THAI JOURNAL OF
AGRICULTURAL SCIENCE
Vol.58 No.3 July-September 2025
https://li01.tci-thaijo.org/index.php/TJAS

Determinants of tractors adoption among smallholder farmers in Makuey district, Gambella region, Ethiopia

Chuol Bor[1,*]
Duol Khon[2]

[1] Department of Rural Development and Agricultural Extension, College of Agriculture and Natural Resources, Gambella University, Gambella 5444, Ethiopia
[2] Department of Economics, College of Business and Economics, Gambella University, Gambella 5444, Ethiopia

*Corresponding author: nyanuer874@gmail.com

Article History

Submission: 12 February 2025
Revised: 20 June 2025
Accepted: 26 June 2025

Keywords

Tractor adoption
Smallholder farmers
Makuey district
Gambella region
Ethiopia

Abstract

Background and Objective: The Gambella region has significant agricultural potential. However, various obstacles have prevented the development of agriculture and limited smallholder farmers' capabilities to increase their income. This study aimed to determine the adoption of tractors by smallholder farmers in the Makuey district.

Methodology: The study sample comprised 250 smallholder farmers from the Makuey district. A multi-stage sampling technique was used, beginning with purposive sampling to choose the district because of its low tractor adoption by smallholder farmers. Simple random sampling was used to select kebelles, followed by random sampling of farmers within each village. Data were gathered through focus group discussions, structured interviews, questionnaires, and key informant interviews. The study employed mean, standard deviation, frequency, percentage, chi-square tests, t-tests, and binary logistic regression to analyze the data.

Main Results: The findings revealed that access to credit was positively associated with farmers' tractor adoption ($\chi^2 = 10.000$, $P < 0.01$). The total annual income showed a statistically significant mean difference ($t = -3.470$, $P < 0.01$) and farming experience ($t = 2.015$, $P < 0.05$) between adopters and non-adopters. Furthermore, binary logistic regression revealed that educational level ($P < 0.05$), cultural norms ($P < 0.01$), total annual income ($P < 0.01$), and access to subsidies ($P < 0.01$) were the main variables that influenced farmers' tractor adoption.

Conclusions: Increasing tractor adoption among smallholder farmers is imperative and will require policy intervention. Increasing access to credit on favorable terms, strengthening farmer training programs, and improving income diversification can each contribute to alleviating financing and knowledge constraints. Reducing cultural norms through sensitization and raising subsidies or cheap loan rates for machinery would also facilitate adoption. Harmonizing these interventions can transform agriculture and enhance farm income in the region.

How to cite : Bor, C. and D. Khon. 2025. Determinants of tractors adoption among smallholder farmers in Makuey district, Gambella region, Ethiopia. Thai J. Agric. Sci. 58(3): 190−208.

INTRODUCTION

Agriculture remains a cornerstone of Ethiopia's economy, engaging approximately 80% of the population and contributing to over 40% of the national GDP (Fekad, 2020). The sector is predominantly composed of smallholder farmers who cultivate approximately 95% of the country's agricultural land using rain-fed traditional practices. These methods result in low productivity and heightened vulnerability to climate change (Zerssa *et al.*, 2021).

To address these challenges, various initiatives have been launched to promote agricultural mechanization. Notably, the Agricultural Mechanization for Smallholder Farmers (AMS) project, led by the Ethiopian Ministry of Agriculture and German Development Cooperation (GIZ), aims to expand access to mechanization through policy reforms, skills development, and institutional support (Teklewold, 2021). Similarly, the Agricultural Mechanization Leasing Project, funded by KfW and implemented by the GFA Consulting Group and First Consult Plc., offers machinery leasing contracts to smallholder farmers (Ayele, 2022). However, in regions such as Gambella, particularly the Makuey district, documentation and evaluation of mechanization efforts remain limited despite emerging evidence of productivity gains (Bor and Deng, 2024).

Tractor adoption, a key driver of mechanization, is shaped by a combination of economic, socio-demographic, cultural, and institutional factors. Larger farm sizes and higher household incomes are positively associated with adoption because of scale efficiencies and financial capacity (Onomu and Aliber, 2021; Hu *et al.*, 2022). Access to credit and government subsidies also significantly increases adoption rates (Aryal *et al.*, 2021; Barbosa, 2024). In contrast, low education levels, entrenched cultural norms, and gender disparities often hinder adoption, particularly among women (Crudeli *et al.*, 2021; Ogisi and Begho, 2023).

While previous studies have explored mechanization in Ethiopia, little is known about tractor adoption in the Makuey district. This study aims to fill this gap by examining the economic, cultural, and institutional factors that influence tractor adoption among smallholder farmers in the region. By identifying both barriers and drivers, this study provides actionable insights for developing targeted policy interventions, extension services, and credit programs. These insights are essential not only for expanding tractor use but also for enhancing broader agricultural practices, including nursery management and crop production, such as coffee farming, which stand to benefit from mechanized land preparation, seedbed formation, and efficient field operations. This research supports efforts to modernize Ethiopian agriculture in an inclusive, sustainable, and locally tailored manner.

MATERIALS AND METHODS

Description of the Study Area

The study was conducted in the Makuey district of the Gambella region, Ethiopia, which was chosen for its agricultural potential and increasing interest in mechanization among smallholder farmers. Several districts bordering the Makuey district are Jekow to the north, Abobo to the west, Itang to the east, and Wanthoa to the south. The region is characterized by its flat terrain and is crossed by several rivers, including the Baro River, which is a significant water source for agriculture and for local livelihoods. The approximate coordinates for the Makuey district are 8.8° N latitude and 34.5° E longitude, with a mean elevation of approximately 500 m (1,640 ft) above sea level. The distance from the Makuey district to Addis Ababa is approximately 800 km by road, and its distance from the capital of the Gambella region is approximately 130 km by road. Recent estimates indicate that the Makuey district has a total population of approximately 73,000, with 35,500 males and 37,500 females. The population is mainly rural, with 63,000 people living in rural areas and 10,000 in urban areas of the city. The climate in the Makuey district is tropical, with a wet season from May to October and a dry season from November to April. The region experiences an average annual rainfall of approximately 1,200–1,500 mm, and its average annual temperature ranges from 24°C to 30°C (Bor and Deng, 2024).

The primary economic activity in the Makuey district is agriculture. Farmers engage in subsistence farming and cultivate crops such as maize, sorghum, millet, and beans. Land and water resources from nearby rivers support these agricultural activities. The district is home to various ethnic groups that practice traditional agriculture and rely on river systems for fishing and farming activities. Raising cattle, goats, and sheep is also important in many homes. Fishing is another important economic activity in the region because of its proximity to rivers such as Baro. Additionally, small-scale trade and local markets play an important role in the economy of the district by facilitating the exchange of agricultural products, livestock, and fish, which contributes to local economic activities (Bor and Deng, 2024).

Research Design

The research design was a descriptive, cross-sectional survey. This design is appropriate for identifying the factors influencing tractor adoption among smallholder farmers at a specific point in time. This study describes the relationship between various factors and tractor adoption. This study employed both quantitative and qualitative approaches, which are mixed research methods.

Sampling Technique and Sample Size Determination

The target population included all small farmers in the Makuey district of the Gambella Region. The sampling frame included a list of registered smallholder farmers in the district received from the local agricultural office and cooperative societies. This study employed a multistage sampling technique. In the first stage, purposive sampling was used to select the Makuey district based on the high concentration of smallholder farmers and its relevance to the research objectives. In the second stage, a simple random sampling technique was used to select three kebelles (the smallest Ethiopian administrative unit) from a total of 23 kebelles in the district. The 250 respondents were then proportionally allocated across the selected kebelles based on the household population to ensure a balanced representation. In the third stage, smallholder farmers were randomly selected from each village to participate in this study. Furthermore, a sample size of 250 smallholder farmers was determined using Cochran’s (Cochran, 1977) formula to calculate the sample size for large populations. The equation used a 95% confidence level, a margin of error of 5%, and an estimated 50% adoption ratio of the tractor. Because no prior data or quality estimates of the adoption ratio of smallholder farmers utilizing tractors were available in the study area, an estimate of 50% adoption was made. This is used in sample size estimation when the population proportion is unknown because it maximizes variability to enable a more conservative but statistically more adequate estimate. This approach minimizes the risk of underestimating the required sample size and ensures that the results are representative and reliable.

$$n = \frac{z^2 \times p \times (1-p)}{e^2} \quad \text{--- [1]}$$

$$n = \frac{(1.96)^2 \times 0.5 \times (1-0.5)}{(0.05)^2} = 250$$

where *n* is the sample size, *Z* is the Z-value (1.96 for 95% confidence level), *p* is the estimated proportion of the population adopting tractors (0.5), and *e* is the margin of error (0.05).

Methods of Data Collection

Structured interviews

Structured interviews were conducted with the selected farmers. The interview schedule was prepared by incorporating both closed and open questions. The questions covered various aspects, such as socioeconomic characteristics, farm size, access to credit, knowledge and perception of the use of tractors, and other factors that influence farmers' decisions to adopt tractors. The main inclusion criteria were as follows: (1) being a smallholder farmer living in the Makuey district, Gambella region, Ethiopia; (2) having been actively farming for the last two consecutive years or more; and (3) holding a decision-making role at the farm level, especially in technology adoption. Both male and female farmers were included to account for gender differences. Structured interviews provided consistency and reduced interviewer bias while permitting the questioning of questionnaire items. This facilitated greater accuracy and reliability of responses, especially in rural areas, where literacy is uneven. In the case of structured interviews, some of the primary questions included: "How many hectares of land do you have?", "Did you hire a tractor on your farm within the last 12 months?", "What are the major hindrances that prevent you from receiving tractor services?", and "How would you judge your knowledge of tractor operation and maintenance?".

Structured questionnaires

A structured questionnaire was designed, pre-tested, and administered to the farmers. The questionnaire included questions about demographic data, agricultural characteristics, agricultural practices, access to extension services, and tractor perceptions. All the farmers were included in the study population and sample frame. The study population comprised smallholder farmers in the Makuey district who met the eligibility criteria. Structured questionnaires were used to collect standardized quantitative information from a representative sample of the farmers. This facilitated the statistical analysis of important variables, such as tractor adoption rates, socioeconomic traits, and farm-level characteristics. In the case of structured questionnaires, some of the primary questions included: "How many hectares of land do you have?", "Did you hire a tractor on your farm within the last 12 months?", "What are the major hindrances that prevent you from receiving tractor services?", and "How would you judge your knowledge of tractor operation and maintenance?".

Focus group discussions (FGDs)

FGDs were conducted to collect qualitative data on the collective views of farmers regarding the adoption of tractors. These discussions helped capture community-level factors and shared experiences. The FGDs yielded rich qualitative information on farmers' attitudes, group problems, and situational drivers of technology usage. They also helped confirm and elaborate on the quantitative findings by uncovering patterns at the community level that could not be ascertained using individual surveys. These were designed to provide quantitative information on farm size, tractor usage patterns, access barriers, and personal capacity of the farmers. In the course of FGDs, questions such as “How do farmers in your locality tend to perceive the application of tractors in farming?”, “Which social or cultural beliefs determine the adoption of tractors?”, and “Are there mechanization community-based initiatives or collaborative services with similar experiences?”. Three focus group discussions were used to gather qualitative data on farmers’ collective perceptions of tractor adoption. The FGD had six to ten participants purposively selected based on their age, gender, farm size, and experience in mechanical farming. Participants were sampled from various kebelles in the study area to gather diverse community-level opinions. Discussions were conducted with trained moderators using a semi-structured guide with open-ended questions to gather an understanding of perceptions of tractor benefits, barriers to access, cultural attitudes, and decision-making dynamics at the community level. The sessions were conducted in the local language, audio-recorded with the permission of the participants, and subsequently transcribed and translated for analysis.

Key informant interviews (KIIs)

Key informant interviews with agriculture extension workers, local leaders, and representatives from non-governmental organizations were conducted to gain insight into the broader perspective of tractor adoption in the study area. Community leaders, agricultural experts, and service providers were consulted through KIIs to obtain expert views regarding the institutional and infrastructural challenges that impact mechanization. The interviews provided a macro-level perspective to augment household-level information. These were designed to question common and community-level perceptions. The KIIs posed questions such as: “What is the extent of the support from the existing government or NGO program towards agricultural mechanization?”, “What have been the observed challenges towards the acceptance of tractors at the community level?”, and “To what extent do existing extension services influence advocating for better ways of farming?”. Agricultural extension officers, local leaders, and representatives of non-governmental organizations were interviewed using the key informant method. They were purposively selected based on their career experience, direct work with farm communities, and close awareness of mechanization activities in farming in the study area. They were important because their opinions enabled one to have a deeper institutional and policy-level understanding of the factors determining tractor adoption by the farmers.

Methods of Data Analysis

Qualitative data analysis

Focus group discussions and key informant interview data were analyzed using thematic analysis. The main themes related to the barriers and facilitators of the adoption of tractors were identified, encoded, and analyzed to complement the quantitative findings. To reduce acquiescence response bias, where participants agreed with statements irrespective of content, the interview guides contained positive and negative framing of the questions. This ensured that participants critically thought through their opinions and experiences instead of responding in a passive manner, thus improving the validity and reliability of the qualitative data. Qualitative data obtained from key informant interviews and focus group discussions were coded using thematic analysis. The transcripts were carefully read and coded manually to discern patterns and emerging themes of tractor use, barriers to access, and institutional support. Inductive codes were generated directly from the data, and deductive codes were guided by the research aims and the prior literature.

Quantitative data analysis

Descriptive analysis

Descriptive statistics, such as means, frequencies, percentages, and standard deviations, were used to analyze the data using the Statistical Package for Social Sciences (SPSS) software version 24. This analysis provides an overview of the respondents' economic, cultural, and institutional characteristics and the distribution of responses regarding tractor adoption.

Inferential analysis

The chi-square test was used to examine the association between categorical variables and tractor adoption. The t-test for analysis of variance was used to compare the means among different groups for continuous variables and tractor adoption rates. An independent samples t-test was employed to compare the means of the two groups (tractor adopters vs. non-adopters); therefore, the t-test was sufficient for this study. One-way ANOVA cannot be used because it compares more than two groups. Binary logistic regression analysis was used to identify the factors that greatly influenced farmers' decisions to adopt tractors. The dependent variable is binary (i.e., whether the farmer has adopted a tractor or not), and the independent variables are economic, cultural, and institutional factors. Tractor adoption is a dummy variable that takes the value 0 for non-adopted farmers and 1 for adopted farmers.

Model Specification

A binary logit regression model was used to determine the influence of selected economic, cultural, and institutional factors on smallholder farmers' tractor adoption. Logistic regression is a method for modelling situations in which there is a binary response variable. Following Green (2003), the functional form of the logit model is specified as:

$$\text{Log}\,(P_i / (1 - P_i)) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_K X_{Ki} + \varepsilon_i$$

where P_i is the probability that farmer i adopts a tractor, $(P_i / (1 - P_i))$ is the odds of tractor adoption, β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_K$ are the coefficients of the explanatory variables, $X_1, X_2, \ldots, X_{Ki}$ are the explanatory variables for farmer i, ε_i is the error term.

In this study, the explanatory variables include: X_1 = farm size (in hectares), X_2 = total annual income (ETB), X_3 = age (in years), X_4 = farming experience (in years), X_5 = access to credit (0 = no, 1 = yes), X_6 = subsidy access (0 = no, 1 = yes), X_7 = gender (0 = male, 1 = female), X_8 = education level (0 = illiterate, 1 = literate), and X_9 = cultural norm (0 = absence, 1 = presence). The final empirical model is thus expressed as:

$$\text{Log}(P_i / (1 - P_i)) = \beta_0 + \beta_1(\text{Farm size})_i + \beta_2(\text{Income})_i + \beta_3(\text{Age})_i + \beta_4(\text{Farming experience})_i + \beta_5(\text{Access to credit})_i + \beta_6(\text{Subsidy access})_i + \beta_7(\text{Gender})_i + \beta_8(\text{Education level})_i + \beta_9(\text{Cultural norm})_i$$

Equation (2): Binary logistic regression model (probability form)

The probability that a smallholder farmer adopts a tractor was computed as:

$$P(Y_i = 1) = \frac{1}{1 + \exp(-\beta_0 + \beta_i X_i)} \qquad \text{--- [2]}$$

Equation (3): Simplified notation using linear index Z_i

For ease of notation, we define:

$$P(Y_i = 1) = \frac{1}{1 + \exp(-Z_i)} \qquad \text{--- [3]}$$

where $Z_i = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ji}$ is a linear combination of the explanatory variables.

Equation (4): Non-adoption probability and complement rule

The probability that a farmer does not adopt a tractor is:

$$P(Y_i = 0) = 1 - P(Y_i = 1) = \frac{1}{1 + \exp(Z_i)} \quad \text{--- [4]}$$

Equation (5): Odds ratio

The odds of adoption (i.e., the ratio of the probability of adoption to non-adoption) is:

$$\frac{P(Y_i = 1)}{1 - P(Y_i = 1)} = \exp(Z_i) \quad \text{--- [5]}$$

Equation (6): Log odds or logit transformation

Taking the natural logarithm of the odds gives the logit model:

$$L_i = \ln\left(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)}\right) = Z_i \quad \text{--- [6]}$$

Diagnostic Test

Multicollinearity test

Before running a binary logistic regression for the independent variables, it was essential to check for multicollinearity. Multicollinearity occurs when there is a strong linear association among independent variables. If the variance inflation factor (VIF) for the continuous variables is less than 10, it indicates the absence of multicollinearity between the independent variables. For categorical variables, multicollinearity can be tested using a coefficient of contingency of less than 0.75 or 75%. However, if two or more variables are highly collinear, this can lead to inefficient estimates (Gujarati, 2004).

Goodness of fit test

Various methods exist for testing the goodness-of-fit of a model, one of which is the Hosmer-Lemeshow test. According to this test, a significant P-value indicates that the model fits the data poorly. Conversely, a non-significant P-value suggests that the model adequately fits the data (Hosmer and Lemeshow, 1980). The definitions of the variables are presented in Table 1.

Table 1 Definition of the variables

Variable names	Measurement	Nature	Expected outcome
Dependent variable			
Tractor adoption	0 = Non-adopter, 1 = Adopter	Dummy	-/+
Independent variable			
Gender	0 = Male, 1 = Female	Dummy	+/-
Age	Number of years	Continuous	+
Education level	0 = Illiterate, 1 = Literate	Dummy	+
Farming experience	Number of years	Continuous	-
Farm size	Hectare	Continuous	+
Total annual income	Ethiopian Birr	Continuous	+
Cultural norm	0 = Absence, 1 = Presence	Dummy	-
Access to credit	0 = No, 1 = Yes	Dummy	+
Subsides access	0 = No, 1 = Yes	Dummy	+

Note: Values ± mean those variables influence tractor adoption negatively and positively, respectively.

RESULTS AND DISCUSSION

Statistical Test for Economic, Cultural, and Institutional Categorical Variables

The results of this study showed that economic, cultural, and institutional factors influence tractor adoption in the study area, with some exerting a more significant influence. As shown in Table 2, these variables include gender, education level, cultural norms, access to credit, and access to subsidies. The findings revealed no significant association between gender and tractor adoption ($\chi^2 = 0.150$, P = 0.698). Among adopters, 65 males (72%) and 25 females (28%) adopted tractors, whereas among non-adopters, 112 males (70%) and 48 females

(30%) did not adopt tractors. This study suggests that gender does not play a relevant role in tractor adoption. Similarly, in Ghana, gender relations and power have been examined, revealing that male and female farmers can adopt technologies when provided with suitable support and training (Quaye *et al.*, 2022). This result also aligns with physiological and labor capacity findings, indicating that mechanized tools reduce the physical burden in farming, thus eliminating traditional gender divisions in manual labor. Tractors provide ergonomic benefits that help reduce musculoskeletal strain and fatigue, especially among women farmers, whose physical labor has often been under-recognized in agricultural development (Deepa and Subramanyam, 2025). Therefore, even though statistical significance is lacking, policy should still integrate gender-sensitive mechanization programs, focusing not only on access but also on the physiological appropriateness of machinery designs and operator training for female farmers. Thus, tractor adoption interventions should be fashioned to increase access to training for male and female farmers, with the aim of stimulating technology uptake that is equally balanced. Thus, interventions to boost tractor adoption in the Makuey district can target improved access to finance (credit and subsidies) and target farmers with larger farm sizes, whose adoption chances are higher for new technologies.

Table 2 Results for dummy variables (n = 250)

Variable	Data set	Adopter		Non-adopter		Chi-square	P-value
		Frequency	Percentage	Frequency	Percentage		
Gender	Male	65	72	112	70	0.150	0.698
	Female	25	28	48	30		
Educational level	Illiterate	40	44	78	49	0.520	0.471
	Literate	50	56	82	51		
Cultural norm	No	55	61	98	61	0.001	0.976
	Yes	35	39	62	39		
Access to credit	No	60	67	80	50	10.000	0.001
	Yes	30	33	80	50		
Subsides access	No	45	50	88	55	0.530	0.467
	Yes	45	50	72	45		

The educational level did not significantly influence tractor adoption ($\chi^2 = 0.520$; $P = 0.471$). Among the adopters, 40 were illiterate (44%) and 50 were literate (56%), while 78 were illiterate (49%) and 82 were literate (51%) among non-adopters. This aligns with Nakano *et al.* (2018) and Khadka *et al.* (2024), who argue that, in remote areas with limited educational access, education alone may not sufficiently influence technology adoption. Instead, access to credit and land size are stronger determinants. These findings suggest that access to credit, subsidized tractor services, and land security are more significant than education levels in formulating a mechanization policy. Locally focused extension services with practical guidance, independent of literacy levels, could enhance adoption and serve as models for other low-literacy rural environments. From a physiological perspective, education is typically expected to enhance the comprehension of technical manuals and safe operation protocols for tractors. However, in low-literacy contexts like Makuey, practical hands-on training often substitutes for formal education, allowing farmers to acquire operational proficiency through demonstration rather than through instruction. This implies that cognitive ability developed through experience and visual learning may compensate for formal literacy when adopting mechanized farming tools (Zincov, 2025). Accordingly, agricultural extension strategies should move beyond written material to embrace oral, visual, and participatory teaching methods tailored to adult learning styles in rural areas.

There was no significant relationship between cultural norms and tractor adoption (χ^2 = 0.001; P = 0.976). Among the adopters, 55 (61%) had no cultural restrictions, and 35 (39%) adhered to cultural norms. Among non-adopters, 98 (61%) had no cultural norms, while 62 (39%) did. This suggests that traditional practices are not obstacles to tractor adoption. Khadka *et al.* (2024) reported similar findings, noting that where knowledge and resources are accessible, traditional norms do not strongly impede innovation. Rogers' Diffusion of Innovations theory suggests that cultural norms act as a "compatibility" filter; in this context, tractor use appears to be compatible with local farming values (Miller, 2015). These results also underscore a potential physiological-cultural synergy: because tractors reduce physical exertion and improve productivity, they may be inherently accepted by communities that value labor efficiency and productivity. This functional advantage may override symbolic resistance to modern tools. In such settings, physiological utility becomes a cultural bridge, accelerating the acceptance of innovation (Mazur and Bański, 2021). Given the lack of cultural resistance, resources should prioritize technical support and infrastructure over cultural sensitization campaigns, making policies more cost-effective and impact-driven. Since cultural norms are not a constraint, policymakers in the Makuey district and other similar regions should shift their attention from cultural sensitization campaigns and instead direct efforts towards expanding access to training, equipment, and funds. Interventions should focus on technical capacity building and infrastructure development, as the absence of cultural resistance offers fertile ground for mechanization adoption.

Access to credit significantly influenced tractor adoption (χ^2 = 10.000, P = 0.001). Among the adopters, 60 (67%) did not have credit access, 30 (33%) had credit access, 80 (50%) did not have credit access, and 80 (50%) had access to credit from non-adopters. This indicates that farmers with formal credit access are more inclined to adopt tractor use. This finding echoes Máquina *et al.* (2024), who demonstrated that credit enhances smallholder access to mechanization by easing liquidity constraint. From a physiological and behavioral economics standpoint, access to credit reduces anxiety associated with high-risk, high-cost decisions such as machinery purchases. By easing financial stress, credit allows farmers to focus on the operational benefits of tractors, such as reduced fatigue, enhanced speed, and increased output, rather than their upfront costs. This psychological security promotes rational investment behavior, aligning with models of time-inconsistent preferences among poor farming households (Gorbachev and Luengo-Prado, 2019). To further enhance tractor adoption, rural finance schemes should incorporate low-interest loans, machinery leasing models, and bundled credit insurance products tailored to the agricultural calendar and climatic uncertainties. To enhance mechanization, interventions in the Makuey district should target the rural extension of financial services. Interventions can take the form of low-interest credit for agriculture, insurance against mechanization, and collaboration with microfinance institutions. A program specifically focused on purchasing or leasing equipment would have a substantial impact on tractor use and farm outputs.

Subsidy access did not significantly influence tractor adoption (χ^2 = 0.530; P = 0.467). Among adopters, 45 (50%) had no subsidies, 45 (50%) had subsidies, 88 (55%) had no subsidies, and 72 (45%) had subsidies, respectively. This suggests that while subsidies may offer temporary financial relief, they are insufficient to drive adoption in isolation. This mirrors the findings of Koppmair *et al.* (2017), who emphasized that subsidies must be paired with complementary support, such as training, technical assistance, and market access, to yield behavioral change. Physiologically, farmers may recognize the utility of tractors, but without ongoing support for training on maintenance or availability of spare parts, the stress and cognitive load associated with machinery breakdowns outweighs the initial benefits. Subsidies reduce purchase costs but do not reduce operational uncertainty. Behavioral inertia persists when adoption imposes unfamiliar learning curves or maintenance burdens (Dawid *et al.*, 2022). Hence, more integrative subsidy models are required, linking financial aid with after-sales services, mobile repair units, and embedded training within subsidy programs. Such hybrid designs address both economic and behavioral barriers to the sustained mechanization of agriculture. Policymakers need to rethink blanket subsidy schemes and instead concentrate on complementary interventions such as technical assistance, training, and market support. In Makuey and elsewhere, it would be more beneficial to couple small subsidies with access to credit and farm cooperatives to attain the maximum benefit and utilization of mechanization support programs.

Statistical Test for Economic, Cultural, and Institutional Continuous Variables

The results presented in Table 3 illuminate the differences between adopters and non-adopters across several economic, institutional and cultural variables. These included age, farming experience, farm size, and total annual income, and their statistical significance was analyzed using independent t-tests. Age showed no statistically significant difference between adopters (45.2 ± 12.5 years) and non-adopters (46.0 ± 13.2 years), with a t-value of -0.456 (P = 0.648). This suggests that age alone is not a physiological barrier to adopting mechanization. According to Martinez *et al.* (2024), older adults are just as capable of adopting new technologies when the perceived usefulness (PU) and perceived ease of use (PEOU) are high, indicating that cognitive evaluations mediate the adoption process more than age. From a neurocognitive perspective, even older farmers retain the decision-making plasticity needed to adapt to mechanized tools if they are exposed to user-friendly training environments (Park and Smith, 2022). Hence, interventions should be inclusive of all age groups and designed to emphasize benefits and usability using age-adapted learning strategies, such as hands-on training, visual aids, and repetitive skill drills. This can help overcome anxiety and resistance rooted in perceived complexity, a phenomenon commonly observed among older users of novel agricultural tools. Because age does not influence tractor adoption, policymakers can design interventions that address all adult age groups without prejudice toward young farmers. Interventions should aim to maximize the perceived benefits and ease of use of mechanization technologies for all age groups through training simulations, demonstration farms, and easy-to-understand operation manuals. They can assist in creating a level playing field for elderly farmers to adopt and benefit from mechanization.

Farming experience, on the other hand, revealed a statistically significant difference (t = 2.015, P = 0.045), with adopters averaging more experience (10.5 ± 5.3 years) than non-adopters (8.7 ± 5.6 years). This implies that experiential learning contributes to more accurate risk-benefit assessments and decision-making regarding technology adoption. From a behavioral standpoint, experienced farmers are likely to have encountered a broader spectrum of environmental and economic variabilities, fostering adaptability and strategic foresight (Kropf and Mitter, 2022). These attributes may translate into a greater propensity to invest in mechanization as a long-term labor-saving and productivity-enhancing solution for farmers.

Table 3 Results for continuous variables (n = 250)

Variable	Adopter		Non-adopter		t-test	P-value
	Mean	SD	Mean	SD		
Age (year)	45.2	12.5	46.0	13.2	-0.456	0.648
Farming experiences (year)	10.5	5.3	8.7	5.6	2.015	0.045
Farm size (ha)	1.2	0.9	1.1	1.0	0.582	0.561
Total annual income (ETB)	13,800	3,900	12,500	3,500	-3.470	0.000

Note: SD = standard deviation.

These attributes may translate into a greater propensity to invest in mechanization as a long-term labor-saving and productivity-enhancing solution for farmers. These results are supported by Degife and Mauser (2017), who highlighted how cumulative farming experience increases receptiveness to innovation. To improve adoption among less experienced farmers, mentorship models should be implemented, wherein seasoned farmers can share practical mechanization benefits, demonstrate operations, and mitigate perceived uncertainties among less experienced farmers. This aligns with the situated learning theory, which states that peer-led learning in a contextual setting improves knowledge retention and behavioral changes. To target less experienced farmers, programs need either mentorship or peer-learning programs, whereby experienced farmers can share their expertise with less experienced farmers, thereby increasing the overall uptake.

Farm size revealed no statistically significant difference (t = 0.582, P = 0.561) between adopters (1.2 ± 0.9 ha) and non-adopters (1.1 ± 1.0 ha). This indicates that the physiological demands of farming larger plots are not the only drivers of agricultural mechanization. While intuition might suggest that larger farms require tractors, this study confirms that smallholders are equally inclined to adopt mechanization when provided with institutional support. This finding resonates with Khaspuria *et al.* (2024), who argue that farm size is an insufficient predictor unless complemented by access to financial and institutional support. Physiologically, mechanization can reduce physical exertion across all farm sizes, alleviating musculoskeletal strain even on small plots, especially for aging or physically limited farmers (Thamsuwan *et al.*, 2020). Thus, policies should focus less on landholding thresholds and more on making tractors accessible through shared ownership models, leasing hubs, or custom hiring centers. This approach democratizes mechanization access and enhances labor efficiency across diverse landholding scales in the region. Interventions in Makuey and elsewhere must de-emphasize farm size threshold levels and concentrate on enabling equitable use of common assets. Encouraging tractor-sharing arrangements, coordinating farmer associations, and subsidizing custom-hiring platforms would make machinery more accessible to smallholders. Such measures would enable even restricted landholders to take advantage of mechanization without necessarily having to own the equipment.

Total annual income showed a highly significant mean difference (t = -3.470, P = 0.000), with adopters reporting higher incomes (ETB 13,800 ± 3,900) than non-adopters (ETB 12,500 ± 3,500). This supports the theory that financial capacity influences farmers' cognitive assessments of affordability and investment risk, making wealthier farmers more likely to adopt cost-intensive technologies such as tractors. This observation aligns with Challa and Tilahun (2014), who emphasized that wealth reduces financial anxiety and facilitates early technology adoption. In physiological terms, higher income is associated with improved food security, health, and mental bandwidth, which, in turn, enhances a farmer's ability to engage in complex decision-making and adopt strategic innovations (Dong *et al.*, 2024). Therefore, to ensure equity in adoption, governments and NGOs should provide targeted financial instruments, such as soft loans, conditional grants, and subsidized group services, particularly to low-income farmers. Combining income support with capacity building may also enhance psychological readiness, which is a key element in behavioral adoption models. To encourage the more widespread utilization of tractor operations for poorer farmers, policy actions should aim to loosen economic constraints, that is, by offering subsidized loans, grants, or group tractor services at the community level. In this way, even poorer farmers will be able to use and enjoy the benefits of newer agricultural technologies.

Factors Influencing Tractor Adoption

As no continuous variable had a variance inflation factor (VIF) more than 5, multicollinearity was not a critical concern in this regression model (Table 4). For categorical variables, all correlation values were less than 0.7, and there was no significant multicollinearity among the categorical variables in this model (Table 5). This indicates that the independent categorical variables did not strongly overlap, and their inclusion in the regression model was statistically valid, as shown in Table 5. Based on the Hosmer and Lemeshow goodness-of-fit test, the P-value (0.448) was greater than 0.05, indicating that the model did not significantly differ from the observed data (Table 6). This suggests that the logistic regression model provides a good fit and accurately explains the relationship between the independent and dependent variables, as shown in Table 6.

Table 4 Multicollinearity test for continuous variables (n = 250)

Variable	Tolerance	VIF
Age	0.40	2.50
Farming experiences	0.55	1.82
Farm size	0.30	3.33
Household annual incomes	0.65	1.54

Note: Values of VIF less than 5 mean no multicollinearity problem for continuous variables.

Table 5 Multicollinearity test for dummy variables (n = 250)

Variable	Gender	Educational level	Cultural norm	Access to credit	Subsides access
Gender	1	0.12	0.02	0.15	0.03
Educational level	0.12	1	-0.05	0.08	0.07
Cultural norm	0.02	-0.05	1	0.10	-0.01
Access to credit	0.15	0.08	0.10	1	0.07
Subsides access	0.03	0.07	-0.01	0.07	1

Note: Values less than 0.75 mean no multicollinearity problem for dummy variables.

Table 6 Hosmer and Lemeshow test (n = 250)

Chi-square	Degree of freedom	P-value
7.85	8	0.448

Note: Data fit the binary logit model properly (P < 0.05).

In addition, the results of the binary logit model provide valuable insights into the factors affecting tractors among smallholders (Table 7). Below is an interpretation of the four important variables aligned with the objectives and hypotheses of this study.

Educational level

The educational level was an economic factor that positively influenced tractor adoption, as expected in the study area. A positive coefficient for educational level (b = 0.400, P = 0.045) suggests that farmers with higher levels of education are more likely to adopt tractors in their farming activities. For an increase in each unit of educational attainment, the possibility of adopting tractors increased by approximately 49.1% (Exp(b) = 1.491). Educational level positively affects tractor adoption, suggesting that more educated farmers are more likely to adopt tractors because they can operate and appreciate advanced agricultural technologies. This result aligns with Ruzzante *et al.* (2021), who emphasized that educated farmers are more likely to understand the potential benefits of adopting modern agricultural technologies and are thus more likely to implement them in their farms. Education may provide farmers with the skills and knowledge needed to operate tractors effectively and make informed decisions regarding their use. Moreover, education enhances the cognitive and psychomotor skills necessary for mechanized farming. Mechanically intensive operations, such as plowing or calibration of implements, require not only a theoretical understanding but also fine motor coordination and spatial reasoning skills, which are more developed in individuals with formal education than in those without. This association reflects broader findings in agricultural technology studies, such as those by Liu *et al.* (2024), who demonstrated that literacy significantly improved farmers' ability to interpret manuals and engage in adaptive learning when using equipment. This study highlights the significance of mainstreaming agricultural education and extension services in Makuey's rural development strategy. Targeted adult literacy training, farmer field schools, and technical training programs should be utilized to improve farmers' technological literacy, thus promoting the broader application of mechanization across all levels of education.

Total annual income

As expected, the total annual income was an economic factor that positively influenced farmers' tractor adoption in the Makuey district. A positive relationship between total annual income and tractor adoption (b = 0.150, P = 0.003) indicates that high-income farmers are more likely to adopt tractors

Table 7 Results of binary logit model (n=250)

Variable	b	SE	Wald	P-value	Exp(b)
Gender	0.250	0.350	0.500	0.620	1.284
Age	-0.250	0.120	0.167	0.341	0.779
Educational level	0.400	0.200	4.000	0.045	1.491
Farming experiences	0.050	0.080	0.250	0.618	1.051
Farm size	0.100	0.120	0.833	0.361	1.105
Total annual income	0.150	0.050	9.000	0.003	1.162
Cultural norm	-0.350	0.100	12.250	0.000	0.704
Access to credit	0.500	0.200	0.250	0.112	1.648
Subsidies access	0.700	0.150	21.000	0.000	2.013

Note: b = regression coefficient, SE = standard error, Wald = Wald statistic, Exp(b) = exponentiated b.

than low-income ones. In particular, for an increase in each unit of total annual income, the possibility of adopting tractors increased by approximately 16.2% (Exp(b) = 1.162). The total annual income also had a positive effect on tractor adoption among smallholder farmers, and better-off farmers were more likely to adopt advanced farming equipment. This finding corresponds to economic theory, which suggests that high-income households have a greater financial capacity to invest in modern agricultural equipment, such as tractors. High-income farmers are better able to manage costs related to tractor procurement, leases, and other related expenses (Wordofa *et al.*, 2021). Physiologically, the decision of higher-income farmers to invest in tractors may be linked to their ability to mitigate the physical strain and fatigue associated with manual labor. Mechanization reduces musculoskeletal stress, a factor particularly relevant to aging rural populations (Naveen *et al.*, 2024). Thus, financial resources not only enhance economic flexibility but also allow farmers to substitute machine power for human labor, thereby minimizing health-related productivity losses. This linkage is supported by Onomu and Aliber (2021), who found that tractor ownership was more prevalent among wealthier farmers, partly because of their interest in improving physical labor efficiency and farm scalability. To address income-related imbalances in the adoption of tractors, interventions must incorporate economic support for poor farmers in the form of targeted subsidies, lease purchases at affordable prices or cooperative ownership arrangements. In addition, income-increasing programs, such as linking farmers to the value chain and providing off-season work, would increase family incomes and indirectly compel mechanization.

Cultural norms

This cultural factor negatively influences farmers' tractor adoption, as expected. The negative coefficient for cultural norms (b = -0.350, P = 0.000) suggests that farmers who follow traditional cultural practices are less likely to adopt tractors for farming. For an increase in each unit of cultural ideal rearing, the possibility of adopting tractors declined by approximately 29.6% (Exp(b) = 0.704). Cultural norms also influenced farmers' adoption of tractors in the wrong way, indicating that cultural practices could prevent the adoption of new technologies. This result corresponds to Jayasekara (2021), who found that cultural norms can sometimes restrict the adoption of modern agricultural practices, especially in areas where traditional farming methods are deeply entrenched. This finding may also reflect a physiological resistance to change, where individuals accustomed to long-standing labor practices develop cognitive conservatism and muscle memory, favoring traditional tools over unfamiliar mechanized equipment. Moreover, cultural prohibitions on machinery use, often seen as violating collective labor traditions, can trigger psychological discomfort and social ostracism (Yaakobi, 2021). However, this negative relationship also means that if farmers are provided with sufficient economic incentives or education, cultural norms can change. The findings indicate the use of culturally adapted interventions in Makuey. Policymakers, opinion leaders, and grassroots leaders must mobilize mechanization; campaigns must be developed that incorporate cultural values and embody the advantages of new machinery; and demonstration farms must be used to image-burst misconceptions. Additionally, integrating new technology with traditional farming practices in pilot studies can stimulate incremental cultural changes.

Subsidy access

The subsidy access was an institutional factor that positively influenced farmers' tractor adoption, as expected. A positive and highly significant coefficient of subsidy access (b = 0.700, P = 0.000) suggests that subsidies greatly increase the likelihood of adopting a tractor. In particular, farmers with subsidy access are more likely to adopt approximately 101.3% more tractor experience (Exp(b) = 2.013). Subsidy access has become a major determinant of tractor adoption, with farmers who receive subsidies having a significantly higher chance of adopting tractors. This result underscores the important role of subsidies in making agricultural technologies more accessible to small-scale farmers. Subsidies reduce financial obstacles to adoption, making tractors less expensive and promoting their widespread use (Xie and Huang, 2021). From a behavioral perspective, subsidies may reduce risk aversion by lowering the perceived costs of failure associated with the use of new technologies. This aligns with the concept of “prospect theory”, wherein individuals are more likely to engage in a risky but potentially rewarding activity when initial losses are minimized (Guo *et al.*, 2022). Moreover, access to subsidies can act as a signal of institutional support, boosting farmers’ confidence in mechanization as a viable and endorsed strategy. This is corroborated by Adesida *et al.* (2021), who demonstrated that farmers receiving subsidies in Nigeria reported significantly higher adoption rates and improved operational efficiency than their non-subsidized peers did. To utilize this finding, development partners and the government must introduce transparent, well-targeted subsidy programs in Makuey. These can be time-limited vouchers for early adopters, performance-based subsidies, and options for dealing with machinery suppliers to reduce front-end payments. Offering subsidy programs to marginalized groups (poor farmers, women, and youth) ensures maximum equity and uptake.

Qualitative Data Analysis

The structured interviews yielded rich quantitative information, whereas the qualitative results of key informant interviews (KIIs) and focus group discussions (FGDs) offered richer insights into individual motivations, perceptions, and cultural values regarding tractor adoption. The thematic analysis identified some of the most significant facilitators and barriers to tractor adoption. Cultural beliefs were the main constraint, with farmers resisting the use of tractors because of traditional agricultural perceptions and uncertainty regarding the technology’s long-term advantages. Credit constraints were also a main area of concern, considering that although access to credit was identified as a key driver of adoption, some farmers indicated that loan and interest rates were still too high, thus deterring the adoption of tractors. However, the perceived advantages of tractor use were well known to be the main facilitators, as the majority of farmers explained that tractors significantly reduced labor needs and enhanced production, particularly during the planting and harvesting periods. Moreover, government support in the form of subsidies and finance support programs was cited by some farmers as an important consideration that made tractors affordable, even though the effect of these programs did not trickle down to all farmers equally.

CONCLUSIONS

This study identifies the determinants of tractor adoption among smallholder farmers in the Makuey district, Gambella region, Ethiopia, and concludes that there is an intricate interaction of economic, social, and institutional factors that significantly influence mechanization adoption. The results indicate that access to credit significantly impacts tractor adoption (P = 0.001). This underscores the necessity of enhancing smallholder farmers’ access to credit, thereby facilitating the modernization of their agricultural practices. Additionally, farming experience was a significant determinant of tractor adoption (P = 0.045), highlighting the potential advantage of focusing outreach programs on more experienced farmers and providing them with support to adopt modern techniques. Furthermore, total annual income emerged as a crucial factor influencing tractor adoption (P = 0.000), suggesting that increasing farmers' income levels could encourage the adoption of modern technologies. This study identified several factors affecting tractor adoption among smallholder farmers in the study area. Educational attainment positively influenced adoption (P = 0.045), indicating that farmers with higher education levels were more likely to adopt tractors because of their enhanced ability to comprehend and utilize modern agricultural technologies. Total annual income also positively affected tractor adoption (P = 0.003), with wealthier farmers being more inclined to invest in modern equipment. Conversely, cultural norms negatively impacted adoption (P = 0.000), suggesting that traditional practices may impede the uptake of new technologies. Access to subsidies is identified as a critical factor in promoting tractor adoption (P = 0.000), with farmers with access to subsidies being significantly more likely to adopt tractors than those without subsidies. The study recommends that the government and non-governmental organizations should improve access to credit, provide training programs, increase income-generating opportunities, and offer modern agricultural technologies through widespread subsidies or low-interest loans to encourage the widespread adoption of precision farming. For coffee growers and nursery managers, these results suggest actionable strategies for modernizing operations. Credits and subsidies should be directed toward mechanized land preparation, composting, and transplanting in coffee nurseries, all of which benefit from increased efficiency and labor savings in the long term. Nursery operators can be trained in tractor-compatible practices, such as raised bed preparation and precision irrigation, to improve seedling quality and survival rates. Encouraging educated and experienced nursery managers to adopt these methods will further increase the adoption and sustainability of mechanization in the coffee value chain in this region. Future research should focus on field trials to evaluate the specific benefits of mechanized operations on nursery coffee productivity and plantation yields. Experimental studies could test the cost-effectiveness of tractors in key nursery tasks, whereas longitudinal research could assess how mechanization impacts farmers' livelihoods over time. An in-depth analysis of gender dynamics and local cultural practices is valuable for designing inclusive and locally appropriate mechanization strategies. By addressing these knowledge gaps, future studies can inform policies that support sustainable and equitable mechanization in Ethiopia's coffee-producing regions.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest related to this research.

ACKNOWLEDGEMENTS

The study was conducted with the participation of smallholder farmers in collaboration with Gambella University. Data collection, analysis, and interpretation were performed by the authors with valuable input from agricultural experts and local stakeholders.

REFERENCES

Adesida, I.M., W. Nkomoki, M. Bavorova and M.Y. Madaki. 2021. Effects of agricultural programmes and land ownership on the adoption of sustainable agricultural practices in Nigeria. Sustainability. 13(13): 7249. https://doi.org/10.3390/su13137249.

Aryal, J.P., D.B. Rahut, G. Thapa and F. Simtowe. 2021. Mechanization of small-scale farms in South Asia: Empirical evidence derived from farm households survey. Technol. Soc. 65: 101591. https://doi.org/10.1016/j.techsoc.2021.101591.

Ayele, S. 2022. The resurgence of agricultural mechanization in Ethiopia: Rhetoric or real commitment?. J. Peasant Stud. 49(1): 137–157. https://doi.org/10.1080/03066150.2020.1847091.

Barbosa, M.W. 2024. Government support mechanisms for sustainable agriculture: A systematic literature review and future research agenda. Sustainability. 16(5): 2185. https://doi.org/10.3390/su16052185.

Bor, C. and K. Deng. 2024. Challenges and opportunities of tractor adoption by smallholder farmers in Gambella region, Ethiopia. Int. J. Mech. Eng. Appl. 12(5): 129–135. https://doi.org/10.11648/j.ijmea.20241205.12.

Challa, M. and U. Tilahun. 2014. Determinants and impacts of modern agricultural technology adoption in West Wollega: The case of Gulliso District. J. Biol. Agric. Healthc. 4(20): 63–77.

Cochran, W.G. 1977. Sampling Techniques. 3rd Edition. Wiley, New York, USA.

Crudeli, L., S. Mancinelli, M. Mazzanti and R. Pitoro. 2021. Beyond individualistic behaviour: Social norms and innovation adoption in rural Mozambique. World Dev. 157: 105928. https://doi.org/10.1016/j.worlddev.2022.105928.

Dawid, I., T. Gebiso and E. Boka. 2022. Comparative advantage of tractor utilization in Southeastern Oromia, Ethiopia. IJDEE. 10(2): 75–101.

Deepa, M. and K.V. Subramanyam. 2025. Empowering rural women - Drudgery reduction through mechanized weed management in Guntur District. Bhartiya Krishi Anusandhan Patrika. 40(1): 119–122. https://doi.org/10.18805/bkap743.

Degife, A.W. and W. Mauser. 2017. Socio-economic and environmental impacts of large-scale agricultural investment in Gambella region, Ethiopia. J. US-China Public Adm. 14(4): 183–197. https://doi.org/10.17265/1548-6591/2017.04.001.

Dong, L., Y. Li, Z. Sun, L. Zhang and H. Tang. 2024. Farmers' non-agricultural income, agricultural technological progress, and sustainable food supply security: Insights from China. Sustainability. 16: 7929. https://doi.org/10.3390/su16187929.

Fekad, M. 2020. Gender, agriculture, food and nutrition security in Ethiopia: A critical review. IJRSAS. 6(2): 14–21. https://doi.org/10.20431/2454-6224.0602003.

Gorbachev, O. and M.J. Luengo-Prado. 2019. The credit card debt puzzle: The role of preferences, credit access risk, and financial literacy. Rev. Econ. Stat. 101(2): 294–309. https://doi.org/10.1162/rest_a_00752.

Green, W.H. 2003. Econometric Analysis. 5th Edition. Pearson, New Jersey, USA.

Gujarati, D.N. 2004. Basic Econometrics. 4th Edition. McGraw-Hill, New York, USA.

Guo, J., J. Chen and Y. Xie. 2022. Determining a reasonable concession period for risky transportation BOT projects with government subsidies based on cumulative prospect theory. Eng. Constr. Archit. Manag. 29(3): 1396–1426. https://doi.org/10.1108/ECAM-11-2019-0612.

Hosmer, D.W. and S. Lemeshow. 1980. Applied Logistic Regression. Wiley, New York, USA.

Hu, Y., B. Li, Z. Zhang and J. Wang. 2022. Farm size and agricultural technology progress: Evidence from China. J. Rural Stud. 93: 417–429. https://doi.org/10.1016/j.jrurstud.2019.01.009.

Jayasekara, D.N. 2021. Can traditional farming practices explain attitudes towards scientific progress?. Econ. Model. 94: 320–339. https://doi.org/10.1016/j.econmod.2020.10.012.

Khadka, D., K. Dhakal, M.S. Teli, H. Pokhrel, P. Sharma and M. Lamichhane. 2024. Status of farm mechanization and factor affecting its adoption among the rice (*Oryzae sativa*) farmers in Sarlahi district, Nepal. Arch. Agric. Environ. Sci. 9(3): 414–421. https://doi.org/10.26832/24566632.2024.090302.

Khaspuria, G., A. Khandelwal, M. Agarwal, M. Bafna, R. Yadav and A. Yadav. 2024. Adoption of precision agriculture technologies among farmers: A comprehensive review. J. Sci. Res. Rep. 30(17): 671–686. https://doi.org/10.9734/jsrr/2024/v30i72180.

Koppmair, S., M. Kassie and M. Qaim. 2017. The influence of farm input subsidies on the adoption of natural resource management technologies. Aust. J. Agric. Resour. Econ. 61(4): 539–556. https://doi.org/10.1111/1467-8489.12220.

Kropf, B. and H. Mitter. 2022. Factors influencing farmers' climate change mitigation and adaptation behavior: A systematic literature review, pp. 243–259. *In*: Alpine Landgesellschaften zwischen Urbanisierung und Globalisierung. Springer VS Wiesbaden, Wiesbaden, Germany.

Liu, X., Z. Wang and X. Han. 2024. The impact of digital literacy on farmers' green production behavior: Mediating effects based on ecological cognition. Sustainability. 16(17): 7507. https://doi.org/10.3390/su16177507.

Máquina, D.A., L.P.D.M. Castiano, B.A. Máquina and A.J.V. da Silva. 2024. Analysis of determinates for the adoption of agricultural technologies by family farmers in the administrative post of OCUA, Northern Mozambique. J. Appl. Biotechnol. Bioeng. 11(3): 54–58. https://doi.org/10.15406/jabb.2024.11.00360.

Martinez, P.D., D. Tancredi, M. Pavel, L. García and H.M. Young. 2024. Technology acceptance among low-income, Asian American older adults: Cross-sectional survey analysis. J. Med. Internet Res. 26: e52498. https://doi.org/10.2196/52498.

Mazur, M. and J. Bański. 2021. Means of production in agriculture, pp. 119–128. *In*: Transformation of Agricultural Sector in the Central and Eastern Europe after 1989. Springer, Cham, Switzerland.

Miller, R.L. 2015. Rogers' innovation diffusion theory (1962, 1995), pp. 261–274. *In*: M. Al-Suqri and A. Al-Aufi, (Eds.), Information Seeking Behavior and Technology Adoption: Theories and Trends. IGI Global Scientific Publishing, Pennsylvania, USA.

Nakano, Y., T.W. Tsusaka, T. Aida and V.O. Pede. 2018. Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania. World Dev. 105: 336–351. https://doi.org/10.1016/J.WORLDDEV.2017.12.013.

Naveen, R., A. Kumar, R. Kumar, H.L. Kushwaha, M. Khanna, V. Ramasubramanian and S. Poojith. 2024. Assessment of whole-body vibration and development of mitigation intervention for single-axle tractor–trailer combination. Front. Mech. Eng. 10: 1426764. https://doi.org/10.3389/fmech.2024.1426764.

Ogisi, O.D. and T. Begho. 2023. Adoption of climate-smart agricultural practices in sub-Saharan Africa: A review of the progress, barriers, gender differences, and recommendations. Farm. Syst. 1(2): 100019. https://doi.org/10.1016/j.farsys.2023.100019.

Onomu, A.R. and M. Aliber. 2021. Factors influencing smallholder farmers' mechanization decisions in Nigeria: The case of tractor use in the Fourth Industrial Revolution era. Asian J. Agric. Rural Dev. 11(2): 199–209. https://doi.org/10.18488/journal.ajard.2021.112.199.209.

Park, D.C. and E.T. Smith. 2022. Facilitation of cognition in older adults: Traditional and non-traditional approaches to inducing change. Med. Res. Arch. 10(10). https://doi.org/10.18103/mra.v10i10.3192.

Quaye, W., J.A. Onumah, M. Boimah and A. Mohammed. 2022. Gender dimension of technology adoption: The case of technologies transferred in Ghana. Dev. Pract. 32(4): 434–447. https://doi.org/10.1080/09614524.2021.2000588.

Ruzzante, S., R. Labarta and A. Bilton. 2021. Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. World Dev. 146: 105599. https://doi.org/10.1016/J.WORLDDEV.2021.105599.

Teklewold, H. 2021. How effective is Ethiopia's agricultural growth program at improving the total factor productivity of smallholder farmers?. Food Sec. 13: 895–912. https://doi.org/10.1007/s12571-021-01175-7.

Thamsuwan, O., S. Milosavljevic, D. Srinivasan and C. Trask. 2020. Potential exoskeleton uses for reducing low back muscular activity during farm tasks. Am. J. Ind. Med. 63(11): 1017–1028. https://doi.org/10.1002/ajim.23180.

Wordofa, M.G., J.Y. Hassen, G.S. Endris, C.S. Aweke, D.K. Moges and D.T. Rorisa. 2021. Adoption of improved agricultural technology and its impact on household income: A propensity score matching estimation in eastern Ethiopia. Agric. Food Secur. 10: 5. https://doi.org/10.1186/s40066-020-00278-2.

Xie, H. and Y. Huang. 2021. Influencing factors of farmers' adoption of pro-environmental agricultural technologies in China: Meta-analysis. Land Use Policy. 109: 105622. https://doi.org/10.1016/J.LANDUSEPOL.2021.105622.

Yaakobi, E. 2021. Can cultural values eliminate ostracism distress? Int. J. Intercult. Relat. 80: 231–241. https://doi.org/10.1016/j.ijintrel.2020.10.014.

Zerssa, G., D. Feyssa, D. Kim and B. Eichler-Löbermann. 2021. Challenges of smallholder farming in Ethiopia and opportunities by adopting climate-smart agriculture. Agriculture. 11(3): 192. https://doi.org/10.3390/AGRICULTURE11030192.

Zincov, A. 2025. Operation of Cars and Tractors: Control, Diagnostic and Adjustment Work: Workshop. INFRA-M Academic Publishing LLC, Moscow, Russia.