal and human population health and improve efficiency in smallholder dairy farming systems (Zegeye et al., 2022). The least adopted technologies identified in this research were a biosecurity plan (44%), record keeping of farm mortality (44%), growing feed/forage on the farm (30%), disinfection footbaths (28%), veterinary visits (27%), improved housing (25%), milking and storage improvements (17%), dry cow therapy (16%), and testing new cattle before introducing them to the herd (14%). Adopting these practices more widely would have an immediate effect on productivity and financial returns. Further research should consider why there is low adoption of these technologies, both individually and together. The levels of literacy identified in this study may affect intentions to adopt documentation and access to resources including financial capital could affect adoption strategies. This should be explored further.

The adoption of forage technology, feed/forage conservation and feeding management by smallholder dairy farmers promises to be an alternative feed/forage source to the traditional teff straw and native pastures and can improve animal nutrition and reduce labor requirements of feeding cattle (Ashley et al., 2018). Animal health, cattle housing and biosecurity practices, internal and external parasitic remedies, and vaccines can reduce cattle disease burden, livestock mortality and mitigate greenhouse gas emissions and improve productivity. Improved animal health and welfare and associated increases in yields could better meet increasing milk demand, reducing motivation and opportunities for milk adulteration (Janssen and Swinnen, 2019). The adoption of hygienic milking and storage and hygienic food handling measures could improve milk quality and reduce the public health risks associated with milk-borne illnesses (Kumar et al., 2011, 2017).

Adoption of technology is limited on some farms (see Table 1) and is dependent on socio-economic conditions. Age is one such factor that determines technology adoption behavior. Dehinenet et al. (2014) findings show that the age of the household head has a negative significant association with the probability of adoption and degree/

TABLE 6	Coefficient	and n	narginal	effect	estimates	of the	negative
binomia	l regression.						

Age0.03 (0.007)0.38 (0.073)Age squared*10^20.004 (0.007)0.042 (0.079)Number of cows0.0055*** (0.001)0.0614*** (0.010)Bishoftu farm location0.095 (0.057)1.066 (0.631)Bole farm location0.050 (0.048)0.558 (0.537)Kaltit farm location0.156 (0.082)1.827 (1.030)Kolfe farm location0.133** (0.056)2.158** (0.715)Sebeta farm location0.103 (0.057)1.159 (0.669)Sebeta farm location-0.154* (0.060)-1.575** (0.580)No education-0.168** (0.050)-0.721 (0.549)No education-0.067 (0.052)-0.721 (0.549)Secondary education0.0169*** (0.005)0.184*** (0.050)Number of famale workers0.004 (0.020)0.038 (0.026)Number of sperience0.028 (0.052)0.305 (0.570)I-5years of experience0.028 (0.052)-1.467* (0.572)Trust information from government information-0.134* (0.052)-1.167 (0.728)Frust information from ther farmers0.133* (0.052)-1.167 (0.728)Perceived fellow farmers as pers0.132* (0.051)1.389** (0.529)Membership in farmer organizations/groups0.132* (0.051)-0.223 (0.471)Additional income0.028 (0.433)0.309 (0.471)Kathin farmer organizations/groups0.028 (0.433)0.309 (0.471)Kathin farmer organizations/groups0.028 (0.433)0.309 (0.471)Kathin farmer organizations/groups0.028 (0.433)0.309 (0.471)	Variables	Coefficient (β)	Marginal effects dy/dx
Number of cows 0.00565*** (0.001) 0.0614*** (0.010) Bishoftu farm location 0.069 (0.057) 0.766 (0.650) Bole farm location 0.095 (0.055) 1.066 (0.631) Kaliti farm location 0.050 (0.048) 0.558 (0.537) Katim location 0.156 (0.082) 1.827 (1.030) Kolfe farm location 0.133 ** (0.056) 2.158** (0.715) Sebeta farm location 0.103 (0.057) 1.159 (0.669) Sendafa farm location -0.154* (0.060) -1.575** (0.580) No education -0.168** (0.065) -0.721 (0.549) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of female workers 0.004 (0.002) 0.038 (0.260) Number of male workers 0.004 (0.020) 0.038 (0.260) Number of experience -0.022 (0.048) -0.236 (0.518) Trust information from ther 0.013 (0.047) 1.466** (0.500) government agencies 0.132* (0.051) 1.389** (0.529) Furst information from other 0.132* (0.051) 1.389** (0.529) farmers -0.021 (0.044) -0.223 (0.472) <td>Age</td> <td>-0.003 (0.007)</td> <td>-0.038 (0.073)</td>	Age	-0.003 (0.007)	-0.038 (0.073)
Bishoftu farm location 0.069 (0.057) 0.766 (0.650) Bole farm location 0.095 (0.055) 1.066 (0.631) Kaliti farm location 0.050 (0.048) 0.558 (0.537) Katema farm location 0.156 (0.082) 1.827 (1.030) Kolfe farm location 0.133 ** (0.056) 2.158** (0.715) Sebeta farm location 0.103 (0.057) 1.159 (0.669) Sendafa farm location -0.154* (0.060) -1.575** (0.580) No education -0.067 (0.052) -0.721 (0.549) Secondary education -0.069 (0.042) -0.743 (0.452) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.103 (0.062) -1.167 (0.728) Trust information from other 0.013 (0.047) 0.140 (0.503) government agencies 0.133 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) perceived fellow farmers as 0.132* (0.051) -0.223 (0.472	Age squared*10^2	0.004 (0.007)	0.042 (0.079)
Bole farm location 0.095 (0.055) 1.066 (0.631) Kaliti farm location 0.050 (0.048) 0.558 (0.537) Ketema farm location 0.156 (0.082) 1.827 (1.030) Kolfe farm location 0.183** (0.056) 2.158** (0.715) Sebeta farm location 0.103 (0.057) 1.159 (0.669) Sendafa farm location -0.154* (0.060) -1.575** (0.580) No education -0.168** (0.065) -1.698** (0.609) Primary education -0.067 (0.052) -0.721 (0.549) Secondary education -0.0669 (0.042) -0.743 (0.452) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) Number of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.103 (0.062) -1.167 (0.728) Trust information from other 0.013 (0.047) 0.140 (0.503) government agencies 0.132* (0.051) 1.389** (0.529) Perceived fellow farmers as 0.132* (0.051) 1.389** (0.529) perrs -0.021 (0.044) -0.223 (0.472	Number of cows	0.00565*** (0.001)	0.0614*** (0.010)
Kaliti farm location 0.050 (0.048) 0.558 (0.537) Ketema farm location 0.156 (0.082) 1.827 (1.030) Kolfe farm location 0.183** (0.056) 2.158** (0.715) Sebeta farm location 0.103 (0.057) 1.159 (0.669) Sendafa farm location -0.154* (0.060) -1.575** (0.580) No education -0.168** (0.065) -1.698** (0.609) Primary education -0.067 (0.052) -0.721 (0.549) Secondary education -0.069 (0.042) -0.743 (0.452) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.103 (0.062) -1.167 (0.728) Trust information from other 0.013 (0.047) 0.140 (0.503) farmers 0.013 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) government agencies 0.132* (0.051) 1.389** (0.529) pers -0.021 (0.044) -0.223 (0.472)	Bishoftu farm location	0.069 (0.057)	0.766 (0.650)
Ketema farm location 0.156 (0.082) 1.827 (1.030) Kolfe farm location 0.183** (0.056) 2.158** (0.715) Sebeta farm location 0.103 (0.057) 1.159 (0.669) Sendafa farm location -0.154* (0.060) -1.575** (0.580) No education -0.168** (0.065) -1.698** (0.609) Primary education -0.067 (0.052) -0.721 (0.549) Secondary education -0.069 (0.042) -0.743 (0.452) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience -0.134* (0.056) -1.407* (0.572) 1-5 years of experience 0.028 (0.052) 0.305 (0.570) More than 10 years of experience -0.022 (0.048) -0.236 (0.518) Trust information from generices 0.013 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) peers -0.021 (0.044) -0.223 (0.472) organizations/groups 0.028 (0.043) 0.309 (0.471) Additional income 0.028 (0.043) 0.309 (0.471)	Bole farm location	0.095 (0.055)	1.066 (0.631)
Kinder and Control 0.183** (0.056) 2.158** (0.715) Sebeta farm location 0.103 (0.057) 1.159 (0.669) Sendafa farm location -0.154* (0.060) -1.575** (0.580) No education -0.168** (0.065) -1.698** (0.609) Primary education -0.067 (0.052) -0.721 (0.549) Secondary education -0.069 (0.042) -0.743 (0.452) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.133 (0.062) -1.167 (0.728) Trust information from other 0.013 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) peers -0.021 (0.044) -0.223 (0.472) organizations/groups 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171 -0.223 (0.472)	Kaliti farm location	0.050 (0.048)	0.558 (0.537)
Sebeta farm location 0.103 (0.057) 1.159 (0.669) Sendafa farm location -0.154* (0.060) -1.575** (0.580) No education -0.168** (0.065) -1.698** (0.609) Primary education -0.067 (0.052) -0.721 (0.549) Secondary education -0.069 (0.042) -0.743 (0.452) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience -0.022 (0.048) -0.236 (0.570) More than 10 years of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.134* (0.052) 1.466** (0.500) government agencies 0.113 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) perceived fellow farmers as 0.132* (0.051) 1.389** (0.529) pers -0.021 (0.044) -0.223 (0.472) organizations/groups 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171	Ketema farm location	0.156 (0.082)	1.827 (1.030)
Sendafa farm location 0.154* (0.060) 1.575** (0.580) No education 0.168** (0.065) 1.698** (0.609) Primary education 0.067 (0.052) 0.721 (0.549) Secondary education 0.069 (0.042) -0.743 (0.452) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience 0.134* (0.056) 1.407* (0.572) 1-5 years of experience 0.028 (0.052) 0.305 (0.570) More than 10 years of experience 0.022 (0.048) 0.236 (0.518) Trust government information 0.133 (0.062) -1.167 (0.728) Trust information from generies 0.013 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) peers 0.028 (0.043) 0.309 (0.471) Additional income 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171	Kolfe farm location	0.183** (0.056)	2.158** (0.715)
No education 0.168** (0.065) 1.698** (0.609) Primary education 0.067 (0.052) 0.721 (0.549) Secondary education 0.069 (0.042) 0.743 (0.452) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience 0.134* (0.056) 1.407* (0.572) 1-5 years of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.103 (0.062) -1.167 (0.728) Trust information from other 0.013 (0.047) 0.140 (0.503) farmers - - - Perceived fellow farmers as 0.132* (0.051) 1.389** (0.529) peers - - - Membership in farmer - - 0.22 (0.472) organizations/groups 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171 -	Sebeta farm location	0.103 (0.057)	1.159 (0.669)
Primary education -0.067 (0.052) -0.721 (0.549) Secondary education -0.069 (0.042) -0.743 (0.452) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience -0.134* (0.056) -1.407* (0.572) 1-5 years of experience 0.028 (0.052) 0.305 (0.570) More than 10 years of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.133 (0.062) -1.167 (0.728) Trust information from government agencies 0.013 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) perceived fellow farmers as 0.132* (0.051) 1.389** (0.529) percs -0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171 -0.223 (0.472)	Sendafa farm location	-0.154* (0.060)	-1.575** (0.580)
Secondary education 0.069 (0.042) 0.743 (0.452) Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience 0.134* (0.056) -1.407* (0.572) 1-5 years of experience -0.028 (0.052) 0.305 (0.570) More than 10 years of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.103 (0.062) -1.167 (0.728) Trust information from other 0.013 (0.047) 1.466** (0.500) government agencies -0.132* (0.051) 1.389** (0.529) Perceived fellow farmers as 0.132* (0.051) 1.389** (0.529) peers -0.021 (0.044) -0.223 (0.472) organizations/groups 0.028 (0.043) 0.309 (0.471) Additional income 0.028 (0.043) 0.309 (0.471)	No education	-0.168** (0.065)	-1.698** (0.609)
Number of female workers 0.0169*** (0.005) 0.184*** (0.050) Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience -0.134* (0.056) -1.407* (0.572) 1-5 years of experience 0.028 (0.052) 0.305 (0.570) More than 10 years of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.103 (0.062) -1.167 (0.728) Trust information from government agencies 0.143** (0.052) 1.466** (0.500) government agencies 0.13 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) perceived fellow farmers as 0.132* (0.051) 1.389** (0.529) organizations/groups 0.028 (0.043) 0.309 (0.471) Additional income 0.028 (0.043) 0.309 (0.471) Inalpha -34.07	Primary education	-0.067 (0.052)	-0.721 (0.549)
Number of male workers 0.004 (0.002) 0.038 (0.026) No years of experience -0.134* (0.056) -1.407* (0.572) 1-5 years of experience 0.002 (0.048) -0.236 (0.518) Trust government information -0.103 (0.062) -1.167 (0.728) Trust information from government agencies 0.013 (0.047) 1.466** (0.500) government agencies 0.143** (0.052) 1.466** (0.500) Trust information from other farmers 0.013 (0.047) 0.140 (0.503) Perceived fellow farmers as 0.132* (0.051) 1.389** (0.529) peers -0.021 (0.044) -0.223 (0.472) Organizations/groups 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171	Secondary education	-0.069 (0.042)	-0.743 (0.452)
No years of experience 0.134* (0.056) 1.407* (0.572) 1-5 years of experience 0.028 (0.052) 0.305 (0.570) More than 10 years of experience 0.022 (0.048) 0.236 (0.518) Trust government information 0.103 (0.062) 1.167 (0.728) Trust information from government agencies 0.143** (0.052) 1.466** (0.500) Trust information from other 0.013 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) peers 0.021 (0.044) -0.223 (0.472) organizations/groups 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171	Number of female workers	0.0169*** (0.005)	0.184*** (0.050)
1-5 years of experience 0.028 (0.052) 0.305 (0.570) More than 10 years of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.103 (0.062) -1.167 (0.728) Trust information from government agencies 0.143** (0.052) 1.466** (0.500) government agencies 0.013 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) perceived fellow farmers as 0.132* (0.051) 1.389** (0.529) government information -0.021 (0.044) -0.223 (0.472) Organizations/groups 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171 1	Number of male workers	0.004 (0.002)	0.038 (0.026)
More than 10 years of experience -0.022 (0.048) -0.236 (0.518) Trust government information -0.103 (0.062) -1.167 (0.728) Trust information from 0.143** (0.052) 1.466** (0.500) government agencies 0.013 (0.047) 0.140 (0.503) Trust information from other 0.013 (0.047) 0.140 (0.503) farmers 0.132* (0.051) 1.389** (0.529) perceived fellow farmers as 0.132* (0.051) 1.389** (0.529) peers -0.021 (0.044) -0.223 (0.472) organizations/groups 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171	No years of experience	-0.134* (0.056)	-1.407* (0.572)
Trust government information -0.103 (0.062) -1.167 (0.728) Trust information from government agencies 0.143** (0.052) 1.466** (0.500) Trust information from other agencies 0.013 (0.047) 0.140 (0.503) Trust information from other farmers 0.132* (0.051) 1.389** (0.529) Perceived fellow farmers as 0.132* (0.051) 1.389** (0.529) Membership in farmer -0.021 (0.044) -0.223 (0.472) organizations/groups 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171 1 Inalpha -34.07 1	1–5 years of experience	0.028 (0.052)	0.305 (0.570)
Trust information from government agencies 0.143** (0.052) 1.466** (0.500) Trust information from other farmers 0.013 (0.047) 0.140 (0.503) Perceived fellow farmers as peers 0.132* (0.051) 1.389** (0.529) Membership in farmer organizations/groups -0.021 (0.044) -0.223 (0.472) Additional income 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171	More than 10 years of experience	-0.022 (0.048)	-0.236 (0.518)
government agenciesInter (unity)Inter (unity)Trust information from other farmers0.013 (0.047)0.140 (0.503)Perceived fellow farmers as peers0.132* (0.051)1.389** (0.529)Membership in farmer organizations/groups-0.021 (0.044)-0.223 (0.472)Additional income0.028 (0.043)0.309 (0.471)Constant2.228*** 0.171-34.07	Trust government information	-0.103 (0.062)	-1.167 (0.728)
farmersInter (arts)Perceived fellow farmers as peers0.132* (0.051)1.389** (0.529)Membership in farmer organizations/groups-0.021 (0.044)-0.223 (0.472)Additional income0.028 (0.043)0.309 (0.471)Constant2.228*** 0.171Inter (arts)Inalpha-34.07Inter (arts)		0.143** (0.052)	1.466** (0.500)
peers -0.021 (0.044) -0.223 (0.472) Membership in farmer organizations/groups -0.028 (0.043) 0.309 (0.471) Additional income 0.028 (0.043) 0.309 (0.471) Constant 2.228*** 0.171		0.013 (0.047)	0.140 (0.503)
organizations/groups 0.028 (0.043) 0.309 (0.471) Additional income 0.228*** 0.171 0.309 (0.471) Constant 2.228*** 0.171 0.111 Inalpha -34.07 0.111		0.132* (0.051)	1.389** (0.529)
Constant 2.228*** 0.171 Inalpha -34.07	*	-0.021 (0.044)	-0.223 (0.472)
Inalpha -34.07	Additional income	0.028 (0.043)	0.309 (0.471)
	Constant	2.228*** 0.171	
N 159	Inalpha	-34.07	
107	N	159	

*p<0.05, **p<0.01, ***p<0.001. *** indicates the variable is significant at the 0.01 level; ** indicates the variable is significant at the 0.05 level; * indicates the variable is significant at the 0.10 level. Values in parentheses are standard errors of the estimate. Marginal effects are computed at the means of the Xs. (*) dy/dx is for discrete change of dummy variable from 0 to 1.

extent of adoption of dairy technologies. Our findings do not show any significant relationship however for the sample population, this may be due to the limitation of having a small sample size, or the purposive and convenience based sampling undertaken. Consequently results from the binary logistic model indicate farm knowledge, accessibility of extension services, gender, farm size, farming experience, and crossbreeds' availability had a positive association with dairy technology adoption, while age and market distance had a negative association (Abbasi and Nawab, 2021).

Trust in information from government agencies was associated with a higher propensity to adopt multiple technologies as was farmer perception of fellow farmers as peers. How they perceive their fellow farmer is important to note as it has an impact on uptake and diffusion of technologies. Fox et al. (2021) findings suggest that farmers look to their peers for advice prior to making a decision on whether or not to adopt technology. Other studies have shown that farmers within a social group learn from each other more fully the benefits and usage of new technology. For example, Uaiene Rafael (2011) suggests that social network effects are important for individual decisions and that farmers share information and learn from each other in adopting agricultural innovation. This is an important finding as it may help policymakers or institutions explore knowledge exchange and diffusion of innovation strategies tailored to specific farming and community situations (Manning, 2013).

Farming experience is essential in dairy production. Specially, longer farming experience generally induces farmers to obtain more information about improved technologies and practices from informal sources, and information gathering from more formal sources is associated with greater exposure to demonstrations or training and membership in farmers groups or cooperatives (Kumar et al., 2020). Past studies have shown that larger-sized farms are generally more likely to adopt technology than smaller ones (Rahelizatovo and Gillespie, 2004). The adoption of new technology often involves substantial initial capital investment, and farmers with greater resources are better able to afford the technology and fully utilize it, and also to derive the maximum benefit. Technology adoption rates increased significantly with increased education level and herd size (Rahelizatovo and Gillespie, 2004; Mekonnen et al., 2010; Kumar et al., 2020). Studies reported here suggests that the interactions could be nuanced, and further research is required to understand the interaction of socioeconomic factors more clearly.

6. Conclusion and policy implications

Smallholder dairy production systems in SSA countries are characterized by low productivity and a low rate of technology adoption. The adoption of modern technologies, singularly or multiple technologies, has been seen to improve farmers' productivity, the welfare of farmed animals, personal farmers' livelihoods, and can potentially drive rural development and poverty reduction. Although the use of technology has increased in recent years, the adoption and diffusion rate of modern technology in the dairy sector in Ethiopia and other countries has been low and slow. The need to stimulate and promote adoption intensity, therefore, is clear and needs to be addressed. The adoption of multiple technologies in dairy farming, from the 19 examined here, remains a promising strategy in Ethiopia for improving the welfare of rural households, reducing poverty, improving food security and ensuring environmental sustainability, but uptake of individual technologies across the sample group of farmers differs greatly. There is limited knowledge in SSA, particularly in East Africa, of what technologies smallholder dairy farmers are adopting and the factors influencing farmer adoption decisions. Therefore, this study sought to address this knowledge gap. Our study variability in both the number of technologies adopted and the types of technologies chosen. Economic return is a driver and the focus is on utility in a given context within a farming business. Differentiated uptake of technology based on socio-demographic factors including farm location, suggests a range of factors of influence including access. At one end of the scale, less than one in five farmers had

adopted technologies such as containers used for milking and storage, dry cow therapy, and testing new cattle before introducing them to the herd. However there was clear strong uptake for technologies that addressed breeding, good nutrition, vaccination and parasite control and disinfection of teats both individually and combined. The findings show trust mediates farmers' decision making on technology adoption especially peer-to-peer trust networks and this is worthy of further study. This study has implications for policy, knowledge exchange and strategies to continue to improve productivity, disease controls and public health in the dairy production in Ethiopia. This study has policy implications beyond Ethiopia. The particular factors of the size of the dairy sector as well as challenges with endemic disease made Ethiopia an interesting lens through which to explore technology adoption, but the findings can be generalized to other countries with similar challenges. Developing guidance programs which can be disseminated through trusted knowledge brokers is essential to increase uptake especially technologies that have low cost implications. This is essential in promoting appropriate disease control strategies as if some farmers do not engage this will mean their farms may harbor zoonoses making them far more difficult to eradicate. The lack of uptake of some of the food safety and food quality interventions also raises concerns about the impact on public health programs. If there is a limited supply chain driver for improving food safety then this will need to be driven more fully at regulatory level. While, previous work has identified that the adoption of modern agricultural technologies in Ethiopia's dairy production system has multiple socio-economic benefits, this study shows that the take-up of such technologies is not consistent limiting the benefits that can be derived. This study would propose that further work needs to be undertaken to increase uptake with a clear focus on geographic differences, and greater knowledge and technology exchange to drive greater adoption intensity.

Data availability statement

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

References

Abbasi, S., and Nawab, K. (2021). Determinants of the dairy technology adoption by the rural Milk producers in district Muzaffarabad, Azad Jammu and Kashmir. *Sarhad J Agric* 37, 921–929. doi: 10.17582/journal.sja/2021/37.3.921.929

Akzar, R., Umberger, W., and Peralta, A. (2019). Adoption of multiple dairy farming technologies by the Indonesian smallholder dairy farmers: a latent class analysis approach. In: 2019 Conference (63rd), February 12–15, 2019, Melbourne, Australia.

Alemayehu, G., Mamo, G., Desta, H., Alemu, B., and Wieland, B. (2021). Knowledge, attitude, and practices to zoonotic disease risks from livestock birth products among smallholder communities in Ethiopia. One Health 12:100223. doi: 10.1016/j.onehlt.2021.100223

Amenu, K., Grace, D., Nemo, S., and Wieland, B. (2019). Bacteriological quality and safety of ready-to-consume Milk and naturally fermented Milk in Borana pastoral area, southern Ethiopia. *Tropl. Anim. Health Prod.* 51, 2079–2084. doi: 10.1007/s11250-019-01872-8

Ashley, K., Wilson, S. Jr., Young, H. C., Vitou, S., Suon, S., Windsor, P., et al. (2018). Drivers, challenges and opportunities of forage technology adoption by smallholder cattle households in Cambodia. *Tropl. Anim. Health Prod.* 50, 63–73. doi: 10.1007/ s11250-017-1400-y

Barrios, D., Restrepo-Escobar, F. J., and Cerón-Muñoz, M. (2020). Factors associated with the technology adoption in dairy agribusiness. *Revista Facultad Nacional de Agronomía Medellín* 73, 9221–9226. doi: 10.15446/rfnam.v73n2.82169

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Funding

This research was financially supported by the Ethiopia Control of Bovine Tuberculosis Strategies (ETHICOBOTS) project funded by the Biotechnology and Biological Sciences Research Council, the Department for International Development, the Economic and Social Research Council, the Medical Research Council, the Natural Environment Research Council, and the Defence Science and Technology Laboratory, under the Zoonoses and Emerging Livestock Systems (ZELS) program, ref.: BB/L018977/1.

Acknowledgments

We would like to acknowledge the farmers in Addis Ababa and Oromia regions who participated in this study and who do great animal health work under resource-constrained conditions.

Conflict of interest

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Burkitbayeva, S., Janssen, E., and Swinnen, J. (2019). Technology adoption and value chains in developing countries: panel evidence from dairy in Punjab. In: Discussion paper 410/2019. LICOS discussion paper series. LICOS discussion paper series. Leuven.

Chagwiza, C., Muradian, R., and Ruben, R. (2016). Cooperative membership and dairy performance among smallholders in Ethiopia. *Food Policy* 59, 165–173. doi: 10.1016/j.foodpol.2016.01.008

Dehinenet, G., Mekonnen, H., Kidoido, M., Ashenafi, M., and Bleich, E. G. (2014). Factors influencing adoption of dairy technology on small holder dairy farmers in selected zones of Amhara and Oromia National Regional States, Ethiopia 2, 11. Available at: https://www.researchgate.net/profile/Ashenafi-Mengistu/ publication/274008456_ The_impact_of_dairy_technology_adoption_on_small_holder_dairy_farmers_ livelihoods_in_selected_zones_of_Amhara_and_Oromia_National_Regional_ States_Ethiopia/links/Seba4eda4585152169c84b55/The-impact-of-dairytechnologyadoptionon-small-holder-dairy-farmers-livelihoods-in-selected-zones-of-Amhara-and-Oromia-National-Regional-States-Ethiopia.pdf

Deneke, T. T., Bekele, A., Moore, H. L., Mamo, T., Almaw, G., Mekonnen, G. A., et al. (2022). Milk and meat consumption patterns and the potential risk of zoonotic disease transmission among urban and Peri-urban dairy farmers in Ethiopia. *BMC Public Health* 22:222. doi: 10.1186/s12889-022-12665-4

Fox, G., Mooney, J., Rosati, P., and Lynn, T. (2021). AgriTech Innovators: A Study of Initial Adoption and Continued Use of a Mobile Digital Platform by Family-Operated Farming Enterprises. *Agriculture* 11, 1283. doi: 10.3390/ agriculture11121283

Gizaw, S., Desta, H., Alemu, B., Tegegne, A., and Wieland, B. (2020). Importance of livestock diseases identified using participatory epidemiology in the highlands of Ethiopia. *Tropl. Anim. Health Prod.* 52, 1745–1757. doi: 10.1007/s11250-019-02187-4

Janssen, E., and Swinnen, J. (2019). Technology adoption and value chains in developing countries: evidence from dairy in India. *Food Policy* 83, 327–336. doi: 10.1016/j.foodpol.2017.08.005

Kebebe, E. G. (2017). Household nutrition and income impacts of using dairy Technologies in Mixed Crop-Livestock Production Systems. *Aust. J. Agric. Resour. Econ.* 61, 626–644. doi: 10.1111/1467-8489.12223

Kebebe, E. (2019). Bridging technology adoption gaps in livestock sector in Ethiopia: a innovation system perspective. *Technol. Soc.* 57, 30–37. doi: 10.1016/j.techsoc.2018.12.002

Kebebe, E., Aj Duncan, L., Klerkx, I. J. M. D. B., and Oosting, S. J. (2015). Understanding socio-economic and policy constraints to dairy development in Ethiopia: a coupled functional-structural innovation systems analysis. *Agr. Syst.* 141, 69–78. doi: 10.1016/j.agsy.2015.09.007

Kumar, R., Singh, B. P., Kumar, V., Kumar, S., and Maousami, A. (2015). Adoption of health technologies among goat farmers in different agro-climatic zones of Bihar. *J. Appl. Anim. Res.* 43, 46–51. doi: 10.1080/09712119.2014.888002

Kumar, A., Takeshima, H., Thapa, G., Adhikari, N., Saroj, S., Karkee, M., et al. (2020). Adoption and diffusion of improved technologies and production practices in agriculture: insights from a donor-led intervention in Nepal. *Land Use Policy* 95:104621. doi: 10.1016/j.landusepol.2020.104621

Kumar, A., Thapa, G., Joshi, P. K, and Roy, D. (2016). Adoption of food safety measures among Nepalese Milk producers: Do smallholders benefit? In: IFPRI—Discussion Paper 1556, IFPRI Discussion Paper 01556, no. October: 1–52.

Kumar, A., Thapa, G., Roy, D., and Joshi, P. K. K. (2017). Adoption of food safety measures on Milk production in Nepal: impact on smallholders Farm-Gate Prices and Profitability. *Food Policy* 70, 13–26. doi: 10.1016/j.foodpol.2017.05.002

Kumar, A., Wright, I. A., and Singh, D. K. (2011). Adoption of food safety practices in Milk production: implications for dairy farmers in India. *J Int Food Agribus Market* 23, 330–344. doi: 10.1080/08974438.2011.621855

Liu, J., Toma, L., Barnes, A. P., and Stott, A. (2019). Farmers uptake of animal health and welfare technological innovations. Implications for animal health policies. *Front Vet Sci* 6:00410. doi: 10.3389/fvets.2019.00410

Manning, L. (2013). A knowledge exchange and diffusion of innovation (KEDI) model for primary production. Br. Food J. 115, 614–631. doi: 10.1108/00070701311317883

Mekonnen, H., Dehninet, G., and Kelay, B. (2010). Dairy technology adoption in smallholder farms in "Dejen" district, Ethiopia. *Tropl. Anim. Health Prod.* 42, 209–216. doi: 10.1007/s11250-009-9408-6

Mwangi, M., and Kariuki, S. (2015). Factors determining adoption of new agricultural technology by smallholder farmers in developing countries, *J. Econ. Sustain. Dev.* 6, 208–216. Available at: https://core.ac.uk/download/pdf/234646919.pdf

Nonvide, G. M. A. (2021). Adoption of agricultural technologies among Rice farmers in Benin. *Rev. Dev. Econ.* 25, 2372–2390. doi: 10.1111/rode.12802

Ojango, J. M. K., Mrode, R., Okeyo, A. M., Rege, J. E. O., Chagunda, M. G. G., and Kugonza, D. R. (ILRI) (2017). "Improving smallholder dairy farming in Africa" in *Achieving sustainable production of milk Volume 2: Safety, quality and sustainability.* ed. N. van Belzen (Cambridge, UK: Burleigh Dodds Science Publishing), 337-362.

Rahelizatovo, N. C., and Gillespie, J. M. (2004). The adoption of best-management practices by Louisiana dairy producers. *J. Agric. Appl. Econ.* 36, 229–240. doi: 10.1017/S1074070800021970

Ritter, C., Jansen, J., Roth, K., Kastelic, J. P., Adams, C. L., and Barkema, H. W. (2016). Dairy farmers' perceptions toward the implementation of on-farm Johne's disease prevention and control strategies. *J. Dairy Sci.* 99, 9114–9125. doi: 10.3168/ jds.2016-10896

Russell, R. A., and Bewley, J. M. (2013). Characterization of Kentucky dairy producer decision-making behavior. *J. Dairy Sci.* 96, 4751–4758. doi: 10.3168/jds.2012-6538

Ruzzante, S., Labarta, R., and Bilton, A. (2021). Adoption of agricultural Technology in the Developing World: a Meta-analysis of the empirical literature. *World Dev.* 146:105599. doi: 10.1016/j.worlddev.2021.105599

Sarrazin, S., Cay, A. B., Laureyns, J., and Dewulf, J. (2014). A survey on biosecurity and management practices in selected Belgian cattle farms. *Prev. Vet. Med.* 117, 129–139. doi: 10.1016/j.prevetmed.2014.07.014

Tschopp, R., Gemechu, G., and Wood, J. L. N. (2021). A longitudinal study of cattle productivity in intensive dairy farms in Central Ethiopia. *Front Vet Sci* 8:698760. doi: 10.3389/fvets.2021.698760

Uaiene Rafael, N. (2011). 'Determinants of agricultural technology adoption in Mozambique. In: *10th African Crop Science Conference Proceedings*, Maputo, Mozambique, 10–13 October 2011. African Crop Science Society.

Yang, W., Edwards, J. P., Eastwood, C. R., Dela Rue, B. T., and Renwick, A. (2021). Analysis of adoption trends of in-parlor technologies over a 10-year period for labor saving and data capture on pasture-based dairy farms. *J. Dairy Sci.* 104, 431–442. doi: 10.3168/jds.2020-18726

Yengoh, G. T., and Ardö, J. (2020). Climate change and the future heat stress challenges among smallholder farmers in East Africa. *Atmos.* 11:753. doi: 10.3390/atmos11070753

Zegeye, M. B., Fikire, A. H., and Meshesha, G. B. (2022). Determinants of multiple agricultural technology adoption: evidence from rural Amhara region, Ethiopia. *Cogent Econ Fin* 10. doi: 10.1080/23322039.2022.2058189