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Assessment of factors influencing adoption of tomato post-harvest loss-reduction technologies in Kaduna state, Nigeria.

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Abstract

The Nigerian government's policy on agriculture supports productivity enhancements, yet tomato production is constrained by post-harvest losses of up to over 45%. 420 tomato farmers were selected for study in Kaduna State, Nigeria. Multinomial Logit Model was used to determine factors influencing losses while factors influencing adoption and intensity were modelled using Tobit. The results showed the adoption rate of (new technologies) RP was 3.57%, CS = 0.47%, RT = 0.71%, MD =0.71%, CD = 100%. Adoption rate of (traditional method) raffia basket was 100%. For farmers, the highest source of losses was those in storage (70.5%), followed by farm level (14.5%). Results on factors influencing PHL showed that in transit, Modern Technology accentuated losses ($p<0.10$), while Car/truck ownership mitigated losses ($p<0.01$) In storage, Modern Technology ($p<0.05$), Farm Distance ($p<0.05$), Farm Size ($p<0.10$), and Own Car/truck ownership ($p<0.10$) mitigated losses, while only Multiple Cropping ($p<0.05$) accentuated losses. In marketing, education ($p<0.05$), modern technology ($p<0.10$), multiple cropping ($P<0.10$), and credit access ($P<0.10$) accentuated losses while age of farmer ($p<0.10$), years of technology adoption ($p<0.10$), farm size ($p<0.10$), and wealth status of farmers ($p<0.05$) mitigated losses. The results factors influencing adoption and adoption intensity of PHL-reducing technology show that Education ($p<0.05$), Age ($p<0.10$), Extension ($p<0.10$), CS_Information_Sources ($p<0.01$), RT_Information_Sources ($p<0.01$), MD_Information_Sources ($p<0.05$), Labour_sourcesT ($p<0.01$), Credit_sourcesT ($p<0.10$), and Farm_Size ($p<0.01$) were positive and had a significant influence. Education had a quadratic (Education^2) negative influence on adoption of PHL-reducing technologies. In conclusion, extension services exposure, large farm holding, and multiple information sources positively influenced adoption of post-harvest loss reduction technologies. The field survey also showed a 100% willingness of the farmers to adopt improved/modern technologies. The study recommends using PPP model to make these modern technologies and farm practices within the financial reach of farmers to mitigate post-harvest losses.

Keywords: *adoption; adoption rate and intensity; Multinomial Logit Model; Post-harvest losses; technologies; Tobit Regression Model*

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Introduction

In Sub-Saharan Africa (SSA), 36% of harvested food is lost, equating to an average of 167 kg/cap per year where only 7 kg is at the consumer level (Winkworth-Smith, *et al.,* 2014). Tomato *(Solanum lycopersicum L.),* which is regarded as both *a* fruit and vegetable, is considered as one of the most widely known and used vegetables in the world (Saeed- Awan *et al.,* 2012). It is an important vegetable crop in Nigeria accounting for 18% of the daily consumed vegetables. It is second only to the Irish potato as the vegetable crop of its most economic importance (Abdullah *et al., 2010;* Babalola *et al.,* 2010; Ebimieowei and Ebideseghabofa, 2013; Arah *et al.,* 2016). Studies reveal that the full potential of tomato farming is not being maximized due to many challenges, despite obvious benefits, for example, most tomato farming in Nigeria (other African countries included) is constrained by post-harvest losses, mostly for the rain-fed farming, pests and diseases incidence and many other factors (Adenuga *et al.,* 2013; Arah *et al.,* 2015). Over 45% (750,000 metric tons) of tomatoes produced in Nigeria are lost through post-harvest activities, and the country still relies on imports (Arah *et al.,* 2015; FAOSTAT, 2016; Ashinya *et al.,* 2021). Post-harvest losses have been identified as one of the determinants of the food problem in most developing countries, hence global efforts to tackle hunger, increase farmers' incomes and improve food security in these countries should give priority to mitigating crop losses (FAO, 2010 and Abera *et al.,* 2020). Cost-effective approaches are required to address the increasing rates of post-harvest losses, as well as creative techniques and agricultural methods that can be applied through the supply chain to prolong tomato shelf-life. When introduced, some of these practices could increase the shelf-life of tomatoes significantly and consequently, reduce disease, raise market demand, and increase incomes for smallholder farmers (Sahel, 2017). According to Golleti (2003) and Nyo (2016), reducing farm post-harvest losses (PHL) has the potential to make significant amounts of food available at a fraction of what it costs to grow the same amount of food. Various technologies and practices for increasing tomato shelf life are common among farmers in Kaduna, Nigeria. These include harvest schedule or interval based on ripening, mode of transport (from the farm to homestead and the local market), and vehicle scheduling and routing (mainly to urban markets) (Tsolakis *et al.*, 2013), packing practices (e.g., packing configuration), storage practices (e.g. stacking methods), use and type of grading standard, selection of the appropriate type of packaging material, monitoring of temperature during storage and transportation and maintenance of the equipment (Macheka *et al*., 2013; Kitinoja, 2013; Gustavsson *et al*., 2011). Tomatoes are best harvested in the morning or evening when the weather is cool. The maximum temperature for storing or transporting tomatoes is 15^{0}C. Because of inadequate electricity supplies especially in Nigeria, farmers and households can also use the low-tech pot-in-pot (zeer) system that uses evaporative cooling thereby keeping tomatoes safe for a few days (Mitcham, 2018); although not so popular in the study area. Other methods found in the study area which can be used to reduce post-harvest losses include drying tomatoes to ensure availability during the offseason. In Nigerian farms and markets, it is customary to save tomatoes in baskets to allow for ventilation and as a tool for grading. Overall, innovations are usually received with both positive and negative outlooks as the intended beneficiaries are more likely to try out a new technology that poses less risk and more advantages compared to existing technologies (Pannell *et al.,* 2006).

Adequate empirical data and information are missing on how these post-harvest reduction technologies act as a driver to the reduction of tomato post-harvest losses in the study area, Kaduna State, being the highest tomato producing State in Nigeria as of 2012 (National Bureau of Statistics, 2012). The specific objective, therefore, was to assess the factors influencing the adoption of post-harvest loss-reduction technologies used in Kaduna State.

Materials and Methods

Study Area

Kaduna State in Nigeria was selected for this study and the choice of this area was anchored on tomato as a key and important crop produced in the area while also being the highest-producing State in the country, at 3.6 million metric tonnes annually (National Bureau of Statistics, 2012). The location was also selected based on a study carried out by The Global Alliance for Improved Nutrition (GAIN) (GEMS4, 2016) which mapped out the tomato production States with data on the production level, number of farmers and clusters, and level of wastages. The mapping was implemented through enumerators' visits to major tomato-producing locations in twelve States, all in northern Nigeria, where farmers were interviewed, and cluster locations were captured via a global positioning system (GPS). Kaduna State is in the North-West Zone of Nigeria, according to the six geo-political zonal classifications of the country, with Sudan-Savannah vegetative cover comprising of grasses, short trees, and little shrubs. The State has a diverse ethnicity of over 60 groups, with the highest number of farmer populations, who are organized into clusters (8,446 females and 73,474 males) (GEMS4, 2016). The Four LGAs:

Soba, Kudan, Zaria, and Makarfi were selected by random sampling. (LGAs with less than 4 farming clusters were excluded from the sampling scheme) The target population of the study was the tomato farmers in Nigeria, while the accessible population were tomato farmers in Kaduna State in Nigeria, selected based on the study carried out by GAIN.

Sampling Procedure and Sample size

Respondents for the study were selected using a multistage sampling technique. The initial step was the purposive selection of Kaduna State location which was based on its volume of tomato production output which stands highest in the country. Then the first stage of sampling was the selection of four Local Government Areas (LGAs) by simple random sampling within the State. The second stage of sampling was the selection of three clusters (villages) within each selected LGA, again by simple random sampling. A cluster (aggregation of rural farmers) is a settlement around low-lying land that is subject to seasonal flooding or waterlogging along the riverbanks, streams, or depressions with favourable agro-environment and ecological conditions, especially for dry-season farming. (Cluster groups often are the creation of national or regional governments and donor agencies, to organise rural farmers into settlements for purpose of target market and outreach service delivery). Equal sampling allocation was done at the cluster level to select 35 farmers (farming households) from each selected cluster, at random; and this constituted the third stage of the sampling process. (Equal sampling allocation was done at the cluster level as the cluster populations were nearly uniform.) Hence, the sample in this study is deemed as an adequate representation of the tomato farmers' population in Kaduna State for valid extrapolation of the result obtained to the entire State.

Mapping of the clusters, farm settlements and villages for the study was done with the help of Community leaders, Extension Agents, and local guides in selected Local Government Areas, to select the required number of villages. Sometimes farmers rotate crops due to market and economic forces (for example, if there was a glut in tomatoes, a farmer could move to rice farming the next season or vice versa). Tomato farmer's association(s) and/or cooperative society leaders were visited and interviewed, and through their membership registers a frame of farmers engaged majorly in tomato farming was constructed for the selected clusters and from which the sample of farmers or farming households were selected. The Global Positioning System (GPS) set was used to record the coordinates of the interview point or homestead of each farmer for reference purposes and ease of location (Figure 1).

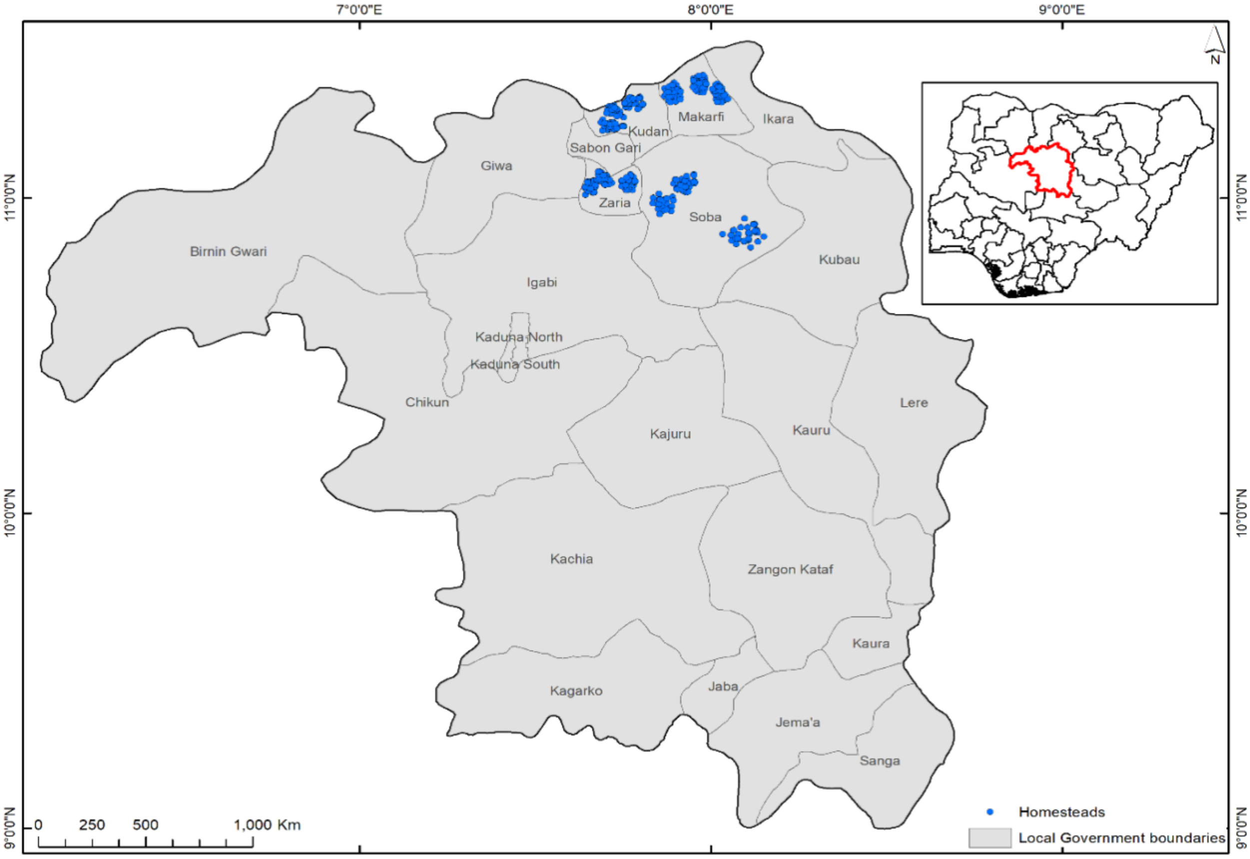

Figure 1. Map of Kaduna, Nigeria showing the study areas and respondent locations.

According to data from surveys done by GEMS4 (2016), there are 82,000 (approximately) tomato farmers in Kaduna State, spread across 47 clusters (communities) in 11 Local Government Areas (LGAs), with approximately 1,745 farmer households per cluster on average. To get the sample size, the Yamane formula (1973**)** was used with a confidence interval of 95% and an estimated error of 5%.

$$n = \frac{N}{1+Ne^2}$$

Where n=sample size

N=population of the study; *(N=81,920)*

e=margin of error (0.05)

(n = 399 minimum)

A 3-stage sampling procedure was applied to obtain a valid and representative spread, comprising a sample of 4 LGAs, and 3 clusters per LGA (that's a total of 12 clusters in the sample.)

With the equal sampling allocation at the cluster level, the sample taken per cluster was approximately 34 (399/12 clusters = 33.25); while the total in the sample was 408 (34 x 12 clusters) farmers. Therefore, the study comprised a theoretical sample of 408 farmers at the household level, however, 420 farming households (35 per cluster) were sampled and interviewed.

Data Collection

Following the satisfaction that the survey instruments were well-validated, tested and migrated to the appropriate collection apparatus (print format), it was then administered to the sampled tomato farmers with the aid of two field research assistants and some local guides. The respondents predominantly speak the Hausa language; therefore, the research assistants and guides were selected based on their local language proficiency. The research assistants received training to familiarize themselves with the survey instruments, and how to administer contingent valuation questions, to avoid structural, content and administration biases. The pre-testing was done on 15 respondent farmers outside the study area, and this helped

to improve the questionnaire instruments and survey strategy to obtain quality results. On arrival at these villages, the village heads were consulted seeking their support in identifying these farmers and their households.
Validation of the questionnaire content was done by relevant experts to scrutinize and assess the relevance of the questionnaire to the objective of the research.

The questionnaires were administered through face-to-face interviews with the heads of farming households. The selected farmers were briefed about the purpose of the study, and permission was sought; the survey questionnaires were administered using the farmers' indigenous language and collected successfully. (There were no objections from farmers experienced as we had the permission of the Village heads transmitted through familiar local guides.)

The survey collected information on various demographic, socioeconomic and farm characteristics (including farm-holding, land-tenure, farm practices, farm inputs, labour-use, on-farm/off-farm income); postharvest loss-reduction technology attributes (including awareness, knowledge, adoption and limitations); extension-service exposure, access to cooperative and/or commercial credit; ownership of a range of household and farm assets; handling, transport and marketing of produce; livestock farming/holding; etc.

Data Handling and Analysis

After data collection using hard print questionnaires, the filled questionnaires were sorted, and their data was entered appropriately into Microsoft Excel spreadsheets followed by data checking and corrections for coding and entry errors. Data analysis was done using the Statistical Package for Social Sciences (SPSS version 22 software) for descriptive statistics, and Stata version 13 for econometric analysis. A Preliminary summary analysis was done using the frequency procedure to show the data overview and sent to supervisors for validation. Descriptive statistics were used to characterize the farmers, their farms, and their socioeconomic profiles where necessary. In addition, Econometric models were used to determine factors influencing post-harvest losses of tomatoes and the adoption of the post-harvest loss reduction technologies under investigation. There were five post-harvest losses reducing technologies that were investigated with one of them having a nearly 100% adoption rate by the farmers. Multinomial Logit Model was used in the determination of factors influencing losses, while factors influencing adoption and intensity were modelled using Tobit with the hypothesis tested as follows:
***H*o**: No relationship exists between selected socio-economic attributes of tomato farmers and the adoption of tomato post-harvest loss-reduction technologies. (Significant differences were evaluated at $p < 0.10$ or 10% alpha level of significance so as not the overlook potentially important effects.)

Multinomial Logit Regression Model for determining factors influencing tomato losses among farmers

Multinomial logit (MNL) is an extension of the logistic regression model. The logistic regression model assumes that the categorical response variable has only two values, in general, '1' for success and '0' for failure. The logistic regression model can be extended to situations where the response variable has more than two values, and there is no natural ordering of the categories. Such data can be analyzed by slightly modified methods used in dichotomous outcomes, and this method is called the multinomial logit (Maddala, 1983; El-Habil, 2012); and it's used to predict the probability that an individual with a certain set of characteristics chooses one of the alternatives (Tiku *et al.*, 2018).

The general form of the multinomial logit model given by Hoffman and Duncan (1988), Ojo *et al.* (2013), and Mustapha *et al.* (2017) is:

$$\Pr(y_i = j) = \frac{exp exp\,(X_i\beta_j)}{1+\sum_{j=1}^{J}\ exp\,(X_i\beta_j)} \quad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

And to ensure identification or unique solution,

$$\Pr(y_i = 0) = \frac{1}{1+\sum_{j=1}^{J}\ exp\,(X_i\beta_j)} \quad \ldots\ldots\ldots\ldots\ldots (2)$$

where for the ith individual, y_i is the observed outcome and X_i is a vector of explanatory variables. β_j is the unknown parameter.

Multinomial logit (MNL) is a widely used model in biomedical, econometrics and social science studies to explain the choice of an alternative among a set of exclusive alternatives (Wanyama *et al.*, 2010; Mustapha *et al.*, 2017; El-Habil, 2012; Mbaye *et al.*, 2014; Peng and Nichols, 2003). Generally, the MNL Model defines probabilities as a function of X_i of the unknown parameter, and the model parameters are typically estimated by the maximum likelihood (ML) method (El-Habil, 2012; Peng and Nichols, 2003; Hoffman and Duncan, 1988)

For this study, the four sources of postharvest tomato losses indicated by farmers were losses at the farm-gate, transportation of the produce, storage, and marketing. Since we are dealing with the categorized dependent variable, numerical values were assigned to those qualitative responses (dummies): 1 = Farm-gate level; 2 = Transportation (in Transit) level; 3 = Storage level; 4 = Marketing level.

The model was summarized as follows:

$$P_{ij} = \frac{exp_{exp}\left(\gamma_j X_i\right)}{1+4\sum j=1\ exp_{exp}\left(\gamma_j X_i\right)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

For j =1, 2, 3, 4

P_{ij} is the probability of being in each of the levels (or channels) 1, 2 and 3.

$$P_{i0} = \frac{1}{1+4\sum j=1\ exp_{exp}\left(\gamma_j X_i\right)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

For j = 0

P_{i0} is the probability of being in the reference level or level 0.

To solve an identification problem and to make the probabilities for all the choices sum to unity, the parameters of the last (j^{th}) or the most frequently used source of PHL was set to zero (the reference level). In this case, losses through the farm-gate level (or channel) were set to zero. The objective is to understand the determinants that cause a farmer to lose farm produce through a particular channel against other alternatives. Hence, for 4 choices only (4 - 1) distinct sets of parameters can be identified and estimated. A farmer is likely to have at least more than one means of loss depending on his socioeconomic characteristics. The decision to have a particular channel of losses is a behavioural response arising from a set of alternatives and constraints facing the farmer.

The explicit or empirical form of the functions is specified as follows (Ojo *et al.*, 2013; Mustapha *et al.*, 2017):

$$P_{ij} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_k x_k \quad \ldots\ldots \text{(5)}$$

P_{ij} = ρ [individual channel of produce losses j], and the individual channel of losses considered were: farm-gate losses, transportation losses, storage losses, and marketing losses; and the farm-gate losses channel was chosen as the reference group. The independent variables x_i's in the model were farm, farmer and institutional-specific characteristics.

Tobit model for determining factors influencing adoption and the intensity of adoption

This can be achieved by knowing the numbers or proportion of PHL-reducing technologies adopted by farmers or quantities of farmers' hectares committed to the innovations (CIMMYT, 1993). Using the Tobit regression model, an analysis was done to see the interaction between the farmer's socioeconomic factors and how the technology is adopted within the farmers' socioeconomic or demographic groupings. The Tobit model is a mixed version of the discrete and the continuous dependent variable which was initially adapted from the work of Tobit (1958). Many studies have since used the Tobit model (Maddala, 1992; Dereje, 2006; Taha, 2007; Guo *et al.* (2019).

Specifying the basic Tobit model below:

$$Y_i^* = X_i\beta + u_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(6)}$$

$Y_i = 0$; if $Y_i^* \leq 0$; $\quad Y_i = Y_i^*$; if $Y_i^* > 0$

$u_i \sim IN\ (0, \sigma^2)$; i= 1, 2, ……, m

Y = limited dependent variable which is the adoption dependent variable and is depicted as the proportion of technologies adopted by farmers or the proportion of farm area where technology is applied. X_i= the socioeconomic and demographic attributes of the farmers.

Results

Socioeconomic Characteristics of the Farming Households

Table 1. Socioeconomic Characteristics of Farm Households

Variables	Percentages (%)N=420	Averages ± SD
Educational status		
Below primary	27.1	
Primary	40.7	
Secondary	15.0	
Tertiary	3.1	
Islamic	14.1	
Education (years)		4.7±4.7
Age (years)		
≤ 30	16.9	
31-50	63.4	
51-60	15.2	
>60	4.5	
Age (years)		42.5±10.8
Marital status		
Married	95.9	
Single	2.1	
Divorced/Separated	1.0	
Widowed	1.0	
Occupation status		
Full time farming	99.8	
Part time farming	0.2	
Farming experience(years)		
<10	6.2	
10-25	54.5	
26-35	26.9	
>35	12.4	
Farm experience (years)		23.5±10.2
Household size		
1-5	15.7	
6-10	35.7	
11-20	48.6	
Household size (number)		9.9±3.7
Labor source		
Family	0.7	
Hired	62.6	
Family + Hired	36.7	
Farm distance to the road		
<10 km	48.1	
10-20 km	44.1	
>20-30 km	5.0	
>30 km	2.8	
Farm distance (Km)		9.6±7.9
Marketing outlet (%)		
Farm gate/homestead	82.9	
Local market	91.2	
Urban/City	60.7	
Processing factory	0.2	
Distance to market(km)		
<10 km	2.9	
10-50 km	31.7	
>50-100 km	12.4	

>100-200 km	14.0	
>200-300 km	26.4	
>300-1000 km	12.6	
Distance to market (Km)		186.5±213.9
First Major mode of transport to the market (%)		
Trekking	0.00	
Bicycle/Motorcycle	3.6	
Cooling vehicle	0.00	
Non-cooling vehicle	96.4	
Second Major mode of transport to market (%)		
Trekking	1.4	
Bicycle/Motorcycle	95.4	
Cooling vehicle	0.3	
Non-cooling vehicle	2.9	
Credit/Loan access & sources (%)	14.0	
Banks	1.0	
Cooperatives	12.1	
Family	0.7	
Other sources	0.2	
Extension visit (monthly)		
0	*86.4*	
Once	*3.6*	
Twice	*8.3*	
Thrice	*1.7*	
Extension visits (number)		0.3±0.7
Cooperative (year)		8.3±5.3
Agricultural land		6.0±5.1
Cultivated land		5.8±4.8
Cultivated crops(number)		6±2
Tropical Livestock Unit (TLU)		4±5

Source: Field Survey, 2020/2021

Results in Table 1 show that most of the household heads fell within the age brackets of 31-50 years, accounting for about 63%. About 20% were above this age range and 17% were below this bracket. The mean age of farmers in this study was 42.5 years. The educational status of the farmers was categorized into four, and the result shows that most of the households (41%) had primary education, and about 18% had above primary (secondary/tertiary) education. Those who could not complete or attain the primary level of education were about 27%, and others with other forms of education like Islamic education accounted for about 14%. The majority (96%) of the tomato farmers were married, while the remaining 4% were either single, divorced, or widowed. Farming is a full-time occupation in the study area (99.8%), with most of the farmers (93.8%) having farm business experience that spans 10 years or greater. The new entrants into the tomato farming business who had less than 10 years of experience constituted about 6.2% of the respondents in the study.

Farming experience has a bearing on the efficiency of performing and managing a specific task that results in high productivity. The results of this study showed that on average, most of the farmers 342 (81.4%) had farming experience averaging 23.5 years. Household size was considered or grouped into three categories and the overall average of these categories gave a household size of about 10 (9.9) persons. A majority (84.3%) had a household size range of 6-20 persons, and households ≤ 5 persons were in the minority (15.7 %). In the study, families that used only family labour constituted only 0.7%, compared to hired labour only which accounted for about 62.6% of the total. Families that combined both family and hired labour constituted 36.7%. Another prominent variable included the distance from the farm to the nearest main road, a majority (92.2%) had their farms within twenty kilometres (≤ 20 km). While about 7.8% had their farms at distances >20 km from the main road. The tomato farmers were observed to have three main market outlets: farm gate or homestead, locally constituted market and urban or city market; and farmers could access more than one of these markets. Of all these marketing outlets, farm gate access (82.9%), local markets access (91.2%), urban/city markets access (60.7%) and processing factory market access accounted for only 0.2%. The distances to these market outlets vary from less than 10 km up to 1000 km from the farmers' homesteads. A majority (65.4%) of the farmers travel beyond 50 km, and some farmers (12.6%) could go beyond 300 km and up to 1000 km distance (outside Kaduna state) to market their produce. Only about 3% (2.9%) of farmers market their produce within a distance of < 10 km close to their homes. This result shows that the first major mode of transportation to the market was the use of non-cooling vehicles, which accounted for about 96.4% of sources of transportation, while the second option (second major mode) used was bicycles/motorcycles which constituted about 95.4%. The households in the study area had three main sources of credit to enhance their farm investment abilities and productivity. They were banks (mostly microfinance), cooperatives and family members. Of the 14% who had accessed credit facilities, 12.1% sourced credit from cooperatives, while only 1.0% sourced credit from the banks, and family and other sources, 0.9%. The result of this study also indicated that about 13.6% of the farmers were visited by extension agents once or up to three times a month, while about 86.4% had no extension service access.

Multinomial Logit (MNL) Model for Post-Harvest Losses Determinants

Table 2. Definition of Variables used for Multinomial Logit Model to determine factors influencing PHL

Variables Names	Nature of Variable	Variable Description	Unit	A priori signs
Dependent variable (Source of losses)	Discrete	Losses at farm level	1	
		Losses in transit	2	
		Losses at storage	3	
		Losses during marketing	4	
Independent variables				
Education (Years)	Continuous No	Years of education of household head	Years	+
Age(Years)	Continuous No	Age of household head	Years	+
Household Size	Continuous No	Family size of farm family	Number	+
Modern_Technology	Frequency	Number of technologies adopted	Number	+
Farm_ Distance (Km)	Continuous No	Distance from home to farm	Km	
Cooperative(Years)	Continuous No	Years of cooperative membership	Years	+
Rooms	Frequency	No of rooms in farmer' house	Number	+
Landcult	Continuous No	Land cultivated	Acres	+/-
Credit	Dummy	Access to credit	Access=1, Otherwise=0	+
Nonfarm Income	Dummy	Have non-farm income	Yes=1, Otherwise=0	+
Poverty (Well off=1)	Dummy	Poverty status	Welloff=1, Otherwise=0	+/-
Multicropping	Frequency	Number of crop grown	Number	+/-

Own Phone	Dummy	Ownership of phone	Yes=1, Otherwise=0	+
Own Car	Dummy	Ownership of car	Yes=1, Otherwise=0	+
Own Bike	Dummy	Ownership of bike	Yes=1, Otherwise=0	+

Table 2 presents the meaning and hypothesized signs of the vector of regressors. It also shows the dependent and independent variables for the MNL regression on factors affecting losses. The rationale for the inclusion of these factors was based on previous agricultural technology diffusion and adoption literature and the analysis of these systems. The explanatory/ independent variables included farmer, farm and institutional factors postulated to influence losses. The dependent variable for factors influencing losses was "Source of Losses", a discrete variable with four levels – losses at farm-gate level; losses in transit; losses at storage; and losses during marketing.

Tobit Model for determination of Factors Influencing Adoption

Table 3. Definition of Dependent and Independent Variables for the Tobit Model to determine factors influencing adoption and intensity of adoption

Variable	Variable description	Unit	A priori signs
Dependent variable			
PHL Technology adoption	Adoption of post-harvest loss reducing technology	Rate/percent age of adoption	
Independent variables			
Education	Years of education of household head	Years	+
Education^2	Square (Years of education of household head)	Years	+
Age	Age of household head	Years	+/-
FExperience	Farm experience of household head	Years	+
Extension	Visitation of farmer by extension agents	Visited=1, Otherwise=0	+
RP_Information_Sources	Number of sources of information the technology	Frequency	+
CD_Information_Source	Number of sources of information the technology	Frequency	+
CS_Information_Source	Number of sources of information the technology	Frequency	+
RT_Information_Source	Number of sources of information the technology	Frequency	+
MD_Information_Source	Number of sources of information the technology	Frequency	+
Labour_sourcesT	Number of sources for labour	Frequency	+
Credit_sourcesT	Number of sources for credit	Frequency	+

Urban_Sales	Sales of tomato in urban area	Yes=1, N0=0	+/-
Crop_Frequency	Number of crop grown	Frequency	-
Non-Farm	Non-farm income	Yes=1, N0=0	+
Farm Size_Tomato	Land cultivated with tomato	Acres	+
Poverty (Well off=1)		Welloff=1, Poor=0	+/-

Table 3 presents the variables used in the empirical model. The explanatory/ independent variables included farmer, farm, and institutional factors postulated to influence the choice of technologies. The rationale for the inclusion of these factors was based on previous agricultural technology diffusion and adoption literature and the analysis of these systems. The dependent variable for factors influencing adoption is described as the rate or percentage of farmers adopting a particular technology.

Household Adoption Characteristics

Table 4. Household Adoption Characteristics

Prioritized Technology	**Use Status Yes**	**Adoption period (years) ≤ 5 years**	**6-15 years**	**> 15 years**
Improved Technology				
Reusable plastic crates	15 (3.6)	13 (86.7)	2 (13.3)	-
Cold Storage Chambers	2 (0.5)	2 (100)	-	-
Refrigerated truck	3 (0.7)	2 (66.7)	1 (33.3)	-
Machine drying	3 (0.7)	1 (33.3)	2 (66.7)	-
Chemical disinfectants	420 (100)	3 (0.7)	194 (46.2)	223 (53.1)
Improved tomato varieties	417 (99.3)	3 (0.7)	193 (46.3)	221 (53.0)
Traditional technology				
Raffia-local basket	420 (100)	1 (0.2)	143 (34.1)	276 (65.7)
Shed/barn storage	40 (9.5)	3 (7.5)	33 (82.5)	4 (10.0)
Non-Refrigerated-truck	417 (99.3)	2 (0.5)	173 (41.5)	242 (58.0)
Sun drying	314 (74.8)	65 (20.7)	166 (52.9)	83 (26.4)
Cold water treatment	4 (1.0)	2 (50.0)	2(50.0)	-
Local tomato variety	16 (3.8)	1 (6.3)	10 (62.5)	5 (31.2)

Figures in parentheses in all tables indicate the percentage distribution

Table 4 shows the various households' adoption characteristics for the six narrowed-down improved technologies for tomato post-harvest management. In this study, there was an overall adoption rate of about 34 % by farming households. Chemical disinfectants were the most popular with about 100% successful use and the least was the use of cold storage chambers (0.5%), and it has only two adopters recorded in the study. Similarly, about 48.1 % of the households used the traditional method prioritized, while 51.9% did not. It was observed that all the farmers (100%) still use the traditional basket as a container for harvesting, movement, and sales of tomato produce, and the least (1.0 %) used the cold-water treatment (Table 4). The use of improved variety has overtaken the use of local variety at 99.3%, over the years, with only 3.8 % still using local variety. In terms of adoption, about 48% of the households had adopted improved technology in the last 5 years, while about 34% fall within the category of 6 to 15 years. Only about 18 % of farmers reported having used the improved technology for over 15 years, and that was mainly Chemical treatment and improved tomato varieties. Otherwise, the adoption of the PHLRT started to manifest in the last five years. Comparatively, the households that adopted the traditional technologies within the past five years, when averaged, was 14.2 %. Those using traditional technologies between 6 and 15 years averaged 53.9%, and 31.8% adopted them in the past 16 or more years.

Sources of Post-Harvest Losses (PHL) in Tomato Production

Table 5. Distribution of Tomato Post-Harvest Losses Frequency and Interventions

Variable	Frequency	Percentage (%)
Sources of PHLs		
Farm-level	61	14.5
Long distance transport	24	5.7
In storage	296	70.5
Marketing	39	9.3
Needed interventions		
Haulage vehicle	75	17.9
Packaging/Container	92	21.9
Loss management training	31	7.4
Storage facility	333	79.3
Finance to adopt improved methods	408	97.1
Feeder access road	30	7.1
Willingness to adopt improved technology	420	100.00

Source: Field Survey, 2020/2021

Table 5 shows the result of the responses of farmers to PHL. It shows that most post-harvest losses occurred in storage, accounting for about 70%, while the remaining 30% of losses were accounted for at the farm level, about 15%; during marketing about 9%; on long-distance transport, about 6% (Table 5). Of all the sample farmers in the study area, about 100% had the willingness to adopt new interventions needed to curb post-harvest losses. However, farmers' responses about where interventions or support were needed, most were finance (97.1%); availing storage facilities (79.3 %); packaging/container (21.9%); and haulage vehicle (17.9%).

Determinants of Factors Influencing Post-Harvest Losses (PHL) using Multinomial Logit (MNL) Regression Model

MNL is used to explain the relationship between one nominal dependent variable and two or more independent variables with the assumption of independence among the categorically dependent variable choices. The categorical dependent variable was the post-harvest loss (PHL) option with a nominal category of "losses at farm-gate level", "losses on transit", "losses at storage", and "losses at marketing". PHL was the dependent variable, while farm, farmer and institutional-specific characteristics were the independent variables. The reference level for the model was 'losses at farm-gate level'; the results in Table 6 show that the model (MNL) fitted the data well as the log-likelihood ratio statistic (Chi^2 = 103.47) was significant at $p<0.01$ probability level; in other words, the test confirms that all slope coefficients are significantly different from zero, meaning that the model has strong explanatory power and variable included are jointly significant.

Pseudo R^2 of 0.30 to 0.50 also confirmed that all the slope coefficients are not equal to zero, i.e., explanatory variables are collectively significant in explaining determinants of PHL of farmers in the study area, and the values are an indication of good fit and correctness of estimated model when compared to values in Hill (1983).

Also, table 6 shows that the set of significant explanatory variables varies across the group in terms of significance levels and signs. Factors with significant positive coefficients tend to increase post-harvest losses; while factors with significant negative coefficients tend to influence PHL in the direction of decreasing losses.

Table 6. Estimated Multinomial Model for Factors Influencing PHL among Farmers.

Variables	**Loss in Transit**				**Loss in Storage**				**Loss in Marketing**			
	B	**Wald**	**Sig.**	**Exp(B)**	**B**	**Wald**	**Sig.**	**Exp(B)**	**B**	**Wald**	**Sig.**	**Exp(B)**
Intercept	0.489	0.017	0.897		6.619**	6.345	0.012		-18.557***	14.657	0.001	
Education (Yrs)	0.053	0.477	0.490	1.055	-0.042	0.727	0.394	0.959	0.295**	4.159	0.041	1.344
Age (Yrs)	-0.041	0.276	0.600	0.959	0.021	0.216	0.642	1.021	-0.201*	2.858	0.091	0.818
Modern_Techs	1.405*	3.290	0.070	4.075	-1.813**	5.541	0.019	0.163	3.921*	3.272	0.072	50.433
Adopt_Period (Yrs)	0.048	0.015	0.901	1.049	-0.079	0.107	0.743	0.924	-1.302*	3.528	0.060	0.272
Farm_Distance	0.045	1.516	0.218	1.046	-0.054**	5.305	0.021	0.948	0.002	0.002	0.960	1.002
Multi-Cropping	0.024	0.010	0.920	1.024	0.329**	5.960	0.015	1.389	0.740*	2.911	0.088	2.097
Cooperative (Yrs)	-0.053	0.319	0.572	0.949	0.008	0.025	0.874	1.008	0.075	0.306	0.580	1.077
Market_Distance	0.421	0.342	0.559	1.585	-0.290	0.369	0.544	0.748	-1.172	1.102	0.294	0.310
Farm_Size	-1.371	0.744	0.388	0.254	-1.622*	2.770	0.096	0.198	-9.576***	6.675	0.010	6.935E-05
Persons/Room	0.478	0.822	0.365	1.612	-0.881**	5.921	0.015	0.414	1.839*	2.967	0.085	6.291
Credit_Access	-0.999	0.886	0.347	0.368	-0.169	0.069	0.793	0.844	5.005*	3.681	0.055	149.217
Non-farm Income	0.454	0.323	0.570	1.574	0.281	0.312	0.576	1.324	0.850	0.414	0.520	2.341
Own Bike	-0.755	0.383	0.536	0.470	-1.007	1.739	0.187	0.365	-15.922	0.000	0.997	1.216E-07
Own Car/Truck	-3.546***	7.939	0.005	0.029	-1.494*	2.704	0.100	0.224	21.905	0.000	0.998	3.259E09
Own Phone	-17.674	0.000	0.998	2.109E-08	-0.294	0.054	0.816	0.745	-15.597	0.000	0.998	1.684E-07
Well-Off	1.163	1.130	0.288	3.200	0.078	0.013	0.908	1.082	-6.455**	5.242	0.022	0.002
No. of Obs	*420*											
LR Chi^2(48)	*103.47****											
Pseudo R^2												
Cox & Snell	*0.41*											
Nagelkerke	*0.50*											
McFadden	*0.30*											

*Note: Regression coefficient is significant for coefficients with: * = p<0.10; ** = p<0.05; *** = p<0.01*

The Factors included in the MNL model were: the number of modern technology adopted (Modern_Techs), adoption period of modern technology (in years) (Adopt_Period), farm distance (Farm_Distance), market distance (Market_Distance), farm size cultivated in acres (Farm_Size), multiple cropping (Multi-Cropping), cooperative membership period (Cooperative), credit access (Credit_Access), number of persons per room (Persons/Room), ownership of car/truck (Own Car/Truck), wealth status of the farmer (Well-Off), education (years of school) (Education), age of the household head (Age), etc.

The wealth index is a 'hyrid' variable derived from component analysis of farmers' household/capital assets (vehicle, radio, TV, cellphone, electric/gas cooker, generator, stove, etc.), financial assets (bank, cooperative, family financial resources), farm assets (farm machinery, livestock and land ownership), human resources (family and hired labour), etc. Farmers with component scores (wealth index) greater than zero are classified as 'Well-off' (Farmer status =1); otherwise, 'Worse-off' (Farmer status = 0) (Langyintuo, 2008; Kuntashula *et al.*, 2015; Gyau *et al.*, 2016).

Results on factors influencing PHL showed that in the 'Transit' category: the number of modern technologies adopted (Modern_Techs, $p<0.10$) and ownership of car and/or truck (Own Car/Truck, $p<0.01$) influenced losses positively and negatively, respectively. Under MNL model, Exp(B), exponentiated regression coefficient is a proxy for Odds Ratio estimate. Odds ratio less than 1.0 indicates that the odds of exposure to losses among farmers in a category are lower than the odds of exposure to losses among farmers in the control category; and in that case, the inverse of Exp(B), [1.0 ÷ Exp(B)], is calculated to give better and meaningful interpretation of the odds ratio (McHugh, 2009).

In the category of 'losses on transit', a unit increase in the use of PHL-reducing technology (Modern_Technology) will significantly ($p<0.10$) increase losses by 4.1 times higher than the reference category (losses at farm level). Car and/or truck ownership by the household head (Own Car) was significant ($p<0.01$) in reducing losses due to transportation. Owning or having easy access to a car/truck for transportation showed decreased losses on transit by over 34 times (1.0 ÷ 0.029) more than at the reference category.

In the 'Storage' losses category: the number of technologies adopted (Modern_Techs, $p<0.05$), farm distance (Farm_Distance, $p<0.05$), farm size cultivated (Farm_Size, $p<0.10$), number of persons per room (Persons/Room, $p<0.05$) and ownership of car and/or truck (Own Car/Truck, $p<0.10$) influenced losses negatively; while only the practice of multi-cropping (Multi-Cropping, $p<0.05$) influenced losses positively under the storage losses category.

A unit increase in the use of PHL reducing technology reduced losses significantly by up to six times (1.0 ÷ 0.163) more than in the reference category, and this agrees with a priori expectation. Farm distance on 'losses in storage category' reduced losses by 1.05 (1.0 ÷ 0.948) times less than losses at farm level. In this study, the number of people per room ratio is a proxy measure of available storage rooms for the produce. The result shows that having fewer people per room (People/Room) reduced post-harvest losses by 2.4 (1.0 ÷ 0.414) times less than the reference category. Having fewer people per room will create space, where produce can be stored before marketing; this will reduce losses. A unit increase in the farm size of a farmer reduced losses five (1.0 ÷ 0.198) times more than in the reference category. Ownership of cars/trucks by farmers for mobility reduced losses in storage over four (1.0 ÷ 0.224) times more than the reference category ('losses at farm level'). Furthermore, it can be observed from Table 6, that the practice of multi-cropping (Multi-Cropping) increases postharvest losses by about 1.39 times more than the reference category.

Again from Table 6, under the 'Marketing' category of losses: education (Education, $p<0.10$), number of modern technologies ($p<0.10$), multiple cropping (Multi_Cropping, $p<0.05$), number of persons per room (Persons/Room, $p<0.10$) and credit access (Credit_Access, $p<0.1$) influenced losses positively, that is, increase losses; while age of household head (Age, $P<0.05$), period of adoption of technology (Adopt_Period, $p<0.10$), farm size cultivated (Farm_Size, $p<0.01$) and wealth status of farmer (Well-Off, $p<0.05$) influenced losses negatively under marketing category, that is, reduced

Determinants of Factors Influencing Post-Harvest Losses (PHL) Technology Adoption using Tobit Regression Model

Table 7. Estimated Tobit model to Determine Factors Influencing Adoption among farmers

Variable	**Tobit Model**				**Multiple Regression**		
	Coef.	**t –value**	**$P>\lvert t\rvert$**	**Marginal Effect (MFX)**	**Coef.**	**t –value**	**$P>\lvert t\rvert$**
Education	0.00321**	2.18	0.030	0.00321	0.00319**	2.13	0.034
Education^2	-0.00027**	-2.43	0.015	-0.00027	-0.00027**	-2.38	0.018
Age	0.00116*	1.74	0.083	0.00116	0.00116 *	1.70	0.090
Farm_Experience	-0.00092	-1.27	0.204	-0.00092	-0.00092	-1.25	0.212
Extension	0.01596*	1.94	0.053	0.01596	0.01589 *	1.91	0.057
RP_Information_Sources	0.00536	1.40	0.163	0.00536	0.00531	1.37	0.173
CD_Information_Sources	-0.00150	-0.38	0.705	-0.00150	-0.00152	-0.38	0.704
CS_Information_Sources	0.02154***	3.38	0.001	0.02154	0.02142 ***	3.31	0.001
RT_Information_Sources	0.03722***	3.56	0.001	0.03722	0.03708***	3.50	0.001
MD_Information_Sources	0.03023**	2.24	0.025	0.03023	0.02987 **	2.18	0.030
Labour_sourcesT	1.55E-06***	8.03	0.001	1.55E-06	0.000002 ***	7.87	<0.001
Credit_sourcesT	0.01297*	1.71	0.089	0.01297	0.01292 *	1.67	0.095
Urban_Sales	-0.00438	-0.86	0.391	-0.00438	-0.00428	-0.83	0.408
Crop_Frequency	0.00153	1.07	0.287	0.00153	0.00152	1.04	0.297
NonFarm	0.00469	0.88	0.379	0.00469	0.00470	0.87	0.385
Farm_Size	0.00334***	4.77	<0.001	0.00334	0.00330***	4.65	<0.001
Poverty (Well off=1)	-0.00884	-1.51	0.131	-0.00884	-0.00882	-1.49	0.138
Constant	0.15134***	8.38	<0.001	0.15134	0.15177 ***	8.28	<0.001
Sigma	0.04900	28.82	<0.001	0.04900			
Number of obs	420						

LR $chi^2(17)$	218.67 ***	
Prob > chi^2	<0.0001	
R-squared		0.40
Adj R-squared		0.38

*Note: Regression coefficient is significant for coefficients with: * = p<0.10; ** = p<0.05; *** = p<0.01*

Table 7 shows the results of assessing factors influencing PHL Reduction technology adoption. Five technologies were considered, and the proportion adopted by each farmer became the dependent variable that was regressed against explanatory variables. Tobit model was run alongside with multiple regression model (MRM), to show the robustness of the results. However, it's used as an explanatory model as it is theoretically preferred in terms of a priori expectation and statistical significance of the variables as well as better fitness of the regression equation. The results of the Tobit model are summarized in Table 7. Based on the log-likelihood chi-square statistic ($Chi^2 = 218.67$) and the significance probability level ($p<0.0001$), the model has an overall good fit. The variables of years of education of household head (Education, $p<0.05$), age of household head (Age, $p<0.10$), extension agent visit (Extension, $p<0.10$), sources of information on cold storage technology (CS_Information_Sources, $p<0.01$), sources of information on refrigerated truck technology (RT_Information_Sources, $p<0.01$), sources of information on machine drying technology (MD_Information_Sources, $p<0.05$), sources of labour (Labour_sourcesT, $p<0.01$), sources of credit (Credit_sourcesT, $p<0.10$), area of land cultivated for tomato (Farm_Size_Tomato, $p<0.01$) were significant. Only $Education^2$ (at a particular higher level of education) negatively influenced the adoption of PHL-reducing technologies.

Discussion

It was observed that the majority of the farmers had farming experience averaging 23.5 years, which is similar to the findings of Komolafe *et al.* (2014) who found high farming experience among the majority of maize farmers. Household size is regarded as the number of persons residing in the same household sharing a common pool of household resources (Ojiako *et al.*, 2015). The average household size of about 10 persons as found in this study may imply more farmhands. This could be attributed to the religion/culture, in the study area, which allows men to marry more than one woman. In adoption studies, household size is considered an important socioeconomic variable used to measure labour availability or endowment in traditional agricultural production (Baffoe-Asare, 2013). This implies that farm households with more individuals are expected to be in a better position to supply the labour need of the household, and as such ready to adopt improved technology packages (Nkamleu, 2007; Teklewold *et al.*, 2013). However, in this study, family labour constituted only about 37.38 % compared to hired labour which accounted for about 62.62% of the total. Again, this could be attributed to short duration (less than three months) and highly perishable crops like tomatoes, with high labour demands, especially during harvesting; unlike yams and cassava which have upwards of nine months cropping duration, far less perishable and could be harvested piecemeal. Again, during the field survey, it was observed some farmers used their cooperatives or associations to send and market their produce in distant urban markets to maximize profit.

In understanding factors influencing PHL applying the MLR Model, having access to credit facilities had a positive relationship with marketing losses. This is possible because the credits are generally reserved for production rather than for marketing tomato produce. Having credit access is supposed to enable the farmers to acquire tools and labour that would enhance production. Perhaps, credit access could be diverted to other needs not deployed to farming, and the unpleasant repayment demands arrive at harvest time. Yigezu *et. al.*, 2018 suggested that farmers who obtained credit were indeed credit-constrained and therefore delayed decisions to adopt technologies. Wealth status (Well-Off) comes out to favour the wealthier farmers. Wealthier farmers seem to be able to manage their products better and incur significantly fewer losses, in marketing produce. Of course, the wealthier farmers have larger farm holdings, produce far more and can market their produce in urban markets for more profit to cover any produce losses due to long-distance transportation. Farm distance reduced losses in storage category more than on farm level. The closer the distance of the farm to the farmer's house or market, the less losses the farmer incurs.

There is a probability that an increasing number of PHL-reducing technology may increase 'losses in transit'. This might mean that the technology is not appropriate for tomato transportation, or the use of the technology is abused or not well managed. This is evident as farmers largely use local raffia baskets (atop tankers transporting fuel) rather than RPC or Refrigerated trucks to transport tomatoes to long-distant markets. Local baskets are cheap and disposable (after one or two usages), while RPC is expensive and prone to rough handling and theft as they make several repeated journeys, adding to revenue losses. During discussions with the farmers, some expressed willingness to adopt RPC technology but they faced constraints of accessibility. There is also a risk of non-return of crates when used for the transportation of tomatoes. The alternative raffia basket could be reusable for not more than two years but the bottom which is usually the most affected area is usually changed or patched up for reuse which does not cost so much to do. The cost of baskets is also quite cheap and they do not mind losing them along the transportation/marketing chain. Chemical disinfectants (CD), mostly synthetic pyrethroid insecticides were quite popular for the treatment of tomatoes given the recurrent pest attacks on fruits such as the common pest they call the 'Ebola' worm (*Tuta absoluta*) or tomato pinworm. The pinworm infestations could cause up to 100% damage or loss (Biondi, 2018). These chemicals, although proven quite effective, may pose some health risks to consumers.

An increase in farm size cultivated and ownership of car/truck significantly lessened losses at storage. Where household heads owned cars, losses were reduced due to transportation as the tomato produce will move more timely and efficiently to the marketplace. Ownership of cars/trucks by farmers for mobility reduced losses in storage could also be interpreted that the use of public transport which could be competitive with delays are reduced.

Similarly, a unit increase in farm size cultivated reduced losses at storage level. It seems that farmers with large farm sizes (hence have more tomato produce) can manage PHL more efficiently than those with smaller farm sizes. Again, an increase in the farm size cultivated would tremendously reduce losses at marketing than in the reference category. Postharvest losses increased under multi-cropping system. This could be due to divided interest and priorities when other crops vie for farmers' attention during harvesting, handling and storage. Furthermore, the study revealed that older ages tend to significantly reduce losses due to marketing considerations as against younger farmers.

The study has shown the factors influencing the adoption of PHL technologies. It showed that education influenced adoption positively, though in a quadratic form. An increase in years of education of the household head increases adoption up to an optimum level and then starts showing diminishing returns (a decreasing rate of adoption), this, to a good extent, agrees with many past articles like Nlerum (2006), Salehin *et al.* (2009,) Ashraf *et al.* (2015), among others. But it was contrary to the HELVETAS and ANSAF (2016) project where it was stated that 90 % of the respondents had education between none and primary education. Advancing age of household heads significantly increased adoption contradicts the work of Rogers (2003), Bokusheva *et al.* (2012), and Ashraf *et al.* (2015), who stated that older people are more reserved regarding the introduction and acceptance of innovations due to declining cognitive and learning abilities; but here we may be considering capital intensive technologies which may not be pocket friendly to younger farmers. Exposure to extension services positively influenced adoption agreeing with Lwelamira and Mzarai (2010), Akpan *et al.* (2012), and Mwololo *et al.*, (2019), Information sources, especially multiple sources increased the probability of adoption of certain technologies, and this is supported by Degaga and Alamerie (2020). Also, having adequate sources of farm labour has been shown to positively influence the adoption and the intensity of the adoption of PHLRT. This result is consistent with other studies where labour availability significantly influences the adoption of technologies (Wanjiku, 2004; Sinjaa *et al.* 2004; Wanyoike, 2004; Atibioke *et al*. 2012; Nasiru, 2014; Conteh *et al*. 2015). Access to credit encourages the adoption and intensity of adoption of technologies, which is supported by Yigezu *et al.* (2018). The study revealing a strong positive relationship between having a large farm holding and increased adoption and its intensity is supported by Sinjaa *et al*. (2004), Wanyoike (2004), Danso-Abbeam, Setsoafia, and Ansah (2014), Sharma *et al*. (2011), and Danso-Abbeam and Baiyegunhi (2017).

Conclusion

The study sought to examine the adoption of post-harvest losses reducing technologies by first examining factors causing losses and how to manage the losses through the adoption of appropriate technologies. Overall, the farmers in Kaduna State face their highest produce losses for tomatoes in storage followed by farm-level losses. Relatively, the farmers who practised mixed-cropping, or grow multiple crops on their farms were more prone to losses which may be due to competing priorities for storage and handling. The provision of financial capital for accessing improved methods of containing losses was shown to be a significant factor. The use of chemical disinfectants was seen to be very popular among the farmers while only very few respondents adopted the other remaining four technologies. Age of household head, transport availability, i.e., truck and/or car ownership, farm size, number of available storage rooms in the farmers' houses and education significantly influence post-harvest losses for farmers in Kaduna. If these factors are managed efficiently, it could curtail unbearable produce losses and financial losses, too. On factors influencing adoption by the farmers, various socioeconomic and demographic factors including education, age, access to extension services, adequate information sources, labour availability, and credit access were shown to be important in a rural farming environment. Therefore, policymakers and other stakeholders should strengthen institutions that will encourage extension services, information transmission and cooperative formation among rural farmers to promote awareness of agricultural technologies among farmers. Farmers should also be encouraged to aggregate themselves into organized formal groups to make extension visits, training, and other government interventions more effective and within reach. This will also promote peer-to-peer (farmer–farmer) learning or influence to adopt improved post-harvest loss reduction technologies, which is also applicable to productivity-enhancing technologies. The constraints farmers face in adopting certain technologies such as the high cost of acquiring these technologies will continue to remain a hindrance to adoption if not addressed at policy levels. Further studies are recommended on the high use of chemical disinfectants (CDs) on consumer or farmers' health given the recent clamour for food safety as part of food security indicators. Alternatively, researchers should come up with more organic means to treat tomatoes and eradicate the pests effectively, especially at the post-harvest stage. The findings of this study are particularly useful to policymakers and developmental organizations to capitalize on the various factors found to influence adoption, including training, extension exposure, targeting of young individuals, including women, and creation of more information channels, while providing infrastructure such as better farm-market access roads, good storage facilities, decent produce transportation, access to 'soft' credit facilities, smart subsidies and strengthening cooperatives through organisational support and training to curb or minimise post-harvest losses.

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