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BRIDGING THE AGRICULTURAL KNOWLEDGE GAP: GENERATIVE AI AND RAG-DRIVEN CONVERSATIONAL SYSTEMS FOR SMALLHOLDER FARMERS

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ABSTRACT

Smallholder farmers, who constitute the backbone of global food security, face persistent challenges in accessing timely, localized, and actionable agricultural information. This study investigates the development and deployment of Farmer.Chat, a scalable, AI-powered, voice-enabled agricultural chatbot designed to bridge this critical knowledge gap. The system leverages Generative AI, Natural Language Processing (NLP), and Multi-Layer Perceptron (MLP) neural networks, along with Retrieval-Augmented Generation (RAG), to process structured and unstructured agricultural datasets including soil profiles, climate records, and crop-specific databases. Farmer.Chat delivers real-time, personalized, multilingual, and context-aware recommendations on crop management, pest control, weather prediction, and market insights. A field deployment across Kenya, India, Ethiopia, and Nigeria engaged over 15,000 farmers, spanning more than 40 value chains, and addressed 300,000+ user queries in six languages through a voice assistant interface that ensures accessibility for low-literacy users. Analysis of adoption patterns and outcomes reveals improved crop yields, greater uptake of sustainable practices, and measurable reductions in input waste and operational costs. These findings suggest that AI-powered conversational agents can transform agricultural extension services, enhance decision-making, and advance equitable access to information in resource-constrained rural settings.

Keywords: Smallholder Farmers, Global Food Security, Agricultural Extension Services, Generative AI, NLP, Crop Management.

1. INTRODUCTION

Global food security depends heavily on smallholder farmers. Nonetheless, they frequently encounter ongoing difficulties in obtaining timely, localized, and useful agricultural information. Their productivity, profitability, and capacity to implement sustainable methods are severely constrained by these issues, particularly in low- and middle-income nations, where small-plot farming conditions differ greatly. Farmers are unable to appropriately assess risks and make well-informed decisions in the absence of trustworthy, plot-specific counsel, which eventually results in lower yields and uncertain revenues. To close this gap, agricultural extension services were created to spread best practices for farming and agronomic expertise. However, these services have historically relied on human extension agents who deal with resource limitations, high farmer-to-agent ratios, and logistical challenges. Providing consistent, tailored guidance is still very difficult in areas with high levels of crop, climate, and geographic variation, such as sub-Saharan Africa. Equal access to agricultural assistance is further hindered by factors like gender inequality, low literacy rates, and a lack of digital infrastructure. Information and communication technologies (ICTs), such as mobile apps, video tutorials, and SMS notifications, have updated agricultural outreach in recent years. Despite their benefits, these methods often depend on human involvement and fixed materials, which limits their ability to scale and adapt to changing agricultural conditions. Conversational AI systems that can engage in real-time, data-driven conversations and consider the language, education, and culture of rural farmers are becoming more important.

Problem Scope: Most chatbot systems today are either rule-based or depend heavily on detailed scripts and human oversight. Because of these limitations, they struggle to address the complexity and unpredictability of smallholder farming. Additionally, traditional systems often don't support multiple languages or can't manage unstructured data, such as photos uploaded by farmers, voice questions, and real-time weather information. These gaps make it harder for farmers with low digital skills, especially women and underserved groups, to adopt the technology. A promising alternative is voice-activated, AI-powered chatbots that use generative AI and natural language processing (NLP).

However, scaling up these solutions while keeping them relevant and trustworthy requires a mix of user-focused design, locally gathered knowledge, and robust machine learning models.

2. LITERATURE REVIEW

The use of conversational AI in agriculture has opened up opportunities to improve the effectiveness and reach of agricultural extension services. This is especially true for smallholder farmers in resource-limited areas. Recent studies have offered important insights into how natural language processing (NLP), multilingual support, voice-enabled chatbots, and AI-IoT integration are changing the digital agriculture landscape.

2.1 Accessible Voice-Based Chatbots

According to Patel et al. (2019), voice-activated agricultural chatbots are becoming more important in rural areas, especially where literacy is low and technical challenges are significant. Their research showed that by offering real-time information on crop diseases, pest control, and weather forecasts, voice-based systems reduced the time farmers spent looking for agricultural solutions and improved overall production. In rural India, where cell phone use is increasing despite lower literacy rates, the authors concluded that these systems are very valuable[01][02].

2.2 Natural Language Processing (NLP) for Agricultural Queries

Busemeyer et al. (2020) looked at how NLP technologies improve chatbot performance in agriculture. Their case study showed that NLP-enabled systems can manage complicated questions about crop management, soil health, and pest identification, especially when tailored to local dialects and agricultural terms. However, the study also pointed out the difficulties of training NLP models to understand everyday language and multiple languages, which are common in farming communities [03].

2.3 User-Centered Design and Interface Simplicity

Ghosh et al. (2020) examined user-centric design for agricultural voice assistants. Their study emphasized the need for intuitive, easy, and conversational interfaces, particularly for areas with poor Internet connectivity and digital literacy. Farmers preferred to use hands-free operation through voice commands, as this enabled them to access information while engaging in farm work. This research recommends systems that support regional languages, accents, and dialects to increase adoption [04].

2.4 Chatbots in Developing Countries

In a Southeast Asia study, Hassan and Kadir (2020) discovered voice-enabled chatbots to democratize agricultural information by providing readily available advice on crop rotation, water and pest management. They recorded decreased crop losses through timely chatbot responses, supporting the potential of such technology in substituting traditional, time-consuming, word-of-mouth support systems in underserved areas.

2.5 AI and IoT Integration for Precision Agriculture

Singh et al. (2021) explored the synergistic use of AI and IoT in chatbot systems to enable precision farming. This study integrated voice assistants with real-time sensors for soil moisture, temperature, and weather, offering farmers dynamic insights into irrigation, fertilization, and pest control. These tools significantly improve resource efficiency and crop yields, and their voice-enabled nature makes them usable even during fieldwork.

2.6 Machine Learning for Pest and Disease Detection

Srivastava et al. (2021) focused on ML-powered chatbots for pest and disease classification. Their system processed voice inputs from farmers describing symptoms and returned context-specific pest-management strategies. This study demonstrated the chatbot’s ability to detect common agricultural threats and offer timely solutions, highlighting the importance of localized data understanding and real-time feedback.

2.7 Comparative Effectiveness of AI Chatbots

Rani et al. (2021) conducted a comparative study on various AI-driven agricultural chatbots, evaluating their impact on decisions related to planting schedules, pest control, and fertilization. The results showed that such systems enhanced decision-making speed, particularly during pest outbreaks, by providing real-time localized recommendations tailored to specific crop and soil conditions.

2.8 Multilingual Capabilities for Wider Adoption

Verma et al. (2021) addressed the issue of linguistic diversity in farming populations. They developed a multilingual chatbot that is capable of understanding and responding in multiple languages. A significant increase in adoption was observed when farmers could interact in their native language. However, limitations in accent recognition and speech-to-text conversion for less-documented dialects pose technical challenges.

2.9 Voice Assistants for Irrigation Management

Roy and Bhattacharya (2021) evaluated the application of voice-driven irrigation management systems. These tools allow farmers to access real-time data from IoT-integrated soil moisture sensors, improving irrigation decisions and reducing water waste. The authors noted that such systems are particularly beneficial for managing large or fragmented plots, where manual monitoring is impractical.

2.10 Sustainability and Eco-Friendly Practices

Choudhary et al. (2021) explored how voice-enabled assistants contributed to sustainable farming in terms of their capabilities of providing real-time information on reducing chemical inputs and water usage and using alternatives for chemical approaches to organic practices. This ability provides farmers with information to be more environmentally sustainable while balancing productivity.

2.11 Smart Farming with Historical Data and AI

Mujtaba et al. (2022) contributed to the smart farming literature through the implementation of AI, historical data, and voice-enabled interfaces. Their research suggests that these systems can increase farm profitability through data-driven predictions and resource use efficiencies. The voice interaction element allowed farmers with little digital literacy to access these advanced tools. The literature, as a whole, suggests that voice-activated, AI-powered chatbots are becoming increasingly important in transforming agricultural extension services. Studies seem to revolve around topics such as adaptability to local languages and farming specifics, accessibility for low literacy users, and integration with IoT and machine learning for improved decision-making. Nonetheless, there are significant gaps in various areas, such as scalable implementation strategies, speech recognition for unusual dialects, and conversational natural language processing.

2.10 Study Objectives:

This study aims to bridge the digital and informational divide in agriculture through Farmer.Chat, a generative AI-driven, multilingual, and multimodal chatbot designed to provide on-demand agricultural support. The core objectives of this study are as follows:

1. To design and deploy an AI-based agricultural advisory platform that delivers scalable, voice-enabled, and context-aware assistance to smallholder farmers.

2. To evaluate the effectiveness of Farmer.Chat in improving accessibility, trust, and user engagement—particularly among low-literacy and underserved farming communities.

3. To assess the impact of the platform on real-world agricultural outcomes, such as yield improvement, input efficiency, and sustainable practice adoption, with a focus on its implementation in Kenya.

3. METHODOLOGY

To develop and assess a voice-enabled agricultural chatbot specifically for smallholder farmers, this study used a multi-layered technical approach that combined Artificial Intelligence (AI), Natural Language Processing (NLP), and image-based diagnostic capabilities. The technique includes system design, data collection, algorithm implementation, and assessment using both qualitative and quantitative metrics.

3.1 System Architecture

The proposed system, Farmer.Chat, consists of the following major components.User Interface (UI): Multilingual and voice-enabled interface accessible through mobile apps, messaging platforms (e.g., WhatsApp), and SMS for low-bandwidth environments.

3.2 Algorithmic Framework

The methodology relies on a hybrid AI framework that combines supervised machine learning, deep learning, and generative AI techniques. The detailed algorithmic flow is as follows:

Algorithm: Context-Aware Agricultural Advisory System

Input: Voice query or text input from user,Optional: Image of crop/disease,Metadata: Location, language, crop typeOutput: Personalized, real-time agricultural recommendation,

Step 1: Input Handling 1.1. Convert voice input to text using Speech-to-Text API (Google, Whisper)

Step 2: Intent Classification and Entity Extraction 2.1. Use NLP model (BERT) to classify user intent (e.g., pest query, irrigation advice, disease diagnosis)

Step 3: Optional Image Analysis 3.1. If image is provided, preprocess it (resize, normalize)Convolutional Neural Network (CNN) trained on crop disease dataset

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Step 4: Knowledge Retrieval (RAG) 4.1. Use intent and entities to formulate query Generative Language Model (e.g., GPT-3.5 or LLaMA) for final answer generation

Step 5: Response Generation 5.1. Generate answer in natural language, adjusted to literacy level

Step 6: Feedback and Logging 6.1. Collect user satisfaction rating and feedback

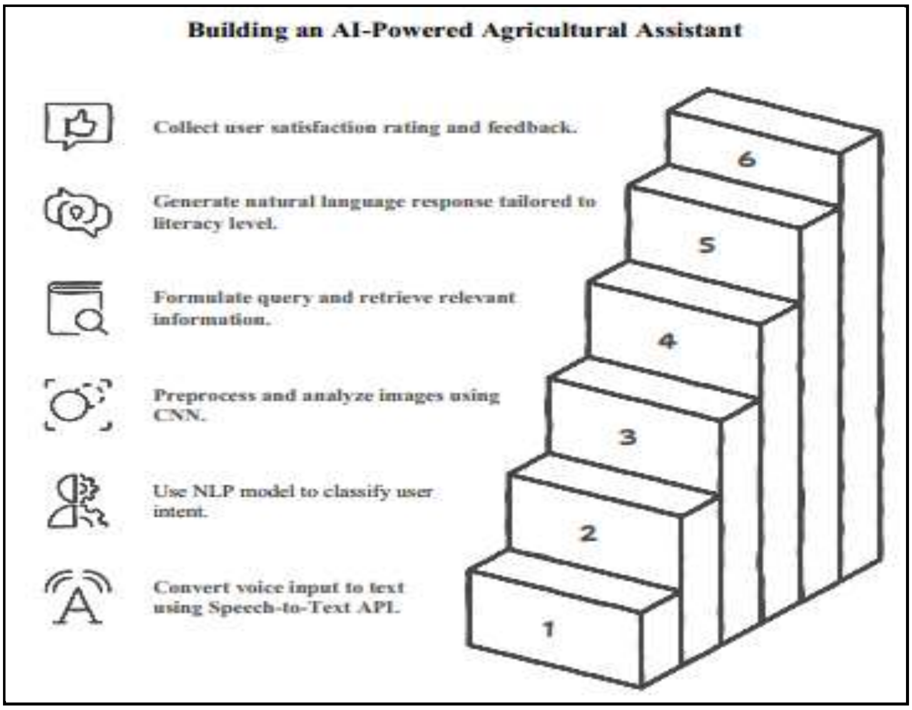

Fig 1: Steps of Agricultural Advisory System

3.3 Model Training and Data Sources

Training Data for NLP: Agricultural extension documents, chatbot transcripts, FAQs from agricultural departments (e.g., FAO, ICAR, and ICRISAT).Training Data for CNN: Public and proprietary datasets of crop diseases (e.g., PlantVillage, iSDA).Language Model Fine-Tuning: A fine-tuned LLM (e.g., GPT-NeoX) on agriculture-specific corpora to ensure contextual relevance and accuracy. Multilingual Corpus: Translated agricultural texts and crowd-sourced queries in local languages (Swahili, Hindi, Luganda, etc.).

3.4 Deployment Environment

The chatbot is hosted in a cloud-native architecture (AWS/GCP) and uses serverless functions to scale with the query volume. The models were deployed via APIs with fallback redundancy for high availability. For edge regions with limited connectivity, the system uses lightweight versions (e.g., BERT-Tiny and MobileNet) and offline voice kits.

4. RELATED WORK

In this section, we review research on (1) Agricultural Extension Services and ICT Interventions, (2) Chatbots and Conversation Agents , and (3) Generative AI in Agriculture, thus contextualizing the key novelty of Farmer.Chat.

4.1 Agricultural Extension Services and ICT Interventions

Traditional agricultural extension services are essential for disseminating knowledge to farmers. However, in many low- and middle-income countries, they face significant challenges, such as limited reach due to an insufficient number of extension agents. In Kenya, for example, the agent-to-farmer ratio is estimated at 1:1000 according to government reports (NASEP, 2012 [13]), but it can be as high as 1:4,000, far below the recommended ratio of 1:400. Additionally, these services tend to be top-down, limiting farmer inputs and reducing engagement. While peer-learning models, such as farmer field schools, aim to address these gaps, they often face resource limitations and inconsistent results due to varying farming contexts, such as soil, climate, and crop variety.

4.2 Chatbots and Conversation Agents in Agriculture

Chatbots and conversational agents are increasingly used in agriculture to provide accessible information through natural language interactions. Projects like Hello Tractor and Avaaj Otalo offer real-time advice on topics such as weather, pest control, and farming techniques via voice or text systems.Although rule-based chatbots are useful for structured, repetitive tasks, they struggle with complex, dynamic queries that require context awareness. Systems such as Avaaj Otalo handle voice queries but are limited in their ability to adapt to evolving agricultural needs. Similarly, FarmChat faces challenges in offering personalized advice due to variables like soil type, climate, and crop variety, and most traditional chatbots lack real-time updates and access to diverse data sources, reducing their effectiveness in dynamic agricultural environments.In contrast, AI-driven chatbots use machine learning and natural language processing (NLP) to deliver flexible, personalized, and data-driven responses. Studies have shown that AI systems outperform rule-based chatbots in terms of user satisfaction, contextual understanding, and scalability. AI-driven chatbots also adapt to real-time data and provide dynamic and personalized advice. Recent studies have highlighted AI's ability of AI to integrate diverse data sources to address complex agricultural needs.

Farmer.Chat builds on these advancements by leveraging AI models to offer personalized and real-time recommendations based on dynamic and context-specific data. Unlike traditional chatbots, Farmer.Chat adapts to changing agricultural conditions and provides tailored advice to farmers.

4.3 Generative AI in Agriculture

Advancements in generative artificial intelligence (AI), particularly large language models (LLMs) such as GPT-3 and GPT-4, are transforming agricultural knowledge accessibility, especially in low-resource settings. Projects like Kisan. AI has deployed LLMs to offer real-time advice on crop management and pest control. However, these systems face challenges in adapting to diverse agricultural ecosystems because of limited knowledge bases and difficulties in ingesting non-digital agricultural information. Additionally, the lack of robust multilingual support and inability to handle multimodal inputs, such as images and audio, further restrict their usefulness in rural contexts.

Most existing LLM-based agricultural chatbots focus on a narrow range of crops and regions, neglecting smallholder farmers' complex needs. Their inability to integrate localized weather and soil data reduces their precision in providing actionable information. Farmer.Chat addresses these limitations by supporting multiple crops, integrating real-time weather and soil data, and delivering personalized recommendations. Its multilingual and multimodal capabilities (audio, image, and video) make it accessible to low-literacy users, which is crucial in rural settings. Using Retrieval-Augmented Generation (RAG) for structured and unstructured data, Farmer.Chat enhances trustworthiness and precision.

Finally, designing AI-driven tools for low-literacy, resource-constrained populations requires intuitive and culturally sensitive interfaces. Prior studies have demonstrated the effectiveness of voice-based systems and image-based interfaces in increasing engagement. Furthermore, several studies highlight the importance of culturally relevant, trust-building designs for sustainable use. Jackson et al. and Sambasivan et al. stressed the need for AI tools to align with local practices and function well in resource-limited environments. Dell et al. underscore offline functionality, while Amershi et al. advocate for clear feedback and user control. These insights shape the design of Farmer. Chat, ensuring personalized, accessible, and context-aware support for low-literacy farmers.

5. RESULT

5.1 Yield responses with the Virtual Agronomist App Version

Yield responses to the Virtual Agronomist app version were encouraging, with mean yield increases of 1.4- to 1.9-fold compared to the farmer practice (Table 4). The profits and fertilizer rates used by the control farmers were not recorded in these earlier studies. The yields in the Virtual Agronomist plots are often constrained by management factors. In Tanzania, VA yields were linearly related to plant population: Yield (t/ha) = 0.70 (SE=0.03) * plant population (plants m-2), where plant population ranged from 1.6 to 4.6 plants m-2. With rice in Tanzania, there was variation in the degree to which farmers followed the recommended nutrient plan, with some farmers not applying any basal fertilizer at all, and yields were related to the amount of basal fertilizer applied: Yield (t/ha) = 5.6 (SE=0.4) + 0.012 (SE=2E-3) * basal fertilizer rate (kg/ha), where the basal fertilizer rate ranged from 0 to 341 kg/ha. In Uganda, VA yields were also linearly related to plant population: Yield (t/ha) = 0.32 (SE =0.03) * plant population (plants m-2), where plant population ranged from 1.3 to 8.7 plants m-2. These relationships suggest that when these management factors are optimal, VA yields are several-fold higher than FP yields.

Table 5.1.1: Grain yield response using Virtual Agronomist app compared with farmer practice

	Sunflower Tanzania	Lowland rice Tanzania	Maize Côte d'Ivoire	Sorghum Uganda
Mean yield (t/ha) FP	0.6	5.2	1.2	1
Mean yield (t/ha) VA	1	7.9	1.7	1.9
Number of farms	41	55	116	30
Pooled SE (t/ha)	0.034	0.207	0.12	0.174

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P<F treatment effect	<0.001	<0.001	0.008	<0.001
VA/FP yield	1.7	1.5	1.4	1.9

FP = Farmer practice; VA = Virtual Agronomist. The mean yields were block-adjusted.

5.2 Uptake of Virtual Agronomist Copilot

The iSDA introduced the Virtual Agronomist copilot to multiple countries (Table 5) using different approaches. The lead farmer model in Uganda and Kenya was primarily implemented by iSDA field staff. In Zambia, field agents were recruited through a partnership between a policy think tank and the Ministry of Agriculture's extension services. In Nigeria, deployment is managed by an aggregator who signed a public-private partnership with the Niger State Government. Some clients who have registered farmers through their own system have requested the issuance of nutrient management plans only without using the chatbot, which the iSDA has accommodated using the geographical coordinates of the fields. By February 17, 2025, over 100,000 plots were registered, and over four million individual messages were received from farmers.

Table 5.2.1: Virtual Agronomist copilot activities by country and crop (17.02 2025)

Country	Crop	Number of lead farmers	Number of famers	Number of nutrient plans
Kenya	Maize	3,559	65,308	74,147
Kenya	Rice	Na	416	453
Kenya	Coffee	Na	4,213	5,003
Malawi	Maize	195	642	769
Uganda	Maize	807	13,845	20,731
Uganda	Rice	Na	559	758
Uganda	Coffee	Na	785	1,192
Zambia	Maize	144	1,543	1,553
Total		5,035	87,311	1,04,606

na = not available

Based on the current data (Table 5.2.1), a lead farmer managed an average of 17 plots. On average, each farmer had 1.2 plots registered with a Virtual Agronomist. Ultimately, the intended method of spreading Virtual Agronomist is via lead farmer to lead farmer "referrals. This allows farmers to share the Virtual Agronomist phone number and train one another so that the spread is not hampered by central training capacity. This approach is gaining traction; in the 2025 season in Bulambuli, Uganda, 272 lead farmers have been registered via referrals versus 162 without referrals. Lead farmers trained by the iSDA registered 13,159 plots; therefore, 43% of the plots were registered by farmers not trained by the iSDA.

Rapid spontaneous uptake occurred in Kericho County (Figure 7). According to the 2019 Kenya Population and Housing Census, the total number of farmers with registered plots was 52,578, compared with 150,625 farming households, of which 67,739 were subsistence farmers (54). The estimated penetration of the county's maize farmer population was approximately 78%. A local agent in Kericho, the Virtual Agronomist, was deployed in partnership with seven coffee cooperatives in Kenya through a local agent in Kericho. This collaboration provided over 5,000 coffee farmers in Kericho with tailored agronomic advice, with each farmer paying for the service provided. The dynamics of tool usage are illustrated for the September 2024 – January 2025 season in Bulambuli, Uganda (Figure 8). The farmers predominantly grew maize and sunflowers. Tool usage generally follows the cropping calendar; plot registration, nutrient plan generation, and planting date recording are performed early in the season. Emergence checks and pest and disease scouting are conducted while the crop is growing, and harvest monitoring is completed after the harvest.

The uptake of Virtual Agronomist tools in Bulambuli was strong. Of the 7,571 registered plots, 98% generated a nutrient management plan, 65% recorded planting dates, 69% conducted emergence scouting, and 81% reported harvesting data. The dashboard results also indicated that farmers frequently used plant health scouting tools, primarily for monitoring pests and diseases. These uptake rates reflect strong farmer engagement and seamless integration of digital agronomic support systems. The results demonstrated active participation in key stages of the crop cycle, enabling farmers to enhance their agronomic practice. Overall, these trends suggest that farmers are beginning to recognize the value of Virtual Agronomist tools and actively incorporate them into their daily activities.

5.3 Delivery Costs

The marginal cost of delivery is currently approximately $1.50 per plot per season and can be separated into technology and incentive costs. Focusing first on the technology costs, our marginal cost of delivery is approximately $0.04 per plot per season. Most of this cost is due to the use of the OpenAI API. During 2024, we were able to significantly reduce AI costs, predominantly because of selecting a price/performance optimal model version of ChatGPT (gpt3.5-turbo) and reengineering prompts to use roughly 10 times fewer tokens during each API call. WhatsApp messages are generally charged per 24-hour conversation, meaning that a lead farmer can serve many farmers within the same time frame. Central technology costs (database hosting and serverless functions) cost $12 per day at the current scale. The total technology cost is estimated at less than $0.20 per plot per season.

Incentive costs were set at approximately $1 per plot per season, as outlined in Section 4, with incentives spread throughout the season to encourage engagement beyond the nutrient plan and planting. With the additional 20% referral incentive and allowing for transaction costs incurred via mobile money payments, the total incentive cost is below $1.30 per plot, per season. As this marginal cost of delivery is dominated by incentive costs, a clear path to significant cost reduction is in the combination of (1) encouraging an increasing number of farmers to use the system directly as connectivity allows, reducing the need for incentives, and (2) bundling the system with other initiatives where lead farmers are already incentivized to help neighboring farmers. Farmers who grow high-value crops pay for the service directly at a rate of $3-$4 per plot per season depending on the crop and location, and the subsequent profit can pay for the service of one or two farmers growing lower-value crops. In practice, we observed a ratio of 1:5 paying vs. free-at-point-of-use farmers, so we believe that any cross-subsidy would be limited due to insufficient farmer numbers in higher value chains.

5.4 Farm level Impacts of Copilot

The impact of farm level on yield, profit, and farmers' quality of agronomic management was assessed through (1) retrospective cohort studies and (2) mining chatbot data. In retrospective studies, a random sample of approximately 100 farmers practicing Virtual Agronomist per location and crop was compared with a similar sample of nearest-neighbor farmers who did not use Virtual Agronomist (control of farmer practice). A questionnaire was administered to both groups of farmers to collect data on yield, expenditure, management practices, and yield-limiting factors. The plot areas were recorded using a GPS. Chatbot data provide a large sample of thousands of plots, providing information on farmers' existing soil and crop management practices, and yield-limiting factors. Preliminary results of retrospective studies on rice in Kenya (55) and maize in Uganda (56) will be reported in a subsequent publication, but generally validate the positive outcomes obtained with the app version of the Virtual Agronomists. These early indications are discussed in the next section in terms of the factors that drive profits.

Examples of information that can be mined from chatbot data are presented in Table 6. In this cohort, the average ratio of farmers to lead farmers was 66. The high number of emergence checks and harvest monitors is encouraging. The median plot sizes are small, and maize has low input characterized by a high frequency of intercropping, continuous maize cropping, and relatively low yields and profit. The frequency of poor emergence indicates a significant problem in crop establishment. Less than 20% of farmers planned to apply manure, and the median application rates were low (approximately 1 t/ha) among those who did.

Table 5.4.1: Summary of data mined from chatbot data for maize in Bulambuli District in Uganda

Variable	Value
Number of farmers	3,501
Number of lead farmers	53
Number of nutrient plans	6,062
Number of emergence checks	4,805

Number of harvest monitors	5,187
Median plot size (ha)	0.2
Median farmer's existing yield (t/ha)	2.5
Planned manure frequency (%)	19
Median manure rate of those applying (t/ha)	1.2
Median expected profit ($/ha)	400
Intercropping frequency (%)	80
Continuous maize frequency (%)	87
High manuring rate frequency (%)	21
Emergence <75% frequency (%)	27
Female farmer frequency (%)	33

6. CONCLUSION

This study demonstrates that Farmer. Chat holds significant potential to democratize agricultural knowledge, especially for smallholder farmers operating in resource-constrained environments. By focusing on accessibility for low-literacy and rural users, the platform exemplifies how AI systems can be designed to serve marginalized groups. Key findings revealed notable improvements in user engagement, query clarity, and response accuracy, while also identifying important challenges such as gender bias and the need for inclusive design practices. The integration of voice-based interactions and follow-up prompts enhanced the intuitiveness of Human-AI collaboration, enabling farmers to interact with the system more naturally. The real-world adoption of Farmer. Chat validates its capability to improve farming practices, including disease management and crop cycle planning, thus addressing the critical challenges faced by smallholder farmers.

This research also has larger implications for AI and human-computer interaction (HCI) as it provides knowledge and understanding when it comes to developing equitable AI tools, with applicability across sectors. As we develop as a field in AI, concurrent and relevant challenges remain related to lack of inclusive language, cultural relevance and bias across various AI-driven products and practices; all of which should strive to achieve equitable outcomes for all users. Also, user feedback will allow for continued iteration with the usability of the platform to become better through continuous engagement with the platform, ultimately leading to a wider consumer base for adoption, with impacts. As Farmer.Chat continues to leverage neural networks, with recent rapid advances in natural language processing, real-time, contextual support and assistance in how agricultural knowledge is provided and actioned has never been more prevalent. This approach to essentially expand or condense agriculture operations that are applicable to sustainable agriculture contribute to an improvement in farming operations albeit in real-time by bringing relevant information for further action or implementation..

Future Research Directions

Integration with Wearable Devices: Future work could explore the integration of the chatbot with wearable devices to enhance real-time agriculture chatbot and provide personalized insights. Enhanced Natural Language Understanding: Improving the chatbot's natural language processing capabilities for nuanced conversations and context-aware responses would be a valuable avenue for future development.

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