

Research Article

Socio-economic and Institutional Factors Affecting the Adoption of Rice Production Innovations by Smallholder Rice Farmers in the West Kano Irrigation Scheme, Kenya

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Abstract

Rice, being the third most widely consumed cereal in Kenya, has had a significant surge in consumption, with a notable increase of 12%. Nevertheless, Kenya has encountered challenges in fulfilling its domestic rice requirements, primarily due to the slow uptake of rice agricultural technologies among smallholder rice producers. The primary objective of this study was to see increase of rice output for enhanced livelihoods and decrease the need for imports in Kenya. The study identified the socio-economic and institutional elements that influence the adoption of these innovations. The researchers obtained primary data by administering a semi-structured questionnaire to a sample of 200 smallholder rice growers in West Kano Irrigation Scheme, Kisumu County. The analysis employed descriptive statistics and a multivariate Probit model. The results of the econometric analysis, analyzed using a multivariate probit model, indicate that there is a significant positive relationship between access to agricultural extension services ($\beta=0.24$, $p<0.01$) and the likelihood of adopting improved rice varieties. Similarly, access to credit ($\beta=0.32$, $p<0.05$) is found to have a significant positive effect on the adoption likelihood of row planting. These findings underscore the importance of enhancing these services in order to promote the adoption of improved agricultural practices. There was a statistically significant association also between male-headed families and greater adoption rates ($\beta=0.22$, $p<0.1$), indicating the presence of gender inequities. The findings of the study furthermore indicate that there is a negative relationship between the size of land and the adoption of land-intensive innovations ($\beta=-0.46$, $p<0.01$). This suggests that smallholders have obstacles when attempting to implement and expand the use of innovative practices on their rice farms. Factors such as the age, level of education, gender and family size of farmers have been identified as significant drivers of adoption. The implementation of targeted policies and interventions that specifically target the characteristics highlighted can effectively facilitate the general adoption of innovation and significantly enhance the domestic production of rice.

Keywords

Rice Production, Agricultural Technologies, Innovations, Irrigation, Smallholder Farmers, Kenya

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1. Introduction

Rice is an important and widely consumed food crop by nearly half of the world's population accounting to about a quarter of global consumption, with the majority of the population concentrated in developing nations [1]. According to [2], approximately 488 million tonnes (MT) of rice were consumed globally in 2018, with Asia accounting for 90% of production and consumption.

Africa is a long way from becoming self-sufficient in rice production and the situation is anticipated to worsen in the future [3]. There are possibilities for bridging the demand-supply gap in African states: increasing size of cultivable rice land, closing the production gap in farmers' fields by introducing new technologies and innovations, raising the production by introducing high-yielding cultivars and reducing postharvest losses.

Rice production innovation adoption has increased agricultural productivity globally. The introduction of these agricultural technology has had a substantial influence on farmer welfare, agricultural productivity and food sector economics, according to [4]. These innovations include; enhanced irrigation systems like water saving culture, pest control measures, use of urea deep placement and crop rotation techniques which aids in increasing output. Furthermore, the increasing use of farm technology has enabled farmers to cultivate land more effectively, allowing them to produce more with less work.

In Kenya, rice is grown in a variety of ecologies, including irrigated paddy, rain-fed upland, and lowland rice production methods. According to [5], 90% of rice produced in Kenya comes from irrigated/flooded systems, totalling 162,000 metric tonnes. The remaining 10%, or 18,100 metric tonnes, comes from rain-fed highland and lowland systems. Mwea irrigation system in the central region, Bunyala in the western area, Tana Delta & Msambweni in the coast region, Ahero, West Kano, Migori & Kuria in Nyanza, and Perkerra in Baringo County are the rice-growing regions in Kenya.

According to [6], smallholder rice farmers in these regions are adopting agricultural technologies like better methods of irrigation, pest control methods, urea deep placement, new varieties, farm mechanization, enhanced rice milling and crop rotation to increase rice yield. Despite the fact that these agricultural innovations that are considered to boost rice output in Kenya, they are less likely to be adopted by smallholder farmers, resulting in stagnating rice production [7].

These smallholder rice farmers are responsible for the majority of rice farming in Kenya and Sub-Saharan Africa. Unfortunately, they are often limited in their access to credit and other financial resources, which makes it difficult for them to afford efficient and effective farming technologies [8, 9]. Despite a population growth of 2.7% per year and an estimated annual need for rice by the government, Kenya has been unable to meet its domestic rice demand of 1.2 million metric tons. Currently, the country produces only 181,000MT,

which is 15% of the consumption (NRDS 2019). This lack of production can be attributed to the farmers' lack of adoption of farm innovations along the production path, according to [10].

According [11], the determinants of rice innovations adoption in Africa can be categorized into socio-economic, cultural and institutional factors. These factors have a direct or indirect influence on the decision of a farmer to adopt an innovation. Socio-economic factors include the education and income level of the farmer, family size, access to credit, land size and availability of extension services.

In Kenya, there are significant challenges in the rice production stages that are affecting the domestic rice subsector, which includes: limited water for irrigation; declining productivity of land; the rising cost of inputs, machinery, and mortgages; low-quality seeds and seedlings; inefficient agricultural practices [12, 13].

However, some smallholder rice farmers in the West Kano irrigation system have implemented the disseminated rice innovations, while others have either partially or not yet adopted the rice innovations. There is a scarcity of data on the elements that influence the adoption of rice farm innovation practices. As a result, the purpose of this study is to fill this information gap by examining the socioeconomic and institutional factors of innovation uptake among smallholder rice farmers in Kisumu County's West Kano irrigation scheme.

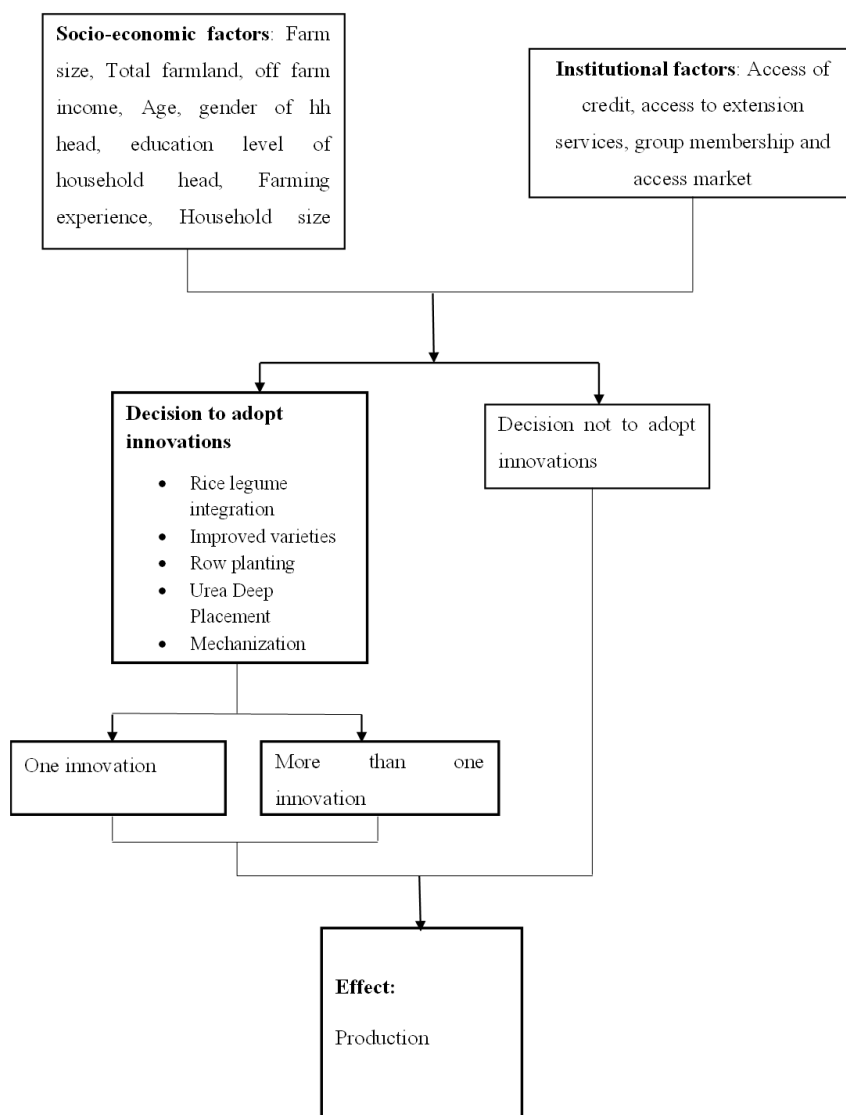
2. Theoretical Framework- Maximum Utility Theory

The study was motivated by the maximum utility theory. Innovations uptake and adoption is driven by utility maximization theory. Maximum utility theory states that people will make decisions that maximize their utility or satisfaction. It suggests that individuals will make rational decisions based on the preferences and constraints they face. Hence, the likelihood of adopting rice farm innovations like use of improved varieties, urea deep placement, mechanization in weeding and harvesting is high if and only if the utility derived from its adoption is superior relative to non-adoption. The farmers are economic agents, and they are rational in nature when making decisions, and they only make decisions that will maximize their utilities subject to some constraints. Therefore, if and only if the utility gained from its adoption is greater than that of not adopting it, there is a good chance that rice production innovation will be adopted. In the event that a farmer i^{th} with ($i = 1, 2, \dots, N$) considers the benefits of implementing the j^{th} innovation—where j represents the decision to adopt improved varieties (IV), line transplanting (LT), urea deep placement (UDP), mechanical weeding (MW), rice legume rice rotation (RLR) and rice harvesters (RH) and irrigation (IR) on the paddy farm.

2.1. Conceptual Framework

The research was conducted based on a conceptual framework that illustrates the interplay between dependent, independent, and intervening variables, as depicted in Figure 1 below. The socio-economic and institutional factors encompass various variables such as farm size, land size, income, age, gender, education level of the household head, farming experience, household size, primary income activity,

access to credit and extension services, group membership, training, access to improved seed, and access to farm equipment. Various socio-economic and institutional factors have the potential to exert effect on the adoption of innovations in agricultural practices, such as the utilization of certified seeds, integrated pest and disease management, line transplanting, and farm equipment and mechanizations. The adoption of these innovations has the potential to contribute to enhanced rice production yields.



Source: Authors Conceptualization

Figure 1. Conceptual Framework.

2.2. Study Area

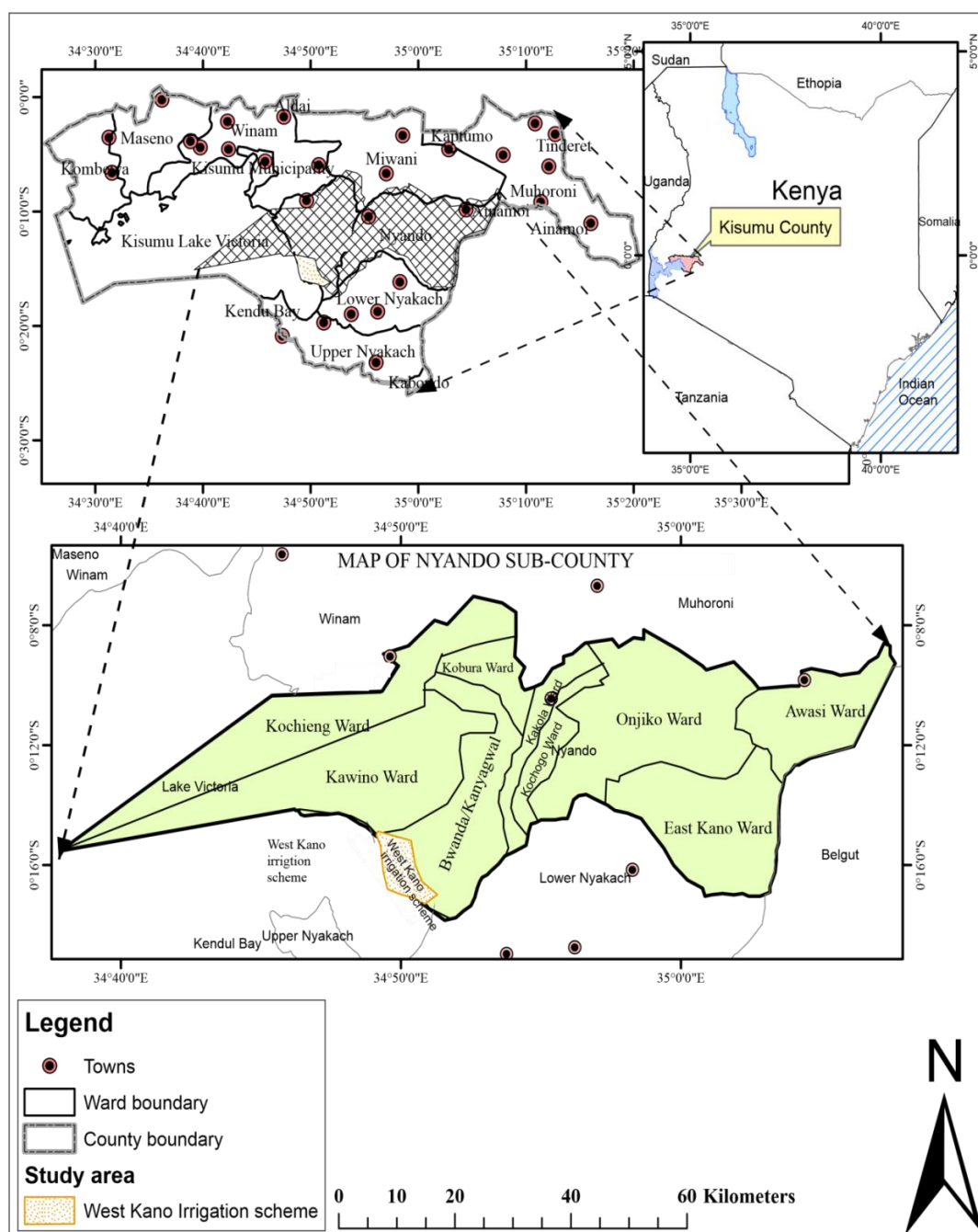
The West Kano Irrigation Scheme, located in the Kano plains between the Nandi escarpment and the Nyabondo plateau in Kisumu County [14], was the location of the study.

The project was initiated in 1974 and completed in 1976. The Kano Plain (0°04'0.20"S; 34°48'35.02"E) has numerous rice cultivation areas scattered across it, east of Winam Bay on Lake Victoria's eastern shore. The plain, which is approximately 1,140 metres above sea level, has seasonal and permanent wetlands dotted around it near the lake's shore. On the

eastern side of the Kano Plain, a rift valley forms the topographical divide between the plain and the Tinderet highland. Numerous rivers flow down from this highland and feed into Lake Victoria via the Kano Plain. The Nyando and Awachi-Kano rivers are significant water sources for the area's rice production [15].

The West Kano irrigation scheme covers a gross area of 4,450 acres, benefiting over 2300 farmers and producing nearly 8,000 metric tonnes of milled rice annually, with an average gross income of 188 million Kenya Shillings [16].

The rice farmland area is 2,830 acres and each smallholder rice farmer owns between 2-4 acres. Irrigation water is extracted via pumping from Lake Victoria, and the water drainage is accomplished via pumping back to the Lake. Around 30,000 people rely on the scheme, and approximately 382 smallholder rice farmers in the West Kano irrigation scheme own less than 3 acres of land (KNBS, 2019 [17]). Therefore, the study was conducted in the West Kano Irrigation Scheme, as depicted in figure 2 below.



Source: Kisumu County Integrated Development Plan 2018-2022

Figure 2. Study Area Map (West Kano Irrigation Scheme).

2.3. Determination of Sample Size

The present study provides information regarding the population size of smallholder rice farmers in West Kano Nyando sub-county. Therefore, the appropriate sample size was found using the formula proposed by Yamane [18]. The formula proposed by Yamane (1967) is of particular utility in cases where the precise size of the population is known. The use of this mathematical equation serves to guarantee that the chosen sample size accurately reflects the characteristics of the total population, consequently enhancing the dependability and credibility of the study findings [19].

According to Kharuddin et al. (2020), the approach for determining sample size in survey research is straightforward and efficient. The method proposed by Yamane (1967) is advantageous due to its incorporation of the margin of error, rendering it suitable for estimating the optimal sample size for both continuous and categorical variables across various degrees of confidence [20]. The sample size was determined using a 95% confidence level with a significance level (α) of 0.05.

$$n = \frac{N}{1 + N(e)^2} \quad (1)$$

Where n is the sample size, N is the population size and “ e ” is the level of precision. Equating smallholder farmers’ population size, which is 382 farmers and the level of precision that is 0.05 then the sample size for the study was 190 smallholder rice farmers.

$$n = \frac{382}{1 + 382(0.05)^2} \approx 200 \text{ Smallholder rice farmers} \quad (2)$$

Hence a sample of 200 smallholder rice farmers will participate in the study.

3. Method of Data Analysis

In cases when a single innovation is under consideration, researchers typically utilize univariate probit and logit models to ascertain the characteristics that influence the adoption process. However, in cases when adoption necessitates many innovations, the utilization of univariate probit and logit models is deemed inappropriate [21]. Smallholder farmers commonly employ a range of innovative approaches across the entirety of the production process in order to mitigate constraints in rice output.

The decision to adopt a particular innovation can be influenced by the adoption of another innovation due to their potential for complementarity, substitution, or supplementation nature. According to [22], failing to account for the

trade-off and combined effect of adopting many innovations can lead to biased and inefficient estimates of the factors that influence the decision to embrace these innovations. Therefore, the multivariate Probit (MVP) technique was employed to examine this objective, since it enables the simultaneous modeling of the effects of several explanatory factors, while also accounting for the correlation among error terms [23]. According to [24], univariate models such as Probit and Logit fail to account for the correlation present in the error components of the adoption equation.

The Multivariate Probit (MVP) model is a statistically rigorous analytical tool that enables the examination of potential connections between unobserved disruptions in equations related to the adoption of innovations, as well as potential linkages between combinations of innovations that may be accepted. The Multivariate Probit model examines the potential for positive correlation (complementarity) and negative correlation (substitutability) among different farm innovations. [26, 25] argue that the failure to adequately justify this impact may be attributed to the limitations of univariate models in adequately accounting for complementarities or substitutability.

Following Aryal et al. (2018), the MVP model can be specified as:

$$\pi_{ij}^* = X_i' \beta_j + \varepsilon_i \quad (j = IV, UDP, LT, MW, RLR, RH) \quad (3)$$

Where; π_{ij}^* is the probability of i^{th} farmer adopting j^{th} innovation.

X_i' is the socioeconomic and institutional characteristics of farmer i

β_j is parameter estimates

ε_i error term

IV- improved varieties

LT- Line transplanting

UDP- urea deep placement

MW- Mechanized weeding

RLR- rice legume rice

RH- Rice harvesters

Equation (1) was used as an indicator function. Therefore, the unobserved preferences in Eq. (1) can be transformed into the observed binary equation for each innovation choice as illustrated in Eq. (2):

$$\pi_{ij} = \begin{cases} 1 & \text{if } \beta_{ij}^* > 0 \\ 0 & \text{Otherwise} \end{cases} \quad (4)$$

For adopting multiple innovations, the stochastic error terms are assumed to jointly follow multivariate normal (MVN) distribution with zero conditional mean. Table 1 below shows the variable that was included in the Multivariate Probit Model.

Table 1. Variables Included in The MVP Model and Expected Signs.

Variable	Definition of variable and their measurement	Measurement	Expected sign
Dependent Variable	Adoption of farm innovations (improved varieties, Line transplanting, urea deep placement, mechanized weeding, rice legume rice and rice harvesters)	Categorical	
Independent Variables			
Age	Age of the decision maker 1 in Years	Discrete	±
Education	Education level of decision-maker years	Discrete	+
Gender	Gender of the decision-maker (1 male, 0 otherwise)	Binay	±
Occupation	Main income activity of the decision-maker (Self-employed, Farming, Salaried employment, Retired and Wage employment)	Categorical	+
Experience	Farming experience of decision-maker in years	Continuous	+
Household size	Household size	Discrete	±
Income	The proportion of income allocated to farming (KES)	Continuous	+
Land size	The proportion of land under farming (hectares)	Continuous	±
Market distance	Distance to the market	Continuous	-
Credit	Amount of credit received in the last 12 months (KES)	Continuous	+
Extension	Number of extension visits in the last 12 months.	Count	+
Group membership	Membership to agriculture-related group (1 yes, 0 otherwise)	Binary	+

¹ The decision maker is the individual who makes major household decisions, including farming.

² KES - Kenya Shillings.

4. Results and Discussion

Table 2. Descriptive Statistics of Continuous and Discrete Socio-Economic and institutional Variables (N=200).

Variable	Mean	Std. dev.	Min	Max
Household size	5.09	2.18	1	10
Off farm income	86558.76	70341.21	2000	303000
Number trainings	5.62	1.47	2	9
Age	41.91	13.77	20	85
Education level	10.82	2.90	5	16
Land size in acres	1.71	0.69	1	3
Extension	3.565	1.41	3	8
Frequency of extension contacts	3.08	1.75	1	9

The findings indicate that the average household size was 5.085, accompanied with a standard deviation of 2.18. The least

documented household size was one, and the greatest recorded household size was ten. These findings suggest that the mean household size among smallholder rice farmers was slightly greater than five, with some degree of variability in family sizes. In relation to income derived from sources outside of agricultural activities, the average value was determined to be 86558.76, accompanied by a standard deviation of 70341.21. The least reported off-farm income was 2000, but the greatest documented off-farm income was 303000. The data presented indicates a significant variation in the level of income derived from non-agricultural endeavors among small-scale rice producers.

The variable "Number of training" denotes that, on average, the participants had engaged in 5.62 training programs, with a standard deviation of 1.47. The least number of training sessions attended was two, whilst the greatest number reported was nine. This finding underscored the participation of smallholder rice farmers in several training programs designed to improve their agricultural knowledge and abilities. The average age of the participants was 41.91, accompanied by a standard deviation of 13.77. The least age documented in the data set was 20, whilst the maximum age seen was 85. The values presented in the study depict the age distribution seen among the smallholder rice growers.

The average education level was found to be 10.82, with a standard deviation of 2.90. The minimum stated level of education was five years of formal schooling, whilst the maximum level reached was 16 years. The findings of the study revealed a diverse variety of educational backgrounds among the smallholder rice farmers, with an average educational attainment slightly exceeding 10 years. The variable "Land size in acres" indicated that the mean land size possessed by the smallholder rice farmers was 1.71 acres, accompanied with a standard deviation of 0.69. The minimum recorded land size was 1 acre, whilst the maximum reported land size was 3 acres. The data presented indicates a range of variations in land ownership among the respondents.

In relation to extension services, the average extension score was found to be 3.57, accompanied by a standard deviation of 1.41. The lowest reported extension score was 3, whereas the highest level was 8. This study examined the accessibility and utilization of agricultural extension services among smallholder rice farmers. Regarding the number of extension contacts, the findings revealed that, on average, the participants reported a mean frequency of 3.08 contacts with extension agents, accompanied by a standard deviation of 1.75. The smallest reported frequency was 1, whilst the maximum frequency was 9. This study observed variances in the frequency of interactions with extension agents among smallholder rice producers.

4.1. Multicollinearity Test

To examine the presence of multicollinearity among the independent variables, the variance inflation factor (VIF) was employed. The VIF assesses the extent of intercorrelations or

associations between the proposed independent variables [27]. The outcomes of this analysis are displayed in Table 3. The variance inflation factor (VIF) test was conducted on the continuous and discrete socio-economic variables of the smallholder rice farmers who participated in the study. The purpose of this test was to examine the presence of multicollinearity, which refers to high inter-correlations between the independent variables. Table 3 presents the VIF values and their reciprocal, 1/VIF, which provides an indication of the degree of multicollinearity.

Table 3. Variance Inflation Factor Test Results for Continuous and Discrete Socio-economic Variables.

Variable	VIF	1/VIF
Education level	1.42	0.702346
Households size	1.40	0.713045
Sex of household head	1.37	0.731189
Extension	1.35	0.742802
Occupation	1.32	0.75626
Age	1.31	0.766177
Number of extension visits	1.30	0.766296
Marital status	1.30	0.766818
Farming experience in years	1.25	0.802572
Training access	1.25	0.802835
Off-farm income	1.23	0.813063
land size	1.22	0.821721
Group membership	1.17	0.851817
Land ownership	1.12	0.889727
The main source of income	1.12	0.895508
Credit access	1.08	0.93022
Mean VIF	1.26	

According to the findings, it can be observed that all variables exhibited Variance Inflation Factor (VIF) values below 2, suggesting a minimal presence of multicollinearity based on established standards [28]. Values that are less than ten are generally regarded as acceptable, however Variance Inflation Factors (VIFs) that surpass 10 indicate a significant level of collinearity. The variables that exhibited the greatest values of Variance Inflation Factor (VIF) in the analysis were Education level (1.42), Household size (1.4), and Sex of household head (1.37). Although these values were the highest seen, they remained much lower than the threshold of 2, suggesting the presence of possible collinearity concerns. A frequently employed and cautious criterion for evaluating

collinearity is a maximum Variance Inflation Factor (VIF) of 2. In this case, the observed maximum VIF value of 1.42 was considerably lower than this threshold. Overall, the extremely low Variance Inflation Factor (VIF) values observed for all variables indicate that there was minimal multicollinearity present. As a result, the validity and stability of the regression results should not have been compromised.

Insights into the strength of collinearity can be obtained by calculating the reciprocal of the variance inflation factor (VIF) values, denoted as $1/\text{VIF}$. Smaller values of the inverse variance inflation factor ($1/\text{VIF}$) are indicative of a reduced level of collinearity. In this instance, it is observed that all variables possess $1/\text{VIF}$ values over 0.70, so providing more evidence to substantiate the assertion that the presence of multicollinearity among the variables considered in the econometric study is not of substantial consequence. The calculated mean VIF of 1.26 falls within an acceptable range, providing additional confirmation that there are no significant issues with multicollinearity in the dataset. The findings suggest that the socio-economic variables incorporated in the econometric analysis demonstrate a minimal degree of multicollinearity. Hence, it was determined that the variables possessed the necessary qualities to be included in subsequent econometric models, as there were no notable problems regarding collinearity [29].

4.2. Heteroscedasticity Test

The White test was utilized to detect heteroscedasticity in the explanatory variables, and the results are presented in Table 4. The White's general test can be regarded as a modification of the Breusch-Pagan test, which allows for the relaxation of the assumption of normally distributed errors. In contrast to the Breusch-Pagan test, which exclusively detects linear manifestations of heteroscedasticity, the White test was selected for its capacity to capture both the extent and direction of variation in non-linear manifestations of heteroscedasticity [30].

Table 4. Test for Heteroscedasticity.

Source	chi ²	Df	P
Heteroscedasticity	179.43	147	0.1355
Skewness	15.31	16	0.5019
Kurtosis	0.88	1	0.3474
Total	195.62	164	0.1464
chi2(147) = 179.43	Prob > chi2 = 0.8264		

The chi-square test result did not provide evidence of statistically significant heteroscedasticity in the dataset. Fur-

thermore, the evaluation of skewness revealed that no statistically significant skewness was identified in the dataset. Moreover, the assessment of kurtosis suggests that the data does not demonstrate substantial kurtosis. The comprehensive test statistics, encompassing the outcomes from all sources, resulted in a p-value of 0.1464. The results suggest that there is no statistically significant evidence of heteroscedasticity in the sample. Based on the aforementioned data, it may be deduced that the absence of heteroscedasticity is supported, as the chi-square test statistic did not yield statistical significance [31].

Table 5. Percentage distribution for Farm Innovations Adoption Rates (N=200).

Farm Innovations	Adoption Rate (%)
Mechanized Harvesting	29
Fertilizer application-UDP	18.4
Improved Rice Varieties	16.5
Mechanized Weeding	16.2
Row-planting	11.9
Crop Rotation	8
Total	100

The findings indicated that the six farm innovations had different levels of acceptance, with machine-like harvesting emerging as the most widely embraced, while row-planting demonstrated comparatively lower levels of adoption. Nevertheless, it is worth noting that the adoption rates of all innovations examined in this study were found to be below 30%. This finding implies that there exists a significant opportunity for enhancing the level of acceptance and utilization of these innovations.

The acceptance rate for each of the six inventions, on average, was roughly 17%. The findings of this study suggest that a portion of farmers have embraced some contemporary methods of farming, although the majority of farmers have yet to adopt them [32] conducted a study examining the factors that influence the adoption of digital technology among small-scale farmers in agricultural value chains AVCs in South Africa. The scholarly publication "Information Technology for Development" argued that the greater adoption of technology may be facilitated by resolving concerns related to access, affordability, and farmer education.

4.3. Socio-Economic and Institutional Factors That Contribute to the Adoption of Farm Innovations by Smallholder Rice Farmers

The study's objective was to determine socio-economic and

institutional factors affecting the adoption of innovations by smallholder rice farmers in the West Kano Irrigation Scheme.

Multivariate Probit (MVP) was used to analyse this objective.

Table 6. Multivariate Probit estimates and marginal effects for the adoption of farm innovations by smallholder rice farmers in West Kano Irrigation Scheme (N=200).

	Mechanical weeding	Improved rice varieties	UDP	Row planting	Crop rotation	Mechanical harvesting
	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
Group membership	-0.03	-0.01	0.08	-0.12	-0.11	0.70**
Extension	-0.13*	0.24***	0.21***	0.18***	0.24***	-0.12
credit access	0.01	0.11	0.24*	0.32**	0.23	0.58*
land size	-0.21	-0.13	-0.04	-0.46***	0.06	-0.65***
Off-farm income	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
Age	0.01	0.01	0.01*	0.02***	0.02**	0.01*
Sex	0.22	-0.44**	0.44*	0.33	0.06	-0.67*
Household size	-0.124*	-0.18**	0.15***	0.03	0.05	-0.22***
Education level	0.27***	0.19**	-0.02	0.02	0.07*	0.15

Legend: * p<.1; ** p<.05; *** p<.01

The findings from the multivariate probit regression analysis offer valuable insights into the determinants influencing the adoption choices of smallholder farmers with regards to various agricultural advances. The study reveals several significant patterns. The probability of adopting new strategies is continually heightened by the availability of institutional services such as agricultural extension and financing. This underscores the crucial significance of these services in facilitating the dissemination of technology by enhancing farmers' knowledge and facilitating their access to inputs. The imperative for quicker adoption lies in the expansion of the scope of extension and credit services.

The adoption of agricultural practices is heavily influenced by farm assets, such as land, as well as off-farm revenue streams. According to [33], farmers who possess larger land holdings exhibit a decreased propensity to use land-intensive techniques such as row planting and mechanization. The

reduction of adoption incentives occurs as a result of decreased reliance on agriculture due to higher off-farm earnings. The implementation of policies aimed at enhancing the profitability of small farms has the potential to motivate and promote the use of such measures.

Furthermore, factors such as the age, level of education, gender, and size of the family of farmers have been identified as significant drivers of adoption. There is a positive correlation between age and education level of farmers and their propensity to adopt new practices. Conversely, the adoption of such practices tends to be hindered by larger household sizes, which can be attributed to limitations in available resources. The effects of gender on technology differ, highlighting the necessity of promoting innovation that is inclusive of all genders. The findings presented in Table 5 demonstrate the relative significance of each independent variable in elucidating the uptake of farm technologies.

Table 7. Relative Importance of Socioeconomic and Institutional Factors on Farm Innovations Adopted by Smallholder Rice Farmers Based on the Summarized Mean Marginal Effects.

Independent Variables	Six Farm innovations for the study					
	Mechanized weeding	Improved rice varieties	UDP	Row planting	Crop rotation	Mechanical harvesting
Group membership	-.0056	-.0072	-.0039	-.0320	-.0696	.2650
Extension	-.0440	.0794	.0772	.0684	.0849	-.0501
Credit access	.0108	.0404	.1205	.1497	.0997	.1659
Land size	-.0633	-.0419	-.0271	-.1448	-.0006	-.2292
Off-farm income	-0.0000	-0.0000	-0.0000	0.0000	-0.0000	.0000
Age	.0028	.0030	.0052	.0091	.0054	-.0003
Sex	.0715	-.1511	.1428	.1132	.0382	-.2140
Household size	-.0420	-.0604	.0468	-.0077	.0149	-.0670
Education level	.0911	.0684	-.0108	.0487	.0553	.0398

The findings indicate that the availability of credit has a significant role in elucidating the uptake of innovation. The results consistently demonstrate positive marginal impacts across all specifications. This implies that improved loan accessibility plays a crucial role in motivating farmers to embrace agricultural advances. The results presented align with the outcomes reported in the research conducted by [34] titled "Do farmer-actor interactions in the agricultural innovation system influence the adoption of technological innovations in Ghana?" Their study revealed a notable correlation between farmers' access to credit and their adoption of technological innovations within the Ghanaian context. Therefore, the enhancement of loan accessibility and the provision of financial assistance to farmers may have a significant impact on the increase in rates of innovation adoption.

The amount of education likewise exhibits consistently favorable marginal impacts across all specifications. The findings presented in this study align with the results obtained by [35] in their research on "Determinants of the Adoption of Climate-Smart Agricultural Practices by Small-Scale Farming Households in King Cetshwayo District Municipality, South Africa [36] found a notable association between the level of education and the adoption of Climate-Smart Agricultural Practices by small-scale farming households in the aforementioned district of South Africa. This suggests that the attainment of higher levels of education has a pivotal role in enabling the acceptance of innovation. Investment in educational programs, training initiatives, and knowledge dissemination can serve as useful measures for fostering the acceptance of innovation within the agricultural community.

Extension services have a multifaceted impact on the adoption of innovation. The marginal effects exhibit variation contingent upon the specification. The negative effects of

mechanical weeding, better varieties, and mechanized harvesting farm innovations were seen, whereas the favorable effects of UDP, row planting, and crop rotation agricultural innovations were revealed. This implies that the efficacy of extension services can differ based on the particular environment and manner of execution. The findings of this study are consistent with the results obtained by [37] in their research titled "A scoping review of the adoption of climate-resilient crops by small-scale producers in low- and middle-income countries. [38] demonstrated that extension services play a crucial role in facilitating the adoption of climate-resilient crops by small-scale producers in middle-income countries. Enhancing the efficacy of extension services and customizing them to cater to the specific requirements and inclinations of farmers might amplify their influence on the adoption of innovative practices.

The variable representing land size consistently exhibits negative marginal impacts across all specifications. While the extent of the impacts may differ, there is generally a negative correlation between bigger land holdings and adoption rates. According to [39], the adoption of innovations among farmers with greater land holdings may be restricted by resource restrictions or alternative farming practices. The implementation of strategies aimed at mitigating obstacles associated with limited land size, such as the promotion of effective resource management or the provision of assistance for smaller-scale innovations, may play a crucial role in enhancing the rates of adoption.

In all parameters, the negative marginal effects of group membership are consistently observed. This finding implies that the affiliation with a particular group significantly affects the acceptance of innovation, leading to unfavourable consequences. The findings presented in this study align with the

results reported by [40], wherein they observed a statistically significant detrimental impact of group affiliation on the adoption of innovations inside small and medium-sized enterprises (SMEs). Although Age consistently exhibits positive marginal effects in all parameters, the extent of these effects is rather modest. The findings presented in this study align with the research conducted by [41] titled "Adoption and diffusion of digital farming technologies integrating farm-level evidence and system interaction." In their study, [42] demonstrated a statistically significant positive relationship between age and the adoption of farming technologies. This finding suggests that age plays a very little role in elucidating the acceptance of innovation compared to other influential factors. Nevertheless, it is crucial to acknowledge that several age-related elements, including but not limited to experience, risk perception, and technical familiarity, may continue to exert an influence on the patterns of adoption. Consequently, it is imperative to examine these issues within a wider framework.

The variables of gender and household size exhibited varying impacts across different specifications. The extent to which they contribute to the explanation of innovation uptake remains uncertain, given their marginal effects exhibit variability in both direction and magnitude. The average marginal impacts of off-farm income exhibit a negligible magnitude across all conditions, suggesting that off-farm income has a minimal role in elucidating the adoption of innovation. The present findings are consistent with the results obtained in the study conducted by Amrullah et al. (2023 [43]) titled "The Influence of Agricultural Extension Accessibility on the Adoption of Technological Innovations and Smallholder Farmers' Income in Banten, Indonesia." In their research, Amrullah et al. found a limited correlation between off-farm income and the adoption of technology. It appears that adoption rates exhibit larger correlations with characteristics such as credit accessibility or level of education.

5. Conclusion

This research has yielded significant findings pertaining to the adoption of agricultural innovation among smallholder rice farmers in the West Kano Irrigation Scheme. The results of the study indicated that there were small levels of acceptance for the majority of innovations, however the rate of uptake varied among different technologies and groups of farmers.

Although several contemporary approaches have been adopted, there are still significant deficiencies in providing farmers with the necessary tools to execute sophisticated practices. The investigation revealed that some institutional factors, such as agricultural extension services and access to credit, are crucial in facilitating the use of technology and driving the transformation of small-scale farming. Nevertheless, the presence of gender inequalities in adoption rates emphasizes the necessity for targeted and comprehensive interventions that take into account the socioeconomic cir-

cumstances of farmers.

The adoption of modern technologies in agriculture is influenced by various factors, including education, revenue sources, assets, and other characteristics of farmers. This highlights the intricate relationship between these situations and the adoption of technology. It is imperative to have a comprehensive approach in fostering innovations that not only evaluate technical factors but also take into account societal factors.

6. Recommendation

The paper identifies priority areas that can facilitate the wider adoption of innovation among smallholder rice farmers.

- 1) To enhance the adoption of underutilized innovations such as row planting and fertilizer application utilizing UDP, it is recommended that the Kisumu County Department of Agriculture intensify localized demonstrations and awareness efforts. This may be achieved by actively involving extension agents who will play a crucial role in promoting these practices.
- 2) It is imperative for both national and county governments to develop inclusive policies that enhance the accessibility of crucial services such as agricultural extension and inexpensive finance for smallholder farmers. It is imperative to prioritize the establishment of equitable access for female farmers, in light of the evident inequities between genders.
- 3) It is important for the development partners and private sector entities to endorse strategies that enable smallholders to enhance their production levels in the face of limited land resources. This may entail the facilitation of access to land-saving technology through the implementation of suitable finance structures and collaborations between public and private entities.
- 4) It is significant for county and national governments to prioritize the allocation of resources towards the investment in farmer skills training and adult education programs. This strategic approach aims to enhance the capacity for innovation adoption within the agricultural sector. The design and implementation of curricula and delivery modalities has to be customized to suit specific local circumstances, taking into consideration the identified deficiencies through agricultural extension efforts.
- 5) The enhancement of financial attractiveness for innovations necessitates the collaborative endeavors of various stakeholders across the rice value chain. These efforts should focus on bolstering market connections, delivering technical support that aligns with market demands, and offering incentives for the adoption of climate-smart practices.

Area for Further Research

Further research might be conducted to better understand the connection among socioeconomic, institutional, and demographic factors in influencing patterns of adoption.

Abbreviations

KNBS	Kenya National Bureau of Statistics
SME	Small and Medium Size Enterprise
AVCs	Additional Voluntary Contribution
IV	Improved Varieties
LT	Line Transplanting
UDP	Urea Deep Placement
MW	Mechanized Weeding
RLR	Rice Legume Rice
RH	Rice Harvesters
MVP	Multivariate Probit

Author Contributions

Hillary Chelal: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Project administration, Resources, Software, Writing – original draft

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Statements and Declarations Ethical Approval

Data collection began following clearance from the National Commission for Science, Technology and Innovation (NACOSTI).

Informed Consent

Informed consent was obtained from the respondents verbally.

Data Availability

Data associated with this study will be made available upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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