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DETERMINANTS OF FARMERS' PERCEPTION AND ADOPTION OF IMPROVED LEGUME VARIETIES AMONG FARMING HOUSEHOLDS IN NORTHERN NIGERIA

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ABSTRACT

Limited understanding of farmers' perception and consideration during the development of improved seed varieties have usually resulted to their low rate of adoption. In light of this, the present study fitted an ordered probit sample-selection model using a sample of 400 legume farming households (LFHs) - 212 adopters and 188 non-adopters - in Northern Nigeria. The results showed that male-headed households (97%) dominated the sampled data with the majority being soybean farmers (81%) and whose standard of living was low. Household heads were adults (43 years old) and married (94%) in most cases with about a junior level of education (9 years). Key determinants of adoption of improved legume varieties (ILV) included education, household size, level of living, and soil conservation practices. Farmers' perception was confirmed to be endogenously determined within the adoption system as being a function of socioeconomic characteristics, farm enterprises and agricultural practices. We recommend that farmers' educational level be improved by increasing their knowledge of relevant agricultural practices such as minimum tillage and alley cropping that will aid the adoption of the ILV through positive perception among farmers. Policies that will enable both male- and female-headed households to have more access to land should be engaged in order to boost the adoption of ILV. Interventions that will aid rural areas in northern Nigeria to have improved standard of living such as better access to light, water, and healthcare facilities should be pursued since this will facilitate the sustainability of ILV adoption.

Key words: Perception, improved legume varieties, ordered probit, sample selection

INTRODUCTION

In recent years, a lot of resources have been committed to the growth and development of major grain legumes farming such as soybean, groundnut, and cowpea in Northern Nigeria with the primary goal of improving rural households' livelihood through increased productivity. For instance, in the last decade, over 100 improved groundnut varieties have been developed through the tropical legume (TL) projects which were implemented especially across five northern States namely Kano, Katsina, Kebbi, Jigawa and Bauchi (Ahmed *et al.*, 2020). Improved soybean varieties such as TGX 1951-3F, TGX 1955-4F, TGX 1904-6F, and an extra-early maturing variety named TGX 1835-10F have equally been released in North East Nigeria (Kamara *et al.*, 2022). However, the dwindling performance in grain legumes farming and the current level of food security both in rural and urban areas of Nigeria are far below the expectations of the research bodies, national partners and the government who have been harnessing resources over the years.

In Africa, Nigeria is the highest producer of groundnut with 3.9 million hectares and 4.5 million tonnes produced (Desmae *et al.*, 2022) and the second largest producer of soybean after South Africa (FAOSTAT, 2021). Yet, the productivity of groundnut is just approximately 1 tonne which is less than the global yield of 1.65 tonne (FAOSTAT, 2021) while that of soybean is clearly below the yield potential of over 3 tonnes (Ronner *et al.*, 2016). Biophysical constraints such as pest and diseases, drought, poor fertility, poor agronomic practices, persistent use of local seed varieties (LSV) are said to have contributed to the observed low yield (Kamara *et al.*, 2014; Khojely *et al.*, 2018). The continuous use of local seed varieties by farmers and the low rate of adoption of ILV have sometimes been attributed to the top-down approach which overlooks farmers' preferences and perceptions in the design and development of improved technologies (ITs) (Rahman *et al.*, 2015). However, there is now a strong belief that taking into account farmers' perception during the design and development of ITs could go a long way to increase their rate of adoption (Pickering, 2015; Kassie *et al.*, 2017; Siri *et al.*, 2020; Yokamo, 2020; Jones-Garcia & Krishna, 2021).

Farmers' perception of ITs attributes is an important factor influencing their decisions to adopt them (Ntshangase *et al.*, 2018; Siyum *et al.*, 2022; Dessalegn *et al.*, 2022). According to Siri et *al.* (2020), farmers' perception of ITs can lead not only to their adoption but also to their disadoption given that ITs can have desirable and undesirable attributes. A positive perception of an improved technology (IT) attribute is often associated with higher probability to adopt the technology while a negative or indifferent perception is usually associated with lower probability to adopt it (Mignouna *et al*., 2011; Wandji *et al.*, 2012; Njuguna *et al.*, 2015; Ntshangase *et al.*, 2018). For instance, Njuguna *et al.* (2015) affirmed that farmers in Kenya who perceived that improved sweet potato varieties were tastier, cooked faster, increased family income, improved food security, mature faster and had a 'ready market' were more likely than their counterparts to adopt improved sweet potato varieties. Ntshangase *et al.* (2018) found that farmers' negative perception of no-till conservative agriculture was negatively related to the adoption of the technology in Kwazulu-Natal, South Africa. More recently, Mahama *et al*. (2020) found that perception of soybean technologies as being risky had a significant influence on the adoption intensity of sustainable soybean technologies in Ghana.

Farmers usually anticipate the benefits to receive when making the decision of whether to adopt a modern technology or not. This has often served as a basis for economists in justifying the assumption of unobserved heterogeneity bias in the process of assigning cases into different treatments or programmes (Dontsop-Nguezet *et al*., 2011; Egwuma *et al.,* 2021). There is, however, an emerging concern surrounding the effect of farmers' perception of technology attributes on the decision to adopt ITs. Although the expected utility theory states that perception of technologies attributes is exogenously determined, other technology adoption frameworks have suggested that perception is an endogenous construct. For instance, Ntshangase *et al.* (2018) have supported the claim that farmers' perception can be influenced by their beliefs, socioeconomic situation, agricultural information available to them and their farm enterprises. In this instance, understanding the relationship between farmers' perception of technologies attributes and their decision to adopt them using standard binary choice models such as logit and probit regression models or without accounting for the endogeneity of farmers' perception would be biased and inconsistent.

Most studies' focus has been on the determination of the effect of farmers' perception on IT adoption (Wandji *et al.*, 2012; Njuguna *et al*., 2015; Ntshangase *et al.*, 2018; Siyum *et al.,* 2022). If farmers' perception of a technology attributes is critical but endogenous within the system as it is likely in real case scenario, then an important question that could arise is: what are the factors influencing farmers' perception of such technology attributes? The knowledge of factors influencing farmers' perception of an IT could enable the design of realistic technologies along with more adequate impact pathways of IT adoption for better outcomes and impact assessment. As far as we are aware of, studies on factors influencing farmers' perception of ILV attributes are very scanty. In an attempt to close this gap, this study aimed at analyzing the determinants of farmers' perception of ILV in Northern Nigeria with special attention on the role of farmers' socioeconomic characteristics, agricultural information, farm enterprises and agricultural practices.

MATERIALS AND METHODS

The Study Area

This study was conducted in Northern Nigeria which is made up of 19 out of the 36 States in the country and lies between latitudes 7^0 and 14^0 N and longitudes 3^0 and 15^0 E. It occupies about two third of the entire land area of the country (692,826 km^2) and consists of Sahel savanna, Sudan savanna, Northern Guinea savanna and Southern Guinea savanna. The climate is tropical, characterized by high temperatures and humidity as well as marked wet and dry seasons with an average annual rainfall of 500 mm. The area has rich vegetation consisting of a great expanse of arable land, rich fertile soil and abundant water resource which makes it suitable for agriculture. The climate of the area supports the cultivation of crops such as maize, millet, sorghum, rice and legumes.

Sampling Procedure and Sample Size

A multi-stage sampling procedure was employed to select respondents from two States in Northern Nigeria where the Commercial Products (COMPRO-II) project of the International Institute for Tropical Agriculture (IITA) was implemented. In the first stage Kano and Benue States were selected using a purposive sampling technique due to the large number of participants in the two states. In the second stage, 4 local government areas (LGAs) were purposively selected each from Kano State (Bichi, Bunkure, Tudun Wada, and Rogo LGAs) and Benue State (Gboko, Buruku, Gwer, and Tarka LGAs) due to large concentration of legume farmers in these areas. In the third stage, random sampling technique was used to select 33 villages from the 8 selected LGAs, where 23 villages were used as treated group while 10 served as control. In the third stage, 200 LFHs from each State were selected using simple random technique to ensure that LFHs in the study were adequately represented. In all, a total sample of 400 LFHs were used for the study. The data used in the analysis were collected during a period of 2 weeks between late November and early December 2016 via questionnaire interviews administered by a team comprised of 9 trained enumerators and 1 supervisor. The data were collected on demographic, economic and farm characteristics; technology awareness, availability, accessibility, adoption; and perception of yield performance of COMPRO-II technologies such as microbial inoculants, inorganic fertilizers, improved varieties, and agricultural farm management practices.

Ordered Probit Sample Selection Model

In this study, farmers' perception of ILV is missing for non-adopters of ILV because of self-selection. Truncating the dataset and dealing exclusively with the adopters would lead to non-randomness of the sample under study. The sample of adopters only would not be a valid representation of the population of LFHs in the study area because the initial sampling design was based on both treated and control areas. Therefore, any finding obtained from such sample of adopters could not be extrapolated over the population of interest but would only be a sample peculiarity inference. Moreover, even if the full sample of adopters and non-adopters are considered in the estimation of the parameters and thresholds, the estimation of the parameters and thresholds would be biased and inconsistent. According to Greene and Hensher (2010), to overcome this model failure, some authors have adopted Heckman (1979) two-step estimator where in the first step, an inverse of mills ratio for all units who participated in the program is estimated from the selection equation and introduced in the second step as an instrument to correct for the missing data (Awotide *et al*., 2016; Mwakatwila & Mishili, 2019; Rabbi *et al.*, 2019; Iticha & Taresa, 2020). But doing that when the outcome of interest is an ordered outcome like in this study would be inappropriate because the outcome equation in the second step is a non-linear model unlike in the classical Heckman sample selection model (Luca & Perotti, 2011; Sunny *et al*., 2022). Thus, to accommodate the problem of selectivity with the outcome equation being a nonlinear model, this study used the parametric ordered probit sample selection model.

Following Luca *et al.* (2011) and Sunny *et al.* (2022), the implicit ordered probit sample selection model which is a form of structural equation can be presented as:

$$\begin{cases} Y_{1i}^{*} = \theta' W_i + u_i \\ Y_{1i} = I\left(Y_{1i}^{*} > 0\right) \end{cases} \quad (1)$$

$$\begin{cases} Y_{2i}^{*} = \alpha' X_i + \varepsilon_i \\ Y_{2i} = \sum_{j=1}^{J} v_j K\left(\mu_{j-1} < Y^{*}_{2i} \le \mu_j\right) \quad \text{if } Y_{1i} = 1 \end{cases} \quad (2)$$

where Y_{1i}^{*} is the unobserved utility following adoption, W_i is the selection covariates, θ is the regression coefficient, and u_i is a random error term, Y_{1i} is the observed decision variable, $I(.)$ is an indication function taking the value of 1 when $Y_{1i}^{*} > 0$ and 0 when otherwise, Y_{2i}^{*} is the unobserved outcome variable, X_i is the outcome covariates, α is the regression coefficient, and ε_i is a random error term, Y_{2i} is the observed outcome variable for positive utilities, $K(.)$ is an observational mechanism defining the categories of the outcome variable. The categories of the outcome variable are integers $v_j = v_n, \ldots, v_J$ such $v_n < v_m$ with $n < m$. $\mu_{n,\ldots,}\mu_{J-1}$ are real numbers such as $\mu_n < \mu_m$ with μ_0 taken as $-\infty$ and μ_J taken as $+\infty$. Equations (1) and (2) are the selection and outcome equations, respectively.

For identification of the ordered probit sample selection model as presented, three conditions must be met as explained by Luca *et al.* (2011). Firstly, it is assumed that the intercept term in α is normalized to zero because it is inseparable from the thresholds. Secondly, W_i contains at least one variable that is not in X_i. Thirdly, both W_i and X_i must contain at least one continuous variable (Sunny *et al.*, 2022). Under the assumption that (u_i, ε_i) follows a bivariate gaussian distribution with mean zero and variance matrix given by $[1 \quad p, p \quad 1]$, the parametric maximum likelihood (ML) estimator ω derived through the maximization of the following log-likelihood function of n observations is consistent:

$$L(\omega) = \sum_{1}^{n} \left\{ \left(1 - Y_{1i}\right) \ln \pi_{0i}(\omega) + \sum_{-1}^{J-1} Y_{1i} I\left(Y_{2i} = j\right) \ln \pi_{1ji}(\omega) \right\} \quad (3)$$

where $\omega = \left(\theta, \alpha, \mu, \rho\right)$ is the vector of all the model parameters and $\left(\pi_0, \pi_{10}, ..., \pi_{1j}\right)$ are conditional probabilities associated with the $J+1$ possible realization of Y_{1i} and Y_{2i}. For operationalization, the explicit form of the model in (1) and (2) can be defined as:

$$\begin{cases} y_{1i}^{*} = \theta_0 + \theta_1 w_{1i} + \theta_2 w_{2i} + \theta_3 w_{3i} + \theta_4 w_{4i} + \theta_5 w_{5i} + \theta_6 w_{6i} + \theta_7 w_{7i} \\ \quad + \theta_8 w_{8i} + \theta_9 w_{9i} + \theta_{10} w_{10i} + \theta_{11} w_{11i} + \theta_{12} w_{12i} + \theta_{13} w_{14i} + \theta_{14} w_{14i} \\ \quad + \theta_{15} w_{15i} + \theta_{16} w_{16i} + \theta_{17} w_{17i} + \theta_{18} w_{18i} + \theta_{19} w_{19i} + u_i \\ \\ y_{1i} = \begin{cases} 1 \text{ if } Q_{1i}^{*} > 0 \\ 0 \text{ if } Q_{1i}^{*} \leq 0 \end{cases} \end{cases} \quad (4)$$

$$\begin{cases} y_{2i}^{*} = \alpha_0 + \alpha_1 w_{1i} + \alpha_2 w_{2i} + \alpha_3 w_{3i} + \alpha_5 w_{5i} + \alpha_6 w_{6i} + \alpha_7 w_{7i} \\ \quad + \alpha_8 w_{8i} + \alpha_{10} w_{10i} + \alpha_{11} w_{11i} + \alpha_{12} w_{12i} + \alpha_{13} w_{13i} + \alpha_{14} w_{14i} \\ \quad + \alpha_{15} w_{15i} + \alpha_{16} w_{16i} + \alpha_{17} w_{17i} + \varepsilon_i \\ y_{2i} = \begin{cases} 0 \text{ if } \mu_{-1} < Q_{2i}^{*} \leq \mu_0 \\ 1 \text{ if } \mu_0 < Q_{2i}^{*} \leq \mu_1 \\ 2 \text{ if } \mu_1 < Q_{2i}^{*} \leq \mu_2 \\ 3 \text{ if } \mu_2 < Q_{2i}^{*} \leq \mu_3 \end{cases} \end{cases} \quad (5)$$

where $Q_{1i}^{*} =$ unobserved utility derived from adopting ILV (soybean, common bean), $Q_{2i}^{*} =$ unobserved true attributes ILV, $Q_{1i} =$ adoption status of ILV, $Q_{2i} =$ perception of yield performance of ILV. The parameters θ and α are the selection and outcome model's parameters respectively, μ are the thresholds while u_i and ε_i are the models' disturbance terms. Under the assumption that u_i and ε_i follow a bivariate gaussian distribution with zero means, unit variance and correlation coefficient ρ, equations (4) and (5) are simultaneously estimated using a parametric maximum likelihood estimator. All other variables used in the model are presented and defined in Table 1.

Table 1: Definition, measurement, a priori expectation and types of variables used in this study

Variable	Definition and measurement	A priori	Type
Dependent variables			
Adoption of ILV (y_{1i})	1 if farmer adopted ILV (Soybean and/or groundnut), 0 otherwise		Dummy
Farmers' perception (y_{2i})	Farmers' perception of ILV in terms of yield (0 = no change, 1= increase but less than double, 2 = increase by double, 3 = increase by more than double)		Ordered
Independent variables			
Farmer's characteristics			
Sex (w_{1i})	1 if household head is male, 0 if female	+/-	Dummy
Age (w_{2i})	Age of household head in years	+/-	Continuous
Marital status (w_{3i})	1 if household head is married, 0 otherwise	+	Dummy
Household size (w_{4i})	Number of persons living in the house	+/-	Continuous
Education (w_{5i})	Number of years of education of household head	+	Continuous
Native (w_{6i})	1 if household head is a native of the village/community, 0 if otherwise	+	Dummy
Living standard (w_{7i})	Index of living standard based on quality of house, access to light, water, etc.	+	Continuous
State (w_{8i})	1 if household head lives in Kano, 0 if Benue		Dummy
Farm characteristics			
Land cultivated (w_{9i})	Land under legume production (hectare)	+	Continuous
Land owned by female (w_{10i})	1 if land cultivated under legumes is owned by a female; 0 if otherwise	+	Dummy
Distance to farm (w_{11i})	Distance from home to farm (km)	-	Continuous
Agric information (w_{12i})	1 if access to agric information through farmers' association, 0 otherwise	+	Dummy
Farm enterprises			
Soybean production (w_{13i})	1 if farmers cultivated soybean, 0 otherwise	+	Dummy
Groundnut production (w_{14i})	1 if farmers cultivated groundnut, 0 otherwise	+	Dummy
Cowpea production (w_{15i})	1 if farmers cultivated cowpea, 0 otherwise	+	Dummy
Agricultural practices			
Minimum tillage (w_{16i})	1 if major soil conservation practice is minimum tillage, 0 otherwise	+	Dummy
Hedges (w_{17i})	1 if major soil conservation practice is the use of hedges, 0 otherwise	+	Dummy
Alley cropping (w_{18i})	1 if major soil conservation practice is alley cropping, 0 otherwise	+	Dummy
Monocropping (w_{19i})	1 if farm system is monocropping, 0 otherwise	+	Dummy

Source: Authors' estimates from survey data (2016)

RESULTS AND DISCUSSION

Socioeconomic Characteristics of Legume Farming Households

The result of the descriptive analysis of the socioeconomic characteristics of LFHs is presented in Table 2. Slightly more than half (53%) of LFHs adopted ILV which implies that there is still an important proportion (47%) of households whose production is essentially based on the use of LSV which are characterized by low yield, poor resistance to pest and diseases and inadequate to thrive well under adverse environmental conditions (Ahmed *et al.,* 2020). The observed rate of adoption in this study is smaller than the one reported by

Kamara *et al.* (2022) who found that 75% and 70% of male- and female-headed households adopted improved soybean varieties in northern Nigeria, respectively. The average perception of the household heads was 1.54 which is approximately 2 with a standard deviation of 0.65. The mean perception of 2 corresponds to the third category of the perception outcome variable. The implication is that farmers' perception of ILV in terms of yield potential was positive which means they would be more favorable to adopt ILV than to continue with the use of LSV. Specifically, an average legume farmer believed that adopting ILV would double their yield which could be as a result of their experiences with the ILV that were promoted by IITA, ICRISAT and their partners in recent years in the study area. The finding is in agreement with Siri *et al.* (2020) who found that one of the major desirable attributes of improved haricot beans in Cameroon is that of high yielding.

Most household heads were males (97%) which appeared odd given the significant role women play in grain legume production (Snapp *et al*., 2019). Moreover, women tend to have more experience in legume farming than their male counterpart since it has been considered for long as women's crop especially in west and central Africa (Nakazi *et al.*, 2017). However, it is equally recognized that men's involvement in grain legumes has grown in importance in recent years especially due to the various opportunities it provides in terms of income and employment generation. Moreover, as pointed out by Ahmed *et al.* (2020), tradition and culture make males the heads of households in Nigeria and that it is only in rare cases of death of the husband that the wife becomes the head. The finding is then consistent with Ahmed *et al.* (2020) who found that groundnut production in Nigeria is dominated by about 92% of male-headed households. The majority of household heads (94%) were married and natives (98%) of their places of residence. Being a native of a community could enhance farmers' ability to find relevant agricultural information. The finding is similar to most studies in Nigeria where heads of farming households are mainly reported to be married (Jirgi *et al*., 2019; Adetomiwa *et al*., 2020). A typical household head was on average 43 years old, which implies that he/she was an adult. The more the number of adults in a household who are educated, the lower the dependency ratio and greater the likelihood to escape food insecurity (Folorunso, 2015). This is in line with previous studies that equally stated that farmers in Nigeria are adults, on average (Moses, 2017; Ovharhe, 2019; Sulaiman *et al*., 2021).

The average household size of 10 can be considered to be relatively large (Folorunso, 2015). Large households are usually regarded as primary source of labour in rural areas which is advantageous for technology adoption. On the other hand, it can put more pressure on households in terms of increased food requirement thereby making them susceptible to food insecurity if the majority of its members are not productive. For instance, Adetomiwa *et al.* (2020) found that household size had a negative and significant influence on food security status in south west Nigeria. The mean level of education of 9 years was about that of junior secondary school (JSS). The implication is that household heads were literate which is expected to facilitate the adoption of new technologies. This finding is in contrast to that of Ahmed *et al.* (2020) and Kamara *et al.* (2022) who found that the level of literacy among groundnut and soybean farmers in northern Nigeria was low with a mean of about 2 to 3 years only. The estimate of the living standard index of 2.49 was below the threshold of 3 thereby suggesting that the living standard was low which is common among farming households in northern Nigeria. Despite the implementation of several agricultural programmes in this part of the country it is still a sad reality that the income level of millions of rural households is still very low inducing many to remain in absolute poverty (Suleiman *et al.*, 2021). The average land cultivated was 3.34 ha with a standard deviation of 2.13 ha which suggests that legume farmers were small-scale farmers as it is the case with other studies (Ambali *et al*., 2021). On the other hand, it is important to note that the variability in land size was significantly high with a range of over 8 ha. This result is clearer when considering the land size owned by women which was very marginal. The highest land size was just 1 ha among the women, a finding which agrees with most studies that emphasized on social and cultural barriers that limit women from accessing land in Nigeria with males having more land than their female counterparts (Ambali *et al.*, 2021; Kamara *et al.*, 2022). In other words, access to land by women in northern Nigeria is a constraining factor for them to engage more actively in legume farming.

The average farm distance was 4km, which is quite a distance to cover and could well be viewed as a constraint in carrying out their farm activities including the adoption of improved technologies due to high transaction costs (Tesfay, 2020). The acquisition of agricultural information by farmers can be achieved through diverse means such as radio, television, newspaper, short message service (SMS), farmers' association, and extension agents. It was observed that 34% of the household heads had access to agricultural information through farmers' association. This implies that a potential way to expose farmers in the study area to agricultural information relative to new technologies is through farmers' association which when well organized could provide useful knowledge and skill required for a successful adoption of the new technologies (Moremedi *et al*., 2019). The sampled data showed that 82% of the households were soybean farmers, 13% were groundnut farmers and 6% were cowpea farmers. Key agricultural practices that were observed among the farmers were minimum tillage (29%), hedges (2%), alley cropping (11%) and monocropping (95%). In other words, farmers used minimum tillage as the main soil conservation practice while monocropping was the major farming system. The implication is that the combination of practices used by the majority of farmers may result in low yield. This is because most of the farmers are likely practicing intensive tillage which leads to soil degradation (Chase & Singh, 2014).

Table 2: Descriptive statistics of the variables used

Variables	**Mean**	**SD**	**Freq**	**Percent**	**Min**	**Max**
Dependent variables						
Adoption of ILV (y_{1i})			212	53	0	1
Farmers' perception (y_{2i})	1.54	0.65			0	3
Independent variables						
Farmer's characteristics						
Sex (w_{1i})			386	97	0	1
Age (w_{2i})	43	13			19	80
Marital status (w_{3i})			374	94	0	1
Household size (w_{4i})	10	7			1	75
Education (w_{5i})	9	6			0	24
Native (w_{6i})			392	98	0	1
Living standard (w_{7i})	2.49	0.62			1	3
State (w_{8i})			200	50	0	1
Farm characteristics						
Land cultivated (w_{9i})	3.34	2.13			0.3	8.43
Land owned by female (w_{10i})	0.11	0.31			0	1
Distance to farm (w_{11i})	3.88	0.56			1.39	4.85
Agric information (w_{12i})			134	34	0	1
Farm enterprises						
Soybean production (w_{13i})			322	81	0	1
Groundnut production (w_{14i})			53	13	0	1
Cowpea production (w_{15i})			25	6	0	1
Agricultural practices						
Minimum tillage (w_{16i})			116	29	0	1
Hedges (w_{17i})			8	2	0	1
Alley cropping (w_{18i})			44	11	0	1
Monocropping (w_{19i})			381	95	0	1

Source: Authors' estimates from survey data (2016)

Determinants of Adoption of Improved Legume Varieties

The maximum likelihood estimate of the ordered probit sample selection for the determinants of adoption of ILV is presented in Table 3. The Wald statistic value of 32.52 was significant at 5% level of probability, which means that all the independent variables jointly and significantly influenced farmers' decision to adopt ILV. The correlation coefficient of the bivariate gaussianly distributed error term was 0.94 and statistically significant at 1% level of probability, suggesting that the selection and outcome equations are not independent. Out of the 19 independent variables, 8 were statistically significant and of these only 3 had a direct relationship with de decision to adopt ILV while others had an indirect relationship. Specifically, the 3 variables were soybean production, cowpea production and alley cropping. In other words, farmers who produced soybean and cowpea were more likely than those who produced groundnut to adopt ILV. Similarly, farmers who practiced alley cropping were more likely to adopt ILV than those who used other agricultural practices such as minimum tillage, hedges, and monocropping. One of the reasons why soybean and cowpea farmers were found to be more likely to adopt ILV could be attributed to the fact that improved soybean and cowpea technologies were highly promoted in Sub-Saharan Africa (SSA) in recent time in general (Mutegi & Zingore, 2014).

The factors that influenced the decision to adopt ILV negatively and significantly were household size, education, living standard, women's land ownership and minimum tillage. The negative influence of household size on the decision to adopt ILV implied that larger households would be less likely than their counterparts to adopt ILV. The finding can be associated to capital constraint faced by farmers as household size tends to influence household's welfare negatively in rural areas (Mekonnen, 2017). Household size is sometimes observed as a positive determinant of the intensity of adoption, but also as a negative determinant of the decision to adopt new technologies (Bannor *et al*., 2020). The negative influence of education on the decision to adopt ILV suggested that less educated farmers would be more likely to adopt ILV than the more educated ones, which is contrary to the a priori expectation (Bannor *et al.,* 2020). Even though economic theory suggests that education influences technology adoption positively, existing empirical findings still provide mixed conclusions. For instance, accounting for the potential negative effect of labour allocation between on- and off-farm activities, Uematsu and Mishra (2010) found that an additional year of education significantly decreased the probability of adoption of genetically modified crops at 1% level of probability among small US farmers. It is important to recognize that the level of education of household heads does not necessarily reflect the level of education of the households. Moreover, it is unknown whether or not the household heads are the only decision takers in the households when it comes to technology adoption.

The negative effect of living standard on the decision to adopt indicated that as the living standard of households increases, the probability to adopt ILV would decrease, which is contrary to the a priori expectation. Standard of living is often modelled as a function of technology adoption (Chatterjee & Kar, 2017; Herath *et al*., 2021). The implication is that in this study, the effect of living standard on adoption of ILV would be biased. However, the finding is still informative and agrees with a limited number of studies which investigated critically the relationship between living standard and adoption of modern technologies in rural economies. In particular, the current finding suggested that poverty affects technology adoption in the manner that rich households are more likely to adopt higher value crops than grain legumes.

Note that the majority of legume farmers in the dataset were mainly soybean farmers. With this knowledge in mind, the finding is consistent with the view that soybean is regarded by many as "poor man's meat" given that it is the cheapest source of protein (Patel *et al*., 2016; Sutar *et al.,* 2019; Borah & Deb, 2020). The negative effect of women land ownership on the decision to adopt ILV implied that women who were owners of land were less likely than their counterparts to adopt ILV, which is contrary to the a priori expectation. Although women are usually well experienced in legume farming, this may not necessarily be the case in terms of ILV. A study by Siri *et al.* (2020) revealed that although haricot bean is still a woman's crop, women appeared to have less experience than men in terms of the adoption of ILV due probably to the risk involved in investing in new technologies. The justification might be supported by other studies that confirmed that female headed households tend to be more risk averse than their male counterparts towards improved technology adoption (Love *et al*., 2014). Furthermore, female-headed households are usually poorer than their male counterparts and face special constraints such as less education, less productive assets and lack of access to credit due to their gender (Vimefall, 2015).

Table 3: Maximum likelihood estimate of the ordered probit sample selection for the determinants of adoption of ILV

	Selection equation			Outcome equation		
Variables	**Coef.**	**Std. Er.**	**T-value**	**Coef.**	**Std. Er.**	**T-value**
Socioeconomic characteristics						
Sex (w_{1i})	-0.51	0.38	-1.36	-0.44	0.38	-1.16
Age (w_{2i})	-0.01	0.01	-1.24	-0.004	0.006	-0.72
Marital status (w_{3i})	0.2	0.3	0.67	0.78**	0.34	2.3
Household size (w_{4i})	-0.02**	0.01	-1.9			
Education (w_{5i})	-0.04***	0.01	-2.74	-0.03**	0.01	-2.08
Native (w_{6i})	-0.8	0.6	-1.35	-0.55	0.48	-1.14
Living standard (w_{7i})	-0.33**	0.14	-2.33	-0.28**	0.13	-2.1
State (w_{8i})	-0.12	0.19	-0.6	-0.11	0.18	-0.62
Farm characteristics						
Land cultivated (w_{9i})	0.06	0.06	1.04			
Land owned by female (w_{10i})	-0.85**	0.3	-2.84	-0.38	0.35	-1.07
Distance to farm (w_{11i})	0.02	0.13	0.13	0.17	0.13	1.3
Agric information (w_{12i})	0.21	0.16	1.33	0.02	0.17	0.13
Farm enterprises						
Soybean production (w_{13i})	0.7**	0.34	2.04	0.21	0.34	0.62
Groundnut production (w_{14i})	-0.0003	0.18	0	-0.32*	0.19	-1.67
Cowpea production (w_{15i})	0.7**	0.34	2.04	0.21	0.34	0.62
Agricultural practices						
Minimum tillage (w_{16i})	-0.27*	0.16	-1.65	-0.37**	0.17	-2.18
Hedges (w_{17i})	0.38	0.64	0.59	0.29	0.62	0.47
Alley cropping (w_{18i})	0.48**	0.24	1.99	0.54**	0.24	2.27
Monocropping (w_{19i})	-0.56	0.42	-1.33	0.1	0.4	0.24
μ_0	-1.88*	1.01	-1.86			
μ_1	-0.68	1.16	-0.59			
μ_2	0.76	1.19	0.64			
ρ	0.94***	0.1				
No. obs	400					
Wald	32.52**					

Source: Authors' estimates from survey data (2016)

Determinants of Farmers' Perception of Improved Legume Varieties

The results of the effect of socioeconomic characteristics, farm enterprises and soil conservation practices on farmers' perception of ILV are presented in Table 4. The first observation is that farmers' perception of ILV attributes especially in terms of yield were effectively determined by household's socioeconomic characteristics, farm enterprises and soil conservation practices. The finding is in agreement with the adoption model of Ntshangase *et al.* (2017). However, the relationship between the independent variables and farmers' perception varied with the level of perception based on the marginal effects of the independent variables. Marital status had a negative marginal effect on P1 (Decrease /no change in yield), but a positive marginal effect on P2 (Increase in yield but less than double), P3 (Increase in yield by double) and P4 (Increase in yield by more than double). In other words, married-headed households would be 25% less likely to perceive P1 but would be 1%, 19%, and 5% more likely to perceive P2, P3, and P4, respectively. The implication is that married-headed households had a positive perception of ILV with respect to yield performance and therefore would be more likely to adopt ILV than their unmarried counterparts, a finding which agrees with our earlier result that showed that marital status had a positive, although insignificant, relationship with ILV adoption.

Table 4: Marginal effect of socioeconomic characteristics, farm enterprises and soil conservation practices on farmers' perception of improved legume varieties

	Robust Marginal Effect			
Variables	**Decrease/no change in yield (P1)**	**Increase in yield but less than double (P2)**	**Increase in yield by double (P3)**	**Increase in yield by more than double (P4)**
Socioeconomic characteristics				
Marital status (w_{3i})	-0.25***(0.09)	0.01 (0.06)	0.19**(0.09)	0.05*(0.02)
Education (w_{5i})	0.009**(0.004)	-0.0003(0.002)	-0.01**(0.003)	-0.002*(0.001)
Living standard (w_{7i})	0.09*(0.05)	-0.003(0.02)	-0.07**(0.03)	-0.02*(0.01)
Farm enterprises				
Soybean production (w_{13i})	0.17**(0.08)	-0.01(0.04)	-0.13**(0.06)	-0.03*(0.02)
Groundnut production (w_{14i})	0.1**(0.06)	-0.003(0.02)	-0.08*(0.05)	-0.02(0.01)
Agricultural practices				
Minimum tillage (w_{16i})	0.12**(0.06)	-0.004(0.03)	-0.09**(0.04)	-0.02*(0.01)
Alley cropping (w_{18i})	-0.17(0.08)	0.01(0.04)	0.13**(0.06)	0.03*(0.02)

Source: Authors' estimates from survey data (2016)

: ***<0.01, **<0.05, *<0.1.

The level of education of household heads and level of living had a positive marginal effect on P1, but a negative marginal effect on P3 and P4, which implied that more educated household heads had a less favorable perception of ILV than the less educated ones. As explained previously, their negative perception could be related to the fact that more educated people with higher standard of living prefer to invest in higher value crops than in soybean enterprise which is rather called a “poor man’s crop”. The result contradicts the findings of Moges & Taye (2017) who found that the educational level of household heads positively and significantly influenced farmers’ perception to invest in soil and water conservation technologies in the north-western highlands of Ethiopia. Similarly, soybean and groundnut production had a positive marginal effect on P1 but a negative marginal effect on P2, P3 and P4, which meant that soybean and groundnut producers had a negative perception of ILV. In the same manner, minimum tillage had a positive marginal effect on P1 but a negative effect on P2, P3, and P4. The implication is that farmers that practiced minimum tillage had a negative perception of ILV. In contrast, alley cropping had a negative marginal effect on P1 but a positive effect on P2, P3, and P4, which implies that farmers that use alley cropping had a better perception of ILV than their counterparts.

CONCLUSION AND RECOMMENDATIONS

This study’s focus was to determine the factors influencing farmers’ perception of improved legume varieties (ILV) in northern Nigeria. The adoption decision of ILV was influenced positively by land size, alley cropping and production of soybean and cowpea, but negatively by household size, education, standard of living, women’s land ownership, and minimum tillage. Farmers’ perception was confirmed to be endogenously determined within the adoption system of ILV as being a function of farmers’ socioeconomic characteristics, farm enterprises and soil conservation practices. Therefore, in order to understand the relationship between farmers’ perception and ILV, we recommend that these factors be accounted for. Furthermore, we recommend that farmers’ educational level be improved by increasing their knowledge of the relevant agricultural practices that will aid the adoption of the ILV such as minimum tillage and alley cropping. Policies that will enable farmers both male and female to have more access to land should be engaged in other to boost the adoption of ILV. Interventions that will provide rural areas in northern Nigeria to have better standard of living such as better access to light, water, and healthcare should be pursued since this will facilitate the sustainability of ILV adoption.

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