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Factors Influencing Adoption of Wave Technologies: Empirical Evidence from North West and North East Nigeria

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Abstract
Agriculture plays an important role in the economy of Nigeria; however, with high risks of natural factors like climate change, pests, and diseases, among others, posing significant threats to agricultural production, food security, and livelihoods in northern Nigeria, resulting in low yields. Therefore, the need for farmers to insure their farms against crop loss is crucial. This study examined factors affecting the adoption and intensity of Cassava Disease Management Technologies (CDMTs) in North West and North East, Nigeria. The study utilizes cross-sectional data, which was collected in 2023 from a randomly selected sample of 536 households (254 in North West and 282 in North East) using a structured questionnaire (Kobo Collect). The data collected from the sample households were analyzed using both descriptive as well as inferential analysis. The result of a double-hurdle econometrics model shows that among the explanatory variables used in the regression analysis, Farmers' decision on adoption of CDMTs was positively affected by educational level, farm size, and farming experience of the smallholder farmers. Similarly, distance to market, extension services, participation in training, caravan, and demonstration plot were also found to be significant., This study highlights the need for development interventions (researchers (Breeder), Policy makers, extension service providers, and NGOs) should aim to target such institutional and psychological factors to promote wider adoption of CDMTs to boost more cassava crop productivity through improved agrarian technology
Keywords: Double Hurdle, Technology adoption, Intensity of adoption, Cassava, WAVE technology

Introduction

Cassava, also known as *Manihot esculenta*, is a tuber crop that is being used as one of the basic and mainly consumed foods in different countries (Fathima *et al.,* 2023). Cassava is an important food security crop in many African farming systems and provides more than half of the dietary calories to over 700 million people in Africa (Szyniszewska, 2020; Amelework *et al.,* 2021). Cassava is produced mainly by smallholder farmers whose average cultivated area is less than one hectare (ha) (Mujuru and Obi, 2020; Dzanku *et al.,* 2021). Most of their production is for household consumption or sold as a food crop to domestic markets (Scott, 2021). It is mainly grown under intercropping systems with other crops such as maize, legumes, and bananas (Monteiro *et al.,* 2020; Ravi *et al.,* 2021).

Cassava is a crop with enormous potential. It provides a stable food base for the food needs of the populace, components in livestock feeds, and raw materials for industries (Amelework, 2021). Cassava also seems to be recording resounding success in sub-Saharan Africa out of the numerous stories of crop intervention failures in the region. As a result of this, many African countries have embraced its cultivation with renewed vigor (Sanusi *et al.,* 2021). Nigeria is one of such African countries. Almost every household in rural Nigeria grows cassava on small farms as one of the staple food crops to feed families and supply the local markets (Nanbol and Namo, 2019; Ndjouenkeu *et al.,* 2021).

Cassava has a high tendency to serve as a relief crop to food insecurity because of its copious consumption in various forms by people and its ability to subsist and give appreciable yields on soils where many other crops fail to perform, which has endeared its cultivation by many smallholder farmers (Anaglo *et al.,* 2020). This was further supported by the assertion of Anyeagbunam *et al.* (2015) that cassava has become a very popular crop in Nigeria and is fast replacing other traditional local staples in the country (Oyelere, 2020). FAOSTAT (2010) maintained that cassava has moved from a minor crop to a major crop in Nigeria and has gained industrial recognition and relevance (Kashyap and Agarwal, 2020; Amelework *et al.,* 2021). This then presupposed that traditional use or utilization of cassava is changing from primarily human consumption to processing into industrial products as well as for exportation (Udoro *et al.,* 2021).

Cassava is important not only as a food crop but even more as a major source of income for rural households. As an income crop, cassava generates cash income for the largest number of households compared with other staples in the same category (Sanusi *et al.,* 2020).

Tropical farmers produce 233 million tons of cassava on 18.6 million hectares (Sajeev *et al.,* 2021). A total of 40 countries in Africa make up more than 50% of the production, while Asia and Latin America contribute 34% and 15% respectively (Crippa *et al.,* 2021). Although socioeconomic factors, market conditions, and abiotic constraints negatively affect cassava production, pests and diseases are well known to substantially reduce yields, resulting in multi-billion-dollar crop losses (Pathak, 2019; Blesh *et al.,* 2023). According to FAO (2018), cassava is a choice crop for rural development, poverty alleviation, economic growth, and ultimately food security (Adebayo and Silberberger, 2020; Adu *et al.,* 2023).

Although Africa is the world's largest cassava producer with 169 million tonnes (61% of global production), the average yield is paradoxically the lowest at 9 tonnes/ha compared to Asia with a yield of 21.5 t/ha (FAOSTAT, 2019). The latest report as of 2017 shows that Nigeria is the largest producer of cassava in the world with 59 million tons of tuberous root production, representing about 20% of global production (Otekunrin *et al.,* 2021; International Institute of Tropical Agriculture (IITA), 2021). Cassava is one agricultural product that can generate foreign exchange for Nigeria, considering its place in the production and exportation of cassava products across the globe (Oyekola *et al.,* 2021).

The steady increase in the world population and climate change are adding pressure to agriculture as the need to produce more food intensifies. South Asia, Latin America, and Sub-Saharan Africa are some of the regions facing the detrimental effects of climate change due to changes in the frequency and severity of drought and floods, in addition to increasing temperatures and decreasing soil water (FAO *et al.,* 2018; WHO, 2018; Vos and Bellù, 2019). An increase in temperature is also anticipated to result in increased abundance of many insect pests through higher rates of growth and population development, as well as their spread and migration (Skendžić *et al.,* 2021). Great efforts are therefore being put into enhancing the management of emerging pests and diseases along with the production of climate-resilient and disease-resistant crops in these regions in an attempt to reduce the risk of hunger (FAO *et al.,* 2018; Mrisho *et al.,* 2020; Osumba *et al.,* 2021).

Some of these diseases that attack cassava are cassava mosaic disease (CMD) and cassava brown streak disease (CBSD), both largely propagated through the exchange of infected planting materials among farmers, resulting in losses of over 1 billion USD annually (Amelework and Bairu 2022) and resulting in about N100 billion (approximately 250 million USD) loss in Nigeria. Currently, CBSD is restricted to East and Central Africa and has not been reported in any West African country (Ferguson *et al.,* 2019; Chen *et al.,* 2019). However, reports of the spread of previously localized virulent strains of CMD to new regions raises concern and necessitates the need for urgent interventions to minimize this trend and ensure continued exclusion of the devastating CBSD from West Africa and/or ensure that the disease is promptly recognized, reported and effectively contained should it be inadvertently introduced into the region (Eni *et al.,* 2019). Cassava viral diseases are among the major constraints currently affecting cassava producers and production in Nigeria (Otero, 2022).

To reduce these losses, several disease management methods such as planting resistant varieties, planting improved variety, Roguing, good agronomic practices and biological control methods have been recommended by WAVE since 2014 through series of campaigns which has been conducted by the Central and West African Virus Epidemiology in Nigeria and in the member countries in Central and West Africa to raise awareness and train the actors of the cassava sector (farmers, seed multipliers, extension agents, etc.) on cassava disease identification, its causes, consequences and management technologies.

Despite such intervention, information about the adoption of cassava disease management technologies on specific factors influencing the adoption and intensity of use of the management technologies being promoted in the regions were not systematically and empirically studied and documented in the study area. Hence, this study was aimed at assessing the level of adoption and factors that influence the adoption and intensity of adoption of CDMTs in order to draw important conclusions and policy implications for future intervention.

Hypotheses

H_O : Cassava farmers' socioeconomic characteristics have no significant influence on the adoption of cassava disease management technologies

Methodology

Description of the Study Area

This study was conducted in the North West and North East, Nigeria.

Nigeria

Nigeria is a country in West Africa that shares land borders with the Republic of Benin in the West, Chad and Cameroon in the East, and Niger in the north. Its coast lies on the Gulf of Guinea in the south, and it borders Lake Chad to the NorthEast. Notable geographical features in Nigeria include the Adamawa Highlands, Mambilla Plateau, Jos Plateau, Obudu Plateau, the Niger River, River Benue, and the Niger Delta. Nigeria is the most populous country in Africa and has 36 States and a Federal Capital Territory (FCT) located in Abuja. The States are also subdivided into smaller administrative units known as Local Government Areas (LGAs). The country is disaggregated into six geopolitical zones: north-east, north-west, north-central, south-east, south-west, and south-south. Found in the tropics, where the climate is seasonally damp and very humid, Nigeria is affected by four climate types; these climate types are distinguishable as one moves from the southern part of Nigeria to the northern part of Nigeria through Nigeria's middle belt. With a population of over 220 million, Nigeria has over 250 ethnic groups, of which the three largest are: Hausa, Igbo, and Yoruba, and these ethnic groups speak over 500 distinct languages and are identified with a wide variety of cultures. Agriculture remains an important sector of the economy, as of 2010, even though it used to be the principal foreign exchange earner of Nigeria. The major crops include cowpea, rice, corn, cassava, millet, guinea corn, yam, soybean, sorghum, and melon, while the cash crops are cocoa, rubber, cashew, kola nut, and oil palm. (Britannica, 2023)

North West and North East: North West and North East encompass 13 states with a combined population of approximately 70 million people. The regions are characterized by diverse geographical features, including savannas, grasslands, and semi-arid savannas. The predominantly muslim population comprises various ethnic groups, including Hausa, Fulani, and Kanuri. Agriculture and trade are significant economic activities, with mineral resources also present. Figure 1 presents a map of the study area.

Sampling Procedure and Sample Size

A multi-stage sampling was used for this study to select the study states and sample. Four states from each of the two geopolitical zones were purposively selected based on the active WAVE activities on cassava disease management in the areas. A purposive selection of one LGA from each senatorial zone of each state based on the intensity of cassava production, and because of the active WAVE activities on cassava disease management in the areas of the zones. A reconnaissance survey was conducted to identify registered participating cassava farmers of WAVE in the States. This was carried out with the assistance of the Nigeria Cassava Growers Association (NCGA) and Agricultural Extension Agents. A random selection of 257 WAVE Beneficiaries, which was determined by Yamane's (1973) method of sample size determination as presented below:

$n = N/\ (1+N\ (e)^2)$ ……… (1)

Where:

n = sample size

N = sampling frame

e = error or significance level (0.05)

Sample size for States and the total respondents sample size were determined by the following formula;

$n = N/\ (1+N\ (e)^2)$ ……. (2)

Where:

n = sample size

N = sampling frame (total number of states)

e = error or significance level (0.05)

The sample size for each state was also determined by the following formula;

$n_i = \frac{n}{N} \times Ni$……… (3)

Where

n_i= State sample size

i = Numbers of the Ni = State

n = total sample size

N=total number of farmers in the study area (population)

Ni = total number of farmers in each State

To effectively study the impact of cassava disease management technologies on adopters, non-adopters were used as a control group for comparative analysis, where 264 non-WAVE Beneficiaries were selected randomly. In all, (528) cassava farmers were randomly selected. However, upon data collection, it was revealed that both groups (WAVE Beneficiaries and Non-WAVE Beneficiaries) contained adopters and non-adopters. Therefore, the final sampling structure consisted of four groups: beneficiaries who adopted, beneficiaries who did not adopt, non-beneficiaries who adopted, and non-beneficiaries who did not adopt. In all, the study comprises (237) adopters and (299) non-adopters, making a total sample size of 536.

Methods of Data Collection

Cross-sectional data were used to meet the objectives of this study. The data was collected from both primary and secondary sources. Primary data was collected from Adopters and non-adopters, using a structured questionnaire (Kobo collect) with the assistance of extension agents from the WAVE project, which serves to support data gathered through the use of questionnaires. Information sourced includes socio-economic characteristics of farmers, the level of adoption of cassava disease management technologies, and factors influencing the adoption of cassava disease management technologies. Before the real data collection, the questionnaire was pretested for further fine-tuning. In addition, orientation was given for enumerators to have a common understanding of the data collection instrument. Finally, the questionnaire was administered by trained enumerators in close supervision of the researcher.

Analytical Tools

Data collected was inputted using SPSS 20 and R software. The researcher used both descriptive and inferential analysis methods to answer the research objectives mentioned above. The descriptive analysis makes use of the usual methods, such as computing mean, standard deviation, frequencies, and percentages using tables, basically to support the inferential analysis. In the inferential analysis, the Double Hurdle model was used to estimate factors influencing the farmers' decision and intensity to adopt agricultural technologies in the study area.

Adoption index

In order to estimate the level of adoption of Cassava disease management technologies (improved cassava variety, disease resistance variety, good agronomic practices, roguing, and biological control), an adoption index was used to achieve objective 3 of the study. The adoption index employed is the following formula, as used by Kebede *et al. (*2017). The average score was 60%. Any respondent who scored 60% or more falls into the high adoption level, while any respondent who scored below the average falls into the low adoption level.

Cragg double hurdle model

Most adoption studies have used the Tobit model to estimate adoption relationships with limited dependent variables. However, the Tobit model is very restrictive for statistical reasons, making this model unsuitable for certain empirical applications. The Tobit model is also statistically restrictive because it assumes that the same set of variables determines both the probability of non-zero adoption and the intensity of use level. That is why recent empirical studies have shown the Tobit model's inadequacy in cross-sectional analysis, stressing alternative approaches. Therefore, this study's appropriate model is the Double-Hurdle model initiated by Cragg (1971). The double hurdle (DH) model is a useful and appropriate approach to analyze technology adoption under constrained access to agricultural inputs. Many Nigerian farmers faced constraints in accessing inputs like fertilizer and improved seed varieties. In this case, the DH model is suitable for analyzing technology adoption. The DH model assumes that farm households face two hurdles in any agricultural decision-making process, such as the participation decision (the decision to adopt), followed by the intensity (the production level decision). Hence, the Double Hurdle model allows for the simultaneous consideration of the determinants of the technology adoption decision of the households and the determinants of use intensity through two separate stages. The Double Hurdle Model uses both probit or logit and truncated regression at different stages. The first stage involves running a probit or logit regression to determine factors affecting farm households' decision to participate in technology adoption. While in the second stage, truncated regression was used to analyze the intensity of adoption on the individuals who passed the first Hurdle (i, on those participating in the use of technology) (Yu *et al.,* 2011). The Double Hurdle model helps a subset of the data pile up at some value without causing bias in estimating the continuous dependent variable's determinants in the second stage. Hence, it is possible to obtain all the data in the remaining sample for the participants. In this model, the zero values in the dependent variable signifying non-adoption of the technology could be resulted either from households that decided not to adopt the technology or households that have the willingness to adopt but are unable to do so due to reasons not embodied in the Tobit framework (for example, the unavailability of inputs discussed above) Thus, there are no restrictions regarding explanatory variables in each decision in the double Hurdle model. Stated differently, it is possible to separately analyze the determinants of adoption decisions and the extent of adoption decisions. Due to this separability, the estimates of production decisions can be obtained by using probit or logit regression. The level of adoption decision can be analyzed using a truncated regression. The general form of the Double Hurdle model employed for analyzing farm households' decisions for adoption and intensity of adoption of technologies is:

$Dh_i^* = \alpha' Z_i + U_i$ (adoption decision equation) …… (4)

$Dh_i^* = 1 \ldots$ if $dh_i^* > 0$

$Dh_i^* = 0 \ldots$ if $dh_i^* \leq 0$

where: dhi* is a latent variable and Dh takes the value 1 if a farmer adopts improved bread wheat technology and zero otherwise, Z is a vector of household socioeconomic and institutional characteristics influencing the initial adoption decision, and α is a vector of parameters.

$Yi^* = \beta' X_i + V_i$ (Intensity production Adoption decision equation) …… (5)

$Yi = Y_i^* \ldots$ if $Yi^* > 0$ and $DH_i^* > 0$

$Yi = 0$ if otherwise

where Y_i is the latent variable describing the intensity of adoption of CDMTs, X_i is a vector of variables influencing how much the household uses technology, and β_i is a vector of parameters. The v and u are error terms and are assumed to be independent between them. If both decisions are made by the individual farmers independently, the error terms are assumed to be independent and normally distributed. The log-likelihood function for the double hurdle model is:

$$\mathrm{LogL} = \sum Ln\left[1 - \Phi\left(\alpha zi\left(\frac{\beta Xi}{\sigma}\right)\right)\right] + \sum ln\left[\Phi(\alpha zi^*)\frac{1}{\sigma}\Phi\left(\frac{Yi - \beta Xi}{\sigma}\right)\right]$$

…..(6)

Under the assumption of the independence between the error terms V_i and U_i, the double hurdle model is equivalent to the amalgamation of the Probit model (1) and the truncated regression model (2) (Greene, 2003). Whether estimations are obtained simultaneously or one regression at a time, the results will be identical because of the separability of Cragg's likelihood function. The general form of the Double-Hurdle Model is employed for analyzing smallholder farm households' decisions for adoption and intensity of production technologies in terms of area coverage in hectares. Measurement and definitions of variables for the adoption of the dependent variables of the Double-Hurdle Model. The model's dependent variable takes a censored value depending on the farmers' decision to adopt or not adopt the CDMTs and the intensity of adoption if they decide to adopt the technology. In this case, it will indicate the number of technologies adopted in the past 5 years. A farmer is said to be an adopter if he/she use any of the technologies on his/her farmland. The Independent variables and their definitions in the Double Hurdle Model. Adoption literature provides a long list of factors that may influence agricultural technologies' adoption.

Hypothesis testing

Logit regression analysis was employed to test the null hypothesis.

Results and Discussion

The data analysis is performed in two steps. In the first section, a description of the socioeconomic characteristics of the sample farmers comparing adopters and non-adopters for both the North West and North East is provided. In the second section, we present the econometric results on the farmers' level of adoption and factors influencing the adoption of cassava disease management technologies in North West and North East.

Descriptive Analysis: (Socio-economic Characteristics of Respondents)

Tables 2 and 3 present the comparison of means of selected variables by adoption status for the surveyed 536 households in Northern Nigeria. It shows that there was a difference between the characteristics of adopters and non-adopters. Some of these characteristics were used as explanatory variables of the estimated models we present further on. The North West dataset contains 254 farm households, and of these, about 48% are adopters, i.e adopted at least one of the disease management practices during the 2022/2023 cropping season. The area under cassava cultivation is about 1.3 ha for adopters. The result shows that there is a mean difference observable in the age of the adopters (41 years) and non-adopters (38 years), although both categories are in their active age. This is supported by the previous studies of Bayissa (2014), who found that the overall mean age of the sampled household head was about 44.6 years; the figure was nearly similar for tef technologies adopters and non-adopters. This result reveals that the average household size was about 9 members for adopters and 8 members for non-adopters. This agrees with the findings of Zegeye *et al.* (2022); Setsoafia *et al.* (2022), who found that, on average, adopters have a larger family size than non-adopters. In addition, based on the gender of the household, the result also shows that about 88% adopters and 98% non-adopters were all found to be male, and this shows that males were dominant in cassava production than their female counterparts. This could be attributed to various reasons, which could be the problem of the economic position of female-headed households, including a shortage of labor, limited access to information, and required inputs due to social position. This agrees with the findings of Bayissa (2014); Zegeye *et al.* (2022) found that of these interviewed farmers, 27 (19%) are female headed and the remaining 113(81%) are male-headed households. For two groups, the corresponding figures are 11 and 27 for adopters and non-adopters respectively. This figures show that male headed household of adopter is higher than that of the female headed. Furthermore, the result of our findings also shows that the groups do not vary in terms of their marital status and educational level. Majority (85%) of the adopters and (86%) of the non-adopters were married. The result of this study reveals that on average, both adopters and non-adopters attained secondary education (about 10 years of schooling). This suggests that education might be uncorrelated with decision to adopt. This agrees with the findings of Asfaw and Shiferaw (2010); Kachilei (2022); Zegeye *et al.* (2022), who report that an average mean level of education in terms of the number of years spent in school is 10 years. This indicates that most of the household heads are fairly educated, with the result showing that 54.67% of the household heads attained the secondary level of education. There is no significant difference observed in the household access to extension services. This implies that extension alone may not be sufficient to drive adoption, and they may require additional support or incentives. This disagrees with findings by Zegeye *et al.* (2022); Setsoafia *et al.* (2022), who reported that institutional factors such as extension contact are higher for adopters than non-adopters. This may show that households getting extension services are expected to have access to information on agricultural technologies and their profitability. Moreover, the average walking distance to the main market is lower for adopters. This agrees with the findings of Bayissa (2014); Zegeye *et al.* (2022); Setsoafia *et al.* (2022) who reported that on average, the adopter households are located near to the market and urban centers than their counterparts significantly. This simple comparison of the two groups of smallholders suggests that adopters and non-adopters differ significantly in some proxies of physical, human, and social capital. The North East dataset contains 282 farm households, and of these, about 41% are adopters, i.e., adopted at least one of the disease management practices during the 2022/2023 cropping season. The result shows that the area under cassava cultivation is about 1.36 ha for adopters. The result of this study shows that no difference is observed in the age and household size for both categories of farmers. This implies that the respondents are more likely to adopt the technologies since young farmers may have a better education. Larger household size implies more active family labour. This study agrees with past studies of Zegeye *et al*. (2022); Setsoafia *et al*. (2022), who found that, on average, younger farmers are more likely to adopt New technology, and a larger household size (9 persons) is more likely to adopt the new technology. No difference is also observed in the marital status, as the majority (91%) of the adopters and (83%) of the non-adopters were married. The result also shows that the level of education of the household head is higher for CDMT adopters (about 11 years of schooling) than that of non-adopters, which is 9 years. This agrees with the findings of Zegeye *et al.* (2022); Siyum *et al.* (2022), who reported that, on average, adopters have a higher education level. This may point out that the education of the household's head matters adoption decision of improved technology. In addition, based on the gender of the household, about 90% adopters and 84% non-adopters were all found to be male, and this shows that males were dominant in cassava production than their female counterparts. This agrees with the findings of Bayissa (2014); Zegeye *et al.* (2022) found that of these interviewed farmers, 27 (19%) are female-headed and the remaining 113(81%) are male-headed households. For the two groups, the corresponding figures are 11 and 27 for adopters and non-adopters, respectively. These figures show that male-headed households of adopters are higher than those of the female headed. There is no difference observed in the household access to extension services. This implies that extension alone may not be sufficient to drive adoption, and they may require additional support or incentives. This disagrees with findings by Zegeye *et al.* (2022); Setsoafia *et al.* (2022), who reported that institutional factors such as extension contact are higher for adopters than non-adopters. This may show that households getting extension services are expected to have access to information on agricultural technologies and their profitability. Moreover, adopters were found to be closer to the main market than non-adopters. This agrees with the findings of Bayissa (2014); Zegeye *et al.* (2022); Setsoafia *et al.* (2022), who reported that, on average, the adopter households are located near to the market and urban centers than their counterparts significantly. This simple comparison of the two groups of smallholders suggests that adopters and non-adopters differ significantly in some proxies of physical, human, and social capital.

Number of CDMTs adopted by Cassava Farmer

The result in Table 4 shows that in North West and North East, the proportion of sample cassava farmers using two new technologies is the largest, accounting for 60.33% and 56.89% respectively, followed by those using three technologies and one technology. Cassava farmers using four technologies account for relatively few in both regions.

Adoption level of Cassava farmers with respect to CDMTs

The result in Table 5 shows that the majority of the cassava farmers in both regions adopted at least 2 technologies, which made them belong to the low adoption category (score below 60%), whereas a few cassava farmers belong to the high adoption category (scored 60% and above). The low level of adoption could have been attributed to a lack of access to the management technologies in the study area.

Econometric Analysis: (Double Hurdle Model)

In this part (Table 6), we analyze factors affecting farmers' adoption decisions and the intensity of adoption of CDMTs by taking the 2022/2023 production year as a reference. To address the researcher's objective, we employed a double-hurdle model because of its superiority, as discussed in the previous sections. The results for the determinants of CDMTs have a binary nature and are hence estimated by the logit model (the first hurdle) and are displayed in Table 5. The Wald chi-square values of 61.04 and 68.77 are statistically significant at 5% and 1% in North West and North East, respectively, indicating that the explanatory variables in the model jointly explain both the probability of adoption and intensity of adoption. There is no theoretical guidance as to which variable to include in each hurdle; hence, an attempt was made to include several explanatory variables in both hurdles. Turning to the estimation results, coefficients in the first hurdle indicate how a given decision variable affects the likelihood (probability) of adopting CDMTs. Those in the second hurdle indicate how decision variables influence the intensity of CDMTs adoption. The result of the first hurdle (Logit Model) indicates that out of the included regressors, the coefficients of seven variables were found to have a significant impact on the likelihood of adoption of CDMTs in the study area.

Significant Explanatory Variables from Logit Regression:

Education Level: As expected, the educational level of the household head has a positive and significant relationship (at 5% level) with the probability of adoption decision of CDMTs in both regions. This implies that the educated farmers are more likely to adopt CDMTs than those who are not educated. This may be due to relatively educated farmers having more access to information, and they become aware of new technology and which enhances the adoption of technologies. This is in line with the findings by **(**Siyum *et al.,* 2022).

Farm size: Land size owned by the farm households is generally believed to play a significant role in the farmers' technology adoption decision Mwangi and Kariuki, 2015). Many researchers have argued that land size is one determinant of technology adoption, as land size can influence other factors determining the adoption decision Lavison, 2013). For this, the estimated coefficient result for this variable was found to have a positive and significant relationship (at 5% level) with the probability of adoption decision of CDMTs in North West, but not found to be significant in North East. This result implies that farmers who have ownership of large farm sizes are likely to use new technology, as they can be able to put aside part of their land to practice a new technology to avoid crop failure if used in their entire land. This is in line with findings by (Danso-Abbeam *et al.,* 2019; Dachito and Angelo, 2021).

Farming experience: The estimated coefficient result for this variable was found to be positive, reflecting a positive effect on the likelihood of adoption decision of CDMTs in both regions. This result implies that farmers, who have more farming experience, are most likely to adopt CDMTs, keeping the effects of other variables constant. This is supported by the obtained statistically significant coefficient at a 10% probability level, which confirms the logical association between producing any crop and the level of farming experience owned by smallholder farmers. This is in line with the findings of (Bayissa, 2014; Fadeyi *et al.,* 2022).

Distance to Market: As expected, distance to market center has a negative and significant relationship (at 5 % level) with the probability of adoption decision of CDMTs in both regions. This implies that households that live near the marketplaces are likely to adopt the technologies than those who live far from the marketplace. Since farmers may have higher access to information on new or improved farm technologies, information on input (output) prices, and also could lead to timely adoption and lower production costs. This is in line with the results of (Bayissa,2014; Wudu, 2017; Belay & Mengiste, 2021; Zegey *et al.,* 2022).

Extension contact: Empirical access to extension services is among the key determinants of technology adoption. Extension agents have a critical role in providing information to farmers about the access and the benefits of new technology, and giving guidance on the farmland and how much to use. Extension agents are assumed to serve as a bridge between technology innovators (research and development) and users of the same technology through facilitating information flow and reducing the transaction cost Genius *et al.,* 2010; Mwangi and Kariuki, 2015). For this study, the estimated coefficient result for this variable was found to have a positive and significant relationship (at the 10% level) with the probability of adoption decision of CDMTs in both regions. The result indicates that the extension agent visit has the tendency to create more awareness and better information for the farming household heads on the importance of CDMTs. This is in line with the findings by Dachito and Angelo (2021), Siyum *et al. (*2022).

Participation in caravan: As expected, the estimated coefficient for the dummy variable indicating households' participation in disease management training (awareness) reveals the positive and significant impact of this variable on the adoption decision of CDMTs in North West at 1% level of significance, but not significant in North East. This implies that the households that participated in the caravan are more likely to adopt CDMTs than those that did not. The plausible reason is that farmers who participated in training are most likely to produce the crop in significant amounts because training might help farmers to create awareness and promote the understanding of the merits of the available information. This is in line with the findings by Jerop *et al. (*2018).

Participation in training: As expected, the estimated coefficient for the dummy variable indicating households' participation in disease management training reveals the positive and significant impact of this variable on the adoption decision of CDMTs in North West and North East at 5% and 1% level of significance, respectively. This implies that the households that participated in training are more likely to adopt CDMTs than those that did not. The plausible reason is that farmers who participated in training are most likely to produce the crop in significant amounts because training might help farmers to create awareness and promote the understanding of the merits of the available information. This is in line with the findings by **(**Bayissa, 2014; Jerop *et al.,* 2018; Krah *et al.,* 2019; Fadeyi *et al.,* 2022; Wu, 2022).

Participation in demo plot: As expected, the estimated coefficient for the dummy variable indicating households' participation in disease management training reveals the positive and significant impact of this variable on the adoption decision of CDMTs in both regions at the 10% level of significance. This implies that the households that participated in the demo plot are more likely to adopt CDMTs than those who did not. The result suggests that on-farm demonstrations are a means of learning by doing, which enables farmers to develop confidence in the given technology. In addition, demonstration plots will create the opportunity for experience sharing among invited and host farmers of the demonstration plots. This result is consistent with Siyum *et al.* (2022); Yigezu*et al.* (2018), who find that both hosting and involvement in on-farm demonstration trials decreases the duration to adoption by 36.5%.

Factors Determining the Intensity of CDMTs Adoption

This section focuses on factors determining the extent of adoption of CDMTs in the study area. Truncated regression was used in this case, which is the second stage of the double-hurdle model, to analyze the problem. The result of the second hurdle indicates that the variables such as educational level, farm size, farming experience, distance to market, extension contact, and participation in (training, caravan, and demo plot) are the significant determinants for adoption intensity of CDMTs in the study area. Educational level positively influenced the adoption intensity of CDMTs in both regions, and this variable was statistically significant at 5%. Education increases the intensity of adoption by 6% and 5% in the North West and the North East, respectively, indicating that farmers who are educated are reluctant to use the CDMTs than those who are not educated. The implication of the result might be related to the fact that educated farmers have more access to information, and they become aware of new technology, and this awareness enhances the adoption of technologies. This is in line with the findings by Dachito and Angelo (2021)**.** Farm size positively and significantly influenced the adoption intensity of CDMTs in North West at a 10% level of significance, but was not significant in North East. An increase in farm size increases the intensity of adoption by 12% in the North West. This result implies that farmers who have ownership of large farm sizes are likely to use new technology, as they can be able to put aside part of their land to practice a new technology to avoid crop failure if used in their entire land. This is in line with findings by (Danso-Abbeam *et al.,* 2019; Dachito and Angelo, 2021). Farming experience positively and significantly influenced the adoption intensity of CDMTs in both regions at 1% level of significance. This positive and significant coefficient reveals the importance of farming experience in the intensity of CDMTs adoption. The justification for this is that experienced farmers might have gained knowledge. The model result indicates that as the farming experience of the household increases by one year, the probability of intensive use of CDMTs increases by 5% and 3.5% in North West and North East, respectively. This is in line with the findings by (Bayissa, 2014; Fadeyi *et al.,* 2022). Distance to market, as expected, distance to market center has a negative and significant influence on the adoption of CDMTs in both regions at a 10% level of significance. The model result indicates that as the distance from the market center is increased by one km, the probability of intensive use of CDMTs decreases by 2% and 4.5% in North West and North East, respectively. The implication is that the longer the distance between farmers' residences and the market center, the lower the probability of CDMTs' intensity use. This may be due to relatively Proximity to the mark*et al*so reduces marketing costs. This is in line with the findings by (Bayissa,2014; Wudu, 2017; Belay & Mengiste, 2021; Zegey *et al.,* 2022). Extension contact positively and significantly influenced the adoption intensity of CDMTs in North West and North East at 5% and 10% levels of significance, respectively. An increase in agricultural extension visits increases the intensity of adoption of CDMTs by 58% and 3.5% in North West and North East, respectively. The result indicates that the extension agent visit has the tendency to create more awareness and better information for the farming household heads on the importance of CDMTs. This is in line with the findings by Dachito and Angelo (2021). Participation in caravan positively and significantly influenced the adoption intensity of CDMTs in the study area at 5% level of significance, but not significantly in the North East. The positive and significant coefficient obtained reveals the importance of participation in the caravan in the intensity of CDMTs adoption in the study area. Participation of farmers in the caravan increases the intensity of adoption by 79% in the North West. The plausible reason is that farmers who participated in training are most likely to produce the crop in significant amounts because training might help farmers to create awareness and promote the understanding of the merits of the available information. This is in line with the findings by Jerop *et al. (*2018). Participation in training positively and significantly influenced the adoption intensity of CDMTs in North West and North East at 5% and 1% level of significance, respectively. The positive and significant coefficient obtained reveals the importance of participation in training in the intensity of CDMTs adoption in the study area. Participation of farmers in training increases the intensity of adoption by 79% and 8.7% in the North West and North East, respectively. The result suggests that training is are means of learning which enables farmers to develop confidence in the given technology. In addition, training will create the opportunity for experience sharing among invited and host farmers. The plausible reason is that farmers who participated in training are most likely to produce the crop in significant amounts because training might help farmers to create awareness and promote the understanding of the merits of the available information. This is in line with the findings by (Bayissa, 2014; Krah *et al.,* 2019; Fadeyi *et al.,* 2022). Participation in the demonstration plot positively and significantly affects the intensity of CDMTs adoption at a 10% level of significance in both regions. Participation of farmers in on-farm demonstration increases the intensity of adoption by 53% and 24% in the North West and the North East, respectively. The result suggests that on-farm demonstrations are a means of learning by doing, which enables farmers to develop confidence in the given technology. In addition, demonstration plots will create the opportunity for experience sharing among invited and host farmers of the demonstration plots. This is in line with the findings by (Siyum *et al.,* 2022; Yigezu *et al.,* 2018).

Hypotheses Testing: (Relationship between Socio-economic Factors and Adoption of Cassava Disease Management Technologies)

The result (Table 6) of the test (logit regression) between respondents' socio-economic factors and adoption of cassava disease management technologies showed that out of the explanatory variables used in the model, eight variables were significant as their calculated t-statistics were greater than the tabulated t-statistics. These were education, farm size, farming experience, distance to market, extension contact, and participation in training, caravan, and demonstration plot. Other socioeconomic factors (age, marital status, and household size) do not significantly influence adoption in the study area. Therefore, the null hypothesis was rejected.

Conclusion

The result of a double-hurdle econometrics model shows that among the explanatory variables used in the regression analysis, educational level, farm size, farming experience, extension services, participation in training, caravan, and demonstration plot were found to significantly influence farm households' adoption decision and intensity of adoption of CDMTs in the study area. The results of the study suggest that to boost cassava crop productivity through improved agrarian technology, access to extension services should be strengthened through adequate provision of logistics, in-house training, and recruitment of agents. Farm households should be encouraged to engage in non-farm economic activities to complement their farm income and enhance the purchase of productive farm inputs. Finally, farm-level policies oriented towards increasing access to Agricultural credit and membership in a cooperative are essential to improving the adoption of farm innovations. Moreover, stakeholders implementing CDMT technology in the farming communities should pay attention to the variables identified to shape farmers' adoption decisions significantly. This will guide them to make an informed decision regarding the design and the implementation of the programmes.

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Authors' contributions

All authors read and approved the final manuscript.

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Availability of data and materials

The data supporting the reported results are accessible from the leading author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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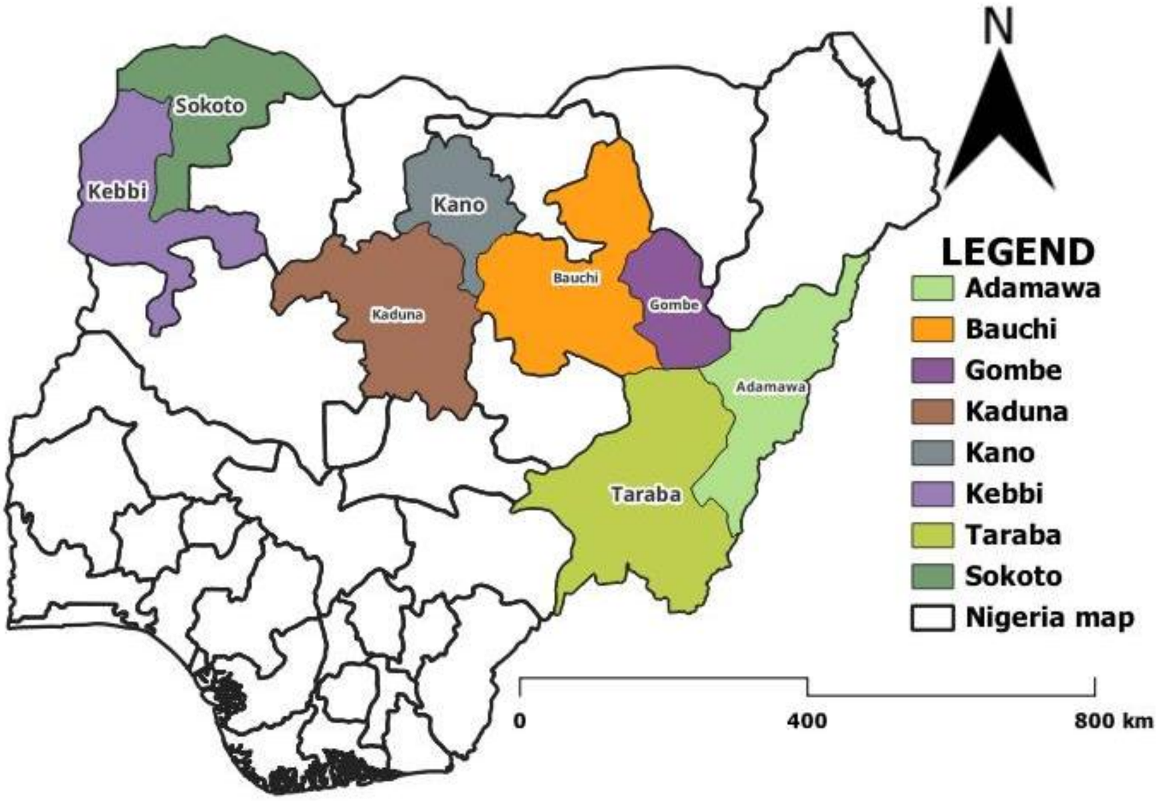

Figure 1: Map of Nigeria Showing Sampled States

Table 1: Description of Variables used in the Study

Variables	Description of variables	Data type	Exp. signs
Dependent			
Adoption of CDMTs technology	1 if the family farm has adopted any of the technology, 0 otherwise	Dummy	
Intensity of CDMTs	Number of technologies adopted in the past 5 years	Continuous	
Independent			
Sex	Sex of respondents (0=female, 1=male)	Categorical	+
Age	Age of respondent in years	Continuous	+ –
Marital status	Indicates a person who is married, single, or otherwise	Categorical	+
Education	A measure of the ability to read and write	Categorical	+
Household size	The number of people living under the same roof and making joint decisions about their welfare	Continuous	+ –
Farming experience	Total number of years engaged in farming	Continuous	+ –
Years of growing cassava	Total number of years engaged in cassava farming	Continuous	+ –
Farm size	Total size of the lands owned by cassava farmers	Continuous	+
Cassava area (ha)	Total size of lands dedicated to cassava farming	Continuous	+
Extension exposure	If the household received extension service (1=Yes, 0=No)	Continuous	+
Participation in training	1= if the head of the family farm has attended any training, 0 otherwise	Dummy	+
Participation in Demonstration farms	1 = if respondent visited demonstration farms, 0 otherwise		
Hired labour	Number of laborers hired on the farm in person-days per cropping season	Continuous	-
Access to credit	If respondent received cash or input credit	Continuous	+
Co-operative member	Household participation in cooperative (1=Yes, 0=No)	Dummy	+

Table 2: Descriptive Statistics of Dummy Variables by Farm Households

Variables	North West				North East			
	Adopters		Non-adopters		Adopters		Non-adopters	
	F	%	F	%	F	%	F	%
Sex								
Male	107	88.0	131	98	104	90	140	84
Female	14	12.0	2	2	12	10	26	16
Marital Status								
Married	103	85.1	115	86	105	90.5	138	83.1
Single	18	14.9	18	14	11	9.5	28	16.9
Hired labour								
Yes	90	74	104	78	91	78	116	70
No	31	26	29	22	25	22	50	30
Family labour								
Yes	99	82	120	90	106	91	147	89
No	22	18	13	10	10	9	19	11
Extension service								
Yes	91	75	107	80	91	78	135	81
No	30	25	26	20	25	22	31	19

Source: Field survey data 2023

Table 3: Descriptive Statistics of Continuous Variables by Farm Household

Variables	North West				North East			
	Adopters		Non-adopters		Adopters		Non-adopters	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Age	41.46	14.75	38.35	12.07	41.34	11.96	41.19	11.94
Educational level	10.63	5.79	10.56	5.45	11.61	5.21	9.79	5.79
Household size	9.22	4.77	8.99	4.96	9.37	5.84	9.42	5.64
Farm size	3.04	4.92	3.64	3.66	4.55	3.75	5.22	8.38
Cassava farm size	1.30	1.01	1.47	1.49	1.36	1.23	1.73	4.04
Yrs of farming exp	18.53	11.51	15.05	9.72	16.17	8.14	16.70	7.98
Yrs of cassava farming	8.00	7.41	9.25	7.15	10.80	7.19	10.95	7.11
Distance to market	5.97	5.74	8.09	8.58	9.43	9.79	10.99	13.19

Source: Field survey data 2023

Table 4: Statistics on the number of CDMTs adopted by Cassava farmers.

	North West				North East			
Number of technologies adopted	1	2	3	4	1	2	3	4
Number of households adopted	18	73	25	5	16	66	30	4
Percentage (%)	14.87	60.33	20.66	4.13	13.79	56.89	25.86	3.44

Source: Field Survey data 2023

Table 5: Adoption level of Cassava farmers with respect to CDMTs

Category of score (%)	Adoption level of farmers	North West		North East	
		Frequency	Percentage	Frequency	Percentage
60 – 100	High	30	24.79	34	29.31
Below 60	Low	91	75.21	82	70.69
	Total	121	100	116	100

Source: Field Survey data 2023

Table 6: Econometric Model Results for the Probability of Adoption and Intensity of Adoption of CDMTs in Northern Nigeria: Estimated by the Cragg Double Hurdle Model

	North West				North East			
	Logit		Truncated		Logit		Truncated	
Variables	Coeff	Std err	Coeff	Std err	Coeff	Std err	Coeff	Std err
Age	-0.015	0.054(-0.277)	-0.021	0.041 (0.512)	-0.019	0.022 (0.863)	-0.021	0.032 (0.656)
Educational level	0.323**	0.138 (2.341)	0.066**	0.029 (2.275)	0.048**	0.023 (2.086)	0.051**	0.018 (2.833)
Household size	0.021	0.018 (1.166)	0.032	0.027 (1.185)	-0.041	0.046 (0.891)	-0.005	0.017 (0.882)
Farm size	0.596**	0.206 (2.892)	0.129*	0.065 (1.986)	0.053	0.060 (0.883)	-0.065	0.053 (1.226)
Cassava farming exp	0.139*	0.078 (1.785)	0.059***	0.019 (3.127)	0.068*	0.035 (1.942)	0.035***	0.011 (3.181)
Distance to market	-0.094*	0.058 (1.624)	-0.027*	0.014 (1.928)	-0.087**	0.043 (2.023)	-0.045*	0.024 (1.875)
Extension contact	0.270*	0.140 (1.925)	0.584**	0.292 (2.001)	0.994*	0.553 (1.797)	0.035*	0.021 (1.666)
Caravan	1.640***	0.491 (3.340)	0.797**	0.334 (2.388)	0.386	0.537 (0.718)	0.537	0.482 (1.114)
Training	5.069**	2.508 (2.021)	0.798**	0.354 (2.253)	1.766***	0.504 (3.503)	0.087***	0.025 (3.466)
Demo plot	6.443*	3.618 (1.780)	0.573*	0.354 (1.621)	2.087*	1.270 (1.643)	0.241*	0.142 (1.697)
Hired labour	0.525	1.278 (0.411)	0.040	0.359 (0.111)	-1.972	1.776 (1.110)	-0.026	0.236 (0.110)
Constant	9.466	5.708 (1.658)	0.902	0.893 (1.010)	1.695	1.850 (0.916)	0.744	0.774 (0.000)
Wald chi2(10)	61.04				68.77			
Prob>chi2	0.03				0.00			
Log Likelihood	-99.48				-186.5			
No of observation	254		121		282		116	

Numbers in parenthesis are Z values, ***p < 0.01, **p < 0.05 and *p < 0.10

Source: Field survey data 2023