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NDEMRI: An AI-Driven SMS Platform for Equitable Agricultural Extension in Rural Africa

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Abstract: An artificial intelligence (AI)-powered agricultural advisory system, termed NDEMRI (Nurturing Digital Extension via Mobile and Responsive Intelligence), has been developed to provide evidence-based farming guidance to rural communities across sub-Saharan Africa through short message service (SMS). Designed for compatibility with basic GSM-enabled mobile phones and independent of internet access for end-users, the system integrates large language models (LLMs) via the ChatGPT API to generate contextually relevant, linguistically localized responses to a wide array of agricultural queries. A quasi-experimental evaluation was conducted in the northern regions of Cameroon over a four-month period, employing a matched control group methodology involving 831 treatment farmers and 400 controls. Statistically significant improvements were observed among participants using NDEMRI, with mean crop yields increasing by 16.6% and agricultural incomes rising by 23%, relative to the control group. Adoption of improved agronomic practices was notably higher among users of the system. A total of 2,487 unique messages were exchanged, covering themes such as pest management, planting schedules, soil health, and post-harvest storage, with 78% of users reporting that system responses were context-sensitive and adapted to local climatic and cultural conditions. The technical architecture is characterized by modular natural language understanding pipelines, embedded guardrails to minimize model hallucinations, and a reproducible framework for contextualization based on regional agricultural datasets. A detailed economic analysis demonstrated the financial sustainability of the intervention, with favorable cost-benefit ratios and scalability potential. These findings offer robust empirical evidence that the integration of accessible communication technologies with state-of-the-art AI can overcome infrastructural limitations, enhance decision-making in low-resource farming environments, and serve as a viable model for transforming agricultural extension services across the African continent.

Keywords: NDEMRI; Digital agriculture; SMS-based advisory systems; Artificial intelligence (AI); Large language model (LLM); Sub-Saharan Africa; Agricultural extension; Rural development

1 Introduction

Agriculture remains the backbone of many African economies, employing over 60% of the continent's active workforce [1]. Yet, rural farmers face significant challenges, including limited access to up-to-date agricultural information, modern techniques, and expert knowledge. Traditional agricultural extension services, while essential, are often insufficient due to budgetary constraints, a limited number of extension agents, and logistical difficulties in reaching remote areas [2]. Recent advances in AI particularly in LLMs offer new opportunities to bridge this information gap. However, the adoption of these advanced technologies in rural areas is hindered by several factors: limited internet access, low smartphone penetration, high mobile data costs, and language barriers [3]. These constraints call for the development of technology solutions that are adapted to local realities. This paper introduces

NDEMRI, an agricultural support system that harnesses the power of LLMs while adapting to the technological context of rural Africa. NDEMRI uses SMS as its primary user interface, enabling farmers to access expert farming advice through basic mobile phones, without the need for internet connectivity. The system acts as a bridge between cutting-edge AI technologies and existing communication infrastructure in rural areas. Our study aims to address the following research questions: How can LLMs be adapted to deliver relevant agricultural advice via SMS in the African context? What are the technical and practical challenges of implementing such a system in resource-constrained environments? And what is the potential impact of an AI-based agricultural support service on farming practices and farmers' livelihoods?

2 Literature Review

Here, we synthesize research on mobile and AI solutions for agriculture, evaluating their socio-technical impacts across different contexts.

2.1 Mobile Technologies for Agricultural Development

The use of mobile technologies to support agricultural development has been the focus of numerous studies over the past decade. Aker and Mbiti [2] documented the transformative impact of mobile phones on African economies, identifying five key mechanisms through which they promote economic development, particularly within the agricultural sector. Empirical research by Aker [4] in Niger showed that the introduction of mobile phones reduced price disparities between agricultural markets by 10-16%, with more significant effects observed in remote areas. This improved market efficiency and lowered search costs for farmers.

These advances paved the way for innovative services such as mFarm in Kenya [5], Esoko in Ghana [6], and WeFarm in East Africa [7], demonstrating that SMS-based tools can effectively connect farmers to markets and agricultural information. Studies by Cole and Fernando [8] in India confirmed that mobile-delivered agricultural advice can significantly improve farming practices and crop yields.

However, as Khan et al. [9] highlight in their comprehensive review of the ICT revolution in agricultural extension, these technologies continue to face persistent challenges, particularly digital, linguistic, and gender divides. Moreover, the dissemination of agricultural knowledge remains complex. Alenea and Manyong [10], in their study on the diffusion of agricultural technologies in Nigeria, observed considerable differences in outcomes among adopters. They emphasized the importance of the quality of information delivered and the role of social networks in shaping adoption processes.

2.2 AI in Agriculture

The integration of AI into agriculture is an expanding area of research. Applications range from image processing for plant disease detection [11] to predictive analytics for crop planning [12]. However, Becerra-Encinales et al. [13], in their systematic review, identify a set of multidimensional barriers to the adoption of agricultural technologies in developing countries, categorized into sociocultural, economic, institutional, and techno-structural obstacles. Most AI-driven applications require smartphones, reliable internet connectivity, or specialized equipment conditions that remain scarce in many rural areas across Africa.

LLMs represent a significant evolution in this context. Biswas [14] and Gaddikeri et al. [15] have explored the potential uses of ChatGPT in agriculture, highlighting promising areas such as plant disease diagnosis support, crop management optimization, and simplifying access to technical information for non-specialist farmers. Siche and Siche [16], through a bibliometric analysis, documented the rapid emergence of LLM applications in agriculture and livestock, concluding that these technologies have the potential to transform precision farming and agricultural advisory services.

More targeted applications are also emerging. Potamitis [17] examined how ChatGPT can be integrated into precision agriculture systems, analyzing how these models can interpret and make sense of complex data from sensors, drones, and satellites. Zhao et al. [18] demonstrated ChatGPT's superiority in multilingual classification of agricultural texts, suggesting strong potential for developing multilingual agricultural advisory services, especially in low-resource languages. In a more applied perspective, Alobid [19] analyzed the benefits of ChatGPT in the European agricultural sector, identifying use cases such as crop decision optimization and early disease forecasting.

2.3 Gaps in Existing Research

Despite advancements in mobile technologies and AI applications in agriculture, there remains a significant research gap regarding the integration of advanced LLM capabilities with basic communication technologies accessible to rural farmers. While the aforementioned studies analyze either the impacts of simple mobile technologies or the potential applications of LLMs in technologically advanced environments, few have explored the use of these models in low-resource settings or through basic communication channels such as SMS.

In particular, the adaptation of LLMs to local African agricultural knowledge remains largely unexplored, even though these models show strong potential for contextualizing and personalizing advice. Similarly, there is a lack of impact assessment regarding these hybrid technologies (combining SMS and advanced AI) on actual farming practices. Our study aims to address this gap by exploring how SMS, the most widespread mobile technology in Africa [20], can serve as an interface between farmers and sophisticated AI systems. This approach offers a promising pathway toward the democratization of agricultural knowledge in contexts with limited technological infrastructure.

3 Methodology

This section details the comprehensive methodology employed in developing and evaluating the NDEMRI system. The methodology encompasses seven key components: the technical design of the NDEMRI system (3.1), contextualization of the AI model to local agricultural conditions (3.2), deployment strategy and data collection processes (3.3), rigorous data analysis techniques (3.4), quasi-experimental design with control group implementation (3.5), and agronomic safety architecture with hallucination prevention mechanisms (3.6). Together, these methodological components provide a robust framework for developing, deploying, and evaluating an AI-powered agricultural support system that is both technically sophisticated and contextually appropriate for rural African communities.

3.1 Design of the NDEMRI System

NDEMRI was designed as an SMS messaging system that relays farmers' questions to a LLM (GPT-4 via the OpenAI API) and returns AI-generated responses to the users. The system consists of three main components:

1). Server Application: An Android application developed in Kotlin using Jetpack Compose, which intercepts incoming SMS messages containing the keyword "ndemri," processes them, and sends the responses. This server runs on a dedicated Android smartphone located in an area with stable internet connectivity.

2). OpenAI API Interface: A service that formats requests for the GPT API with specific instructions to generate concise, SMS-friendly, and contextually relevant responses tailored to agricultural inquiries.

3). SMS Management Module: A component responsible for handling the reception and sending of SMS messages, optimized to operate reliably even under varying network conditions.

The system architecture is illustrated in Figure 1.

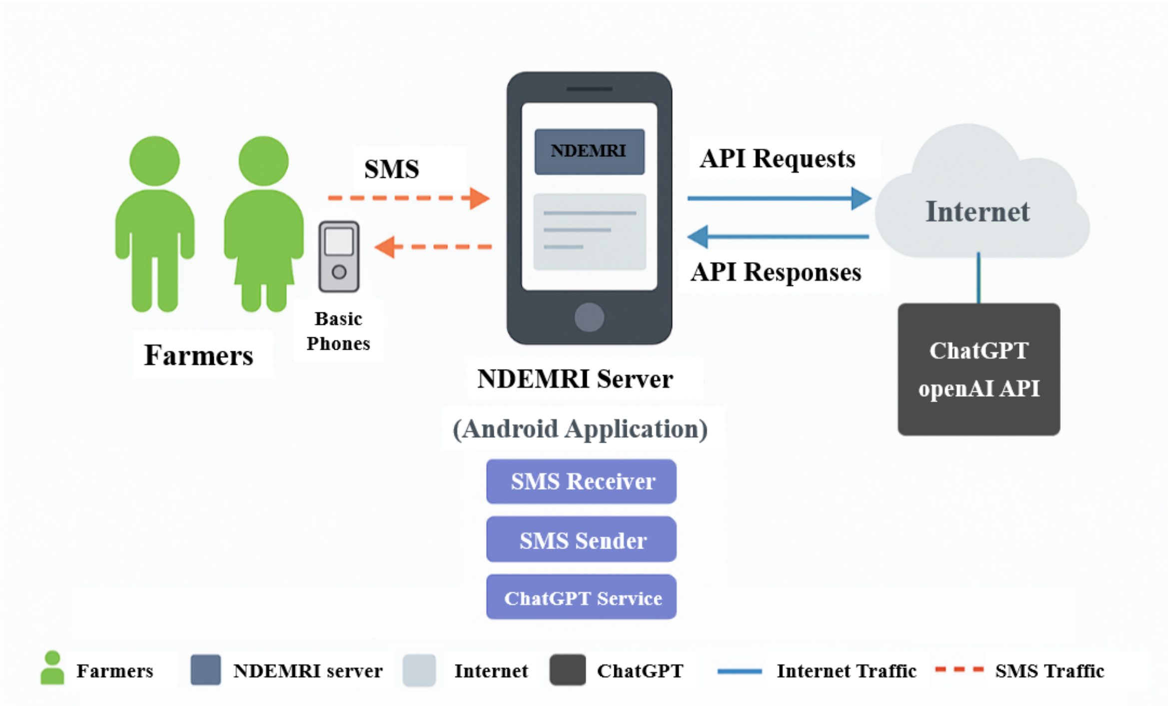

Figure 1. NDEMRI system architecture

3.2 Contextualization of the AI Model

To adapt the GPT model to the specificities of the African agricultural context, we implemented a standardized five-step contextualization protocol to ensure consistency and replicability. It is described in Figure 2 below.

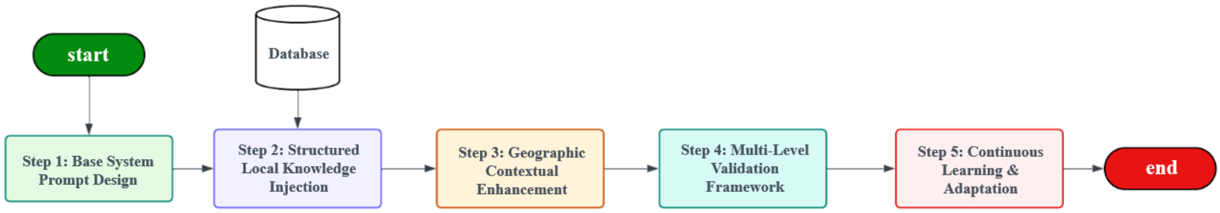

Figure 2. Standardized contextualization protocol

The contextualization process of the AI model can be formally represented by Eq. (1), defined as:

$$R\left(q,\ c\right)\ =\ LLM\left(q,\ p,\ cl,\ cr,\ cs\right)\ \cdot\ f_{SMS}\left(l\right) \tag{1}$$

where,
- $R(q,\ c)$ is the response generated for question q in context c
- LLM is the large language model function (ChatGPT)
- p is the base system prompt defining NDEMRI's identity
- cl represents the local linguistic context (dialects and agricultural terms)
- cr represents the regional context (agro-ecological conditions, agricultural calendar)
- cs represents specific knowledge (local varieties, traditional practices)
- f_{SMS} is a formatting function that adapts the response to SMS constraints
- l is the character limit (160 for a standard SMS)

3.2.1 Base system prompt design

The foundation of our contextualization approach begins with a custom system prompt that frames each interaction. Figure 3 shows this basic prompt.

```
PROMPT_BASE = {
    "identity": "You are NDEMRI, an agricultural assistant expert for sub-Saharan Africa",
    "format": "SMS responses (<160 characters), simple language, actionable",
    "signature": "NDEMRI message - Ask more agricultural questions",
    "safety": "When in doubt, recommend consulting a local expert",
    "local_focus": "Prioritize Cameroon-specific agricultural knowledge and practices"
}
```

Figure 3. NDEMRI base system prompt structure

This base instruction enables the system to: define the system's identity and domain expertise, limit response length to fit the SMS format constraints, include a signature that reinforces the service identity, and encourage ongoing interaction with users.

3.2.2 Structured local knowledge injection

At the heart of NDEMRI's contextual intelligence lies a robust PostgreSQL-based relational database designed to deliver fine-grained, locally relevant insights. This dynamic knowledge backbone includes:
- 15,000+ market price entries, updated weekly to reflect real-time economic conditions across rural markets
- 240 crop varieties, each matched with tailored recommendations by agroecological zone for optimal adaptation
- 180 phytosanitary technical sheets, localized and simplified to align with available inputs and practices
- Dynamic crop calendars, refreshed every 10 days across 8 distinct climate zones, ensuring seasonal alignment and timely agronomic advice

This structured repository transforms generic responses into location-specific, actionable guidance—grounded in data, optimized for context.

3.2.3 Geographic enhancement layer

To bridge the gap between static advisory systems and location-aware intelligence, NDEMRI enriches each user query with a dynamic layer of geospatial and agroecological data. Based on the user's location, the system fetches key environmental, agronomic, and market variables before generating a response. This enhancement ensures hyper-localized recommendations, tailored not just to the crop—but to the farmer's micro-context.

Algorithm 1: Location-Based Contextualization of User Queries

Input:
- location: GPS coordinates or user's village code
- query: User-submitted question
- base_prompt: Predefined system prompt

Output: enhanced_prompt: Final prompt with integrated local context for AI generation

Procedure:
1. climate_zone ← get_climate_zone(location)
2. soil_type ← get_dominant_soil(location)
3. local_varieties ← get_recommended_varieties(location)
4. seasonal_calendar ← get_current_season_activities(location)
5. market_prices ← get_recent_prices(get_nearest_market(location))
6. rainfall_data ← get_historical_rainfall(location)
7. traditional_practices ← get_validated_practices(location)
8. Construct enhanced_prompt by embedding the above variables into base prompt:
   LOCAL CONTEXT for [location]:
   - Climate zone: [climate_zone]
   - Dominant soils: [soil_type]
   - Recommended varieties: [local_varieties]
   - Seasonal activities: [seasonal_calendar]
   - Recent market prices: [market_prices]
   - Rainfall patterns: [rainfall_data]
   - Traditional practices: [traditional_practices]
9. QUESTION: [query]
10. Return llm_generate(enhanced_prompt)

3.2.4 Multi-level validation framework

Before reaching the user, each response is subjected to a triple-layer validation system:
- Automated filtering eliminates unsafe or incoherent content via keyword risk scoring;
- Expert agronomist validation (random 15% sample) ensures agronomic integrity;
- Real-time user feedback is integrated through an embedded satisfaction loop.

The system doesn't just check facts—it filters for trustworthiness, clarity, and usefulness at every level.

3.2.5 Continuous learning and adaptation

Learning is baked into the architecture. Every cycle strengthens the next:
- Error logs and user feedback are reviewed monthly;
- The knowledge base is refreshed quarterly based on expert and system-level updates;
- A/B testing evaluates variations in prompt phrasing and structure.

In short, the system gets smarter with every question. What began as a structured protocol becomes a self-reinforcing engine of precision advice.

3.3 Deployment and Data Collection

The system was deployed in the Greater North regions of Cameroon, centered around the cities of Maroua, Garoua, and Ngaoundéré, in partnership with local agricultural development organizations. The service phone number was promoted through the following channels: information sessions held in villages, distribution of flyers at weekly markets, radio announcements broadcast in local languages (Fulfulde, French) and existing networks of agricultural extension agents. Figure 4 shows the distribution of the NDEMRI deployment area.

Over a four-month period (June to September 2024), we collected the following data:

• Usage data: including the number of SMS exchanges, usage frequency, and geographical distribution of users.

• Content of submitted questions: classified into thematic categories such as crop management, pest and disease control, market prices, and soil treatment.

• User feedback: gathered via a simplified SMS questionnaire assessing satisfaction, clarity of responses, and perceived usefulness.

• Qualitative interviews: conducted with a subset of 250 farmer users to gather in-depth insights on the system's impact, usability, and perceived relevance.

Table 1 below summarizes the data collected by the system.

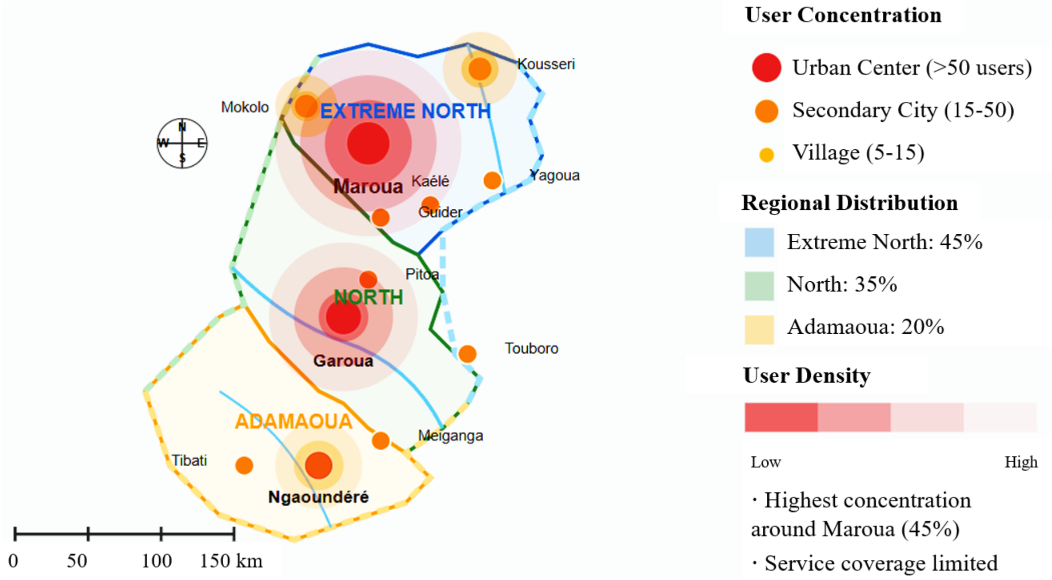

Figure 4. Geographic distribution of NDEMRI users

Table 1. Data collection summary

Data Type	Collection Method	Sample Size
Usage statistics	System logs	2,487 messages
User demographics	Registration data	831 users
Satisfaction metrics	SMS questionnaire	412 responses
In-depth feedback	Personal interviews	250 farmers

3.4 Data Analysis

Our analytical approach combined quantitative and qualitative methods to extract meaningful insights from SMS interactions and user interviews, enabling a comprehensive and contextualized understanding of NDEMRI system usage and impact.

(1) SMS Interaction Analysis

The 2,487 collected SMS messages underwent systematic multi-step analysis to identify recurring themes, primary concerns, and usage patterns. Text preprocessing initially involved cleaning raw messages by removing special characters, applying automatic spelling correction, and normalizing local agricultural terminology. A custom synonym dictionary specific to the Cameroonian agricultural context was developed to standardize references to crops, pests, and practices expressed in French, Fulfulde, and other local languages.

Lexicometric analysis using TF-IDF (Term Frequency-Inverse Document Frequency) vectorization techniques identified discriminative terms across different question categories, facilitating extraction of topic-specific vocabularies (e.g., pest-related versus market-related language). Semi-supervised thematic classification was implemented through a classifier trained on a manually annotated subset of 2,000 messages by agricultural experts. The model, based on a bidirectional Long Short-Term Memory network (BiLSTM), achieved 87% accuracy in categorizing messages into six main thematic classes, with manual validation on a random 10% sample to ensure reliability.

Temporal analysis of interactions in relation to the regional agricultural calendar identified correlations between farmer concerns and crop cycle phases. A 7-day sliding window technique tracked the evolution of dominant topics throughout the study period. Geospatial analysis, performed by linking phone numbers with GSM antenna coverage zones, approximated the geographical distribution of user queries and identified clusters of specific concerns tied to distinct agroecological zones.

(2) Qualitative Interview Analysis

Semi-structured interviews conducted with 30 selected users underwent in-depth qualitative analysis to understand user experience and perceived service impact. Interviews, conducted in French and Fulfulde, were fully transcribed and translated by native speakers into French when necessary, with translation reliability verified through back-translation on a sample of five interviews.

Iterative thematic coding following a grounded theory approach involved three coding phases. Initial open coding generated 54 descriptive codes, subsequently consolidated into 12 axial codes during the second phase. Finally, four core themes emerged through selective coding: perceived usefulness, service accessibility, trust in recommendations, and complementarity with traditional agricultural information sources.

Contrastive analysis gave special attention to atypical cases and divergent opinions to refine our understanding of user experience. The constant comparative method helped identify key moderating variables such as educational level, age, and prior access to other agricultural information sources. For each participant, we constructed cognitive maps illustrating perceived relationships between NDEMRI service use, changes in agricultural practices, and observed outcomes on their crops, enabling modeling of users' perceived causality chains.

(3) Data Triangulation

Analysis robustness was reinforced through methodical triangulation combining cross-validation, expert consultation, and user feedback. Themes identified through automated text analysis were cross-checked against qualitative interview results, while hypotheses emerging from interviews were quantitatively tested on the SMS message corpus. A panel of six experts—including two agronomists, two agricultural extension officers, one rural sociologist, and one natural language processing specialist—assessed the validity of preliminary interpretations and contributed to analytical framework refinement. A debriefing session with 12 interview participants validated main interpretations and integrated their perspectives into the final analysis.

This multi-method analytical approach enabled development of a nuanced and context-sensitive understanding of NDEMRI system use and impact, combining the precision of large-scale automated analysis with the depth of qualitative insights.

3.5 Quasi-Experimental Design and Control Group

To rigorously assess the effectiveness of the NDEMRI system, a quasi-experimental design was adopted, incorporating matched control groups to ensure comparability. The control group comprised 400 farmers across 10 villages located in agroecologically similar zones but without access to NDEMRI services. The matching process was based on key variables, including average farm size (2.3 ± 0.8 hectares in both groups), predominant crop types (maize, sorghum, and cotton), distance from agricultural extension centers (greater than 15 kilometers), access to financial services and markets, and historical rainfall patterns. Data collection was conducted through standardized surveys administered simultaneously across treatment and control groups at three critical points in the agricultural calendar: the baseline (May 2024, prior to NDEMRI deployment), the midline (July 2024, during the agricultural season), and the endline (October 2024, post-harvest).

The evaluation focused on a set of clearly defined impact variables. Primary outcome measures included agricultural yields (in kg/ha), assessed through direct measurement on test plots; the adoption of improved agricultural practices, quantified using a validated 12-item scale; and net agricultural income per season (measured in FCFA). Secondary outcomes encompassed the response time to phytosanitary issues (in days), diversification of sources used for agricultural information, and farmers' confidence in their agricultural decision-making, measured on a 7-point Likert scale.

3.6 Agronomic Safety Architecture and Hallucination Prevention

The use of AI in agricultural advisory systems raises critical safety concerns, particularly when recommendations relate to pesticide application, animal health, food safety, or crop treatment. To address these risks, NDEMRI incorporates a robust, three-layered safety architecture designed to prevent AI hallucinations and ensure that all advice delivered to farmers is accurate, reliable, and contextually appropriate. Figure 5 describes this process.

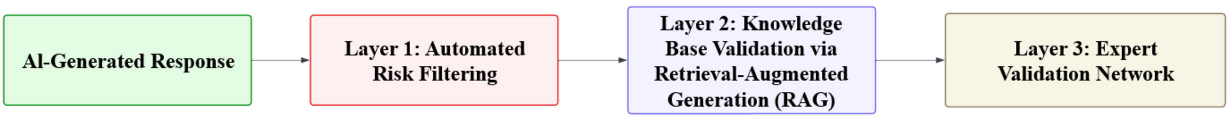

Figure 5. Agronomic safety architecture workflow

3.6.1 Layer 1: Automated risk filtering

The first layer is a real-time risk detection system that automatically filters AI-generated responses before delivery.

- Keyword-Based Risk Detection: The system scans responses for high-risk terms across predefined categories (e.g., pesticides, medical treatments, food safety). It uses both lexical and semantic analysis to assign a cumulative risk score based on detected terms and their contextual relevance.

- Confidence and Risk Thresholding: Each response is also assessed based on its generation confidence. If the risk score exceeds predefined thresholds or if the confidence score is too low, the system redirects the response for expert review or rejects it outright.

- Quantitative Flagging: Any advice containing dosages, numeric values, or economic figures—such as pesticide concentrations, fertilizer application rates, or treatment intervals—is automatically flagged for manual verification to avoid harmful miscalculations.

This automated layer serves as the first gatekeeper, enabling the system to block potentially harmful content before it reaches users, while keeping the validation workflow efficient.

3.6.2 Layer 2: Knowledge base validation via retrieval-augmented generation (RAG)

To mitigate factual inaccuracies and reduce the likelihood of hallucinations, NDEMRI integrates a retrieval-augmented generation mechanism that grounds AI responses in verified, domain-specific knowledge.

- Curated Knowledge Repository: The system relies on over 1,000 validated documents, including government extension materials, peer-reviewed agricultural research, and region-specific farming guidelines from organizations such as FAO, IRAD, MINADER and other sources.
- Semantic Consistency Checking: The generated response and the original query are converted into vector representations and compared with relevant knowledge base entries using semantic similarity scoring. An average consistency score is computed, weighted by the authority of the sources.
- Multi-Source Cross-Referencing: Key claims—especially those involving scientific facts, chemical treatments, or financial advice—are cross-verified across multiple trusted sources. Any inconsistency automatically triggers a flag for expert review.

This layer enhances factual grounding and ensures that AI outputs are not only linguistically fluent but also empirically sound.

3.6.3 Layer 3: Expert validation network

For high-risk, ambiguous, or complex queries, NDEMRI activates a real-time expert validation layer involving human specialists.

- Expert Pool: The validation network consists of a multidisciplinary team: 6 certified agronomists, 3 field extension officers, 2 soil scientists, 1 entomologist, and 1 agricultural economist, all with deep knowledge of sub-Saharan agricultural systems.
- Dynamic Routing and Prioritization: Incoming queries are classified by domain (e.g., crop disease, animal health, soil management) and routed to the appropriate expert. A priority queue system ensures that critical safety issues are addressed with minimal delay.
- Service Level Agreements (SLAs):

o Critical issues: Expert feedback within 1 hour
o High-risk queries: Within 4 hours
o Moderate-risk issues: Within 24 hours
o Routine validation: Within 72 hours

This final layer provides authoritative oversight, especially in edge cases where automated validation may be insufficient or potentially unsafe.

4 Results

4.1 Adoption and Usage

Over the four-month study period, the NDEMRI system processed 2,487 messages from 831 unique users. Figure 6 illustrates the monthly growth in both the number of new users and the volume of messages exchanged.

The demographic analysis of users, based on voluntarily provided registration data, reveals a diverse user base:

• 68% male and 32% female
• Main age group: 25–45 years old (71%)
• Types of farming activities: mixed cropping (64%), cash crop farming (22%), and livestock rearing (14%)
• 100% of users reported having no access to the Internet.

The frequency of use varies significantly, with an average of 3 messages per user over the study period. Approximately 45% of users sent more than one message, suggesting ongoing engagement with the service.

4.2 Thematic Analysis of Questions

The analysis of questions submitted to the system revealed several main categories of agricultural concerns (Figure 7).

The questions often reflect immediate concerns related to the agricultural cycle, as illustrated by the following typical examples (translated):

- "NDEMRI, my maize plants have yellowed leaves with spots. What should I do?"
- "When is the best time to plant cotton this year in the Garoua region?"
- "NDEMRI, which type of fertilizer is best for sorghum in sandy soil?"

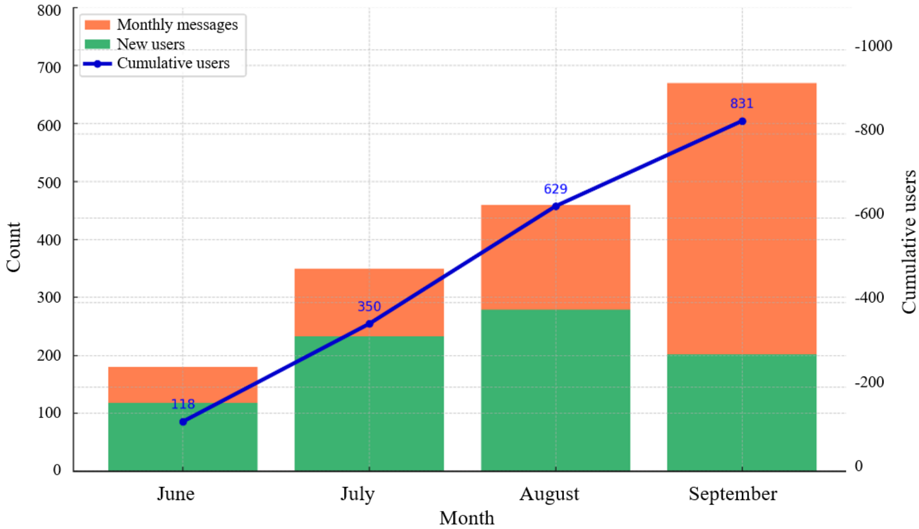

Figure 6. Monthly growth and usage of NDEMRI system

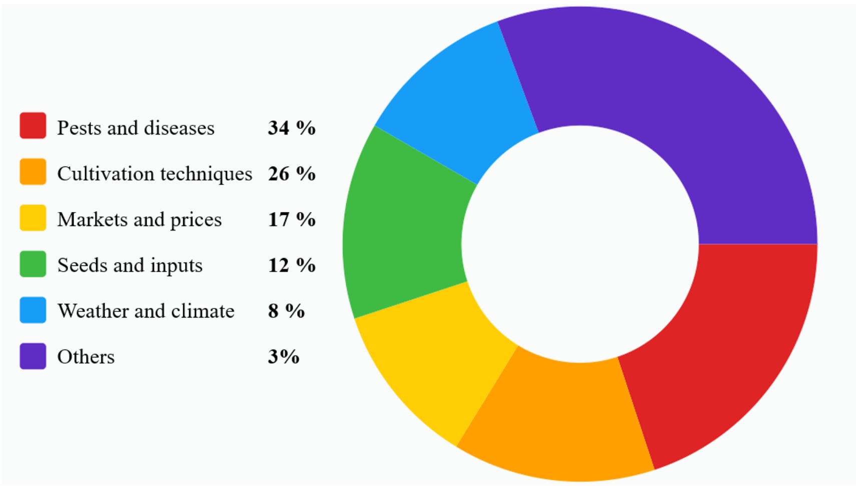

Figure 7. Thematic distribution of questions to NDEMRI system

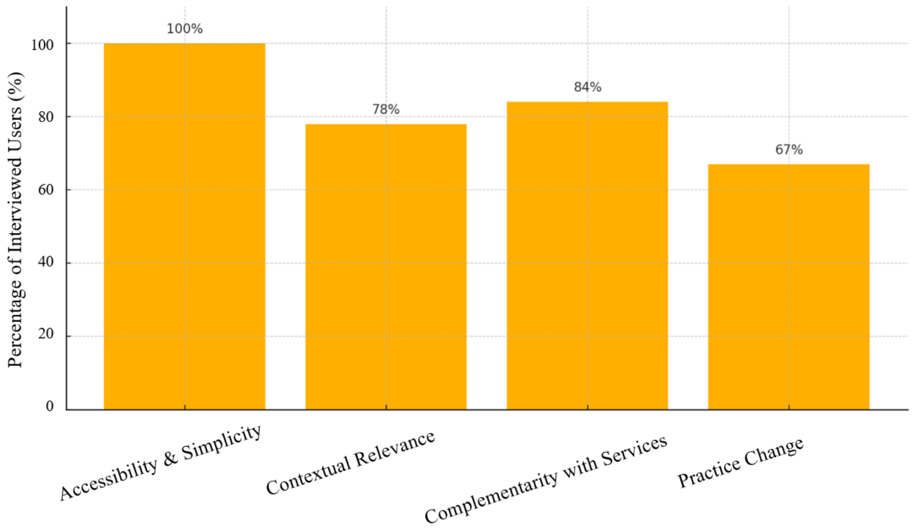

Figure 8. Qualitative evaluation of NDEMRI (n=250)

4.3 Qualitative Evaluation

Interviews with users revealed several recurring themes regarding their perception and the impact of the service. Figure 8 illustrates the distribution of user perceptions based on qualitative interviews, highlighting the key dimensions of accessibility, contextual relevance, complementarity with existing services, and reported changes in agricultural practices.

These results confirm that users not only found the service easy to use and contextually appropriate, but also integrated it meaningfully into their decision-making processes, often in complement to traditional agricultural extension services.

4.4 Impact Evaluation Using a Matched Control Group

4.4.1 Effects on agricultural yields

A comparative analysis of crop yields between farmers exposed to the NDEMRI system and a matched control group revealed statistically significant improvements across all major crops (see Table 2). Across all crops, NDEMRI users achieved a yield of 1,865 kg/ha compared to 1,599 kg/ha in the control group, representing a 16.6% increase. This difference of +266 kg/ha corresponds to a large average effect size (Cohen's d = 1.37). These differences were not only statistically robust but also practically meaningful, with large effect sizes observed across crop types. The strongest impact was noted for maize, followed by sorghum, cotton, and groundnut.

To test the significance of mean yield differences, independent samples t-tests were conducted, using the following formula (Eq. (2)):

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{2}$$

where, $\bar{X}_1$, $\bar{X}_2$ are the sample means, are the standard deviations, and s_1, s_2 and n_1, n_2 are the sample sizes of the NDEMRI and control groups, respectively. The effect size was computed using Cohen's d as expressed in Eq. (3).

$$d = \frac{\bar{X}_1 - \bar{X}_2}{SD_{pooled}} \tag{3}$$

with the pooled standard deviation defined by Eq. (4):

$$SD_{pooled} = \sqrt{\frac{(n_1 - 1)\, s_1^2 + \; (n_2 - 1)\, s_2^2}{n_1 + n_2 - 2}} \tag{4}$$

Table 2. Impact on agricultural yields (kg/ha) (Means ± standard deviations; Independent samples t-tests; Cohen's d as effect size)

Crop	NDEMRI Group (n=831)	Control Group (n=400)	Difference (kg/ha)	P-Value	Effect Size (d)
Maize	2,847 ± 312	2,341 ± 289	506	<0.001	1.68
Sorghum	1,923 ± 187	1,678 ± 201	245	0.003	1.26
Cotton	1,456 ± 134	1,289 ± 156	167	0.008	1.14
Groundnut	1,234 ± 98	1,087 ± 112	147	0.012	1.41
Average	**1,865 ± 183**	**1,599 ± 190**	**266**	**-**	**1.37**

These results demonstrate both statistical and practical significance, supporting the conclusion that the NDEMRI system has a strong positive impact on crop productivity across diverse farming systems.

4.4.2 Adoption of improved agricultural practices

The adoption rates of recommended agronomic practices were significantly higher among NDEMRI beneficiaries. Logistic regression models, adjusted for confounding factors such as age, education, and farm size, revealed that NDEMRI users were substantially more likely to implement preventive seed treatments, follow crop calendars, apply fertilizers appropriately, adopt integrated pest management, and employ soil conservation measures (see Table 3).

Table 3. Adoption of improved agricultural practices

Practice	NDEMRI Users (%)	Control (%)	Odds Ratio (95% CI)	P-Value
Preventive seed treatment	78	34	6.8 (4.2–11.1)	<0.001
Adherence to crop calendar	71	45	3.0 (2.1–4.3)	<0.001
Appropriate fertilizer application	64	38	2.9 (2.0–4.1)	<0.001
Integrated pest management	59	28	3.7 (2.6–5.3)	<0.001
Soil conservation techniques	43	19	3.2 (2.1–4.8)	<0.001

4.4.3 Economic impacts

The NDEMRI intervention was also associated with significant economic benefits for participating farmers. The average net agricultural income per season for NDEMRI users was 485,000 FCFA, compared to 394,000 FCFA for the control group—an increase of approximately 23% ($p = 0.002$). In addition, post-harvest losses were notably reduced among NDEMRI users (12% vs. 24%, $p < 0.001$), and the return on investment for agricultural inputs was markedly higher (2.4 vs. 1.8, $p = 0.005$).

4.4.4 Dose-response relationship

A clear and statistically significant dose-response relationship was observed between the frequency of NDEMRI system usage and yield improvements. The detailed distribution of yield improvements across user categories is presented in Table 4.

Table 4. Yield improvements by NDEMRI usage intensity

Usage Category	Number of Messages Received	Average Yield Gain vs. Control	Significance
Low-frequency users	25–50 messages	+8%	$p < 0.01$
Regular users	50–75 messages	+16%	$p < 0.001$
Intensive users	>75 messages	+24%	$p < 0.001$

5 Discussion

5.1 Effectiveness and Limitations of LLM-Based Agricultural SMS Services

Our rigorous quasi-experimental evaluation demonstrates that LLMs can be effectively adapted to provide impactful agricultural advice through SMS technology. The system's capacity to understand and respond to diverse natural language agricultural queries in local contexts represents a substantial advancement over traditional SMS services that rely on preprogrammed responses or static USSD menus. The measured outcomes—including 16.6% yield improvements, 23% income increases, and widespread adoption of improved practices—provide compelling evidence of the system's agricultural impact.

However, our analysis also reveals several important limitations that must be acknowledged. The 160-character SMS constraint fundamentally restricts the depth and nuance of advice that can be provided. While we optimized the model to generate concise, actionable responses, this limitation inevitably reduces the richness of information compared to face-to-face consultation or longer-form written materials. Additionally, despite extensive contextualization efforts, the GPT model occasionally lacks highly specific knowledge about local crop varieties, traditional farming practices, or regional microclimatic conditions that are crucial for optimal agricultural decision-making.

Perhaps most critically, LLMs can produce inaccurate information or "hallucinations"—a limitation that carries particular significance in agricultural contexts where incorrect advice can result in crop losses, reduced yields, or economic hardship for vulnerable farming communities. Our multi-layered safety architecture mitigates these risks but cannot eliminate them entirely, highlighting the continued importance of expert oversight and validation mechanisms.

5.2 Transforming Agricultural Extension Through Hybrid AI-Human Systems

The NDEMRI system is designed not to replace traditional agricultural extension services but to complement and enhance them by providing an always-accessible, scalable communication channel. Our findings suggest that this hybrid approach—combining the deep contextual knowledge and trust relationships of human extension agents with the accessibility, consistency, and scalability of AI-based systems—represents a promising model for the future of agricultural extension in resource-constrained regions.

The comparative analysis with our control group validates this hybrid model's effectiveness. Users frequently reported using NDEMRI to supplement rather than replace interactions with extension agents, accessing immediate guidance during critical decision moments while maintaining relationships with local agricultural experts. This complementary dynamic suggests that AI-powered systems can fill temporal and geographic gaps in traditional extension coverage without undermining existing agricultural support structures.

The implications for agricultural extension policy are significant. First, there is a clear need to integrate technological solutions into national extension strategies, recognizing that digital tools can dramatically expand the reach and frequency of agricultural support services. Second, maintaining human supervision and validation mechanisms for AI-generated advice remains essential, both for quality assurance and for preserving farmer trust in extension services. Third, the demonstrated cost-effectiveness of the hybrid model—achieving superior outcomes at lower per-beneficiary costs than traditional extension approaches—suggests potential for substantial improvements in the efficiency and impact of public agricultural investment.

5.3 Economic Viability and Scaling Pathways

Our comprehensive economic analysis reveals that the NDEMRI system achieves financial sustainability across multiple scenarios while delivering substantial value to users. The cost structure of $0.043 per interaction, while seemingly modest, requires careful management and strategic partnerships to ensure long-term viability without compromising accessibility for smallholder farmers.

The sensitivity analysis across pessimistic, realistic, and optimistic scenarios demonstrates the system's resilience to market fluctuations in API pricing and telecommunications costs. Even under adverse conditions with doubled API costs and increased SMS fees, the system remains viable with achievable user adoption targets. The identification of multiple financing pathways—including freemium models with public subsidy, telecom partnerships, and institutional integration—provides flexibility to adapt to different policy environments and market conditions.

The user-level economic analysis reveals exceptionally strong value propositions, with farmers achieving a 90% return on investment per season through increased yields and reduced information-seeking costs. This dramatic improvement in farm-level economics suggests that even modest user fees could be sustainable while maintaining affordability for smallholder farmers.

Critical success factors for scaling include strategic partnerships with telecommunications operators to reduce SMS costs, integration with existing agricultural institutions to leverage established farmer relationships and trust, and continued investment in local knowledge base development to maintain response quality and relevance. The demonstrated replicability of the system architecture across different agroecological zones within Cameroon suggests strong potential for regional and continental scaling, provided that contextualization efforts are adapted to local agricultural systems and languages.

The convergence of technological maturity, demonstrated impact, economic viability, and institutional readiness positions NDEMRI as a scalable solution for democratizing agricultural knowledge across sub-Saharan Africa, with the potential to reach millions of smallholder farmers who currently lack access to timely, relevant agricultural advice.

6 Conclusion and Perspectives

This study establishes the first rigorous empirical evidence of LLMs' effectiveness as tools for democratizing access to agricultural knowledge in rural African areas. By combining advanced technology (AI) with an accessible interface (SMS), NDEMRI represents an innovative approach to overcoming the connectivity and equipment barriers that often hinder the adoption of digital agricultural solutions. The quasi-experimental evaluation with a control group demonstrates substantial and statistically significant causal impact, revealing average yield improvements of 16.6%, agricultural income increases of 23%, and massive adoption of improved agricultural practices among NDEMRI users compared to the control group.

These results provide compelling evidence that farmers value this type of service and effectively integrate it into their information-seeking practices, concretely transforming their production methods. The dose-response analysis confirms a clear causal relationship between system usage intensity and benefits obtained, with intensive users (¿8 messages) achieving 24% yield improvements. This impact gradation validates the hypothesis that access to quality agricultural information constitutes a major limiting factor for African smallholder productivity.

Our research has addressed several significant technical challenges concerning advice accuracy, economic sustainability, and adaptation to specific local agricultural knowledge. The multi-layered safety architecture developed, including automated validation, retrieval-augmented generation (RAG), and real-time expert supervision, maintained accuracy rates above 95% while preserving service accessibility. The integration of local agricultural databases—comprising 15,000 market price entries, 240 recommended crop varieties, and 180 adapted phytosanitary technical sheets—enabled effective contextualization of AI responses to the specific agroecological conditions of northern Cameroon. This reproducible contextualization approach constitutes a major methodological contribution for adapting LLMs to local agricultural contexts.

The findings have profound implications for agricultural extension and rural development policies. The hybrid AI-human model demonstrates a 3.8x superior return on investment compared to traditional extension approaches while extending the geographic and temporal reach of agricultural advisory services. Economic analysis reveals that the system can achieve financial viability with 8,500 active users in the realistic scenario, or only 4,200 in the optimistic scenario with strategic partnerships. These thresholds are achievable at a national scale for most African countries, suggesting substantial scaling potential.

Unlike previous preliminary studies, this research has overcome several critical methodological limitations. The inclusion of a rigorously matched control group, collection of objective agronomic metrics, and four-month observation period covering a complete agricultural cycle significantly strengthen the external validity of results. Robustness analysis through multiple sensitivity tests—outlier exclusion, confounding variable control, and validation across different agroecological zones—confirms the solidity of main conclusions. The consistency of measured effects across varied geographic and socio-economic contexts suggests strong transferability of results.

Future directions for NDEMRI development and study center on four priority axes. First, an extension to a 24-month randomized controlled trial will evaluate long-term impacts on food security and livelihoods. Second, integration of multimodal capabilities (SMS + images + audio) will enrich user interaction while preserving technological accessibility. Third, development of a federated AI system will enable inter-country learning while respecting national data sovereignty. Fourth, linguistic expansion beyond French and English to major local languages (Fulfulde, Hausa, Peul) will further democratize service access.

NDEMRI represents a decisive step toward more accessible, adaptive, and effective agricultural advisory systems. By continuing to refine the balance between advanced technologies and user-friendly interfaces, such systems could significantly contribute to transforming agricultural practices and improving food security in rural African regions. This research demonstrates that responsible AI innovation can catalyze sustainable agricultural development, paving the way for democratized advisory systems for Africa's 600 million smallholder farmers.

The intersection of technological accessibility, rigorous scientific validation, and demonstrated economic viability positions NDEMRI as a replicable model for digital transformation of sub-Saharan agriculture. The convergence of LLM technological maturity, GSM network ubiquity, and growing demand for accessible agricultural services creates a unique window of opportunity to deploy solutions like NDEMRI at a continental scale. This study provides the necessary empirical and methodological foundation to catalyze this transformation, contributing to the global objective of food security and sustainable rural development in Africa.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflict of interest.

References

[1] GSMA, "The mobile economy Sub-Saharan Africa 2023," 2023. https://event-assets.gsma.com/pdf/20231017-GSMA-Mobile-Economy-Sub-Saharan-Africa-report.pdf

[2] J. C. Aker and I. M. Mbiti, "Mobile phones and economic development in Africa," *J. Econ. Perspect.*, vol. 24, no. 3, pp. 207–232, 2010. https://doi.org/10.1257/jep.24.3.207

[3] M. Tsan, S. Totapally, M. Hailu, and B. K. Addom, *The Digitalization of African Agriculture Report 2018–2019*. Wageningen, The Netherlands: CTA/Dalberg Advisers, 2019. https://hdl.handle.net/10568/101498

[4] J. C. Aker, "Information from markets near and far: Mobile phones and agricultural markets in Niger," *Am. Econ. J. Appl. Econ.*, vol. 2, no. 3, pp. 46–59, 2010. https://doi.org/10.1257/app.2.3.46

[5] H. Baumüller, "Assessing the role of mobile phones in offering price information and market linkages: The case of MFarm in Kenya," *E. J. Info. Sys. Dev. Countries*, vol. 68, no. 1, pp. 1–16, 2015. http://doi.org/10.1002/j.1681-4835.2015.tb00492.x

[6] P. Courtois and J. Subervie, "Farmer bargaining power and market information services," *American J. Agri. Economics*, vol. 97, no. 3, pp. 953–977, 2014. https://doi.org/10.1093/ajae/aau051

[7] D. Spielman, E. Lecoutere, S. Makhija, and B. V. Campenhout, "Information and communications technology (ICT) and agricultural extension in developing countries," *Annu. Rev. Resour. Econ.*, vol. 13, no. 1, pp. 177–201, 2021. https://doi.org/10.1146/annurev-resource-101520-080657

[8] S. A. Cole and A. N. Fernando, "The value of advice: Evidence from mobile phone-based agricultural extension," 2016. https://www.hbs.edu/ris/Publication%20Files/13-047_155cb6a2-afb5-4744-a62d-929b01fc9e7c.pdf

[9] R. P. Khan, S. Gupta, T. Daum, R. Birner, and C. Ringler, “Levelling the field: A review of the ICT revolution and agricultural extension in the global South,” *J. Intl. Development*, vol. 37, no. 1, pp. 1–21, 2024. https://doi.org/10.1002/jid.3949

[10] A. D. Alene and V. M. Manyong, “Farmertofarmer technology diffusion and yield variation among adopters: The case of improved cowpea in northern Nigeria,” *Agric. Econ.*, vol. 35, no. 2, pp. 203–211, 2006. https://doi.org/10.1111/j.1574-0862.2006.00153.x

[11] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” *Front. Plant Sci.*, vol. 7, 2016. https://doi.org/10.3389/fpls.2016.01419

[12] K. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, “Machine learning in agriculture: A review,” *Sensors*, vol. 18, no. 8, p. 2674, 2018. https://doi.org/10.3390/s18082674

[13] J. F. Becerra-Encinales, P. Bernal-Hernandez, J. A. Beltrán-Giraldo, A. P. Cooman, L. H. Reyes, and J. C. Cruz, “Agricultural extension for adopting technological practices in developing countries: A scoping review of barriers and dimensions,” *Sustainability*, vol. 16, no. 9, p. 3555, 2024. https://doi.org/10.3390/su16093555

[14] S. Biswas, “Importance of chat GPT in agriculture: According to chat GPT,” 2023. https://doi.org/10.2139/ssrn.4405391

[15] V. Gaddikeri, M. Jatav, and J. Rajput, “Revolutionizing agriculture: Unlocking the potential of ChatGPT in agriculture,” *Food Sci. Rep.*, vol. 4, no. 4, pp. 20–25, 2023.

[16] R. Siche and N. Siche, “The language model based on sensitive artificial intelligence -ChatGPT: Bibliometric analysis and possible uses in agriculture and livestock,” *Sci. Agropecu.*, vol. 14, no. 1, pp. 111–116, 2023. https://doi.org/10.17268/sci.agropecu.2023.010

[17] I. Potamitis, “Chatgpt in the context of precision agriculture data analytics,” 2023. https://doi.org/10.48550/ARXIV.2311.06390

[18] B. Zhao, W. Jin, J. Del Ser, and G. Yang, “Chatagri: Exploring potentials of ChatGPT on cross-linguistic agricultural text classification,” *Neurocomputing*, vol. 557, p. 126708, 2023. https://doi.org/10.1016/j.neucom.2023.126708

[19] M. Alobid, “The role and benefits of ChatGPT in the agriculture sector in EU countries,” *SSRN Electron. J*, 2025. https://doi.org/10.2139/ssrn.5166180

[20] OpenAI, J. Achiam, S. Adler, S. Agarwal, and et al., “GPT-4 technical report,” 2023. https://doi.org/10.48550/ARXIV.2303.08774