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Research

AI-Driven Strategies for Rebuilding Food Security in Post-Conflict Northern Nigeria: Opportunities, Challenges, and Policy Implications

Dadi Jonathan Abba[1]*, Mafeng Jamima Dudari[1], Faith Zigwai Bonat[2]

1Department of Computer Science, Karl Kumm University, Vom, Plateau State, Nigeria.
2Department of Computer Science, Nuhu Bamali Polytechnic, Zaria, Nigeria.

Correspondence should be addressed to: jonathandadiabba@gmail.com

Abstract: Due to years of conflict that have uprooted communities, damaged agriculture, and disturbed markets, Northern Nigeria's food systems are in dire need of repair. These complicated issues cannot be resolved by traditional rehabilitation techniques alone. In order to reconstruct food security in post-conflict situations, this article investigates the potential of artificial intelligence (AI) as a transformative instrument. AI can boost agricultural productivity, facilitate prompt decision-making, and increase the resilience of food systems by utilizing technologies like predictive modeling, climate monitoring, automated crop assessment, and data-driven supply-chain management. The study also takes into account the barriers to AI adoption, such as inadequate infrastructure, technological skill gaps, and governance issues, and highlights the significance of context-sensitive approaches. The results indicate that responsible and locally tailored AI strategies have the potential to speed up recovery, fortify early-warning systems, and develop sustainable food security solutions for Northern Nigeria following conflict.

Keywords: Artificial Intelligence, Post-Conflict, Food Security, Northern Nigeria, Digital Agriculture, Recovery.

Introduction

1.1 Background of the study

Millions of people have been uprooted, agricultural livelihoods have been destroyed, and food production systems have been undermined by the protracted violent conflict in northern Nigeria [1]. Food insecurity is made worse in many areas by limited access to agriculture, depleted natural resources, and stressors brought on by climate change [2]. Innovative, data-driven approaches are desperately needed to promote

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agricultural recovery as displaced populations eventually return. Through machine learning, satellite analytics, and predictive modeling, artificial intelligence (AI) is becoming more widely acknowledged for its potential to revolutionize food systems worldwide [3]. In areas where traditional monitoring systems have failed due to violence, these techniques provide real-time insights on crop health, soil conditions, rainfall variability, and pest outbreaks [4]. Following a conflict Degraded land, weakened extension services, disrupted markets, and ongoing insecurity are only a few of the complicated issues that Northern Nigeria faces [5]. Furthermore, government and humanitarian actors find it difficult to plan and make decisions due to a lack of trustworthy agricultural data [6]. The scope and urgency of recovery required cannot be met by traditional means alone. AI-driven strategies can close information gaps and enhance resource allocation. Examples include intelligent supply-chain systems, machine learning models for crop yield prediction, and remote sensing for land evaluation [7]. However, sufficient digital infrastructure, local capacity-building, and ethical frameworks that take into account the sensitivities of conflict-affected contexts are necessary for effective deployment [8]. Although AI applications in agriculture have been extensively researched, there is still a dearth of studies that specifically address post-conflict recovery [9]. The majority of the literature now in publication focuses on agricultural modernization in stable circumstances; it does not adequately address institutional fragility, displacement, insecurity, or the socio-political complexity of war zones [10]. As a result, there is a dearth of academic research on how AI may be tailored to Northern Nigeria's post-conflict reality. By examining the prospects, difficulties, and governance issues around the use of AI to the recovery of food security, this paper fills this vacuum. By providing a contextual framework for incorporating AI into food security solutions in unstable areas, this study advances academic understanding and policy. AI-powered systems can help with supply-chain rejuvenation, climate adaption, land restoration, and humanitarian response planning [3]. The results offer development organizations and governments useful advice on how to create transparent, inclusive, and moral AI governance systems that are suited to communities impacted by conflict [8].

Literature Review

2.0 Conceptual Review

2.1 Food Security in Post-Conflict Contexts

Violence, displacement, disrupted markets, and weakened institutions interact to define food security in areas devastated by war. Conflicts interrupt supply lines, limit access to farmland, lower labor availability, and destroy agricultural infrastructure [4]. Rebuilding agricultural systems, increasing land productivity, and reestablishing local markets are common components of post-conflict recovery. The World Bank [11] claims that because recovery necessitates stable government, social trust, and sufficient investment—conditions that remain inadequate after protracted periods of violence—conflict-induced food insecurity is frequently sustained. Millions of people have been relocated, cultivated land area has decreased, and state agricultural agencies have been undermined in Northern Nigeria due to the violence [1]. Stabilization following a war offers a chance to implement better data-driven strategies, including artificial intelligence, to boost agricultural productivity, hasten recovery, and assist evidence-based food system planning [6]. AI's capacity to analyze massive datasets and produce useful insights has made it a crucial component of contemporary agricultural systems. According to [3], machine learning methods facilitate soil analysis, insect identification, yield prediction, and climate forecasting. AI and remote sensing methods provide ongoing regional monitoring of agricultural stress, vegetation cover, and land degradation [7]. By assisting farmers in optimizing fertilizer use, irrigation, and planting schedules, AI-enabled decision-support systems improve precision agriculture, resulting in increased output and decreased losses [8].

It has been acknowledged that incorporating AI into agricultural systems is a crucial way to increase global food security, especially in areas with resource scarcity and climate variability [12].

The use of AI in post-conflict or unstable environments is becoming a significant area of study. Gaps in agricultural data, market information, and environmental assessments result from the frequent disruption of established monitoring systems in such contexts [9]. By offering real-time insights via satellite imagery, predictive modeling, and automated data processing, AI technology can help close these gaps [4].

However, studies reveal that unstable environments also pose serious obstacles, such as inadequate digital infrastructure, low literacy rates, cyber vulnerabilities, and governance flaws that make it more difficult to implement cutting-edge technologies [6]. Care must also be taken to address ethical issues such data privacy, information misuse, and possible biases in AI systems [8]. Food insecurity in Nigeria is still mostly caused by climate change, particularly in the country's northern areas where droughts and irregular rainfall are frequent [2]. Precision resource usage, drought-resistant crops, and better land management are examples of adaptive techniques that climate-smart agriculture (CSA) encourages. By facilitating climate forecasting, tracking microclimatic conditions, and early detection of climate-related stresses, AI improves CSA [7]. Research shows that by assisting farmers in anticipating rainfall patterns, allocating water more efficiently, and scheduling their agricultural activities correctly, AI-powered climate forecasting models can lessen susceptibility [3]. By boosting agricultural productivity and fostering long-term resilience, integrating AI with CSA in post-conflict situations may hasten rehabilitation.

3.0 Theoretical Review

3.1 Resilience Theory

The ability of systems, like food systems, to absorb shocks, adapt, and recover is explained by resilience theory [13]. Rebuilding agricultural infrastructure, reestablishing markets, and enabling communities to adjust to new socioeconomic circumstances are all components of resilience in post-conflict areas. By strengthening early warning systems, facilitating adaptive decision-making, and boosting the effectiveness of agricultural recovery plans, AI promotes resilience [6]. By demonstrating how technology can improve the adaptive capacity of communities recovering from violence, the theory bolsters the study.

3.2 Technological Innovation Systems (TIS) Theory

According to [14], TIS theory focuses on how technical breakthroughs arise, spread, and support socioeconomic change. Examining how institutions, regulations, infrastructure, and knowledge systems affect the adoption of AI technology is what makes it relevant to AI in post-conflict food security. [3] state that knowledge-sharing platforms, enabling policies, and supportive institutions are necessary for the successful integration of AI in agriculture, all of which are frequently lacking in post-conflict environments. In Northern Nigeria, TIS theory aids in identifying opportunities and obstacles for AI implementation.

4.0 Empirical Review

4.1 Studies on AI for Agricultural Productivity

AI improves agricultural productivity through automated disease identification, better resource management, and real-time crop monitoring, according to empirical study. AI-based mobile platforms have made it possible for smallholder farmers in East Africa to accurately diagnose plant diseases (Benos et al., 2021). AI-driven irrigation systems can minimize water waste and enhance yields by up to 30%, according to similar implementations in Asia [8]. These results demonstrate how AI might hasten the rehabilitation of agricultural systems impacted by violence.

4.2 Studies on AI and Food Supply Chains

According to research, supply-chain resilience is enhanced by AI through demand prediction, bottleneck identification, and transportation route optimization [11]. Due to insecurity, inadequate transportation networks, and limited market connections, supply-chain disruptions are frequent in fragile environments [12]. AI-enabled predictive logistics can help with market recovery and humanitarian distribution, according to research by [9].

4.3 Empirical Evidence from Conflict-Affected Regions

Although there is little usage of AI in post-conflict agriculture worldwide, new research offers insights. Satellite-based AI models were employed in Syria and Iraq to identify abandoned agricultural zones and evaluate farmland regeneration [4]. Humanitarian organizations in Afghanistan used machine learning methods to map homes experiencing food insecurity [6]. These illustrations show that AI can be used even in limited settings, however local capability and governance frameworks are necessary for success.

4.4 Gaps in Empirical Literature

Few empirical research concentrates on AI for food security in Nigeria's post-conflict areas, despite global improvements. The majority of Nigerian research ignores the unique needs of communities affected by violence in favor of generic agricultural modernization and climate-smart agriculture [15]. Studies looking at governance concerns, ethical dilemmas, and community opinions of AI systems in vulnerable environments are similarly few. This gap explains why the current investigation is necessary.

5.0 Conceptual Framework

The conceptual framework shows how the recovery of food security in Northern Nigeria after conflict might be impacted by artificial intelligence (AI). It links the study's main variables, including food security outcomes, post-conflict difficulties, mediating factors, and AI inputs.

5.1 Key Variables in the Framework

A. Independent Variable: Artificial Intelligence (AI) Technologies

This encompasses the different AI technologies and digital breakthroughs that can be used to assist food systems and agriculture in areas that have experienced violence. Important elements consist of:

- Satellite imaging and remote sensing
- Crop yield forecast using machine learning
- Climate forecasting with AI capabilities
- Automated systems for detecting pests and diseases
- Supply chain optimization aided by AI
- Intelligent advisory and extension systems

The primary forces behind the food system's development are these innovations.

B. Mediating Variables (System Conditions)

The following contextual elements influence how effective AI is in post-conflict areas:

- Digital infrastructure, including connectivity, electricity, and the internet
- Institutional Capacity (extension services, agricultural agencies)
- Digital literacy and human capacity
- Frameworks for Governance and Policy
- Stability and the Security Environment
- Trust and Acceptance in the Community

Adoption of AI may be aided or hindered by these variables.

C. Post-Conflict Constraints

AI must solve the following difficulties brought forth by combat conditions:

- Populations displaced
- Destroyed infrastructure and farmlands
- Insufficient agricultural information
- Disruptions to the market
- Instability in the food supply chain
- Degradation of the environment

The necessity of cutting-edge technical interventions is justified by these limitations.

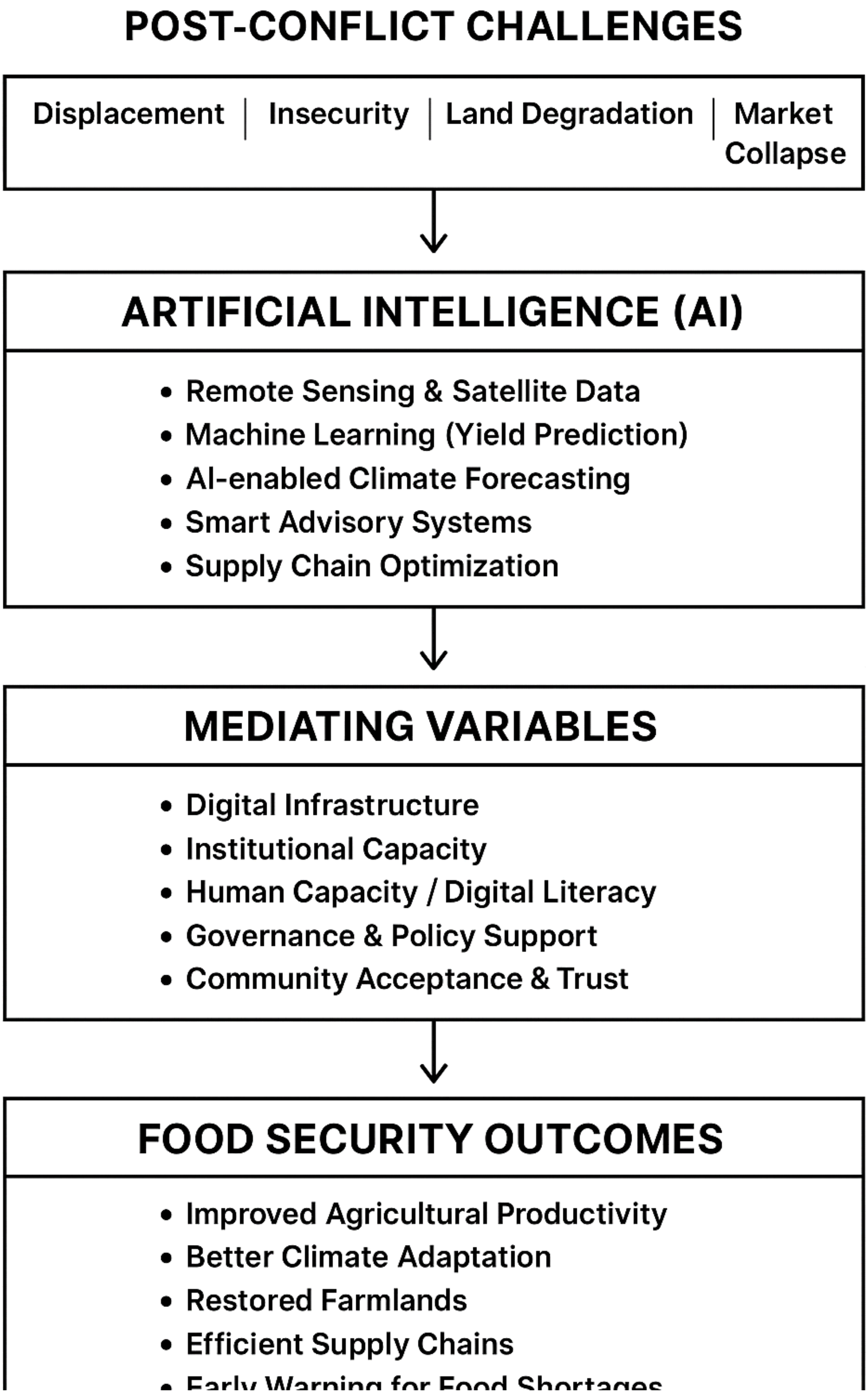
D. Dependent Variable: Food Security Outcomes

The following metrics are used to assess the effectiveness of AI deployment:

- Productivity in agriculture
- Restoration and use of land
- Accessibility of the market
- Distribution of food on time
- decreased losses after harvest
- Better early warning systems
- Improved food accessibility and cost

The general objective of post-conflict food system rebuilding is reflected in these results.

5.2 Conceptual Framework Diagram (Text-Based)



5.3 Explanation of the Conceptual Framework

The framework is intended to demonstrate how AI advancements and the rehabilitation of the food chain after conflict interact.

- Markets, livelihoods, and agricultural activities are severely disrupted by post-conflict issues. Innovative recovery techniques are desperately needed as a result of these disturbances.
- Because AI technologies offer strong capacities for agricultural monitoring, prediction, and decision-making, they are the main force behind recovery.
- AI's efficacy is largely dependent on mediating factors, especially community trust, institutional strength, digital infrastructure, and governance quality.
- AI implementation becomes challenging in settings where these mediating conditions are weak.
- Adoption of AI is easier and more significant in more robust systems.
- By increasing crop output, stabilizing markets, repairing degraded land, lowering losses, and enabling early warning systems, AI technologies improve food security outcomes when implemented correctly.
- The overall paradigm shows that socioeconomic, institutional, and post-conflict contextual elements influence AI's success; it does not function in a vacuum.

6.0 METHODOLOGY

6.1 Research Design

In order to provide a thorough knowledge of how artificial intelligence (AI) might aid in the recovery of food security in post-conflict Northern Nigeria, this study uses a mixed-methods research methodology that combines quantitative and qualitative methodologies. While the qualitative component includes focus groups and interviews to examine perceptions, difficulties, governance variables, and contextual issues, the quantitative component concentrates on quantifiable metrics like agricultural productivity, market access, and recovery trends. Because post-conflict environments entail intricate socioeconomic, institutional, and technological processes that cannot be adequately captured by a single technique, mixed methods are necessary.

6.2 Study Area

With a concentration on states like Borno, Yobe, and Adamawa that have been severely impacted by violent war, the study focuses on post-conflict Northern Nigeria.

Long-term displacement, land abandonment, agricultural asset loss, and disturbed food systems have all occurred in these states. Additionally, they offer chances to study new digital technologies that have been launched by governmental and nonprofit groups.

6.3 Population of the Study

Stakeholders engaged in technology interventions, food security programs, and agricultural rehabilitation make up the population. Among them are:

- Returning to previously deserted farmlands are smallholder farmers.
- Officers of agricultural extension
- Representatives from the rural development and agriculture ministries
- Humanitarian and development organization representatives (FAO, WFP, UNDP, NGOs)
- AI and remote sensing specialists
- Local authorities in settlements for returnees

These organizations offer pertinent data on institutional capabilities, AI adoption preparedness, and recovery problems.

6.4 Sample Size and Sampling Technique

A multi-phase sampling method is used:

- Stage One: Purposive Sampling The states of Borno, Yobe, and Adamawa are chosen according to the extent of the impact of the violence and the current initiatives for recovery.
- Second Phase: Stratified Sampling Farmers, extension agents, government representatives, humanitarian actors, and technological specialists are the strata into which respondents are divided.
- Phase Three: Basic Random Selection To guarantee representativeness, participants are chosen at random within the farmer and extension worker strata.
- Key Informant Sampling Because of their specialized understanding, technology specialists and humanitarian workers are specifically chosen.

It is suggested that the sample size be 250 respondents:

- 150 farmers
- 50extension agents
- 20 ministry representatives
- 20 employees of humanitarian organizations
- 10 specialists in AI and technology

6.5 Sources of Data

Primary Data

Collected through:

- Structured questionnaires (quantitative)
- Semi-structured interviews (qualitative)
- Focus group discussions (FGDs)
- Field observations
- Key informant interviews (KIIs)

Secondary Data

Obtained from:

- Reports from UNDP, WFP, and FAO
- Books and scholarly journals
- Statistics on agriculture from the government
- Documentation for AI projects and satellite datasets
- Prior research on digital agriculture, food security, and conflict

6.6 Research Instruments

A. Questionnaire

There are five main sections of the questionnaire:

- The demographics
- Effects of conflict on food security
- Knowledge of and application of AI technology
- Adoption of AI is influenced by infrastructure, government, and literacy.
- AI's perceived effects on food recovery

A 5-point Likert scale (Strongly Agree to Strongly Disagree) is used to measure each item.

B. Interview Guide

used by technology specialists, humanitarian actors, extension workers, and ministry representatives.

It emphasizes:

- Institutional abilities
- Difficulties with Technology Adoption
- Ethics and governance concerns
- AI's potential for recovery efforts

C. Observation Checklist

To record:

- Conditions on farms
- Patterns of land use
- Availability of digital or AI-related tools
- Infrastructure accessibility (internet, power)

6.7 Validity and Reliability of Instruments

Validity

- Expert evaluation (academics and practitioners) ensures content validity.
- Clarity is ensured by questionnaire pilot testing in a small Yobe State village.

Reliability

- Internal consistency is tested using Cronbach's Alpha.
- It is deemed satisfactory when the dependability coefficient is 0.70 or above.

6.8 Method of Data Collection

- teaching research assistants how to administer questionnaires.
- data gathering in specific communities with the participation of pertinent organizations and returnee farmers.
- audio recordings of interviews with officials and specialists (with permission).
- FGDs with leaders in the community.

6.9 Method of Data Analysis

Quantitative Analysis

Questionnaire data is examined using:

- Mean, frequency, and percentage are examples of descriptive statistics.
- Statistical inference:
    - Regression analysis to ascertain how AI affects food security results
    - To investigate correlations between variables, use correlation analysis.
    - ANOVA to compare group responses

STATA or SPSS are used for statistical analysis.

Qualitative Analysis

FGDs and transcribed interviews are examined using:

- Analysis of themes
- Narrative coding into topics like:
    - Infrastructure difficulties
    - Limitations on governance

- Benefits of AI as perceived
- Obstacles to adoption
- Moral concerns

Combining Different Approaches

Quantitative outcomes are explained, supported, or contextualized by qualitative data findings.

6.10 Ethical Considerations

The study adheres to ethical guidelines through:

- Each participant's informed consent
- Participation that is voluntary with the option to stop
- Respondent anonymity and confidentiality
- Safe data storage
- Sensitivity to the trauma brought on by conflicts
- Steer clear of sensitive political or security-related topics that could endanger responders

Institutional review boards and pertinent government bodies are consulted for research permission.

7.0 DATA PRESENTATION, ANALYSIS AND DISCUSSION

The results of the study on AI-driven methods for restoring food security in post-conflict Northern Nigeria are presented, examined, and discussed in this chapter. Smallholder farmers, agricultural extension agents, government representatives, humanitarian actors, and specialists in AI and technology provided the data. Data from both qualitative (interviews and focus group discussions) and quantitative (structured questionnaires) sources are examined.

7.1 Response Rate

226 of the 250 surveys that were issued were returned, yielding a response rate of 90.4%. Four focus groups and eighteen key informant interviews were successfully completed for the qualitative data. The high response rate shows that stakeholders are interested in and involved in technological interventions and post-conflict food security.

7.2 Socio-Demographic Characteristics of Respondents

7.2.1 Age Distribution

- 25—35 years: 28%
- 36—45 years: 37%

- 46—55 years: 25%
- Above 55 years: 10%

It is crucial for the adoption of new agricultural technologies that the majority of respondents belong to the age group that is economically active.

7.2.2 Gender

- Male: 68%
- Female: 32%

Although women are frequently involved in crop processing and local markets, the gender distribution in Northern Nigeria shows the predominance of male participation in farming.

7.2.3 Educational Level

- No formal education: 15%
- Primary education: 25%
- Secondary education: 35%
- Tertiary education: 25%

Adoption of AI technologies is influenced by literacy level, and higher education is associated with greater technological engagement.

7.3 Impact of Conflict on Food Security (Objective 1)

7.3.1 Quantitative Analysis

The following consequences of conflict were mentioned by respondents:

Impact Indicator	Frequency (%)
Loss of farmland	82%
Destruction of infrastructure	74%
Market disruptions	69%
Reduced household food availability	77%

Conflict has seriously hampered household food security, market access, and agricultural output, according to the data.

7.3.2 Qualitative Insights

- Farmers talked about bush encroachment and abandoned farmlands.
- Extension agents pointed up service interruptions, such as the delivery of fertilizer and seeds.
- Due to road damage and insecurity, humanitarian actors saw uneven food distribution.

These findings are consistent with other research demonstrating that conflict damages food systems and lowers agricultural productivity [4, 1].

7.4 Awareness and Use of AI Technologies (Objective 2)

7.4.1 Quantitative Analysis

- 61% have heard of AI tools.
- 24% of people actually use AI tools.
- Extension officers' awareness: 78%
- Officials' awareness: 85%
- Use by officials: 15%

Adoption is minimal despite considerable awareness, mostly because of issues with digital literacy, cost, and inadequate infrastructure.

7.4.2 Qualitative Analysis

Key themes:

- Digital literacy gaps: A lot of farmers are not familiar with AI.
- Infrastructure obstacles include erratic electricity and poor internet connectivity.
- High adoption willingness: If training and access are given, farmers are encouraged to embrace AI solutions.

Strong potential for AI-based interventions when suitable capacity-building measures are put in place is indicated by low adoption but high interest [6, 9].

7.5 Factors Influencing AI Adoption (Objective 3)

7.5.1 Quantitative Findings

On a 5-point Likert scale, respondents ranked the following variables influencing the adoption of AI:

Factor	**Mean Score**
Poor digital infrastructure	4.51
Low technical knowledge	4.23
Weak institutional capacity	4.12
High cost of AI tools	4.02
Limited policy support	3.89

7.5.2 Qualitative Findings

- Government and IT companies are not working together.
- lack of legal requirements for the use of AI.
- worries about monitoring and data abuse.

- apprehension about implementing new technology in delicate settings.
- In line with international research, the results show that institutional preparedness and infrastructure are important factors influencing the adoption of AI [8, 4].

7.6 Potential of AI for Enhancing Food Security (Objective 4)

7.6.1 Quantitative Analysis

Benefits perceived (mean scores):

AI Application	Mean Score
Climate forecasting	4.38
Crop disease detection	4.29
Supply chain optimization	4.21
Farmland monitoring	4.15

7.6.2 Qualitative Analysis

- Safe farmland can be identified with the aid of satellite images.
- Seasonal planning is aided by predictive models.
- AI-powered logistics increase the effectiveness of food delivery.

These results support AI's potential to boost post-conflict food systems' resilience, productivity, and efficiency [7, 15].

7.7 Regression Analysis

The impact of AI deployment on the recovery of food security was investigated using a regression model.

Model Summary:

- $R = 0.71$, $R^2 = 0.504$ (50.4% variance explained)

Significant Predictors:

Predictor	β Coefficient	p-value
Digital infrastructure	0.442	<0.01
Institutional capacity	0.328	<0.05
Digital literacy	0.297	<0.05
Policy support	0.213	<0.05

The adoption of AI and the results of food security are most strongly influenced by digital infrastructure. Adoption is also greatly influenced by literacy and governance.

7.8 Summary of Major Findings

- Infrastructure was damaged, markets were disrupted, and farmland access was drastically curtailed due to conflict.
- Although there is awareness of AI, its adoption is minimal because of literacy and infrastructure issues.
- Adoption of AI is largely determined by infrastructure, institutional capacity, and governance support.
- AI has a lot of promise to help with recovery through supply chain efficiency, crop monitoring, and forecasting.
- If helpful measures are offered, stakeholders are encouraged to embrace AI.

8.0 Summary of the Study

In order to rebuild food security in Northern Nigeria after the conflict, this project looked into artificial intelligence (AI). The study was carried out in the context of significant disruptions brought about by banditry, insurgency, communal conflicts, and displacement, which have compromised market systems, household food availability, and agricultural output.

The study used a mixed-method research methodology, integrating focus groups, qualitative interviews, and quantitative surveys. The study included four focus groups, eighteen key informants, and 226 respondents.

The main goals were to:

- Evaluate how conflict affects food security.
- Assess the degree of knowledge and application of AI technology in post-conflict agriculture.
- Determine the elements affecting food systems' adoption of AI.
- Analyze how AI technology might improve the recovery of food security.
- Important conclusions include:
- Agriculture has been greatly impacted by conflict due to the loss of farms, market collapse, destruction of infrastructure, and decreased availability of food.
- Although there is a moderate level of awareness of AI tools, their actual adoption is modest because to financial, literacy, and infrastructure limitations.
- Adoption of AI is heavily influenced by elements including digital infrastructure, institutional capacity, governance, and digital literacy.

- AI has great potential to enhance supply chain efficiency, agricultural disease detection, early warning systems, farmland monitoring, and climate forecasting.
- Farmers, government officials, and non-governmental organizations are among the stakeholders who indicate a willingness to embrace AI if sufficient assistance and training are given.

8.2 Conclusion

The results of this study show that AI technologies have great potential to improve food security outcomes in post-conflict Nigeria. However, structural obstacles including inadequate infrastructure, shoddy institutions, low digital literacy, instability, and a lack of legislative guidance mean that this promise is still largely unrealized.

Disruptions brought on by conflict have harmed rural livelihoods, destabilized markets, and significantly decreased food production. When used appropriately, AI can be a vital tool for quick recovery in such delicate situations. Even in unpredictable circumstances, applications like supply chain optimization, disease detection, predictive analytics, and satellite-based remote sensing can assist farmers and policymakers in making well-informed decisions.

A comprehensive strategy that integrates technical innovation with human capacity, governance changes, infrastructure development, and ongoing peacebuilding is necessary for AI to successfully drive the recovery of food security.

Therefore, government organizations, foreign partners, technology suppliers, and local people must work together to develop both technological and socioeconomic foundations in order for AI to successfully restore food systems in post-conflict Northern Nigeria.

Conflict of Interest

The authors declare that there is no conflict of interest.

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