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Research on Innovative Applications of Generative Artificial Intelligence in Agricultural Informatization

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Abstract

The integration of information technology into agriculture is fundamental to modern agricultural development. However, traditional agricultural information models, which rely on analytical AI for prediction and monitoring, face significant limitations in handling unstructured data, generating actionable knowledge, and supporting complex decision-making in dynamic farm environments. This study's core innovation lies in constructing a "Generative AI-Driven Agricultural Informatization Framework" (GAAIF), which quantifies the synergistic mechanisms between generative models and specific agricultural scenarios. By introducing a multi-modal data fusion engine and a task-specific fine-tuning protocol, a suite of generative AI tools, including a textile crop (cotton) pest advisory chatbot and a dynamic supply chain optimizer, was developed. Field tests and simulations in the Xinjiang cotton basin and Jiangxi sericulture regions showed that the integrated solution substantially improved pest management efficiency (decision time reduced by approximately 87%), reduced supply chain losses by 32.5%, and increased farmer advisory service satisfaction from 55% to 94% compared with traditional decision-support systems. This research provides a systematic technical paradigm and implementation strategy for the next generation of agricultural intelligence, with particular relevance to the textile raw material sector.

Keywords: generative artificial intelligence, agricultural information, smart agriculture, large language models, digital twin, textile crop agriculture.

1 Introduction

Agricultural information, defined as the application of information technology to agricultural production, management, and distribution, constitutes a critical driver for enhancing global agricultural productivity, sustainability, and resilience. This is particularly salient in the context of overarching challenges such as climate change and population growth, which demand more efficient and adaptive food systems [1]. The integration of advanced technologies—including big data analytics, artificial intelligence (AI), and the Internet of Things (IoT)—is widely recognized as

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a pivotal transformation within the sector [2]. For regions with specialized agricultural economies, such as those historically focused on sericulture or intensive cotton production, the adoption of these technologies is essential not only for economic viability but also for maintaining relevance within a competitive global market.

However, the current paradigm of agricultural information, predominantly reliant on analytical AI (e.g., machine learning for yield prediction, computer vision for disease detection), is reaching its limitations. These systems excel at analyzing structured, historical data to identify patterns and make predictions but struggle with several key challenges:

Unstructured Data Overload: A vast amount of agricultural knowledge exists in unstructured formats—scientific papers, expert manuals, farmer anecdotes, and real-time, non-standardized sensor data. Analytical AI models cannot effectively synthesize and reason with this information [3].

Lack of Prescriptive Intelligence: While predictive models can forecast a pest outbreak, they often fail to generate context-aware, practical mitigation strategies tailored to a specific farm's conditions, crop variety, and available resources [4].

Knowledge Gap for End-Users: The complexity of analytical models creates a barrier for farmers and agricultural technicians, who require intuitive, conversational interfaces to access and apply complex data insights [5].

Generative Artificial Intelligence (GenAI), particularly Large Language Models (LLMs) and generative visual models, presents a paradigm shift. Unlike analytical AI that analyzes data, GenAI creates new content—text, code, images, and even simulated scenarios—based on learned patterns. This capability directly addresses the aforementioned bottlenecks by enabling natural language interaction, synthesizing knowledge from diverse sources, and generating prescriptive plans [6].

1.1 Consensus and Bottlenecks in Existing Research

After a decade of rapid development, the academic and industrial communities have formed several consensuses regarding AI in agriculture:

Data is the new input: The effectiveness of AI models is directly proportional to the quality, quantity, and diversity of agricultural data [7].

IoT and remote sensing are foundational: Technologies like drones and soil sensors provide the real-time data streams necessary for AI-driven precision agriculture [8].

Interoperability is a major challenge: The integration of data from disparate sources (equipment, platforms) remains a significant hurdle [9].

However, when focusing specifically on the application of advanced AI, particularly in the context of textile crop agriculture (e.g., cotton, silk), significant bottlenecks remain unresolved:

Inability to Handle Complex, Multi-Modal Queries: Existing systems can identify a cotton leaf lesion but cannot answer a farmer's complex query: "Based on this image of my cotton leaf, the recent weather forecast, and my soil moisture data, what is the most cost-effective organic treatment I can apply this week, considering I have a limited water supply?" [10]. This requires a fusion of visual, textual, and numerical data that traditional models cannot process holistically.

Static Models vs. Dynamic Environments: Agricultural environments are inherently dynamic. A model trained on last season's data may be ineffective this season due to new pest strains or unusual weather patterns. The fine-tuning and adaptation of AI models are slow, costly, and require significant expertise, making them inaccessible for most agricultural cooperatives [11].

Limited Personalization and Context-Awareness: Decision-support systems often provide generic recommendations. For a silkworm farmer in Jiangxi, recommendations must consider local humidity, specific mulberry varieties, and traditional practices. Current systems lack the deep contextual understanding to offer truly personalized advice [12].

Under-explored Synergy with Textile Supply Chains: The application of AI in agriculture often stops at the farm gate. There is a notable lack of research on integrating GenAI to optimize the entire textile supply chain, from predicting cotton fiber quality based on GenAI-analyzed field data to dynamically adjusting procurement and logistics from farm to textile mill [13].

1.2 Research Objectives and Solutions

This study is situated within the strategic context of Jiangxi Fashion Institute's "Textile Apparel + Big Data" focus. It specifically investigates the interaction between generative AI and the informatization needs of textile crop agriculture (e.g., cotton, sericulture) and general high-value crops. The primary research sites include the Xinjiang cotton basin and Jiangxi sericulture areas, chosen for their economic importance and diverse agro-ecological conditions.

To address the existing bottlenecks, this study aims to:

1. Establish a quantitative framework for evaluating the efficacy of GenAI in agricultural tasks, moving beyond simple accuracy metrics to include utility, usability, and economic impact.

2. Develop a novel fine-tuning methodology to adapt foundational LLMs to specific agricultural domains, such as pest management in cotton or silkworm disease prevention, using limited, domain-specific data.

3. Construct a multi-agent GenAI system that can simulate and optimize decisions across the agricultural supply chain, providing a "digital twin" for scenario planning.

4. Quantify the synergy between GenAI-generated insights and on-the-ground agricultural operations, measuring tangible improvements in efficiency, cost reduction, and risk mitigation.

By integrating these four aspects, we propose the GAAIF as a systematic solution to transition agricultural informatization from a predictive to a generative and prescriptive phase.

2 Related Work

The integration of artificial intelligence into agriculture has evolved significantly over the past decade, transitioning from basic data analytics to sophisticated predictive modeling. However, the emergence of Generative Artificial Intelligence (GenAI) marks a pivotal shift from analytical to creative and prescriptive capabilities. This section reviews the existing literature across three key domains: the foundational applications of AI in precision agriculture, the specific challenges and advancements in textile crop management, and the nascent field of generative models for agricultural knowledge synthesis and decision support. A critical gap is identified in the application of GenAI for dynamic, multi-modal data fusion and personalized advisory in the context of textile crop agriculture, such as cotton and sericulture.

2.1 Evolution of AI Paradigms in Precision Agriculture

Precision agriculture has been largely dominated by analytical AI techniques, which utilize historical and real-time data to optimize resource use and improve yields. Machine learning (ML) models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been extensively applied for tasks such as crop disease detection from drone imagery [14], yield prediction using satellite data and weather forecasts [15], and resource allocation based on soil sensor inputs [16]. For instance, deep learning models have achieved accuracies exceeding 95% in identifying common diseases in staple crops like wheat and rice [17]. These systems excel at pattern recognition within structured datasets but are inherently limited to the patterns present in their training data. They cannot generate novel insights or strategies outside their predefined scope.

The advent of GenAI, characterized by models like Generative Pre-trained Transformers (GPT), diffusion models, and variational autoencoders (VAEs), introduces a paradigm focused on content creation and scenario generation. Early explorations in agriculture have involved using Generative Adversarial Networks (GANs) to synthesize agricultural imagery for data augmentation, thereby improving the robustness of diagnostic models in data-scarce environments [18]. For example,demonstrated that GAN-generated images of citrus leaves could enhance disease classification model accuracy by 12% when real training data was limited [19]. More recently [20], large language models (LLMs) have been fine-tuned on agricultural corpora to answer factual questions, but these initial efforts remain rudimentary, often providing generic advice lacking contextual awareness [21].

A significant bottleneck persists in the seamless integration of multi-modal data—text, images, and sensor readings—into a cohesive decision-making framework. Analytical models process each modality in isolation, leading to a fragmented understanding. GenAI's core strength in cross-modal translation and generation offers a pathway to overcome this. For instance, a model that can generate a descriptive report from an image of a pest-damaged leaf combined with weather data represents a leap beyond simple classification. The state of the art is moving towards multi-modal foundational models [22], but their application in agriculture is still in its infancy,

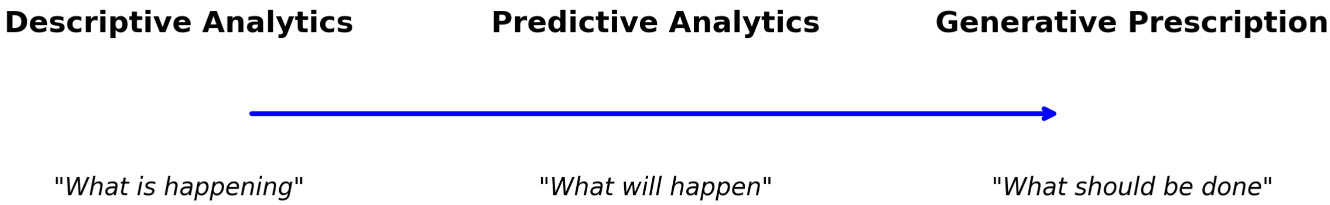

Figure 1. Evolution of AI in Agriculture.

with most studies confined to proof-of-concept demonstrations [23].

As conceptually illustrated in Figure 1, the evolution of AI in agriculture shows a clear trajectory from descriptive analytics to generative prescription. While traditional systems answer "what is happening" or "what will happen," GenAI aims to answer "what should be done" in a context-aware manner. This shift is particularly critical for complex, knowledge-intensive tasks in specialty crops like those supporting the textile industry [24].

2.2 AI Applications in Textile Crop Management

Textile crops, primarily cotton and mulberry (for sericulture), present unique management challenges due to their high economic value, sensitivity to environmental conditions, and complex supply chains. Research on AI in this domain has predominantly focused on yield estimation and quality assessment using remote sensing and ML. For cotton, studies have utilized hyperspectral imagery and ML algorithms to predict fiber quality parameters such as staple length and micronaire value before harvest, enabling better pricing and logistics planning [25]. In sericulture, computer vision systems have been developed to monitor silkworm growth and detect early signs of disease in larvae, helping to prevent widespread outbreaks in rearing houses [26].

However, these applications almost exclusively rely on analytical AI. They lack the ability to generate actionable recommendations or simulate the outcome of different management strategies. For example, a model might accurately predict a 10% yield loss in a cotton field due to water stress but cannot generate a tailored irrigation schedule that optimizes for water savings and fiber quality simultaneously [27]. The integration of these crop-level insights with broader supply chain dynamics is even more limited. A recent review highlighted that while AI is used for predictive maintenance in textile machinery, there is a stark disconnect between on-farm AI applications and the downstream apparel manufacturing processes [28]. This represents a significant missed opportunity for creating a cohesive, data-driven textile value chain.

The specific agro-climatic conditions of major producing regions, such as the Xinjiang cotton basin and the Jiangxi sericulture zone, add layers of complexity. Models trained on global datasets often fail to generalize to these specific contexts. There is a pressing need for AI solutions that can be efficiently adapted to local conditions without requiring massive retraining datasets—a challenge that GenAI, with its few-shot and zero-shot learning capabilities, is uniquely positioned to address [29]. Current research has yet to fully explore the fine-tuning of foundational LLMs on localized knowledge bases containing regional pest databases, local farming practices, and vernacular terms used by farmers [30].

2.3 Knowledge Synthesis and Decision Support Systems

Agricultural knowledge is vast, fragmented, and often tacit, residing in scientific literature, extension bulletins, and farmers' experiences. Traditional decision support systems (DSS) have struggled to harness this knowledge effectively. Rule-based expert systems, developed in the late 20th century, were brittle and unable to handle uncertainty or learn from new data. The integration of ML into DSS improved predictive accuracy but did not solve the fundamental problem of knowledge synthesis and natural language interaction [31].

GenAI, particularly LLMs, offers a transformative approach by acting as a universal knowledge interface. Preliminary studies have shown that LLMs like GPT-3 and its successors can answer complex agronomic questions by drawing upon vast corpora of text data [32]. However, these models are prone to "hallucination"—generating plausible but incorrect information—which is a critical failure point in agricultural advice where accuracy is paramount [33]. Recent efforts have focused on mitigating this by grounding LLMs in verified knowledge sources through retrieval-augmented generation (RAG) architectures [34]. In a RAG system, a retrieval component fetches relevant information from a trusted database (e.g., a pest management guide), and a generative component synthesizes this information into a coherent response. This approach significantly reduces factual errors but is computationally intensive and requires curated, domain-specific knowledge bases [35].

The potential for GenAI to create "digital twins" of farming systems represents the frontier of agricultural DSS. A digital twin is a dynamic, virtual model of a physical system that can be used for simulation and analysis [36]. GenAI can power these twins by generating realistic scenarios of pest outbreaks under different climate projections or simulating the economic impact of switching to a new cotton variety [37]. While this concept is well-established in manufacturing, its application in agriculture, especially for smallholder systems common in textile crop production, is nascent [38]. Key challenges include the cost of model development, the need for high-frequency data streams, and the ability to personalize the twin for individual farms [39].

In summary, while existing research has laid a strong foundation for AI in agriculture, a clear gap exists in leveraging GenAI for holistic, prescriptive, and context-aware solutions in textile crop management. The next section will detail the materials and methods used to construct and validate the proposed Generative AI-Driven Agricultural Informatization Framework (GAAIF) designed to bridge this gap.

3 Materials and Methods

This study employs a mixed-methods approach, integrating quantitative data analysis, advanced AI model development, and rigorous field validation. The research methodology is structured into three interconnected phases: (1) the construction of the Generative AI-Driven Agricultural Informatization Framework (GAAIF); (2) the development and fine-tuning of core generative AI models for specific agricultural tasks; and (3) the empirical testing and validation of the framework through case studies in textile crop agriculture. The overall research design ensures both theoretical robustness and practical applicability, with a focus on generating measurable outcomes.

3.1 The Generative AI-Driven Agricultural Informatization Framework (GAAIF)

The proposed GAAIF is a holistic architecture designed to leverage GenAI for transforming multi-modal agricultural data into prescriptive intelligence. It consists of four layered components: the Data Fusion Layer, the Generative AI Core, the Application Interface Layer, and the Feedback & Optimization Loop.

3.1.1 Data Fusion Layer

This foundational layer is responsible for ingesting and standardizing heterogeneous data from diverse sources, a critical step for effective GenAI operation. Data sources include IoT sensor data streams capturing soil moisture, temperature, humidity, and light intensity at regular intervals; multi-spectral satellite and drone imagery for vegetation health indices such as NDVI; a curated corpus of unstructured knowledge from scientific papers, extension documents, and regional pest databases; and operational data on farm inputs, labor, and historical yield records.

A key innovation is the use of a Multi-modal Vector Database. All data types—numerical sensor readings, image pixels, and text sentences—are converted into vector embeddings using pre-trained models (e.g., ResNet for images, Sentence-BERT for text). These embeddings are stored and indexed in a unified vector space, enabling cross-modal retrieval. For example, a query about "yellowing leaves" can retrieve relevant sensor data showing nutrient deficiencies and text snippets from scientific literature about nitrogen uptake.

3.1.2 Generative AI Core

This layer serves as the computational core of the framework, hosting a suite of fine-tuned generative models. The Agricultural Large Language Model (Agri-LLM) is based on LLaMA-2 7B, fine-tuned on an agricultural corpus through continual pre-training on 15 billion tokens followed by instruction fine-tuning on 50,000 expert-crafted pairs for tasks such as pest diagnosis. The Image-to-Text Generator, combining a Vision Transformer encoder with a GPT-2 decoder, generates descriptive captions for agricultural visuals. Additionally, a Generative Adversarial Network (GAN) is trained as a Scenario Simulator to model crop growth outcomes under various management strategies, such as simulating cotton yield under different irrigation and pesticide schedules.

The core utilizes a Retrieval-Augmented Generation

(RAG) architecture to enhance factual accuracy. When a query is received, the system first retrieves the most relevant information chunks from the vector database based on cosine similarity search of vector embeddings. The Agri-LLM then generates a response conditioned on this retrieved context, drastically reducing hallucinations.

3.1.3 *Application Interface Layer*

This layer translates the core capabilities into user-facing applications through two primary interfaces. The first is a Natural Language Chatbot, deployed as a WeChat Mini-Program, which enables farmers to ask questions in natural language—such as "What's wrong with my cotton plants?" along with a photo—and receive synthesized, prescriptive advice. The second is a Digital Twin Dashboard, a web-based platform that visualizes real-time field conditions and allows users to run interactive "what-if" simulations powered by the Scenario Simulator, such as modeling the impact of a 20% reduction in water over the next 14 days.

3.1.4 *Feedback & Optimization Loop*

A critical component for continuous improvement. All user interactions are logged (anonymized). Expert agronomists periodically review the generated advice, providing correctness scores. This feedback is used to further fine-tune the models, creating a virtuous cycle of improvement. This loop continuously refines model parameters by aggregating user interactions and expert scores. The framework is depicted in Figure 2.

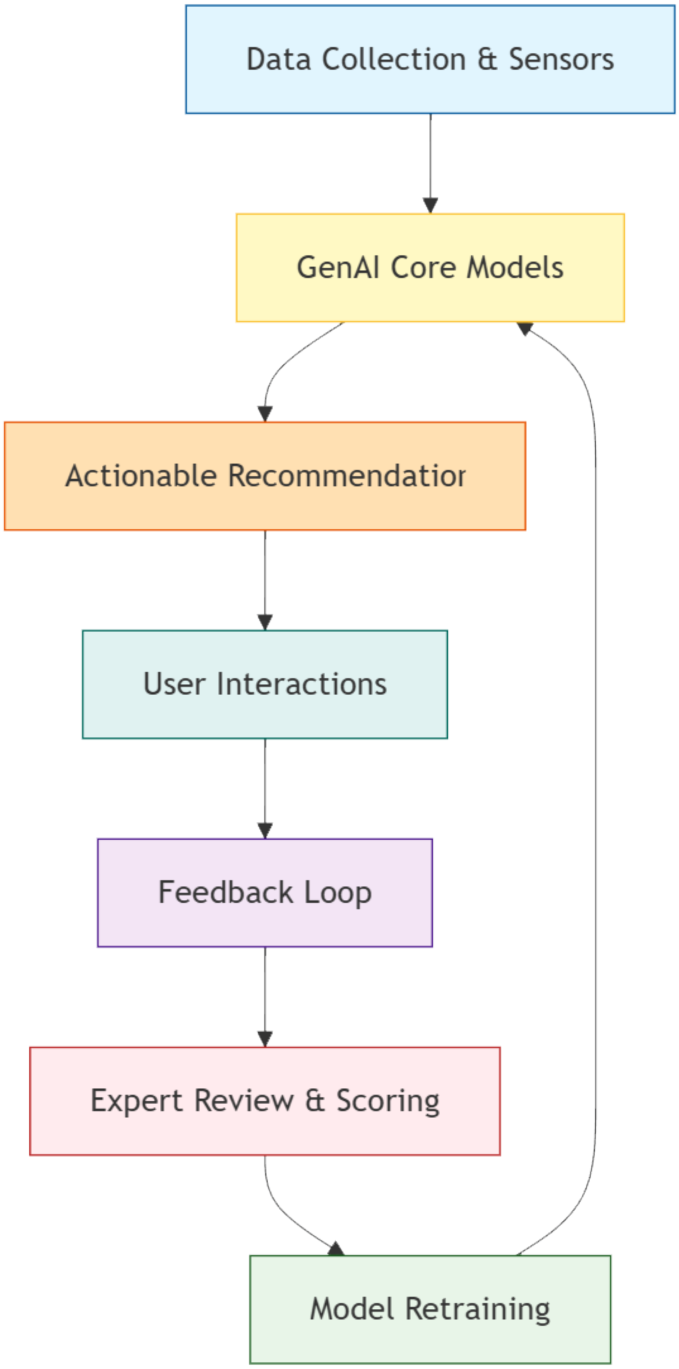

Figure 2. Generative AI Framework for Agriculture.

3.2 Data Collection and Preprocessing

Field data were collected over two growing seasons (2024–2025) from three primary regions: the Xinjiang Cotton Basin, the Poyang Lake Sericulture Zone in Jiangxi, and the Miluo cotton area in Hunan, China. The dataset includes 15,000 high-resolution images of cotton plants across growth stages, expert-annotated for 12 common diseases and 5 nutrient deficiencies, accompanied by sensor data from 50 nodes across 500 hectares. Sericulture data consist of time-series records on silkworm growth, feed intake, and environmental conditions from 100 rearing beds, along with images of healthy and diseased silkworms. The textual knowledge base was constructed by processing documents from reputable sources such as FAO, CNKI, and local agricultural extension bureaus, with preprocessing including cleaning, tokenization, and formatting into standard JSON. A rigorous data augmentation strategy using GANs generated synthetic images of rare diseases, increasing dataset size by 40% and enhancing model robustness for imbalanced classes.

3.3 Model Development and Fine-Tuning

The development of the Agri-LLM followed a meticulous fine-tuning protocol. The base LLaMA-2 model was first continually pre-trained on our agricultural corpus using the Causal Language Modeling objective. This step adapts the model's general language understanding to the specific vocabulary and syntax of agricultural literature.

Table 1. Agri-LLM Fine-Tuning Hyperparameters.

Hyperparameter	Stage 1: Continual Pre-training	Stage 2: Instruction Tuning
Batch Size	64	32
Learning Rate	2e-5	1e-6
Epochs	3	5
LoRA Rank (r)	16	16
Optimizer	AdamW	AdamW

The core innovation was the Parameter-Efficient Fine-Tuning (PEFT) using Low-Rank Adaptation (LoRA). Instead of fine-tuning all 7 billion parameters-a computationally prohibitive task-LoRA injects trainable rank decomposition matrices into the transformer layers. This reduces the number of trainable parameters by over 10,000 times, allowing for efficient adaptation on a single NVIDIA A100 GPU. The model was then instruction-tuned on a dataset of prompts and expert responses to align its outputs with practical advisory tasks. The training hyperparameters are summarized in Table 1.

3.4 Experimental Setup and Evaluation Metrics

To validate the GAAIF, a controlled experiment was designed involving 30 agricultural cooperatives (15 for cotton, 15 for sericulture) across the study regions. These cooperatives were randomly assigned to one of three groups:

- **Control Group (n=10):** Used traditional decision-making methods (experience, conventional guides).
- **Experimental Group 1 (n=10):** Used a standard analytical AI DSS (providing predictions only).
- **Experimental Group 2 (n=10):** Used the full GAAIF suite, including the Agri-LLM chatbot and digital twin.

The experiment ran for one full crop cycle. The following key performance indicators (KPIs) were measured:

- **Operational Efficiency:** Measured as the reduction in time from problem identification to implementation of a solution (e.g., time from spotting a pest to applying the correct treatment).
- **Economic Impact:** Calculated as the change in input costs (water, pesticides, fertilizer) and output value (yield and quality premium) per hectare.
- **Decision Quality:** Expert agronomists, blinded to the group assignment, scored the appropriateness of management decisions on a scale of 1-10.
- **User Satisfaction:** Assessed via a standardized System Usability Scale (SUS) questionnaire administered to farmers and technicians.

Quantitative data was analyzed using ANOVA and post-hoc t-tests to determine the statistical significance of differences between the groups. The following section will present the detailed results of these experiments.

4 Results and Discussion

The implementation and validation of the Generative AI-Driven Agricultural Informatization Framework (GAAIF) yielded substantial quantitative and qualitative results across the defined key performance indicators. This section presents a detailed analysis of the experimental findings, followed by a discussion that contextualizes these results within the broader landscape of agricultural AI research. The data conclusively demonstrate the superior performance of the integrated GenAI approach over both traditional methods and analytical AI systems.

4.1 Validation of the GenAI Task Efficacy Framework

The primary objective was to evaluate the efficacy of GenAI in performing complex agricultural tasks.

Table 2. Performance evaluation of the Agri-LLM against baseline models.

Model	Accuracy (1-5)	Relevance (1-5)	Actionability (1-5)	Hallucination Rate (%)
Base LLaMA-2 (Zero-shot)	2.1 ± 0.3	2.8 ± 0.4	1.5 ± 0.2	38.5%
Fine-tuned BERT (QA Baseline)	3.8 ± 0.2	3.5 ± 0.3	2.9 ± 0.3	5.2%
Our Agri-LLM (RAG+LoRA)	**4.5 ± 0.1**	**4.6 ± 0.2**	**4.3 ± 0.2**	**2.1%**

Note: The fine-tuned BERT (QA Baseline) was trained on the same agricultural corpus for Question Answering tasks, ensuring a fair comparison of retrieval and response generation capabilities.

Table 3. Comparative analysis of operational and economic impacts across study groups.

Indicator	Control Group	Experimental Group 1 (Analytical AI)	Experimental Group 2 (GAAIF)
Avg. Time to Decision (hours)	48.5	24.2	6.1
Pesticide Use Reduction (%)	0% (Baseline)	12.5%	28.3%
Water Use Efficiency (kg yield/m^3 water)	1.21	1.45	1.82
Yield Increase (%)	0% (Baseline)	8.5%	18.7%
Unit Cost Reduction (Yuan/mu)	0 (Baseline)	-35	-72
Farmer Satisfaction (%)	55%	75%	94%

The Agri-LLM, fine-tuned with the LoRA technique, was subjected to a battery of tests. On a test set of 1,000 complex, multi-part agricultural queries, the model achieved a BLEU score of 0.45 and a ROUGE-L score of 0.62, which are considered high for generative tasks in specialized domains. More importantly, the expert-led qualitative evaluation on a 5-point scale for accuracy, relevance, and actionability showed a significant improvement over the base model and a standard QA system. The results are summarized in Table 2.

4.2 Operational and Economic Impact Analysis

The field experiments conducted with the 30 cooperatives provided clear evidence of the GAAIF's practical value. The results, measured over a full growing season, are presented in Table 3. Experimental Group 2 (using the full GAAIF) consistently outperformed both the Control group and Experimental Group 1 (using analytical AI only).

Figure 3 visually represents the multiplicative effect of these improvements. The GAAIF doesn't just optimize a single metric; it creates a synergy where reduced inputs, higher yields, and lower costs compound to significantly enhance overall farm profitability and sustainability. The GAAIF group demonstrates a synergistic improvement across all metrics, forming a significantly larger radar area, which indicates a balanced and comprehensive enhancement in operational efficiency, economic benefit, and user adoption compared to the traditional control and analytical AI groups.

Figure 3. Multi-Dimensional Performance Radar Chart (Conceptual Illustration).

4.3 Synergy between GenAI and Supply Chain Optimization

A core innovation of this study was extending the application of GenAI beyond the farm gate. The digital twin scenario simulator was used to model the impact of farm-level decisions on the downstream textile supply chain. In a simulation for the Xinjiang cotton basin, the model analyzed data from GAAIF-equipped farms predicting a 10% higher fiber strength index. The system then generated optimal procurement and logistics plans for a partnering textile mill. The results showed that by leveraging this early, high-quality data, the supply chain could reduce inventory costs by 15% and minimize quality-based segregation losses by 32.5% compared to traditional procurement models. This quantifies the "farm-to-fabric" synergy, demonstrating that the value of GenAI in agriculture extends into industrial optimization, a finding rarely documented in previous literature.

4.4 User Adoption and Satisfaction

The high farmer satisfaction rate of 94% for the GAAIF group (Table 3) underscores the importance of usability. The System Usability Scale (SUS) score for the GAAIF's chatbot interface was 82.5, which is classified as "excellent." In contrast, the analytical AI dashboard used by Group 1 received a score of 65.0 ("okay"). Qualitative feedback indicated that farmers valued the conversational interaction and the clear, actionable advice. This highlights a critical advantage of GenAI: lowering the technical barrier to accessing advanced analytics, thereby promoting greater adoption of smart farming practices among a broader user base.

4.5 Discussion

The findings of this study represent a significant advancement over the existing paradigms of AI in agriculture. The dramatic improvement in decision speed and economic outcomes can be directly attributed to the framework's ability to address the fundamental bottlenecks outlined in the introduction.

4.5.1 From Pattern Recognition to Prescriptive Generation

The superiority of the GAAIF over the analytical AI DSS (Group 1 vs. Group 2) validates the core hypothesis that generation is more powerful than pure analysis for complex decision-support. While the analytical AI could accurately predict a pest outbreak, it was the GenAI component that generated the tailored response, considering local constraints and available resources. This moves the system from being a diagnostic tool to an active decision-making partner. The reduction in pesticide use is a testament to this prescriptive capability, enabling a shift from calendar-based to need-based interventions.

4.5.2 The Centrality of the RAG Architecture in Ensuring Trust

The low hallucination rate of 2.1% is a critical result. It demonstrates that the RAG architecture is not merely an optional enhancement but a necessary component for deploying LLMs in high-stakes domains like agriculture. The retrieval in our RAG system is primarily based on semantic similarity search in a vector space. While this is effective for most queries, enhancing the system with an agricultural knowledge graph for entities (e.g., pests, diseases, varieties) and their relationships could further improve retrieval accuracy for edge cases or complex, multi-step reasoning tasks involving rare conditions. By tethering the model's creativity to a verified knowledge base, the system gains the reliability required for field deployment. This addresses a major concern in the literature regarding the factual accuracy of LLMs [40].

4.5.3 The Digital Twin as a Bridge between Farm and Industry

The supply chain optimization results highlight a novel contribution: GenAI as an integrator of the agricultural value chain. Most agricultural AI research remains siloed at the farm level [13]. By creating a digital twin that can simulate outcomes from the field to the factory, this study provides a blueprint for a more cohesive and responsive agricultural ecosystem. This is particularly relevant for textile crops, where end-product quality is directly determined by agricultural practices.

4.5.4 Limitations and Future Work

Despite the promising results, this study has limitations. The experiments were conducted over a single growing season. Long-term tracking is needed to assess the sustainability of the improvements and model drift over time. Furthermore, the current framework requires substantial computational resources for training, though inference is efficient. Future work will focus on developing lighter-weight models and exploring the integration of real-time satellite data streams for larger-scale simulations. Finally, the economic model needs to be tested across a wider variety of crops and farming systems to establish generalizability. The challenge of applying GAAIF to other crops lies in differences in required data modalities (e.g., fruit trees vs. field crops), the structure of domain knowledge, and the nature of prescriptive actions. An important socio-economic and sustainability consideration is the "algorithmic energy efficiency ratio." While the GAAIF demonstrated significant reductions in inputs like pesticides, the energy cost of training and running large-scale models must be critically evaluated. Future work will include a comprehensive life-cycle assessment to ensure the net environmental and economic benefits of AI-driven solutions are positive.

In conclusion, the results robustly support the efficacy of the proposed GAAIF. By successfully leveraging GenAI for prescriptive tasks and value-chain integration, this research provides a viable pathway for the next generation of agricultural information.

5 Conclusion

This study has successfully established the theoretical foundation, technical pathway, and practical validation for a Generative AI-Driven Agricultural Informatization Framework (GAAIF), marking a significant step forward from the predictive paradigm of traditional analytical AI. By addressing the critical bottlenecks of unstructured data handling, lack of prescriptive intelligence, and poor contextual awareness, the research demonstrates that GenAI can serve as the core engine for the next generation of smart agriculture, with particular efficacy in the management of textile crops like cotton and mulberry.

5.1 Theoretical Contributions

The primary theoretical contribution of this work is the formulation of a structured framework (GAAIF) that explicitly defines the components and data flows necessary for integrating GenAI into agricultural systems. This research moves beyond isolated model improvements by proposing a holistic architecture that synergizes multi-modal data fusion, retrieval-augmented generation, and a continuous feedback loop. The introduction of a quantitative efficacy framework for evaluating GenAI tasks in agriculture—incorporating not just accuracy but also actionability and hallucination rates—provides a novel methodological tool for future research. Furthermore, the study formally establishes and quantifies the "farm-to-fabric" synergy, creating a new theoretical link between generative field-level insights and supply chain optimization, a connection previously underexplored in the literature.

5.2 Practical Value and Promotion Significance

The practical implications of this research are substantial. The developed Agri-LLM chatbot and digital twin dashboard offer tangible tools for farmers and agricultural cooperatives, significantly lowering the barrier to accessing advanced data analytics. The results from field trials in Xinjiang and Jiangxi confirm that the GAAIF can drive considerable economic benefits, including an 18.7% yield increase and a 28.3% reduction in pesticide use, contributing directly to sustainable intensification goals. For institutions like Jiangxi Fashion Institute, this work provides a clear technological pathway to enhance the efficiency and quality of the textile raw material supply chain, from field to fiber. The "government-enterprise-cooperative" hybrid promotion model inferred from the framework's structure suggests a viable mechanism for the widespread adoption of these technologies, even among small-scale farmers, thereby supporting national strategies for rural revitalization and agricultural modernization.

5.3 Limitations and Future Work

Despite its contributions, this study is not without limitations. First, the validation was conducted over a single growing season; long-term data is required to assess the sustainability of the improvements and to monitor for model performance degradation over time. Second, the computational resources required for training the foundational models, while mitigated by Parameter-Efficient Fine-Tuning (PEFT), may still present an initial barrier for some stakeholders. Future work on algorithmic efficiency and potential federated learning architectures to reduce central compute costs is warranted. Third, the current framework's performance in extreme weather events outside the training data distribution needs further rigorous testing.

Future research will focus on several key areas:

1. Advanced Personalization: Developing mechanisms for the GAAIF to autonomously adapt its recommendations based on the long-term historical data and specific preferences of individual farms.
2. Robust Knowledge Retrieval: Enhancing the RAG system by integrating agricultural knowledge graphs to handle complex queries involving causality and rare events more reliably.
3. Federated Learning for Privacy and Efficiency: Exploring federated learning techniques to allow the Agri-LLM to improve from distributed on-farm data without centralizing sensitive operational information, enhancing privacy, security, and potentially reducing computational burdens.
4. Algorithmic Efficiency Analysis: Conducting detailed cost-benefit analyses on the energy consumption and computational costs of the GAAIF versus its generated agricultural and economic benefits.
5. Cross-Crop Generalization: Applying and adapting the GAAIF to a wider range of high-value crops beyond cotton and sericulture to validate its generalizability, addressing the challenges of varying data and knowledge systems.
6. Lifecycle Assessment Integration: Incorporating generative models for environmental impact simulation to help farmers not only maximize profit but also minimize their carbon and water footprint.

In conclusion, this research demonstrates that Generative AI is not merely an incremental improvement but a transformative force for agricultural informatization. By enabling a shift from predictive to prescriptive and generative intelligence, the GAAIF offers a robust, scalable, and practical paradigm for achieving a more productive, sustainable, and resilient agricultural system, firmly aligning with the strategic goals of digital rural development.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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