Asian Journal of Agricultural Extension, Economics & Sociology

Volume 42, Issue 1, Page 49-61, 2024; Article no.AJAEES.109956
ISSN: 2320-7027

Effect of Socio-economic Factors on Level of use of Improved Maize Varieties in Bungoma County, Kenya

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Authors' contributions

This work was carried out in collaboration among all authors. Authors MSN and ER conceptualized and designed the survey, supervised the data collection, interpreted data, contributed and compiled the paper. Author WJK Contributed to the paper. Authors NF and TCO supervised the data collection, contributed to the paper. Author GET did data analysis and interpretation. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/AJAEES/2024/v42i12346

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/109956

Original Research Article

Received: 04/10/2023
Accepted: 08/12/2023
Published: 20/01/2024

ABSTRACT

Maize is Kenya's primary staple food, where 75% of producers are smallholder farmers. Maize consumption exceeds production with imports bridging the gap. Improved maize varieties have been adopted by smallholder farmers but the deficit gap still exists. The study's objective was to determine factors influencing the adoption intensity of improved maize varieties in Bungoma County. Primary data was collected from 500 smallholder farmers using a structured questionnaire. Data was analysed using the Statistical Package for Social Sciences Version 27 software and a fractional logit model applied. Factors influencing adoption intensity of improved maize varieties

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were personal characteristics of the farmer (age, and household size), institutional factors (extension service) and varietal factors (early maturity, pest and disease resistance, drought resistance). Age, household size and extension services reduced the intensity of adoption, while varietal factors increased the intensity of adoption of improved maize varieties. The recommendations from the study is that even if the extension agents discouraged increased acreage under maize, they need to address and manage risk aversion among the old farmers through providing information and support groups. Counties should nurture a strong research-inkage with researchers to demonstrate demonstrate technology benefits.

Keywords: Smallholder farmers; intensity of adoption; fractional response model; extension services; varietal attributes.

1. INTRODUCTION

Maize is the primary staple food of ordinary Kenyans, and the cheapest source of calories among the cereal grains. In Kenya, 90% of its population depends on maize as a key staple food crop, with 75% of maize producers being small holder farmers located in low to mid altitude ecologies [1]. According to the Agricultural Sector Transformation and Growth Strategy for the year 2019-2029, maize accounts for about 50% of cereals value, and the maize value chain is one of the crop value chains with the highest potential for agricultural transformation [2]. Among crop farmers, 58% of small-scale farming land is allocated to maize production but only 10-15% of incomes for these farmers come from maize [2]. Kenya's per capita maize consumption is the highest in Eastern Africa, standing at 103 kg/year compared to 73 kg/year for Tanzania, 52 kg/ year for Ethiopia and 31 kg/year for Uganda [3]. Currently, maize consumption in Kenya outweighs its production, and the former is bound to increase with the increase in population. According to KNBS [4], aggregate maize production decreased from 4.21 million metric tonnes-MT in 2020 to 3.67 million MT in 2021. It is also stated in [4] that the volume of imported maize nearly doubled from about 274,000 MT in 2020 to 487,000 MT in 2021and the value of imports from Tanzania nearly doubled from Kenya shillings (KES) 27.9 billion in 2020 to KES 54.5 billion in 2021 partly attributable to increase in imports of maize and rice from this country.

To bridge this gap, a yield increase of 157% is required [5]. Maize production therefore needs to be increased to meet demand and avoid overreliance on imports. A study by Abodi et al. [6] highlights the perennial maize imports in Kenya and shows that the net effect of maize imports on economic welfare is negative, and asserts that increased domestic production benefits both producers and consumers while facilitating efficient allocation of resources in the maize sub sector.

Improving the productivity of maize needs increased efforts in influencing the farmer to use improved maize varieties. In Kenya, maize yield fluctuates from 1.5-1.8 tonnes/hectare against a potential of 4.5 tonnes/hectare [5]. This yield gap highlights the need to increase yield, and one of the ways to do this is through improved technologies such as improved maize varieties. New/improved maize varieties with better genetic gains have been developed and adopted through the years, yet the yield gap exists. The use of genetically impure seeds hinders the realization of maize yield potential, for instance a one percent decrease in varietal purity could lead to a loss of 135kg/ha in maize production [7]. This paper highlights the socioeconomic issues around the use of improved maize varieties by farmers in Bungoma County. Agriculture drives the economy of Bungoma County, where almost all households plant improved maize varieties. The county is the fourth largest maize producer after Trans Nzoia, Uasin Gishu and Nakuru counties. Maize is both a food and cash crop for smallholder households in Bungoma County.

Many studies have viewed adoption as a binary process when in reality the adoption process is partial and incremental, meaning that it is the levels of a technology that are adopted, and this levels may be increased over time. Past studies have shown that it is important to go beyond mere adoption studies that estimate factors influencing adoption to estimating factors that determine the level (intensity) of adoption of technologies at the household level. This is because various adoption studies have shown that factors determining adoption and those that determine intensity of adoption of a technology can be different. In their study on modeling the adoption and use intensity of improved maize seeds in Benin West-Africa, [8] identified more factors that influence the intensity of adoption than those that influenced the adoption of improved maize varieties in Benin. In their study on the determinants of adoption of improved faba bean cultivars in the central highlands of Ethiopia [9] asserts that the decisions to adopt the improved cultivars and how much land to be covered (intensity of adoption) appeared to be explained by different processes. The decision to adopt improved faba bean cultivars was influenced by family size, farmers' awareness about the existing improved cultivars, and extension contact but the intensity of adoption was determined by livestock holding and access to market information. A study by Kolady et al. [10], also noted differences in factors affecting adoption and those influencing intensity of adoption of precision agriculture technologies (PAT). In the study on factors influencing adoption of irrigation technologies among smallholder farmers in Machakos County, Kenya, [11] found that sex of household head, education, farm size, off-farm income, access to credit and access to extension services positively influenced adoption while adoption intensity was positively influenced by gender, off-farm income, farming experience, primary occupation and extension services. These studies show that a binary econometric model, which is used in many adoption studies, is not sufficient to highlight the socioeconomic constraints influencing the intensity of adoption of any given technology. The studies therefore underscore the contribution of intensity of adoption studies to adoption studies, and the need to estimate the determinants for the level of adoption of any given technology.

In order to identify the appropriate model to use for data analysis, a review of the models used in similar studies is necessary. The double hurdle Tobit model was used by Mahoussi et al. [8] to identify factors affecting adoption as well as the intensity of adoption of improved maize varieties in Benin. However, the Tobit model is suitable when the depended variable is bounded on one side. In our study, the depended variable, which is the proportion of the area devoted to maize production with improved maize seeds is continuous but bounded between 0 and 1. According to Gallani and Krishnan [12], Tobit models rely on distributional assumptions that are frequently not reflected in survey data. For instance, the observations/responses may be skewed on one side of the scale. An assumption of the Tobit model is that zeros in the dependent variable represent censored values of an underlying normally distributed latent variable [13], which may not be the case when the dependent variable is the proportion of land under a particular crop. The zero in the latter means that a crop was not grown by the respondent. The double hurdle Tobit model was used by Kassa et al. [9] to analyse the decision to adopt faba bean cultivars in the first stage and the area of land under bean (intensity of adoption) in the second stage. The Probit and Poisson regression models for the analysis was employed by [10], where the Probit model was used for the decision to adopt (1) or not to adopt (0) while the Poisson regression model was used where the number of technologies adopted was the dependent variable. A study by Kwawu et al. [14] also used the Poisson regression model and the dependent variable was the number of improved maize technology package elements adopted by farmers. According to Gallani and Krishnan [12], the Poisson regression models are appropriate for discrete variables, and where the number of technologies used are many. In their study on the intensity of adoption of conservation agriculture by smallholder farmers in Zimbabwe [15] used the Poisson regression model because the model had eight conservation agriculture practices in the dependent variable. The Poisson regression model may not be appropriate in this study because the dependent variable, which is the proportion of land under improved maize varieties is a continuous variable. In a study by Muluki et al. [11], the Probit model was used to analyze the factors influencing the decision to adopt irrigation technologies, while the Ordinary Least Squares (OLS) regression was used to analyze the factors influencing the area put under irrigation. According to Gallani and Krishnan [12], the OLS is inappropriate to estimate models of bounded dependent variables because the predicted values may be outside the bounded variables. In addition, the partial effects estimated by OLS regressions are constant and independent of the value of the predictor.

The fractional response model (FRM) on the other hand overcomes many limitations of established linear and non-linear econometric solutions in the study of bounded data. Studies that have estimated the intensity of adoption by use of the FRM include [16,17,18]. The fractional logit model was used to analyze the intensity of adoption of integrated pest management practices in Rwanda in [16]. The dependent variable was acres of maize under PPT divided by the total acreage under maize per farm. The FRM was used by Arslan et al. [17] to estimate the determinants for the intensity of adoption of conservation practices, which was defined as the proportion of land cultivated with conservation practices. In their study on adoption of improved maize varieties among farm households in the northern region of Ghana, [18] used the FRM to estimate the factors influencing the intensity of adoption of improved maize varieties, and the dependent variable was the proportion of the total farmland allocated to the cultivation of improved maize varieties.

This study contributes to the growing body of literature on intensity of adoption by use of the FRM. It uses the FRM to examine socioeconomic factors influencing the intensity of adoption of improved maize varieties in Bungoma County. The study is in line with Vision 2030 and more recently, the Agricultural Sector Transformation and Growth Strategy 2019-2029 that strive to attain 100% food security for all Kenyans by 2030. These two documents emphasize the need to increase land productivity for smallholder farmers for the country to attain food security in 2030. High maize productivity translates to increased maize supply which results into lower consumer prices. More maize translates to higher revenue for producers hence reduced poverty levels and reduced malnutrition. The low consumer prices due to increased maize supply leads to a reduced share required to purchase food hence increasing consumer welfare. The factors determining the intensity of adoption from this study will act as a guide to researchers, producers and other stakeholders in the maize value chain in their quest to increase food security in Kenya.

2. METHODOLOGY

2.1 Study Area

Fig. 1 shows the map of Bungoma County. The selected sub-counties; Webuye, Kabuchai, Mt. Elgon, Sirisia and Tongaren were the main maize growing areas in the county. The annual rainfall in Bungoma County ranges from 400 -1800 mm, while the annual temperatures vary between 14.80C and 27 ºC, and the main agro ecological zones are upper highlands (UH), lower highlands (LH), upper midlands (UM) and lower midlands (LM). The different agro-ecological zones give room for growing different maize varieties ranging from hybrid maize, OPVs and local varieties.

2.2 Sample Size and Sampling

The household survey used the national statistical sample frame developed by the Kenya National Bureau of Statistics (KNBS). A total of 500 households were randomly selected, a sample size that was determined using the formula [19].

$$N=N/(1+N(e)$$

Where n is the sample size, N is the population size, e is the level of precision (taken as 10%)

The calculated minimum sample size in each selected sub-county was therefore 100, making a total of 500.

Pretesting of the questionnaire was conducted in Kanduyi sub-County. Farmers were selected using a systematic sampling approach, where a main land mark such as a road, church or school was the starting point of the transect that enumerators used to walk along, and select every 5th farmer for interview on the alternative side of the road or path. A structured questionnaire mounted on the open data kit (ODK) was administered to the 500 households by trained enumerators through face to face interviews. Data was collected in January-February 2022.

2.3 Theoretical Framework

Two theories, the random utility theory (RUT) and expected utility theory (EUT) guide the discrete choice models used to model the process of decision making to adopt and utilize a technology. Both theories assume that given a set of alternatives, a farmer will always make a choice on the alternative that yields the maximum utility [20]. The EUT is used when the preferences are stated and the choices are made in the presence of uncertainties and there is an expected outcome [21]. The farmers are assumed to weigh the expected benefits and costs from adoption of the technology against the benefits and costs of not adopting it. The farmer adopts a technology if the expected utility from adoption decision (Uά) is higher than that derived when one does not adopt (Uη) [22]. The RUT is applicable when preferences of the outcome are revealed and outcome decisions are made in an environment with no uncertainties. The utility is derived from the underlying characteristics or attributes of a given technology or good [23].

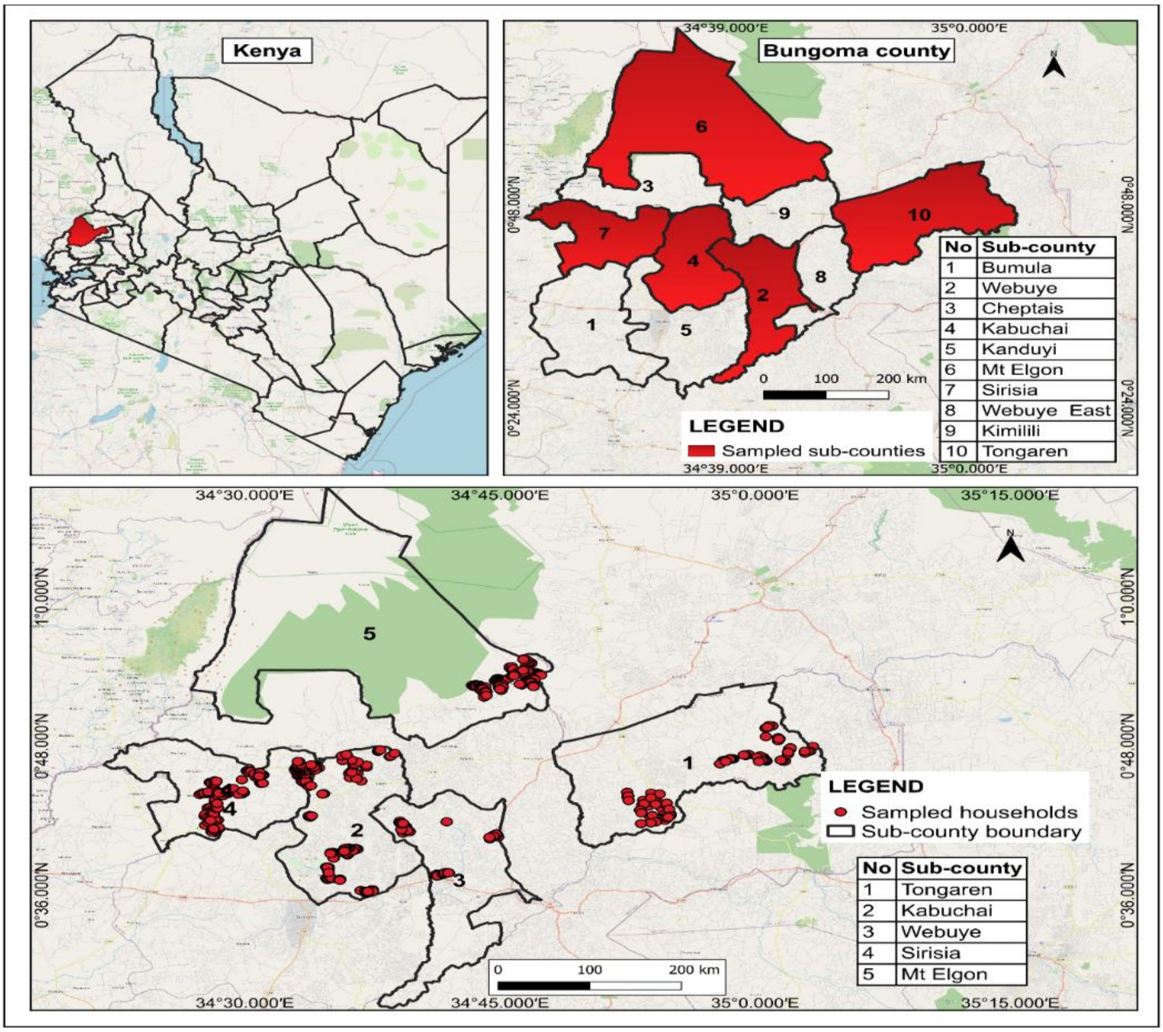

Fig. 1. Map of Bungoma County showing the study sites

Therefore, a good is described by its attributes that yield satisfaction to the small holder farmer if adopted. Adoption and use of a technology is taken as an outcome of optimization by heterogenous farmers which takes place in the presence of availability of the technology, budget constraints and information asymmetry [24]. The RUT was employed in the study to examine the determinants of the level (intensity) of adopting improved maize varieties.

The RUT considers adopter households as agents who make rational decisions to maximize utility in the presence of budget constraints, information asymmetry and technology availability [25]. According to Baiyegunhi et al. [26], random utility suggests that a utility maximizing maize farmer will add a proportion of land under improved maize variety if the total benefits are greater than zero. According to Asiimwe et al. [27], the random utility function for a maize smallholder farmer facing a decision to increase a proportion of land under improved maize varieties was specified as;

$$P_{im}=\bar{P}_{im}+\varepsilon_{(im)}=X_{im}\theta+\varepsilon_{im},\ i=1,\ldots,n$$

Where, P_{im} is the utility of alternative m for farmer i, and is a function of deterministic component $\bar{P}_{im}$ and the random component $\varepsilon_{(im)}$, X is the demographic characteristics (such as age, gender, land size, extension, credit access) and the technology specific attributes (such as high yielding, early maturity, pest and diseases resistance and drought resistance) and a disturbance term assumed to be normally distributed with zero mean and constant variance, while ε_{im} is the stochastic element of the utility function which represent the unobserved attributes affecting farmer i choice on land allocation and measurement errors.

Therefore, a rational farmer would increase land under improved maize production if the expected utility is driven from an additional proportion of land P_i1 was higher than the one generated on normal land allocation P_i0 in the presence of production constraints.

2.4 Empirical Framework

To analyze the intensity of technology adoption, several empirical models have been used, which include Truncated regression, Tobit regression and censored, Poisson, Fractional response and Double hurdle models. The Truncated regression, Tobit regression and censored models are normally used to estimate continuous dependent variables that are restricted or bounded [16,28]. In this study, the dependent variable is the intensity of adoption, which is defined as the total land under improved varieties divided by the total land allocated to production which is a fraction or proportion. Hence, Tobit, truncated and censored models will give biased estimates since they are constrained. Therefore, to account for this limitation the study used the Fractional Response Model (FRM) since FRM affirms more specific interpretations especially where observations at the end of the distribution are of importance for analysis. The FRM accounts for nonlinearity, and relaxes the numerous restricting assumptions that are necessary in traditional econometric models. The FRM extends the general linear models (GLM) to a class of functional forms that overcome the limitations of the outdated econometric models for variables that are bounded in nature [29].

The study applied fractional logit model which assumes a logistic distribution of random disturbances and binds the estimated intensity of adoption of improved maize varieties between zero and one [28]. The intensity of adoption was defined as the proportion of land under improved maize varieties per household divided by the total number of acres per household, which is bounded between zero and one. The general model of intensity of adoption is specified following the functional form for the expected intensity of adoption of improved maize varieties

Table 1. Description of explanatory variables used in the Fractional Response Model

Variable Name	Variable description	Unit of Measurement	Expected signs
Dependent variables			
Adoption intensity	Acres allocated to improved maize variety divided by total acres of farming land	Proportion	+
Independent variables			
Household characteristics			
Age	Age of household head in years	Years	+/-
Gender	Gender of the household head	1= male ,0= female	+/-
Farm experience	Number of years farmer farmed maize	Years	+
Household size	Number of persons in the household	Continuous	+
Off-farm income	Annual income outside the farm	Continuous	+
Group membership	Membership to a farmers group	(1= yes; 0 = otherwise)	+
Institutional attributes			
Extension service	Farmer contact with extension officer	(1=yes; 0 = otherwise)	+
Access to credit	Farmers access to any form of credit	(1 = yes; 0 = otherwise)	+
Varietal attribute			
High yielding	Variety is perceived to be high yielding	(1 = yes; 0 = otherwise)	+
Early Maturity	The variety is perceived to mature early	(1=yes; 0 =otherwise)	+
Pest and Disease tolerance	The variety is perceived to be resistance to pest and diseases	(1=yes; 0 =otherwise)	+

Y_i of the i th farmer conditioned by X_i explanatory variables [28] as;

$$E(Y \mid X_i) = \mu(\beta X_i)$$

Where Y_i represents the adoption intensity of improved maize varieties, X_i is a vector of farmer characteristics and technology-specific attributes and β a vector of unknown parameters to be estimated. The cumulative distribution function that follows a logistic distribution function is defined by $\mu(\cdot)$ which represents a nonlinear link function satisfying $0 \leq \mu(\cdot) \leq 1$ to ensure that the value approximated lie in the interval of 0 and 1 and E is the expectations operator.

The variables included in the model are specified in Table 1. The dependent variable was the intensity of adoption, which was specified as a fraction of the total land the farmer had under improved maize. The independent variables include household characteristics, institutional attributes and varietal attributes. Some of the independent variables were dropped due to multicollinearity.

3. RESULTS AND DISCUSSION

3.1 Farmer Characteristics, Environment and Preferences

A consideration of farmer characteristics and farmer environment is important in order to explain/support the econometric results from the FRM model. This section looks at the household characteristics, farmer constraints and farmers' varietal preferences. Table 2 shows household characteristics of the surveyed households. The average land acreage in the Bungoma County study sites was 3 (2.89), with an average of 1.4 acres allocated to maize pure stand. According to the key informants, agricultural land per household in the county has been declining due to sub-division for inheritance. The average age of the household head was 51 years, meaning that the farming population in the study site was aging.

Approximately 33% (n=500) produced maize for subsistence and did not sell any maize. The reasons for producing maize subsistence only were given as: no surplus to sell (67% of the respondents), objective for production was purely for consumption (28%) and small land sizes (2%). Table 3 shows the constraints mentioned by the respondents, and the constraints mentioned most frequently were re high cost of inputs, pests and diseases and unpredictable weather.

A wide range of improved varieties was grown in Bungoma County but the ones grown by most households include H6213, H513, WH505, DK8031 and H516. The main reasons given for planting the stated varieties were that they were high yielding (30% of the respondents), had good taste (17%), had resistance to pests and disease (14%) and were early maturing (14%). It is apparent that farmers were responding to attributes that minimize crop failure and those that addresses consumer tastes and preferences.

Table 2. Household characteristics in Bungoma County, Kenya

Variable	**Bungoma (n=500)**	
	Mean	**Standard deviation**
Household head age (years)	51.1	13.8
Household size (number of people)	7	3
Total land size (acres)	3.00	2.89
Total land under maize (acres)	1.7	1.9
Number of maize plots (number)	2	2
Size of main maize plot (acres)	1.4	1.6
Gender of household head	Frequency	Percent (%)
Female	111	28
Male	389	72
Level of education	Frequency	Percent (%)
Secondary	205	41.0
Primary	163	32.6
College/University	128	25.6
None	4	0.8

Source: survey data, 2022

Table 3. Maize production and marketing constraints in Bungoma County

Constraint	Frequency (n=500)	Percent
	Production constraints	
High cost of inputs	144	28.8
Pests and diseases	142.5	28.5
Unpredictable weather	138.5	27.7
Post-harvest losses	37.5	7.5
Poor seed quality	21	4.2
Poor fertilizer quality	10.5	2.1
Others	6	1.1
Marketing constraints (n=500)		
Low prices	369	34.8
Low yields	161	15.2
Excess supply of maize	133	12.5
Post-harvest losses	103	9.7
Unpredictable weather	93	8.8
Long distance to markets	58	5.5
Other	144	13.6

3.2 Fractional Logit Model Results

Table 4 presents the coefficients and marginal effects estimates from the results of the fractional logit model. The mean Variance Inflation Factor (VIF) score was 1.42, less than the critical value of 10, meaning that there was no multi-collinearity detected among the independent variables. The Breusch-pagan test fails to reject the null hypothesis of homoscedasticity (Chi2 (1) = 0.04; Prob > chi2 = 0.837, thus indicating that there was no heteroscedasticity. The Wald statistic (Wald chi2(11) = 72.59) was significant at a one percent level, meaning that the model has high predictive power. A total of five variables were identified as determinants for intensifying improved maize varieties in Bungoma County as shown in Table 4:

Table 4. Determinants of intensity of adoption of improved maize varieties

Independent variables	Coefficient (robust std error)	Marginal effects (robust std error)
Age	-0.011(0.0043) **	-0.0026(0.0011) **
Sex	-0.053(0.0910)	-0.013(0.0223)
Farming Experience	-0.004 (0.0049)	-0.001(0.0012)
Household size	-0.027(0.0151) *	-0.007(0.0037) *
Off-farm income	-0.121(0.0825)	-0.029(0.0202)
Extension service	-0.228(0.0898) **	-0.056(0.0219) **
Group membership	0.054(0.1006)	0.013(0.0246)
Access to credit	0.041(0.0888)	0.009(0.0217)
High yielding	0.117(0.0891)	0.029(0.0218)
Read early maturity	0.294(0.0787) ***	0.0719(0.0191) ***
Tolerance to pests and diseases	0.134(0.0754) *	0.033(0.0184) *
Constant	0.689(0.2072) ***	
Number of Observations		498
Wald chi2(11)		58.78***
Breusch–Pagan/Cook–Weisberg Test for heteroscedasticity		Chi2(1) = 0.04 Prob > Chi2 = 0.8370
Pseudo R2		0.0149
log pseudolikelihood		-339.96322
Mean Variance Inflation factor		1.42

Source: Authors' own computation, 2023.

Note: Values in parentheses are standard errors, 10 percent, 5 percent; and 1 percent significant levels are denoted by $*$, $**$, $***$ *respectively*

The sample size used for analysis was 498 because 2 respondents had missing data, therefore did not meet the threshold for analysis.

The study findings show that a year's increase in the age of the household head reduced the probability of intensifying maize production by about 0.3%, meaning that older farmers put a smaller proportion of their land under improved maize production than the younger ones. This finding corroborates that of Mwaura et al. [30], who found that older farmers had a negative influence on the intensity of adoption of organic based technologies. Similarly, Olawuyi and Mushunje [31] found a negative effect of older farmers on the intensity of use of soil and water conservation technologies in Nigeria. In a study by Uddin [32] a negative correlation between age and adoption of agricultural technologies in South Dakota is reported. In addition, a study in Ghana by Addison et al. [33] shows that age reduced the intensity of adoption of improved rice technologies. These findings confirm the age-old fact that risk aversion among farmers increases with their age. This can be explained by the fact that the ability to provide sufficient labor, good management and receive information reduces with age, thus setting in risk aversion. It is easy to resonate with this result for the study area because improved maize varieties require more inputs, and in the face of unreliable rainfall due to climate change, risk aversion among farmers will increase, thus reducing the area under improved maize production, especially among older farmers. Bungoma County is a high rainfall area but it has increasingly received unreliable rainfall in the past years

A larger household size reduced the intensity of adoption of improved maize varieties in the study area by about 1%, meaning more family members reduced the chance of putting more land under improved maize varieties. On the contrary, some studies have reported a positive correlation between household size and intensity of adoption. A positive correlation between household size and the intensity of adoption of mulch and manure is reported by Mwaura [30]. A study by Uddin [33] reports a positive correlation between the number of adults in a household and adoption of improved rice technologies. The total household size strongly influenced (positively) the intensity of adoption of improved maize varieties in Benin [8]. All these studies show that household size was a proxy for labor availability in the household, which may not always be the case in all studies. A household can be termed as either a production or consumption unit. A household with a higher proportion of family members who are not productive on the farm (the very young, sickly and old) can be termed as a consumption unit while those with a higher proportion of family members who are productive (young adults) can be termed as a production unit. Therefore, a labor-intensive technology in a household that is a consumption unit may have a negative effect on the intensity of adoption, while a labor-intensive technology in a household that is a productive unit may have a positive effect on the intensity of adoption. The effect of household size on the intensity of adoption may therefore depend on the composition of the household size and the nature of the technology. In this study, the households may have been a consumption unit, where a higher proportion of household members were not productive on the farm. The household size of 7 in the study area was higher than the national average household size of 4. According to CRA [34], the age dependency ratio of Bungoma County ranks 10th out of the 47 counties, where out of every 100 people, 104 people below 14 years and above 65 years depend on them. This is above the national average of 82.

In this study, access to extension services reduced the probability of intensifying maize adoption by about 6%. This is contrary to the positive effect of extension to the intensity of adoption reported in some studies. For instance, [35] found a positive effect of extension to the intensity of adoption of genetically modified maize in the Eastern Cape Province of South Africa. In their study, [15] deduced a positive influence of access to extension to intensity of adoption of conservation agriculture by smallholder farmers in Zimbabwe. A study by [8] found that access to extension services had a significant and positive influence on the decision to intensify the use of improved maize seed Benin West-Africa. In their study conducted in Ghana, [14] found access to extension services having a positive effect on the intensity of adoption of maize technological packages. Similarly, [11] found that a household's access to extension services gave a positive impact on the intensity of adoption of irrigation technologies in Machakos County. Finally, [36] found access to extension to have a positive impact on intensity of adoption of odorless fufu technologies. However, the negative effect of extension on the intensity of adoption (increase of proportion of land under maize) of improved maize varieties in the study area could be due to the fact that extension agents encouraged farmers to grow other crops that can increase food security in the face of climate change, and since the land size is fixed, the acreage under improved maize was reduced. Due to climate change, the national and county governments have encouraged smallholder farmers to diversify crop production to minimize crop failure. Most improved maize varieties require high rainfall and purchased inputs like inorganic fertilizer. Unreliable rainfall therefore makes farmers plant more drought and pest resistant crops like sweet potatoes, sorghum and cassava at the expense of improved maize varieties. Maize as a staple food in Kenya, and more so in Bungoma County is therefore threatened, and this may be a threat to food security if the production of climate smart crops does not increase significantly. The goal of every county in Kenya is to increase food security.

The study results show that the positive attributes anticipated from growing improved maize varieties by farmers increased the intensity of adoption. The anticipated early maturing and disease tolerant varieties attributes increased the probability of adoption by 7% and 3.3% respectively. This finding lends support to similar studies conducted in Africa. In their study on intensity of adoption of integrated pest management practices in Rwanda, [16] found that perceived benefits of the push-pull technology had a positive impact on the intensity of adoption of the technology. A study in Ghana by [33] shows that perceived intensive use of labour and capital significantly reduced the probability of adoption of rice technologies. The expectation of increased yield from improved maize seeds highly influenced the intensity of adoption of improved seed in a study conducted in Ethiopia [8]. A producer’s perception of profitability strongly influences the probability of adoption of precision agriculture technologies in South Dakota, in the United States [10]. According to Derwisch et al. [37] increased maize variety adoption has been attributed to their high yield potential followed by early maturity and drought tolerance as key traits in Malawi. A study by Marenya et al. [5] reports that farmers were willing to pay for novel traits such as drought tolerance, good ear aspect, high adaptation while forgoing on high yield performance. These studies are a pointer to the fact that the inherent technology characteristics as well as the complementary inputs are a strong determining factor in adoption intensity.

4. CONCLUSIONS AND RECOMMENDATIONS

This study sought to find out the factors influencing the intensification of improved maize varieties in Bungoma County, where primary data from 498 households out of the 500 households’ samples was used for analysis. This paper contributes to the literature on the intensification of agricultural technologies, specifically to intensification of improved maize varieties. In this study, the factors influencing the adoption intensity of improved maize varieties can be categorized into personal characteristics of the farmer (age, and household), institutional factor (extension service) and varietal factors (early maturing benefit).

To increase food security, older smallholder farmers should be given special attention to address the causes for their risk aversion given that the results show that the farmers are on average aged (51 years). The perceived benefits of improved varieties came out as a strong determinant for the intensity of adoption, thus demonstrating how the possibility of getting benefits from a technology can intensify its adoption. To intensify the use of new technologies research should start from the user of the technology to understand the farmers’ desired attributes of a technology, and once the technology is developed, farmers need to be sensitized on the positive attributes of the technology. These results underscore the need to have a strong research-extension linkage in the counties where researchers can demonstrate technology benefits to the end-users.

The strong influence that extension has on food security by influencing farmers to reduce the proportion of land under maize is noted in this study. They may have encouraged the production of other crops at the expense of putting more land under improved maize varieties.

ACKNOWLEDGEMENTS

Acknowledgements to God for enabling the authors conduct the study, to the collaborating institutions for allowing their staff to conduct the study and for providing the infrastructure to do the work, to all the extension staff and enumerators in Bungoma County who were involved in data collection.

Funds for this work was given by the the National Research Fund (NRF), Kenya.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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Peer-review history:
The peer review history for this paper can be accessed here:
https://www.sdiarticle5.com/review-history/109956