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Context-Adaptive Agricultural Advisory Framework: A Conversational AI Approach For Rural Indian Farmers

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Abstract
Artificial intelligence-based advisory systems are increasingly being explored as tools to improve agricultural decision-making; however, many existing solutions assume sta- ble connectivity, uniform user literacy, and low-risk operating conditions. Such assumptions limit their applicability in rural farming environments, where language diversity, infrastruc- ture constraints, and advisory errors can significantly impact livelihoods and ecological sustainability. This paper proposes a context-adaptive agricultural advisory framework implemented through a conversational interface, designed to support farmers operating under low-connectivity and low-literacy conditions. The framework dynamically adjusts advisory content based on inferred user context, linguistic preference, and the risk level associated with a given query. In contrast to static chatbot systems, the proposed approach integrates risk-aware response controls and prioritises locally relevant knowledge sources to enhance reliability and trust. Additionally, the framework is structured to operate under low-bandwidth and intermittent connectivity, reducing dependence on continuous cloud access. The study demonstrates how context-sensitive adaptation and safety-aware design can improve the practical usability and acceptance of AI-driven advisory systems in rural agricultural settings.

Index Terms: *Agricultural advisory systems, context-adaptive AI, conversational interfaces, rural agriculture, decision support systems*

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I. Introduction

Agriculture continues to play a central role in India's eco- nomic stability and social structure, supporting the livelihoods of a large population of small and marginal farmers. Decision- making in agriculture is highly time-sensitive, with outcomes influenced by factors such as weather variability, crop health, pest outbreaks, and market conditions. For many farmers, especially in rural regions, access to timely and reliable advisory information remains limited. Traditional agricultural extension mechanisms, while valuable, often struggle to pro- vide personalised and real-time guidance at scale.

In recent years, digital technologies and AI-based advisory systems have been explored to bridge this information gap [1], [2]. However, in the Indian rural context, their effectiveness remains constrained by linguistic diversity, limited literacy, intermittent connectivity, and trust-related challenges.

Recent development-oriented studies and policy frameworks underline the growing importance of digital public infras- tructure in agriculture, particularly for improving the reach and effectiveness of advisory services in developing regions. These frameworks stress that technological solutions must be aligned with rural connectivity limitations and user capability in order to deliver meaningful impact at scale [13]. Similar observations have been reported in recent national and in- ternational studies highlighting the role of digital advisory platforms in strengthening agricultural extension services in developing economies [14].

A key limitation of current AI-driven agricultural chatbots lies in the assumptions underlying their design. Most systems are developed for environments with stable network access, uniform language usage, and low-risk advisory scenarios. In contrast, Indian farmers often operate under conditions where advisory errors—particularly those related to pesticide use, fertilizer application, or disease management—can have serious economic and environmental consequences. Moreover, the lack of context awareness in existing systems leads to generic responses that do not adequately reflect local practices, resource constraints, or user capability.

Motivated by these challenges, this paper proposes a context-adaptive agricultural advisory framework implemented through a conversational interface. The proposed approach is designed to dynamically adjust advisory behaviour based on inferred user context, including linguistic preference, con- nectivity conditions, and the risk level associated with a given query. Rather than treating all interactions uniformly, the framework emphasizes safety-aware response control and prioritizes locally relevant knowledge sources to enhance reliability and user trust. The system is structured to function effectively under low-bandwidth and intermittent connectivity scenarios commonly encountered in rural India.

The primary contributions of this work are threefold. First, it introduces a context-adaptive advisory framework tailored to the constraints of Indian rural agriculture. Second, it incorpo- rates a risk-aware mechanism that applies stricter validation for high-impact agricultural recommendations. Third, it outlines a low-connectivity-oriented design that reduces dependence on continuous cloud access. The remainder of this paper is organized as follows: Section II reviews related work in digital agricultural advisory systems, Section III describes the proposed methodology, Section IV presents the system architecture, Section V discusses results and observations, and Section VI concludes the paper with directions for future work.

II. Related Work

The application of digital technologies in agricultural ex- tension has been widely explored as a means to improve in- formation dissemination and decision-making among farmers. Early digital advisory systems primarily relied on static mobile applications, SMS-based services, and helpline models to deliver generalized recommendations related to crop manage- ment, weather updates, and government schemes. While these approaches improved reach compared to traditional extension methods, they often lacked interactivity and personalization, limiting their effectiveness in addressing farmer-specific con- texts [3], [4], [5].

With advancements in artificial intelligence, conversational systems have emerged as an alternative interface for agricul- tural advisory services. AI-driven chatbots have been proposed to provide real-time responses to farmer queries related to crop selection, pest and disease identification, irrigation scheduling, and market information. These systems typically employ natu- ral language processing techniques to interpret user input and retrieve relevant recommendations from structured knowledge bases or data-driven models. Several studies report improved accessibility and responsiveness when compared to static advi- sory platforms. However, many existing chatbot solutions are designed with assumptions of stable internet connectivity and standardized language usage, which restrict their applicability in rural environments [6], [7], [8].

Language diversity represents a major challenge in the deployment of AI-based agricultural chatbots, particularly in multilingual countries such as India. Prior research has ex- plored multilingual and regional language support to enhance accessibility, yet most systems remain optimized for formal language structures or a limited set of dominant languages. Code-mixed language usage, where users alternate between languages within the same conversation, further complicates interaction handling and is not adequately addressed by exist- ing systems [9], [10].

The risk associated with agricultural advisories is another critical consideration that has received limited attention in current chatbot designs. Recommendations involving pesticide application, fertilizer dosage, or disease treatment carry signif- icant economic and environmental consequences if incorrect. Existing conversational advisory systems generally treat all queries uniformly, without applying differential validation or caution based on the potential impact of the advice provided. This limitation can undermine farmer confidence and result in poor decision-making outcomes [11], [12].

Recognizing these limitations, this paper proposes a frame- work that integrates context awareness, risk sensitivity, and connectivity resilience to address practical constraints in rural agricultural advisory systems. Recent survey-based studies further indicate that context-aware and human-centered design principles are critical for improving the adoption of AI-driven advisory systems among smallholder farmers [19].

Table I
Comparison Of Existing Agricultural Advisory Approaches

Category	Approach	Limitation
Chatbot-based systems	NLP-driven or rule-based responses	Limited ability to handle context and high-risk queries
Mobile advisory platforms	SMS or application-based information delivery	Dependence on stable network connectivity and limited personalization
AI-driven recommendation models	Data-oriented prediction and analysis techniques	Lack of transparency and limited adaptation to local conditions

While existing agricultural advisory systems have made notable progress, several practical limitations remain. Many current solutions do not sufficiently adapt to variations in user context, particularly in terms of language diversity and connectivity constraints. In addition, the absence of risk- sensitive response mechanisms reduces their reliability when dealing with critical agricultural decisions. These limitations highlight the need for a more adaptive framework that can adjust responses based on context while also handling high- impact queries with additional caution, which motivates the approach presented in this work.

III. Proposed Methodology

The proposed context-adaptive agricultural advisory frame- work is designed to respond dynamically to user interactions by considering linguistic preference, connectivity conditions, and advisory risk level. The methodology consists of four interconnected components: context identification, knowledge retrieval and validation, adaptive response generation, and feedback monitoring. Each component is structured to address specific limitations observed in existing agricultural chatbot systems.

To better describe the operational flow of the proposed system, the overall processing steps are summarized in an algorithmic form.

Context Identification

The context identification component infers relevant at- tributes from user input to guide subsequent advisory be- haviour. Three primary dimensions of context are considered: language and code-mixing patterns, connectivity conditions, and advisory risk level.

Language identification involves detecting the primary lan- guage or languages used by the farmer, including code- mixed usage where multiple languages are present in the same query. This is accomplished using lightweight language detection models that can distinguish between major Indian languages and English, as well as identifying mixed-language expressions common in rural communication. The inferred language preference influences both the retrieval of region- specific knowledge and the formulation of responses in an appropriate linguistic style.

Connectivity context is inferred from network indicators such as latency, bandwidth availability, and connection stabil- ity. This information is used to determine whether the interac- tion should prioritize lightweight processing and reduced data transfer, or whether full cloud-based retrieval can be safely employed. When low connectivity is detected, the system defaults to locally cached knowledge and simplified response structures.

Risk level assessment categorizes each query based on the potential impact of the advisory content. Queries related to general crop information or weather updates are treated as low-risk, while queries involving pesticide application, fertilizer dosage, or disease treatment are classified as high- risk. This classification is based on keyword analysis and query intent recognition, which identifies terms and patterns indica- tive of high-consequence decision points. High-risk queries trigger additional validation steps and cautionary framing in responses.

To further describe how risk is estimated, a simple weighted formulation is considered:

$$RiskLevel = w_1 \cdot K + w_2 \cdot I + w_3 \cdot C$$

where K represents keyword-based indicators, I corre- sponds to the inferred intent of the query, and C reflects the contextual impact associated with the request. The weights w1, w2, and w3 control the relative contribution of each factor in determining the overall risk level.

Knowledge Retrieval and Validation

The knowledge retrieval component accesses information from multiple sources, prioritizing locally relevant and ver- ified content. Unlike conventional chatbot systems that rely primarily on large-scale pre-trained models or generic web- based knowledge, the proposed framework emphasizes curated agricultural knowledge bases that have been validated by agricultural experts and extension professionals.

For low-risk queries, the system retrieves information from a combination of local knowledge repositories and general agricultural databases. Responses are generated based on the best available match, with minimal additional filtering. For high-risk queries, a multi-layered validation mechanism is applied. First, retrieved information is cross-checked against multiple authoritative sources to ensure consistency. Second, recommendations are compared against established guidelines and best practices documented by agricultural institutions. Third, the response includes explicit cautionary language and encourages consultation with local extension officers when uncertainty exists.

The validation process also accounts for regional agri- cultural practices, recognizing that optimal recommendations may vary across different agro-climatic zones. The system maintains region-specific knowledge modules that adjust advi- sory content based on inferred or explicitly stated geographic context.

Adaptive Response Generation

The adaptive response generation component tailors the structure, length, and language of responses based on the in- ferred user context. For users identified as having low literacy or limited familiarity with technical terminology, responses are simplified and delivered in short, action-oriented statements. For users demonstrating higher proficiency, more detailed explanations and supporting rationale are included.

Language adaptation involves generating responses in the detected language or code-mixed style. For code-mixed queries, the system mirrors the user's language usage pat- tern, maintaining consistency in linguistic style throughout the conversation. This approach reduces cognitive load and enhances comprehension, particularly for users who are more comfortable with informal or hybrid language usage.

For high-risk advisories, responses include explicit dis- claimers, emphasize caution, and recommend verification with local agricultural experts. The system avoids presenting high- consequence recommendations with unqualified certainty, in- stead framing advice in a manner that encourages informed decision-making rather than blind adherence.

Feedback and Monitoring

The feedback and monitoring component collects interac- tion data to support continuous improvement without dis- rupting real-time advisory delivery. Feedback mechanisms include implicit indicators such as query reformulation, session duration, and repeated queries, as well as optional explicit feedback where users can rate the relevance and usefulness of responses.

Monitoring focuses on identifying patterns that indicate potential issues, such as frequent reformulation of high-risk queries, which may suggest that responses are unclear or insufficient. This information is used to refine knowledge retrieval logic and response templates. Privacy considerations are integrated into the design, ensuring that user data is anonymized and used solely for system improvement pur- poses.

Algorithmic Flow

The overall working of the proposed system can be outlined through the following sequence of steps:

Algorithm 1: Context-Adaptive Advisory Processing Input: User query Q

Output: Context-aware advisory response R

1) Accept user query Q
2) Identify the language and check for code-mixed patterns
3) Determine current connectivity condition (low or stable)
4) Analyze the query to estimate its risk level
5) Retrieve relevant information from available knowledge sources
6) If the query falls under high-risk category:
   - Perform additional validation checks
   - Attach cautionary guidance to the response
7) Generate response R based on identified context
8) Deliver the response to the user

These steps provide a simplified representation of how the system integrates context awareness and validation during advisory generation.

IV. System Architecture

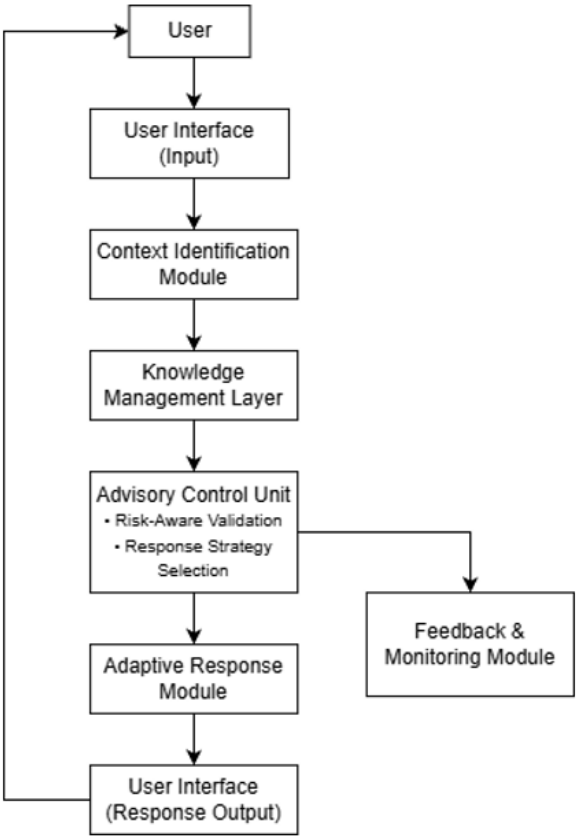

Fig. 1. System architecture of the proposed context-adaptive agricultural advisory framework.

Fig. 1 provides an overview of the proposed system archi- tecture.

The system architecture is organized into modular compo- nents that collectively implement the proposed methodology while maintaining flexibility for deployment in diverse connec- tivity environments. The architecture consists of five primary layers: the interaction interface layer, the context processing layer, the advisory engine layer, the knowledge management layer, and the feedback layer.

Interaction Interface Layer

The interaction interface layer provides the primary point of user engagement. It is designed to operate through text-based conversational interfaces accessible via mobile applications or simple web interfaces that function under low-bandwidth conditions. Voice-based input and output capabilities are also supported to accommodate users with limited literacy. The interface layer handles initial input processing, including lan- guage detection and basic query interpretation, before passing structured data to the context processing layer.

Context Processing Layer

The context processing layer implements the context iden- tification logic described in the methodology section. It re- ceives raw or pre-processed input from the interface layer and generates a context profile that includes language preference, connectivity status, and risk level classification. This pro- file guides subsequent processing stages and influences both knowledge retrieval and response generation behaviour. The context processing layer operates with minimal computational overhead to ensure rapid response times even under resource- constrained conditions.

Advisory Engine Layer

The advisory engine layer serves as the central decision- making component. It coordinates knowledge retrieval, applies validation logic for high-risk queries, and invokes response generation functions based on the context profile. The advisory engine maintains a rule-based framework that defines how different combinations of context attributes should influence advisory behaviour. For example, a high-risk query submitted under low-connectivity conditions triggers simplified retrieval from locally cached knowledge with enhanced cautionary framing in the response.

Knowledge Management Layer

The knowledge management layer organizes agricultural knowledge into structured repositories that can be accessed efficiently. Knowledge is segmented into domain-specific mod- ules covering crop management, pest and disease control, irrigation, soil health, market information, and government schemes. Each module includes metadata indicating geo- graphic applicability, risk level, and source authority.

The knowledge management layer prioritizes lightweight storage and retrieval mechanisms to support offline or low- connectivity operation. Core knowledge modules are pre- loaded onto local devices or edge servers, reducing depen- dence on real-time cloud access. Updates to knowledge repos- itories are performed asynchronously during periods of stable connectivity, ensuring that the system remains current without disrupting active interactions.

Feedback Layer

The feedback layer collects and aggregates interaction data for post-processing and system refinement. Feedback is stored in anonymized form and analyzed periodically to identify trends, common query patterns, and areas where response quality may be improved. Insights derived from feedback analysis inform updates to knowledge modules, validation rules, and response templates.

In addition to conversational interaction, the proposed framework supports a lightweight dashboard-style interface for presenting advisory outputs. The dashboard visually summa- rizes critical information such as crop-specific alerts, weather- based notifications, advisory messages, and associated risk levels. This visual representation reduces cognitive load for users with limited literacy and enables quicker comprehension compared to text-only responses. Prior studies indicate that dashboard-driven decision support systems improve usability and trust in digital agricultural platforms, particularly in low- resource rural environments [15], [16].

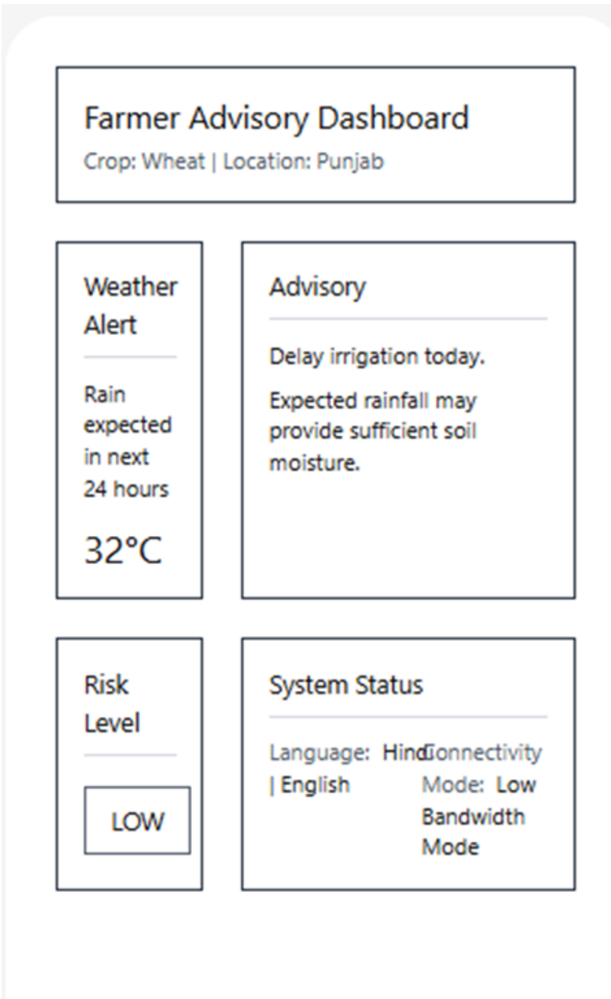

Fig. 2. Conceptual dashboard interface for the proposed context-adaptive agricultural advisory system.

Fig. 2 illustrates how the advisory output is visually summarized to support low-literacy users and low-connectivity environments.

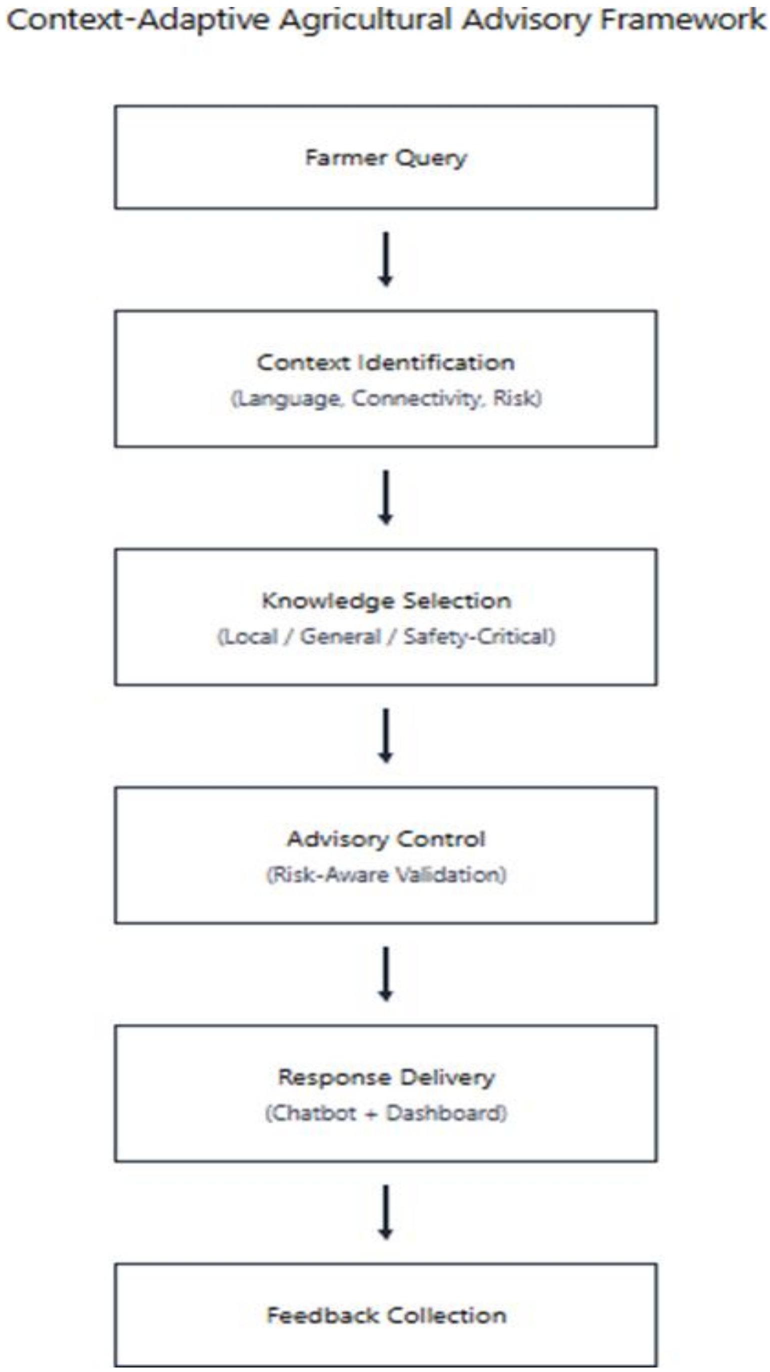

Fig. 3. Interaction flow of the proposed context-adaptive agricultural advisory framework.

Fig. 3 demonstrates the operational workflow from farmer query to feedback collection.

V. Results And Discussion

To assess how well the proposed framework works in real-world situations, we used a scenario-based evaluation method. The focus of this evaluation is on how effectively the system handles different types of user queries, especially in terms of context awareness, handling of high-risk agricultural advice, and operation under varying network conditions. As a full-scale real-world deployment was not carried out, the evaluation is based on representative use cases that reflect common interactions between farmers and advisory systems. The behaviour of the proposed framework is also compared with that of existing chatbot-based systems to highlight key differences.

A comparative analysis was conducted to highlight the dif- ferences between conventional chatbot-based advisory systems and the proposed framework.

Table II
Comparative Analysis Of Advisory Systems

Feature	Conventional Chatbot Systems	Proposed Framework
Context Handling	Responses are generally generic and do not consider user-specific conditions	Responses are adjusted based on user context such as language, connectivity, and query type
Risk Awareness	No clear distinction between low-risk and high-risk queries	High-risk queries trigger additional validation and cautionary responses
Connectivity Dependency	Requires stable internet connectivity for proper functioning	Designed to operate under low or intermittent connectivity using local data
Language Support	Offers limited multilingual support, mostly using formal language	Supports regional languages and code-mixed input for improved usability
Response Quality	Often provides standard answers without localization	Generates context-aware responses aligned with local practices
Reliability	May produce unchecked or generalized recommendations	Incorporates validation steps to improve reliability of responses

Another important situation involves low or unstable in- ternet connectivity, which is quite common in rural areas. In such cases, traditional chatbot systems may struggle to respond or show delays. The proposed framework handles this more effectively by using locally stored knowledge whenever needed, ensuring that advisory support is still available even with limited connectivity.

These observations indicate that the proposed approach is more adaptable and reliable compared to conventional chatbot- based advisory systems.

A few key performance aspects were considered to under- stand how the proposed framework behaves under different operating conditions.

Table III
Observed Behaviour Of The Proposed Framework

Aspect	Observation
Response Time	Faster responses were observed in low-network conditions due to the use of locally available data
Risk Handling	High-risk queries were identified with consistent identification across most evaluated scenarios based on scenario-level analysis
Response Suitability	Outputs were more aligned with user needs due to context-aware adjustments
System Stability	The system continued to function even when network connectivity was unstable
User Interaction	Responses were easier to follow, especially when simpler language or mixed language was used

A. Scenario-Based Evaluation

To get a clearer idea of how the proposed framework performs in practical situations, a set of representative user query scenarios was considered. These scenarios were chosen to reflect common interactions that typically occur between farmers and agricultural advisory systems, covering both low- risk and high-risk queries.

In the case of low-risk queries, such as general crop information or weather-related questions, both conventional chatbot systems and the proposed framework tend to provide similar responses. However, the proposed system adjusts the response based on user-specific factors like language prefer- ence and network conditions, which makes the output easier to understand and more usable in real situations.

For high-risk queries, especially those related to pesticide usage or disease management, the difference becomes more noticeable. Conventional systems usually provide direct rec- ommendations without checking the possible impact. On the other hand, the system includes an additional validation step, where the response is verified using multiple sources and presented along with cautionary advice. This helps in reducing the chances of unsafe or incorrect suggestions.

Based on the above evaluation, one of the key observations of the proposed approach is improved contextual relevance of advisory responses. Unlike static chatbot systems that generate uniform responses irrespective of user conditions, the proposed framework dynamically adapts advisory behaviour based on inferred language preference, connectivity constraints, and advisory risk level. This adaptation is expected to reduce ambiguity in farmer interactions and improve comprehension, especially for users with limited literacy or reliance on infor- mal language usage. By prioritizing locally relevant knowledge sources, the system further mitigates the issue of generic recommendations that often fail to align with region-specific agricultural practices.

Safety-aware advisory control represents another signifi- cant outcome of the proposed design. Existing chatbot-based advisory platforms frequently treat all queries as low-risk interactions, which can be problematic when recommendations involve pesticide application, fertilizer dosage, or disease treat- ment. The incorporation of risk-aware validation mechanisms in the proposed framework introduces an additional layer of caution for high-impact advisories. This design choice is expected to reduce the likelihood of harmful or misleading guidance, thereby strengthening farmer trust in automated advisory systems.

Connectivity resilience is a critical factor influencing the usability of digital advisory tools in rural environments. Many existing solutions rely heavily on continuous cloud connec- tivity, leading to degraded performance in low-bandwidth or intermittent network conditions. The proposed architecture addresses this limitation through a connectivity-conscious design that emphasizes lightweight processing and reduced dependence on real-time cloud access. As a result, the system is better suited for deployment in rural regions where network reliability cannot be guaranteed.

From a usability perspective, the adaptive response gener- ation mechanism contributes to a more inclusive interaction experience. By adjusting response length, language style, and complexity, the system accommodates a broader range of user capabilities and preferences. This contrasts with conventional advisory systems that assume uniform user proficiency and often overwhelm users with overly technical explanations. Similar usability trends have been observed in recent eval- uations of AI-based agricultural decision support systems deployed in rural contexts [17]. The inclusion of a feedback and monitoring component further supports long-term system refinement without disrupting real-time interactions.

While the proposed framework demonstrates several ad- vantages, certain limitations must be acknowledged. The ef- fectiveness of context inference is influenced by the quality and diversity of user interactions, and inaccuracies in context classification may affect response suitability. Additionally, the framework emphasizes decision support rather than au- tonomous decision-making, which may require complemen- tary human extension services for complex or ambiguous scenarios. These limitations highlight opportunities for future work, including empirical user studies and controlled field evaluations to quantify system impact.

Overall, the results indicate that integrating context sensitiv- ity, risk awareness, and connectivity-conscious design princi- ples can substantially enhance the practical applicability of AI- driven agricultural advisory systems. The proposed framework offers a balanced approach that prioritizes reliability and user trust, making it well aligned with the operational realities of rural agricultural environments.

VI. Conclusion And Future Work

This paper presented a context-adaptive agricultural advi- sory framework designed to address the practical limitations of existing AI-based chatbot systems in rural agricultural environments. Motivated by challenges commonly observed in the Indian context, including language diversity, intermittent connectivity, and the high-risk nature of certain agricultural advisories, the proposed approach emphasizes adaptability, safety awareness, and accessibility. By integrating context identification, risk-aware advisory control, and connectivity- conscious response delivery, the framework moves beyond static conversational systems and offers a more reliable form of decision support for farmers.

The proposed methodology and system architecture high- light how agricultural advisory systems can be designed to align more closely with real-world farming conditions rather than idealized digital environments. The emphasis on adaptive response behaviour and cautious handling of high-impact advisories contributes to improved usability and trust, which are critical factors for the sustained adoption of digital tools in rural agriculture. While the framework is motivated by Indian agricultural settings, the underlying design principles are applicable to other regions facing similar infrastructural and socio-linguistic constraints.

Future work will focus on empirical validation of the proposed framework through user studies and field-level evalu- ations involving farmers and agricultural experts. Quantitative analysis of usability, response relevance, and trust-related in- dicators will provide deeper insight into system effectiveness. Additional extensions may include richer context modeling, integration of multimodal inputs such as images for crop disease identification, and enhanced offline capabilities to further reduce connectivity dependence. Recent studies also emphasize that scalable deployment of agricultural AI systems depends on user trust, institutional support, and long-term in- tegration with extension services [18]. These directions aim to strengthen the role of context-aware AI systems in supporting sustainable and informed agricultural decision-making.

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