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Assessing the Linkages between Resilience and Poverty Transition among Rural Farming Households in Nigeria

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Abstract— *Insecurity in Nigeria through terrorism, communal clashes, kidnapping for ransom and banditry have subjected many households to poverty depending on their resilience which varies from one household to the other. The unpredictability of the situation makes households' welfare status (poor/non-poor) to be transitory. The high poverty incidence recorded in the north compared to the south was corroborated by the large number of shocks experienced (58.5%) by the households. Less than half of rural households were resilient in the two waves. The majority of the resilient households were found in the south. Only a small proportion (0.35) of the households exited poverty while a large proportion remained poor. The study showed that resilience status positively influenced the exit of households from poverty in the two waves while household size and age (2018) posited a negative relationship. Membership of association and access to phones were the components of the resilience index that significantly influenced the poverty transition. The study recommends that rural households can benefit from NGOs' sensitization campaign about the need to develop social capital (membership of association) by joining cooperatives, which serve as a means of obtaining credit in addition to improving member-to-member social interactions.*

Keywords— Rural farming households, Resilience to poverty, Poverty transitions, Markov chain

I. INTRODUCTION

Poverty poses a significant challenge to economic growth and development, with nearly 900 million individuals struggling to make ends meet on less than US$1.90 daily (United Nations Children's Funds (2017). The first Sustainable Development Goal aims to eradicate poverty, with rural households particularly vulnerable [1]. In Nigeria, efforts being made to combat extreme poverty are not showing significant effects as terrorism and communal clashes persist leading to mass abandonment of production areas by farming households to Internally Displaced Persons Camps [2]. Rural farming households have evolved measures over the years to weather the storms hindering their well-being or predisposing them to dangers. This tenacity against unfavourable situations (communal clashes, flood, landslide, terrorism, loss of loved ones and crop failure among others). The 2022 Multidimensional Poverty Index survey showed that 63% (133 million) of Nigerians are multi-dimensionally poor, with 6 out of 10 living on less than $1.90 per day [3]. Factors such as limited access to basic services, unemployment, and corruption exacerbate poverty. [4-5]. Rural households use different coping strategies such as non-farm activities, remittances, and social networks to mitigate poverty. The ability to endure hardships or bounce back swiftly from difficulty (resilience) varies from one rural household to the other depending on the available coping strategy. Resilience describes the ability of households to withstand shocks and maintain well-being [6]. Resilience helps prevent negative stressors from causing long-lasting negative development repercussions. [7]. [8] highlights the importance of resilience capability in reducing exposure to shocks and avoiding adverse effects.

Poverty rate in Nigeria has consistently been high in the rural area. According to [9], the National MPI 2022 showed that multidimensional poverty is higher in rural areas (72%), compared to 42% of people in urban areas. Nigerian rural poverty is attributed to several issues, including poor education levels, restricted access to credit facilities, insufficient healthcare facilities, and gender disparity in the availability of productive resources [10]. The World Bank assessment reveals that Nigeria's efforts to reduce poverty are hindered by slow growth, inadequate human capital, labour market flaws, and exposure to shocks. Shocks, such as death, illness, flooding, and inflation, are major drivers of poverty, pushing households below the threshold [11]. Building smallholders' resilience capacities is a successful strategy for reducing poverty, as it reduces negative consequences on rural household welfare [12].

Nigerian rural farming households are particularly susceptible to a range of shocks, including as changes in the climate, shifts in the market, and health emergencies. For them to have sustainable livelihoods, they must possess resilience—the ability to endure shocks and bounce back from them. By improving these households' adaptive capacity, resilience factors can help them become more capable of handling risks and uncertainties [13] [14]. While a great deal of research has been done on resilience and poverty independently, few narrative studies [15, 16, 17] have been written about how resilience and poverty transition are related to rural farming households in Nigeria. This research attempts to close this gap. Moreover, since a large portion of Nigeria's rural farming population is impoverished, it is important to understand the variables influencing their ability to escape poverty to develop effective ways to reduce it. The research is in line with both domestic and global development objectives, including the Sustainable Development Goals (SDGs) of the United Nations, especially Goals 1 and 2 (No Poverty and Zero Hunger). To achieve the objective of the study, the following research questions are raised; what are the socio-economic characteristics of rural farming households in Nigeria? What is the poverty status of rural farming households? What is the resilience status of rural farming households? How does resilience affect the poverty status of rural farming households?

II. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

The socioeconomic theory of resilience and the cyclical theory of poverty support the study. Socioecological resilience refers to the ability of social and ecological systems to persist, adapt, and transform in response to disturbances, shocks, or environmental changes [18]. Rural farming households use socioecological theories, such as adaptive capacity, persistence, and transformation, to adapt to shocks and maintain equilibrium. Farming households adapt to changes in the ecological system by adjusting farming practices, diversifying livelihood options, and fostering social relationships through cooperatives or farmers' groups [19]. Understanding this theory would help rural farming households develop social safety nets, market connections, and capacity-building initiatives to help them escape poverty [20]. The cyclical theory of poverty emphasizes the interdependence of individual circumstances and community resources in a failing economy, arguing that a failing economy leads to people lacking resources to participate in the economy, making it harder for communities to survive economically [21]. It recognizes the cyclical nature of poverty, where farming households go through times when their economic situation either improves or deteriorates as a result of shocks [22]. Long-term interventions, such as access to education, healthcare, credit, land, markets, cooperatives, and leadership, are needed to address the underlying factors contributing to the cycle of poverty and create opportunities for sustained poverty reduction and resilience building [23].

Various methods have been used in literature to build index structure of interest. Among the commonly used analytical tools are Factor Analysis (FA), Structural Equation Model (SEM), and Principal Component Analysis (PCA). The pros and cons of these analytical approaches were considered before the choice was made to generate the resilience index for each of the rural farming households. Several resilience studies have adopted each of these analytical tools: Factor Analysis [24] [25] [26] [27], Structural Equation Model [28] [29] [30], Principal Component Analysis [31] [32] [32] [33]. [21] highlights the issue of interpretation in factor analysis, which can be subjective and affect the reliability of indexes generated depending on the sample used. SEM has drawbacks, including high sample numbers needed for reliable estimations, inaccurate estimates, insufficient statistical power, and deceptive outcomes. It might not be able to fully convey complicated and dynamic constructs [34]. PCA provides independent, uncorrelated features of data, reduces noise in data, and selects features (to a limited extent). Additionally, PCA enables data visualization and the examination of clustering and classification systems [35]. The study utilizes PCA as enshrined in RIMA as adopted by [36] to group the pillars of the resilience index, which include Access to Basic Services, Assets, Social Safety Net, and Adaptive capacity.

Expenditure (food and non-food), income, and asset-based (multidimensional) are the two approaches commonly used to measure poverty. Several poverty studies adopted expenditure [37] [38] [39] [40] and asset [41] [42] [43] approaches. According to [44], the family's ability to cover its urgent expenses with cash is indicated by their present cash income. Little information about the family's potential consumption spending is provided by the income method. Due to changes in health, work shifts, or unemployment, annual income for many families varies significantly over time. [45] affirmed the difficulty of data collection for multidimensional indicators. Inequality within households or inequality between the impoverished is not captured by multidimensional poverty. The study adopts an expenditure approach that takes into account both food and non-food expenses. It provides a more comprehensive picture of household well-being by accounting for key living costs such as housing, healthcare, education, and transportation in addition to basic nutritional needs.

Several methods (fixed effects model, survival analysis, Shapley decomposition, and Markov transition model) have been used in literature to measure dynamics in socioeconomic variables. [46] noted that although fixed-effects estimates control for time-invariant omitted variables, they “are notoriously susceptible to attenuation bias from measurement error.” Survival analysis necessitates "special" procedures, according to [47], in part the possibility of not observing the event of interest for some individuals. Furthermore, one cannot immediately apply straightforward methods based on the normal distribution because the distributions of survival analysis data are frequently skewed (asymmetric). On the other hand, [48] found that when features are correlated, the Shapley value method—like many other permutation-based interpretation techniques—is hampered by the presence of erroneous data instances. The feature is marginalized to mimic that a feature value is absent from a coalition.

Moreover, Markov transition models [49] [50] [51] [52] use transition probabilities to model the likelihood of moving between poverty states, assuming that future states depend only on the current state. Markov chains help uncover probabilistic patterns within continuous processes measured over time. Markov chain analysis also assists simulation of uncertain environments to enable better decisions [53]. Markov chain was used to determine the poverty transition among the households.

Analytical framework of Markov chain

The Markov chain uses transition matrices to predict individual or household status in the future based on observation. The Markov chain is used to derive the transition matrices for poverty status. The items in the transition matrix shown in Eq. 1 is the simple first-order Markov model are converted into probability values of entering and exiting poverty by dividing each item by the corresponding row total to give the following transition matrix (square matrix). This captures the welfare status (poor/non-poor) of the household in two successive periods.

$$\begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} \ldots\ldots\ldots\ldots(1)$$

Where:

P_{11}, P_{12}, P_{21}, and P_{22} are probability matrices to determine the probability that an individual will retain his status or transit from one status to another, whether poor to non-poor or vice versa.

A multi-state model depicts how a person transitions between a variety of states over time, and fitting a multi-state Markov model to panel data often relies on the Markov assumption that future evolution solely depends on the current state [54]. To predict future change, Markov chain model explains change in the variable of interest (e.g. welfare status measured by poverty status) from one time to another [55]. In transition intensity; suppose an individual is in state 'r' at time 't'. The movement on the discrete state space S = {1,2,3,4,5} is governed by transition intensities Q_{rs} (r, s=1, 2, 3, 4, 5), representing the instantaneous risk of moving from state 'r' to state 'S' [56]. Furthermore, transition probability Prs (t, t + u) is the probability of being in the state (S) at time 't + u', given the state at a time 't' is 'r'. It was calculated in terms of Q using the Kolmogorov differential equations. The transition probability matrice is derived from Markov chain analysis [57], and they are considered the key finder in the Markovian chain [58]. At equilibrium, the probability transition matrix is given as:

$$e = ep \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where:

e represents the proportion of variable (poor and non-poor) at equilibrium)

p represents the transition probability matrix

That is:

$$(e_1 \quad e_2 \quad e_3) = (e_1 \quad e_2 \quad e_3)\begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Also at equilibrium, it is true that:

$$e_1 + e_2 + e_3 = 1 \ldots\ldots\ldots (4)$$

Probit Regression Model

This model is nonlinear in terms of coefficients that allow the probabilities to remain between "0" and "1". When the dependent variable yi is binary, Pi is expressed as

$$p_i = E(y = 1 / x_i) = \phi(x_i \beta) \ldots\ldots\ldots\ldots\ldots\ldots(5)$$

Here, P_i=E(y=1|x_i) is the probability of the binary outcome variable Y taking the value 1 given the values of the predictor variables X, ϕ is the cumulative distribution function of the standard normal distribution, and $\beta$are parameters for the model that need to be estimated or the maximum likelihood coefficients of the standard normal distribution, X_i are predictor variables. The probit model assumes that the basic dependent variable is normally distributed likewise the error term.In dealing with the persistence of dichotomous outcomes, a probit model is increasingly used. It has been employed in poverty dynamics [8]. The marginal effect of probit model is expressed as:

$$M.E_{probit} = \frac{\partial E(y_i * / x_i)}{\partial x_{ik}} = \phi(x_i \beta)\beta_k \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

III. METHODOLOGY

Description of the study area

The study focuses on Nigeria which is situated in the West African region witha land mass of 923,768 sq. km. The main latitude and longitude of Nigeria are 10° North and 8° East respectively. Nigeria measures about 1,200 km from East to West and about 1,050 km from north to south. It is bordered to the north by the Republics of Niger and Tchad; it shares borders to the west with the Republic of Benin, while the Republic of Cameroun shares the eastern borders right down to the shores of the Atlantic Ocean which forms the southern limits of Nigerian Territory. Rainfall averages over 2000 mm per annum in the southeast, 1000 mm in the center reducing to as low as 500 mm in the northeast. The mean annual precipitation in Nigeria is 1,165.0 mm.Over 90% of Nigeria's agricultural output comes from peasant farmers who dwell in the rural area where 60% of the population live.

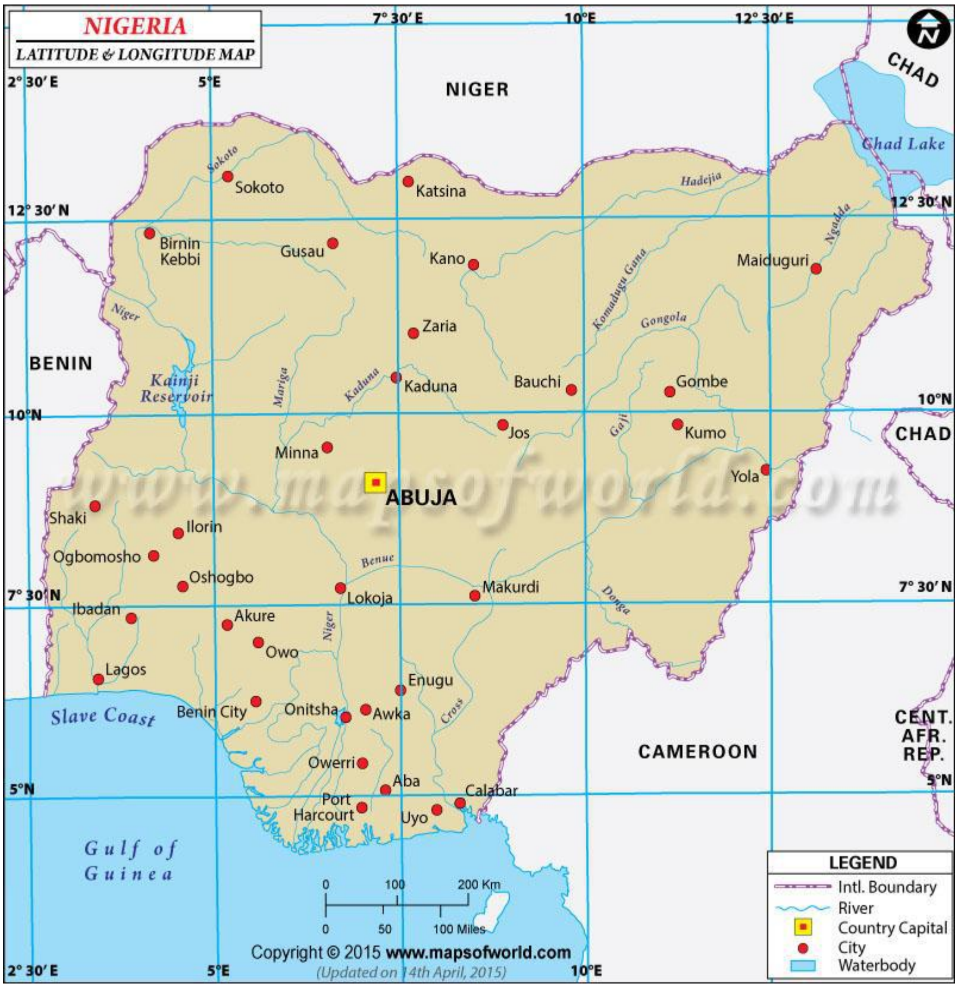

Fig.1: Map of Nigeria

Source: Retrieved from Maps of the World [59]

Source and Type of data used

The study used secondary data (General Household Survey [GHS]). The National Bureau of Statistics carried out the GHS panel data. The waves I and II of the survey were used in the study. After the cleaning and merging the data, 750 rural farming households in waves I and II ((2015/2016, and 2018/2019) were used for the analysis. Data extracted included the socioeconomic characteristics of the household head (age, sex, educational level, household size, geopolitical zones, occupation, occupation, marital status, monthly income, access to credits, farm size, membership of cooperatives and extension access), household food and non-food expenditures, resilience status, shocks encountered and poverty status.

IV. METHOD OF DATA ANALYSIS

Data were analysed using descriptive statistics (frequency distribution, percentages, measures of central tendency and dispersion), Principal Component Analysis, Markov chain and probit regression analysis.

Descriptive statistics was used to profile the socioeconomic characteristics, the shocks experienced and the poverty status of the rural farming households. The study utilised the expenditure approach (food expenditure, non-food expenditure and household size).

Determination of household poverty status of household

Two-thirds of the mean per capita household expenditure (MPCHE) was used as the poverty line.

$$\text{Household per capita total expenditure} = \frac{\text{Total household annual expenditure}}{\text{Household Size}} \quad \ldots\ldots\ldots\ldots\ldots\ldots(8)$$

$$\text{Mean per capita total expenditure} = \frac{\sum_{i=1}^{N} \text{per capita annual expenditure}}{N} \ldots\ldots\ldots\ldots\ldots\ldots(9)$$

$$\text{Poverty line} = \frac{2}{3}\left(\frac{\sum_{i=1}^{N} \text{per capita annual expenditure}}{N}\right) \ldots\ldots\ldots\ldots\ldots\ldots(10)$$

Where: N represents the total households

The categories of the poverty status are given as follows:

- Poor: Farming households with per capita annual expenditure less than two-third of the mean per capita annual expenditure
- Non-poor: Farming households with per capita annual expenditure greater than two-thirds of the mean per capita annual expenditure

Principal Component Analysis was used to generate the resilience index of each of the farming household using the adapted RIMA, following [8, 36, 60], the conceptual model to measure resilience is based on equation (11). The equation explains that the resilience index is a function of four major dimensions or pillars.

$$R_{i,t} = f\left(ABS, A, SSN, AC\right) + \varepsilon_{i,t} \ldots\ldots\ldots(11)$$

Where:

R represents the resilience index for each household *i* at time *t*.

Access to Basic Services (ABS) = Health access (Yes=1, No=0), Phone access (Yes=1, No=0), Distance to market (km)

Assets (A) = Asset value (₦), Land ownership (Yes=1, No=0)

Social Safety Nets (SSN) = Remittance (Yes=1, No=0), Cooperatives (Yes=1, No=0) Adaptive Capacity (AC) = Years of education, Loan access (Yes=1, No=0).

Nine indicators were used to create resilience indices for farm households. Using PCA, variables with a KMO statistic greater than or equal to 0.5 were retained. Latent resilience pillars were estimated and used as covariates [8]. The index or scores of each household were predicted and households whose indexes were between negative to zero scores were classified as non-resilient and those with positive indexes were classified as resilient.

Poverty transition in the study was determined using the Markov chain. In this analysis, the poverty status (poor or non-poor) of each farming household in the first wave was compared with the second wave (poor or non-poor) using the Transition Probability Matrix as shown in Table 1

Table 1: Transition Probability Matrix for rural farming households

	Poverty Transition	**Wave II**	
		Poor (P_1)	Non-poor (P_2)
Wave I	Poor (P_1)	P_{11}	P_{12}
	Non-poor (P_2)	P_{21}	P_{22}

Where:

P_{11} represents poor in Wave I and poor in Wave II

P_{21} represents non-poor in Wave I and poor in Wave II

P_{12} represents poor in wave I and non-poor in wave II

P_{22} represents non-poor in wave I and non-poor in wave II

Probit regression was used to evaluate the effects of household resilience on the poverty transition of farming households. The dependent variable considered the transition as binary (poor in wave I to non-poor in wave II). The rural farming households that transited to non-poor as well as the households who were non-poor in the two waves are considered as the dependent variable using a dummy in eq. (11); the resilience index was among the independent variables without any variables used to generate the index. To enhance specific policy recommendations, in eq. (12) variables used to generate the resilience index (resilience status not included) and socioeconomic variables were used as the independent variables. The critical independent variable is resilience status. The probit model is explicitly expressed as:

$$Y_i = \beta_0 + \beta_1 X_1 + + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon_i \ldots\ldots\ldots (11)$$

Where: Y represents poverty status (Households that moved out of poverty and the households were non-poor in the two waves =1, others=0); β_0 represents the constant term; β_1 to β_7 represent the regression coefficients; X_1 represents the age (year) of the respondent; X_2 represents the sex of the respondent (Male=1, Female=0), X_3 represents the marital status of the respondent (Married=1, Unmarried=0); X_4 represents household size of the respondent; X_5 represents farm size (ha), X_6 represents access to extension service (Yes=1, No=0) and X_7 represents resilience status (1= Resilient, 0= Non-Resilient).

In eq. (12), constituents of the pillars of resilience and the socioeconomic characteristics are the independent variables. In case the resilience index is significant in eq. (11), it is important to know the variables that are significant among the ones used to generate the index.

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \beta_{11} X_{11} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots (12)$$

Where: Y represents poverty status (Households that moved out of poverty and the households were non-poor in the two waves =1, others=0); β_0 represents the constant term; β_1 to β_{11} represent the regression coefficients; X_1 represents sex of respondent (Male=1, Female=0), X_2 represents age (year) of the respondent; X_3 represents marital status of the respondent (Married=1, Others=0); X_4 represents household size of the respondent; X_5 represents farm size (ha); X_6 represents access to extension service (Yes=1, No=0); X_7 represents membership of association (Yes=1, No=0); X_8 represents health access (Yes=1, No=0); X_9 represents phone access (Yes=1, No=0); X_{10} represents credit access (Yes=1, No=0); X_{11} represents remittance (Yes=1, No=0).

V. RESULTS AND DISCUSSION

Socio-economic characteristics of respondents

The study revealed an average age of (40.08) in 2015 and (44.14) in 2018 with a mean household size of (7.04) in 2015 and (7.32) in 2018. This agrees with the findings of [44]. The result shows that the majority of the farmers had no formal education (43.07%) in 2015 and (36.27%) in 2018, and a majority of farmers (99.73%) and (99.86%) had farm sizes that were below 0.5 hectares in both 2015 and 2018 respectively. The majority had no access to credit (81.60% in 2015 and 87.73% in 2018), extension (98.80% in 2015 and 97.60% in 2018), and remittance (99.20% in 2015 and 98.13% in 2018), were non-members of cooperative (96.80% in 2015 and 89.87% in 2018). Many (90.25% in 2015 and 74.13% in 2018) of them had access to phones. However, the majority (94.67%) in 2015, and (92.27%) in 2018 had asset values lower than ₦277,490, with an average asset value of ₦81,700.44 in 2015 and ₦113,403.54 in 2015. The averages of the annual food expenditure by rural farming households were ₦190,564.16 and ₦292,313.15 in 2015 and 2018, respectively. Also, the averages of the annual household non-food expenditure were ₦17,006.72 and ₦25,282.24 in 2015 and 2018, respectively (Table 2).

Table 2: Socioeconomic characteristics of respondents

	2015			2018		
Socio economic variables	Frequency	Percentage	Mean	Frequency	Percentage	Mean
Sex						
Male	363	48.40		325	43.33	
Female	387	51.60		425	56.67	
Education						
No formal	323	43.07		272	36.27	
Formal	427	56.93		478	63.73	
Age			40.08			44.14
17-34	421	56.13		277	36.94	
35-52	152	20.27		220	29.34	
53-70	132	17.6		185	24.66	
71 above	45	6.0		68	9.07	

Household size			7.04			7.32
1-7	439	58.53		414	55.20	
8-14	293	39.07		310	41.33	
15 above	18	2.40		26	3.46	
Member of cooperative						
Yes	24	3.20		76	10.13	
No	726	96.80		674	89.87	
Access to credit						
Yes	138	18.40		92	12.27	
No	612	81.60		658	87.73	
Extension						
Yes	9	1.20		18	2.40	
No	741	98.80		732	97.60	
Remittance						
Yes	6	0.80		14	1.87	
No	744	99.20		736	98.13	
Phone access						
Yes	676	90.25		556	74.13	
No	73	9.75		194	25.87	
Total	750			750		
Asset value (₦)			₦81,700.44			₦113,403.54
100 – 277,490	710	94.67		692	92.27	
277,490 – 554,880	20	2.67		32	4.27	
554,880 – 832,270	2	0.27		11	1.47	
832,270 -1,109,660	11	1.47		6	0.80	
1,109,660 above	7	0.93		9	1.21	
Food expenditure (₦)			₦190,564.16			₦292,313.15
1,920 - 565,632	726	96.80		652	86.93	
565,632 - 1,129,344	21	2.80		74	9.87	
1,129,344 - 1,693,056	0	0		18	2.40	
1,693,056 - 2,256,768	2	0.27		5	0.67	
2,256,768 - 2,820,480	1	0.13		1	0.13	
Non-food expenditure (₦)			₦17,006.72			₦25,282.24
2,400 - 78,720				702	93.60	
78,720 - 155,040				37	4.93	
155,040 - 231,360				9	1.20	
231,360 - 307,680				1	0.13	
307,680 - 384,000				1	0.13	

Source: Author's Computation (2023)

Distribution of shocks experienced by households

Figure 1 shows that households in the north experienced more shocks (58.5%) than in the south. Death due to bandit attacks, cattle rustling, kidnapping, and flooding are more common in the north. Most especially in the rural areas. Prominent shocks in the south include kidnapping and attack by herdsmen. According to the [61], conflict-related occurrences have multiplied in tandem with an increase in climate shocks, uprooting populations, upsetting markets, and negatively impacting Nigerians' livelihoods. Over the past 20 years, fatal conflict incidents have increased throughout Nigeria, particularly in the north.

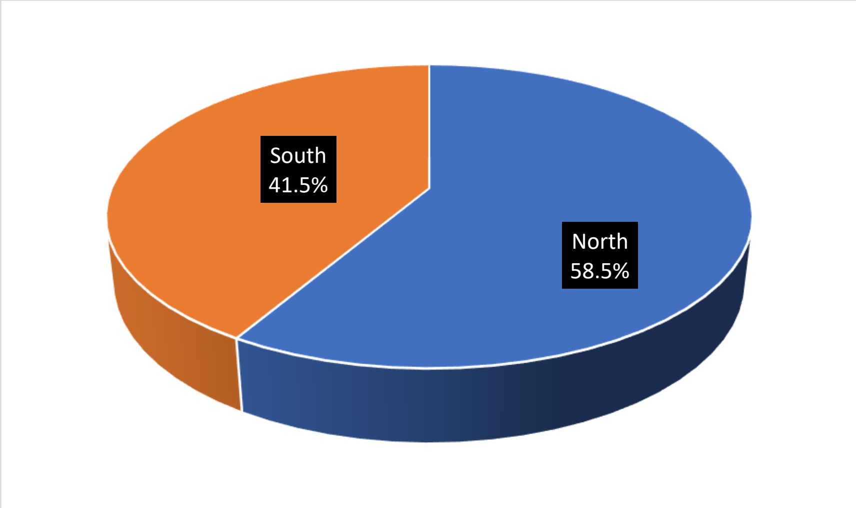

Fig.1: Distribution of shocks by zones

Poverty status of the households

Table 2 reveals that the mean per capita annual household expenditure of households in 2018 is ₦53,228.71 and ₦33,835.59 in 2015. The higher value of the annual mean per capita household expenditure in 2018 may be attributed to the time value of money. The same reason can be attributed to the higher poverty line (₦35,485.81) in 2018 compared to 2015 (₦22,557.06). The study found that 50.93% of the rural farming households were poor and 49.07% were non-poor in 2018, implying that slightly more than half of the respondents were poor. However, in 2015, 43.60% of rural farming households were poor while 56.40% were non-poor. The result shows that more households became poorer in 2018 than in 2015. This may be attributed to the unstable persistent insecurity in most farming rural communities, and unstable economic policies which reflects in increasing inflation.

Table 3: Poverty status of rural farming households

	2015			2018	
Poverty Status	Frequency	Percentage		Frequency	Percentage
Non-Poor (0)	423	56.40		368	49.07
Poor (1)	327	43.60		382	50.93
Total	750	100		750	100
MPCHE/Annual	₦33,835.59			₦53,228.71	
Poverty Line	₦22,557.06			₦35,485.81	
Poverty Incidence	0.44			0.51	
Poverty Depth	0.17			0.25	
Poverty Severity	0.10			0.16	

Source: Author's Computation (2023)

Determination of household's Resilience status

The Kaiser-Meyer-Olkin (KMO) value indicates that the data is suitable for PCA. Table 4 displays the PCA estimation results for each resilience pillar (Asset to basic services, Asset, Social safety net, and Adaptive capacity) with all relevant indicators. Principal components with eigenvalues greater than 1 are considered the most informative and give the resilience index for farm households. All resilience indicators had a KMO value greater than 0.5 indicating a moderate correlation between variables. The first principal components explained 36%, 53%, 54%, and 52% in 2015 and 35%, 56%, 52%, and 52% in 2018 of the total variations of the indicators of the dimensions/pillars respectively. Positive component loading coefficients indicate a higher resilience score, while negative coefficients indicate lower resilience. The sign of the loading coefficient provides information on the direction and the magnitude of the coefficient indicates the strength of the relationship between the variables and the principal components.

In 2015, distance to market which is one of the indicators of the access to basic service pillar has a negative coefficient that indicates that long distance to market lowers the resilience of the household, which can affect the availability and affordability of essential goods leading to higher costs of these goods. Also, if households are located far from markets, they may face higher transportation costs and limited access to buyers, which can reduce their ability to generate income and diversify their livelihoods. However, in 2018 the positive loading component of the distance to the market variable is positive, which is unexpected and contrary to knowledge. This could be because households located farther from markets have developed coping strategies like adopting alternative transportation modes, such as walking or cycling that allow them to overcome the challenges of distance. Phone access and health access are also indicators of ABS which had positive component loadings that contributed positively to resilience levels in both 2015 and 2018.

Under the Asset pillar in Table 4, the Asset value has negative loading components in 2015 and 2018. This suggests that households with higher asset values are more likely to have lower resilience scores and this is contrary to preexisting knowledge, as assets are often seen as a key factor in building resilience. This negative sign could be because the quality and productivity of the farming or household assets may be more important for resilience than the overall value, if households have access to high-quality seeds, tools, and irrigation systems, they may be better able to cope with shocks and stresses than if they have lower-quality assets of higher value. Land ownership on the other hand, in the asset pillar has a positive loading component coefficient of 0.71 in both years, this indicates that this variable is strongly correlated with resilience scores. The social safety net pillar indicators have a positive component loadings coefficient of 0.71 in both years which indicates that the variables, access to remittance, and membership in a cooperative contribute strongly to the resilience scores. They displayed the expected signs of the effects of the variables on households' resilience levels. Likewise, the Adaptive capacity pillar has variables which are years of education and loan access with a positive component loading coefficient of 0.71 in 2015 and 2018. This also means that each variable is strongly correlated with resilience level.

Table 4: Principal component analysis (PCA) result of resilience indicators

Variables	Component Loading (2015)	Component Loading (2018)
Access to Basic Service (ABS)		
Distance to market	-0.68	0.62
Phone access	0.53	0.50
Health Access	0.50	0.61
The proportion of Variation Explained	0.36	0.35
The eigenvalue of the first component	1.07	1.04
Kaiser-Meyer-Olkin measure of sampling adequacy (KMO)	0.51	0.51
Asset (AST)		

Asset value	-0.71	-0.71
Land ownership	0.71	0.71
The proportion of Variation Explained	0.53	0.56
The eigenvalue of the first component	1.05	1.12
Kaiser-Meyer-Olkin measure of sampling adequacy (KMO)	0.50	0.50
Social Safety Net (SSN)		
Remittance	0.71	0.71
Cooperatives	0.71	0.71
The proportion of Variation Explained	0.54	0.52
The eigenvalue of the first component	1.09	1.05
Kaiser-Meyer-Olkin measure of sampling adequacy (KMO)	0.50	0.50
Adaptive Capacity (AC)		
Years of education	0.71	0.71
Loan access	0.71	0.71
The proportion of Variation Explained	0.52	0.52
The eigenvalue of the first component	1.03	1.03
Kaiser-Meyer-Olkin measure of sampling adequacy (KMO)	0.50	0.50

Source: Author's Computation (2023)

Distribution of the resilience status of farming households

Table 5 shows that more than half of the households are non-resilient, with 56.93% in 2015 and 54.40% in 2018. Households with a negative resilience index to zero are classified as non-resilient while those with a positive index are classified as resilient. From the result, over 50% of the households in both years are not resilient. This depicts that most households are vulnerable to shocks such as the death of loved ones, illness, flooding, and inflation (increase in prices of goods and services). High conflicts and banditry activities might have contributed to the low resilience among the households. For instance, [62] conducted in Borno State found that there was low resilience among the households as a consequence of internal displacement and returnee households.

Table 5: Distribution of resilience status of rural farming households

	2015		2018	
Resilience Status	Frequency	Percentage	Frequency	Percentage
Non-resilient	427	56.93	408	54.40
Resilient	323	43.07	342	45.60
Total	750	100.00	750	100.00

Source: Author's Computation (2023)

The disaggregation of the poverty rate (see Table 6) shows that in 2015 the households in the Northern region (North West, 27.52%, North East, 22.02%, North Central, 20.18%) were poorer than households in the Southern region (South East, 12.84%, South-South, 11.31%, South West, 6.12%). This may be attributed to the several shocks (caused by banditry and conflicts) experience in the North, which suggests that the resilience of the households in the North will be lower than the South and therefore lead to increased poverty in that region. In

2018 also, the Northern region (North East, 26.44%, North West, 22.77%, North Central, 20.16%) was poorer than households in the Southern region (South East, 13.61%, South-South, 13.09%, South West, 3.93%). Expectedly, northeast had the highest percentage of the poor. This is attributed to the severe climate crisis and conflict in the region. The region is characterized by high rates of poverty, low human capital, and poor access to key services [63]. According to [9], 65% of poor Nigerians (86 million) are located in the North while 35% of the poor (nearly 47 million) are located in the South. In general, a disparity between the North and South is evident in both the incidence and intensity of multidimensional poverty, with the North being poorer [9].

Table 6: Distribution of poverty status across geopolitical zones

	2015		2018	
	Non-poor (0)	Poor (1)	Non-poor (0)	Poor (1)
Geographical Zones	Freq (%)	Freq (%)	Freq (%)	Freq (%)
North Central	64(15.13)	66(20.18)	53(14.40)	77(20.16)
North East	66(15.60)	72(22.02)	37(10.05)	101(26.44)
North West	72(17.02)	90(27.52)	75(20.38)	87(22.77)
South East	98(23.17)	42(12.84)	88(23.91)	52(13.61)
South South	93(21.99)	37(11.31)	80(21.74)	50(13.09)
South West	30(7.09)	20(6.12)	35(9.51)	15(3.93)
Total	423(100.00)	327(100.00)	368(100.00)	382(100.00)

Source: Author's Computation (2023)

Poverty transition among rural farming households

The Markov chain poverty transition result shows that 65% of the households were poor in 2015 and remained poor in 2018, while 35% exited poverty. Moreover, 40% of the households moved from non-poor in 2015 to poor in 2018 (see Table 7). This may be attributed to the ward off the shocks encountered during the period. That is the inability of the households' resilience to surmount the challenges faced (examples are crop failure, attack by bandits, flood, and death of the head of household among others). Sixty percent of the households maintained their non-poor in 2015 and 2018. The predicted value shows that 51% of the households would be poor in 2024. The probability of being poor in 2024 is higher, and this may lead to extreme poverty influencing hunger and nutritional status, affecting the ability of individuals and households to access food through purchase or production, while hunger and malnutrition reduce current productivity and, in the future, and keep people focused on survival [64].

Table 7: Transition in poverty status among rural farming households

		2018 (Year 2)		
		Poor (1)	Non-poor (0)	Total
	Poor (1)	213 (0.65)	114 (0.35)	327
2015 (Year 1)	Non-poor (0)	169 (0.40)	25 (0.60)	423
	Total	382 (0.51)	368 (0.49)	750

Source: Author's Computation (2023)

Transition matrix in parenthesis

Effect of household's resilience on poverty transition of rural farming households in Nigeria

The significance of likelihood ratio chi^2 statistics in the two waves (Tables 8 and 9) indicates that at least one of the predictor's regression coefficients is not equal to zero. The high negative values of the log-likelihood that the models (Waves I and II) have a good fit. Using log-likelihood as a yardstick, Wave II (Table 8) is the best fit. Table 8 shows that the coefficients of resilience status were positive and significant in Waves I and II. This means that for every resilient household, the probability of exiting from poverty/being non-poor in Wave I and Wave II increased by 23.4% and 19.2%, respectively. In a similar study, [65] USAID and LEO (2019) found that resilience helps households stay out of poverty over the long run, despite stressors and shocks. That is, households possessing a set of resilience capacities can fend off poverty and have a higher chance of achieving a sustainable exit from it. The finding also agrees with [66] that strengthening household resilience ability is necessary to reduce structural and stochastic poverty.

Table 8: Probit regression analysis results with resilience status

	Wave 1			Wave 2		
Explanatory variables	**Coeff. (Std.)**	**P-value**	**dy/dx**	**Coefficient (Std. error)**	**P-value**	**dy/dx**
Age (Years)	-0.0015 (0.0033)	0.648	-0.0006	-0.0061** (0.0027)	0.026	-0.00244
Sex	-0.1401 (0.0964)	0.146	-0.0558	-0.1080 (0.0971)	0.266	-0.04305
Marital status	0.1161 (0.1093)	0.288	0.0463	0.1395 (0.1019)	0.171	0.05558
Household size	-0.1162*** (0.0163)	0.000	-0.0463	-0.1161*** (0.0152)	0.000	-0.04631
Farm size (ha)	0.3270 (0.2751)	0.235	0.1303	-0.8947 (0.6048)	0.139	-0.35672
Access to Extension	0.0179 (0.4335)	0.967	0.0071	0.1636 (0.3144)	0.603	0.065156
Resilience status	0.5946*** (0.0970)	0.000	0.2337	0.4849*** (0.0965)	0.000	0.19156
_cons	0.4060 (0.2640)	0.124		1.1852 (0.3114)	0.000	

Wave 1 (Number of observations 750, Log Likelihood = -465.51, LR Chi^2 = 108.43, Prob> chi2 =0.0000, Pseudo R^2 = 0.1043), Wave 2 (Number of observations 750, Log Likelihood = -470.16148, LR Chi^2 = 99.14, Prob> chi2 =0.0000, Pseudo R^2 = 0.0954)

Table 9 analysis is important to know which components of pillars of resilience contributed to the significance of the resilience index. The coefficients of household size ($p<0.01$), membership of association ($p<0.05$, $p<0.10$), and access to phone ($p<0.01$) were significant in Waves I and II. The coefficient of age of household head ($p<0.05$) was only significant in Wave II (see Table 9). Membership in an association and access to phone positively influenced the likelihood of households exiting poverty/remaining non-poor in 2015 and 2018. The variables (membership of the association and access to phone) are components of the pillars of resilience. The table shows that the age of the household head reduced the probability of households exiting poverty by 0.25%. Membership of associations (examples are co-operative society, age group, religious group, farmers associations (yam, cassava, maize, millet/sorghum livestock) and access to phone increased the likelihood of households exiting poverty/staying out of poverty by 12.63% and 11.50%, respectively. [67], membership in an association as social capital can take two forms: forming bonds with people in the group or building relationships with people outside the group. He posited that social capital can be applied to promote healing and resilience. The role of social capital in building household resilience was affirmed by [68]. They found that social capital accounts for 68.1% of the variation in resilience. The influence of access to phones on exiting poverty maybe because it is an asset that promotes social capital. It also affords rural farmers access to information on farm inputs and the change in the price of produce. [69] submitted that good communication accentuated through access to phones is the foundation of robust and resilient households. It enables household members to communicate their wants, voice their worries, and offer support to one another during trying times.

Table 9: Probit regression result with pillars of resilience

	Wave 1			Wave 2		
Explanatory variables	**Coeff. (Std.)**	**P-value**	**dy/dx**	**Coeff. (Std)**	**P-value**	**dy/dx**
Sex	-0.104 (0.0963)	0.276	-0.04183	-0.0994 (0.0973)	0.307	-0.0396
Age (Years)	-0.001 (0.0034)	0.616	-0.00069	-0.0062** (0.0027)	0.024	-0.0025
Marital status	0.1165 (0.1102)	0.291	0.035394	0.1277 (0.1021)	0.211	0.0509
Household size	-0.1233*** (0.0165)	0.000	-0.04917	-0.1156*** (0.0153)	0.000	-0.0461
Farm size (ha)	0.3206 (0.2459)	0.192	0.046458	-0.9240 (0.6072)	0.128	-0.3685
Access to Extension	0.1443 (0.4286)	0.736	0.057523	0.1461 (0.3137)	0.641	0.0582
Membership of association	0.7896** (0.327678)	0.016	0.291523	0.3198* (0.1648)	0.052	0.1263
Health Access	0.1522 (0.2686)	0.571	0.060645	0.0949 (0.1208)	0.432	0.0378
Access to Phone	0.5755*** (0.1696)	0.001	0.218585	0.2899*** (0.1112)	0.009	0.1147
Access to credit	0.0887 (0.1268)	0.484	-0.04183	0.2283 (0.1454)	0.116	0.0907
Remittance				1.3258 (0.5438)	0.015	0.4191
_cons	0.1312 (0.2952)	0.657		1.1148 (0.3203)	0.001	

Wave 1 (Number of observations 743): Log Likelihood =-468.172, LR Chi^2 = 93.19, Prob> chi2 =0.0000, Pseudo R^2 =0.0905), Wave 2 (Number of observations 750): Log Likelihood = -469.93, LR Chi^2 = 99.6, Prob> chi^2 =0.0000, Pseudo R^2 = 0.0958

VI. CONCLUSION AND RECOMMENDATIONS

The study affirmed the importance of strengthening household resilience to increase the number of households that exited poverty or could sustain their non-poor status. Severe shocks (banditry, conflicts, loss of loved ones, menace of herdsmen and flooding among others) were more prevalent in the north; manifested in the high poverty compared to the south. Moreover, less than half of rural households were resilient in the two waves. Only a small proportion of the households exited poverty while a large proportion remained poor. The study showed that resilience status positively influenced the exit of households from poverty in the years under consideration while household size posited a negative relationship. Access to phones and membership of associations are the critical components of the resilience status of household resilience. The study recommends NGO's sensitization campaign on the need to build social capital (membership of association) can be achieved among rural households through cooperatives which will play a dual role of not only social interactions among members but also as an avenue to source for credit. Also, the collaboration of the NGOs with the local associations to facilitate easy access to simple and cheap phones for deserving rural households is recommended. Moreover, the health department units of the LGAs in the rural areas should intensify campaigns on the need for family planning to curb the effects of large household size on exiting poverty.

REFERENCES

[1] Sasu, D. D. (2022). Health in Nigeria - statistics and facts. Statista. https://www.statista.com/topics/6575/health-in-nigeria/#dossierKeyfigures

[2] Kanu, S.I., Anyanwu, F.A., and Nwaimo, C.E. (2017). Analysis of drivers of incidences of poverty in Nigeria. *Journal of Economics and Sustainable Development*. ISSN 2222-1700 (Paper) ISSN 2222-2855 (Online) Vol.8, No.4, 2017.

[3] D'Errico, M., Romano, D., and Pietrelli, R. (2018). Household resilience to food insecurity: evidence from Tanzania and Uganda. *Food Security*, *10*(4), 1033–1054. https://doi.org/10.1007/s12571-018-0820-5

[4] Abdulmalik, S. (2015). Unemployment, Poverty, and Challenges of Security in Nigeria: Issues and Perspective. *Journal of Arts and Social Sciences.* 1(1): 109–120.

[5] TANGO International. (2018). Methodological Guide: A Guide for Calculating Resilience Capacity. Produced by TANGO International as part of the Resilience Evaluation, Analysis, and Learning (REAL) Associate Award.

[6] Omoniyi, B. B. (2018). An examination of the causes of poverty on economic growth in Nigeria. Africa's Public Service Delivery and Performance Review, 6(1). https://doi.org/10.4102/apsdpr.v6i1.175

[7] Brück, T., d' Errico, M., and Pietrelli, R. (2018). The effects of violent conflict on household resilience and food security: Evidence from the 2014 Gaza conflict. World Development. doi:10.1016/j.worlddev.2018.05.008

[8] Haile, D., Seyoum, A., and Azmeraw, A. (2021). Does building the resilience of rural households reduce multidimensional poverty? Analysis of panel data in Ethiopia. *Scientific African*, 12, e00788. https://doi.org/10.1016/j.sciaf.2021.e00788

[9] National Bureau of Statistics (2022). Nigeria Launches its Most Extensive National Measure of Multidimensional Poverty—press release www.nigerianstat.gov.ng.

[10] SciSpace (2024). *What are the main causes of rural poverty in Nigeria?* Available on www.https://typeset.io/questions/what-are-the-main-causes-of-rural-poverty-in-nigeria-57wbny3lx0

[11] Holland, J.H. (2006). Studying complex adaptive systems. J Syst Sci Complex 19(1):1–8

[12] Bailey, I., and Buck, L. E. (2016). Managing for resilience: a landscape framework for food and livelihood security and ecosystem services. Food Security, 8(3), 477–490. https://doi.org/10.1007/s12571-016-0575-

[13] Odozi, J. C., Adeyonu, A. G., & Fanifosi, G. E. (2022). Measuring Farm Households' Resilience Capacity in times of Pandemic Crisis: Evidence from Nigeria. *Journal of Agriculture and Food Sciences*, 20(1), 168–178. https://doi.org/10.4314/jafs.v20i1.13

[14] International Fertiliser Development Centre (2021). *Feed the Future Nigeria Rural Resilience Activity*. Available on www. https://ifdc.org/projects/nigeria-rural-resilience-activity-rra/

[15] Smythe, A., Martins, I., and Andersson, M. (2023). Inequality, poverty, and resilience to economic shrinking. *International Journal of Development Issues*, *23*(1), 40–81. https://doi.org/10.1108/ijdi-06-2023-0168

[16] Shumba, A. (2010). Resilience in Children of Poverty. *Journal of Psychology in Africa*, *20*(2), 211–213. https://doi.org/10.1080/14330237.2010.10820367

[17] Williamson, A., Witzel, B., & Steven, B. (2016). Instilling Resilience in children of Poverty. The Winthrop McNair Research Bulletin, 2, 13. https://core.ac.uk/download/pdf/214419261.pdf

[18] Bradshaw, T. K. (2006) Theories of Poverty and Anti-Poverty Programs in Community Development. Rural Poverty Research Centre (RPRC) Working Series No.06-05 Oregon State University and University of Missouri.

[19] Omideyi, A.K. (2008). Poverty and development in Nigeria: Trailing the MDGs? Special issue paper, Afr. J. Infect. Dis. 1(1): 3 – 17.

[20] Addae-Korankye, A. (2019). Theories of Poverty: A Critical Review. *Journal of Poverty, Investment, and Development.* doi:10.7176/jpid/48-08

[21] Schreiber, J. B. (2020). Issues and recommendations for exploratory factor analysis and principal component analysis. Research in Social and Administrative Pharmacy. doi:10.1016/j.sapharm.2020.07.027

[22] Acock, A. C. (2013). Discovering Structural Equation Modeling Using Stata. Stata Press.

[23] Bollen, K. A., Bauer, D. J., Christ, S. L. and Edwards, M. C. (2007). An overview of structural equation models and recent

elaborations. In: *Recent Developments in Social Science Statistics*. New York, John Wiley, pp. 37-79.

[24] Zebardast, E. (2022). The Hybrid Factor Analysis and Analytic Network Process (F'ANP) model modified: Assessing community social resilience in Tehran metropolis. Sustainable Cities and Society, 86, 104127. https://doi.org/10.1016/j.scs.2022.104127

[25] Alexandre, Pedro, J., Raquel Luiza Santos, Kimura, N., Alice, M., & Cristina, M. (2021). Factor analysis of the Resilience Scale for Brazilian caregivers of people with Alzheimer's disease. *Trends in Psychiatry and Psychotherapy*. https://doi.org/10.47626/2237-6089-2020-0179

[26] Cimellaro, G. P., Malavisi, M., & Mahin, S. (2018). Factor Analysis to Evaluate Hospital Resilience. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, *4*(1), 04018002. https://doi.org/10.1061/ajrua6.0000952

[27] Eisenman, D. P., Adams, R. M., & Rivard, H. (2016). Measuring Outcomes in a Community Resilience Program: A New Metric for Evaluating Results at the Household Level. *PLoS Currents*. https://doi.org/10.1371/currents.dis.15b2d3cbce4e248309082ba1e67b95e1

[28] Cardwell, K. L., Koch, L., McKenna, O. J., Pilutti, L. A., & Afolasade Fakolade. (2023). Mapping Resilience: Structural Equation Modeling of Psychological Resilience in Multiple Sclerosis Care Partners. *International Journal of MS Care*, *25*(6), 245–251. https://doi.org/10.7224/1537-2073.2023-078

[29] Klainin-Yobas, P., Vongsirimas, N., Ramirez, D. Q., Sarmiento, J., & Fernandez, Z. (2021). Evaluating the relationships among stress, resilience and psychological well-being among young adults: a structural equation modelling approach. *BMC Nursing*, *20*(1). https://doi.org/10.1186/s12912-021-00645-9

[30] Tomás, J. M., Sancho, P., Melendez, J. C., & Mayordomo, T. (2012). Resilience and coping as predictors of general well-being in the elderly: A structural equation modeling approach. *Aging & Mental Health*, *16*(3), 317–326. https://doi.org/10.1080/13607863.2011.615737

[31] Lazorec, M., Pintilescu, C., & Viorica, E.-D. (2023). Determinant Factors of Economic Resilience Output Indicators. a Principal Component Regression Approach. *Journal of Public Administration, Finance & Law*, *28*, 200–219. https://doi.org/10.47743/jopafl-2023-28-16

[32] Borsekova, K., & Korony, S. (2022). Resilience and vulnerability of regional labour markets: principal component analysis of labour market efficiency in the EU. *Regional Studies*, 1–18. https://doi.org/10.1080/00343404.2022.2042507

[33] Shirali, Gh. A., Mohammadfam, I., & Ebrahimipour, V. (2013). A new method for quantitative assessment of resilience engineering by PCA and NT approach: A case study in a process industry. *Reliability Engineering & System Safety*, *119*, 88–94. https://doi.org/10.1016/j.ress.2013.05.003

[34] Deng, L., Yang, M., and Marcoulides, K. M. (2018). Structural Equation Modeling with Many Variables: A Systematic Review of Issues and Developments. Frontiers in Psychology, 9. doi:10.3389/fps.2018.00580

[35] Bigabid (2021). *What is Principal Component Analysis (PCA) & How to Use It?* Available on www.https://www.bigabid.com/what-is-pca-and-how-can-i-use-it/#:~:text=Other%20benefits%20of%20PCA%20include

[36] Adem, M., and Azadi, H. (2018). The dynamics of multidimensional food security in rural Ethiopia. College of Business and Economics, Department of Economics, Bahir Dar University, Ethiopia.

[37] Brown, C., Calvi, R., Penglase, J., & Tommasi, D. (2022). Measuring poverty within the household. *IZA World of Labor*. https://doi.org/10.15185/izawol.492

[38] Fitzgerald, J., & Moffitt, R. (2022). The Supplemental Expenditure Poverty Measure: A New Method for Measuring Poverty. *Brookings Papers on Economic Activity*, *2022*(1), 253–305. https://doi.org/10.1353/eca.2022.0017

[39] Stoyanova, S., and Stoyanova, S. (2017). *An expenditure-based approach to poverty in the UK - Office for National Statistics*. Ons.gov.uk. https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/articles/anexpenditurebasedapproachtopovertyintheuk/financialyearending2017

[40] Falkingham, J., and Namazie, C. (2002). *Measuring health and poverty: a review of approaches to identifying the poor Issues paper Measuring health and poverty: a review of approaches to identifying the poor*. https://assets.publishing.service.gov.uk/media/57a08d46ed915d622c0018bd/Measuring-health-and-poverty.pdf

[41] Wang, Q., Shu, L., & Lu, X. (2023). Dynamics of multidimensional poverty and its determinants among the middle-aged and older adults in China. *Humanities and Social Sciences Communications*, *10*(1), 1–9. https://doi.org/10.1057/s41599-023-01601-5

[42] Joshua, O. A., Kayode, A., & Gbenga, E. F. (2017). An analysis of multidimensional poverty and its determinants in rural Nigeria. *Journal of Development and Agricultural Economics*, 9(11), 303–311. https://doi.org/10.5897/jdae2017.0857

[43] Carter, M. R., & Barrett, C. B. (2006). The economics of poverty traps and persistent poverty: An asset-based approach. *Journal of Development Studies*, *42*(2), 178–199. https://doi.org/10.1080/00220380500405261

[44] Haveman, R. H. (2001). Poverty: Measurement and Analysis. *Elsevier EBooks*, 11917–11924. https://doi.org/10.1016/b0-08-043076-7/02276-2

[45] Next IAS Content Team (2023, September 20). *Multidimensional Poverty Index: Dimensions, Report, Significance, & Limitations*. https://www.nextias.com/blog/multidimensional-poverty-index/#:~:text=Limitations%20of%20the%20Multidimensional%20Poverty%20Index&text=Gathering%20data%20for%20multidimensional%20indicators

[46] Angrist, J. D. and Jörn-Steffen, P. (2009): Mostly Harmless Econometrics: An Empiricist's Companion. *Statistical Papers*, 52(2), 503–504. https://doi.org/10.1007/s00362-009-0284-y

[47] Kartsonaki, C. (2016). Survival analysis. *Diagnostic Histopathology*, *22*(7), 263–270. https://doi.org/10.1016/j.mpdhp.2016.06.005

[48] Molnar, C. (2019). *Interpretable machine learning : a guide for making Black Box Models interpretable*. Lulu.

[49] Abhilash, Satishkumar M, Joshi, A. T., Manoj Kumar G, & Reddy, B. S. (2024). An Application of Markov Chain Analysis to Study the Indian Cocoa Products Export Performance. *Advances in Research*, *25*(3), 259–265. https://doi.org/10.9734/air/2024/v25i31070

[50] Gupta, A., Abha Dargar, Majid, A., Shashi Kant Dargar, M. Senthil Kumar, & Raju, M. (2023). *Markov Chain Model Used in Agricultural Yield Predictions Utilizing on Indian Agriculture*. https://doi.org/10.1109/aic57670.2023.10263850

[51] Chen, H., Chen, H., Zhang, W., Yang, C., & Cui, H. (2021). Research on Marketing Prediction Model Based on Markov Prediction. *Wireless Communications and Mobile Computing*, *2021*, 1–9. https://doi.org/10.1155/2021/4535181

[52] He, Z., & Jiang, W. (2017). A new belief Markov chain model and its application in inventory prediction. *International Journal of Production Research*, *56*(8), 2800–2817. https://doi.org/10.1080/00207543.2017.1405166

[53] Omkar, R. (2024, February 14). *Markov Chain Analysis in Data Science*. Jaro Education. https://www.jaroeducation.com/blog/markov-chain-analysis-in-data-science/#:~:text=Markov%20chain%20analysis%20provides%20powerful

[54] Jackson, C.H., (2011). Multi-State Models for Panel Data: The MSM Package for R. J Stat Softw. 2011;38(8):1–28

[55] Kumar, S., Radhakrishnan, N., Mathew, S. (2014). Land use change modeling using a Markov model and remote sensing. Geomat. Nat. Hazards Risk 2014, 5, 145–156.

[56] Manqiong, Y., Chuanhai, X., & Fang, Y. (2022). The transitions and predictors of cognitive frailty with multi-state Markov model: a cohort study.National Natural Science Foundation of China. https://doi.org/10.1186/s12877-022-03220-2

[57] Nadoushan, M.A, Soffianian, A., Alebrahim, A. (2015). Modeling land use/cover changes by the combination of Markov chain and cellular automata Markov (CA-Markov) models. J. Earth Environ. Health Sci. 2015, 1, 16–21

[58] Ozturk, D. (2015). Urban growth simulation of atakum (Samsun, Turkey) using cellular automata-markov chain and multi-layer perceptron-markov chain models. Remote Sens. 2015, 7, 5918–5950.

[59] Maps of the world, (2015). Retrieved from https://www.mapsofworld.com/lat_long/nigeria-lat-long.html

[60] Gutierrez, E., Zereyesus, Y.A, Ross, K, and Amanor-Boadu, V. (2017). Building a Resilience Index in Northern Ghana Context. Research in agricultural and applied economics.

[61] *World Bank Group (2022). A Better Future for All Nigerians.* Available on https://documents1.worldbank.org/curated/en/099730003152232753/pdf/P17630107476630fa09c990da780535511c.pdf

[62] Food and Agriculture Organisation (2019). *Resilience analysis in Borno State, Nigeria. Available on* www.fao.org. https://www.fao.org/agrifood-economics/publications/detail/en/c/1186495/

[63] International Centre for Investigative Reporting (2021). Poverty rate worst in Nigeria's North-East. Available on https://www.icirnigeria.org/poverty-rate-worst-in-nigerias-north-east-new-world-bank-report-says/#:~:text=The%20report%20reveals%20that%20more,poor%20access%20to%20key%20services.

[64] Food and Agriculture O., (2019). The role of agriculture and rural development in achieving SDG 1.1.

[65] Chronic Poverty Advisory Network. (2014). Resilience And Sustained Escapes from Poverty: Highlights from Research In Bangladesh, Ethiopia And Uganda. *Chronic Poverty Report*. Retrieved from https://www.resiliencelinks.org/system/files/documents/2019 08/leo_brief_resilience_and_sustained_poverty_escapes_synthesis_final1.pdf

[66] Haile, D., Seyoum, A., & Alemu Azmeraw. (2023). Structural and stochastic poverty, shocks, and resilience capacity in rural Ethiopia. *Cogent Economics & Finance*, *11*(2). https://doi.org/10.1080/23322039.2023.2256124

[67] Kerr, S. E. (2018). Social Capital as a Determinant of Resilience. *Resilience*, 267–275. https://doi.org/10.1016/b978-0-12-811891-7.00022-0

[68] Moslem S., Jafari, A., and Sheheytavi, A. (2024). The impact of social capital to improve rural households' resilience against flooding: evidence from Iran. *Frontiers in Water*, 6. https://doi.org/10.3389/frwa.2024.1393226

[69] Glenda, C. (2024). *Why communication matters. Available on* Linkedin.com. https://www.linkedin.com/pulse/role-communication-building-resilience-home-glenda-clare-ph-d--ohgfe/