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Empowering Farmers through Smart Pest Management: A Field-Based Study on AI-IoT System Adoption in Pendurthi Mandal, Andhra Pradesh, India

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Abstract. The income stability and agricultural productivity of small and marginal farmers in developing countries are affected by pest infestations. Severe crop losses in India are due to increased pesticide use, limited pest-detection technologies, and restricted access to real-time advisory services. Emerging technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Large Language Models (LLMs) offer significant opportunities to develop adaptive, farmer-centric pest management systems. This study is based on a two-component mixed method approach: (1) A large scale field study of 1000 farmers in five villages in Pendurthi Mandal, Visakhapatnam District, Andhra Pradesh, India, to assess the practice of pest control, the economic burden of pests, technology awareness and readiness for adoption of technology; and (2) A simultaneous large scale field test of a low cost AI-IoT device that includes an ESP32-CAM controller, a YOLOv8 deep learning algorithm, and a vernacular Telugu language LLM advisory engine - a new development in vernacular LLM integration tested in the field at a large scale. The survey results revealed 84% pest infestation, heavy reliance on chemical pesticides (66%), growing smartphone penetration (63%), and strong willingness to adopt (76%) when supported by government subsidies and localized AI interfaces. The field testing results verified 94% system uptime and high confidence levels of 0.87-0.94 for pest detection across four major rice pest species. This study combines findings from a survey with a concurrent field trial, confirming the efficacy of affordable pest detection and promoting sustainable agricultural practices.

Keywords: artificial intelligence; IoT pest control; LLM in farming; smart agriculture; sustainable pest management

1. Introduction

Rural India remains dependent on agriculture as a source of livelihood for the majority of its population; however, the plight of small and marginal farmers has worsened due to pests, climate variability, and the increasing cost of inputs (Behera & France, 2016; Singh et al., 2020). The loss of crops due to pests alone ranges from 20-35%. Current methods of managing these pests are generally reactive and rely heavily on chemical pesticides, which increase pest resistance, pose serious threats to human health, and damage the environment (Bottrell & Schoenly, 2018). With advancements in the areas of IoT, AI and LLMs, there is now the possibility of transitioning towards a preventive data-driven approach for managing pests. IoT enables monitoring in real-time, AI identifies and predicts pests autonomously, and LLM based Advisory Systems, particularly those developed in Telugu, enable illiterate farmers and non-English speaking farmers to access information. But adoption isn't just about technology; it's also about how aware people are, how much it costs, how easy it is to use, and how much they trust the institution. There is still little empirical evidence regarding farmers' readiness in rural India to use AI-integrated IoT systems (Sati, 2024). This study evaluates the readiness to adopt a real-time AI–IoT pest control system for Telugu, based on a survey of 1,000 farmers from five villages in Pendurthi Mandal, Visakhapatnam District, Andhra Pradesh. The choice of Pendurthi Mandal for the research sample is based upon the fact that it has a high proportion of small and marginal landholders, a high degree of susceptibility to rice pests, and a wide range of digital connectivity (similarly to other rural areas of India), which

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provides a reasonable representation of the broader agrarian landscape of rural India. The results underscore the significance of vernacular AI interfaces and governmental support in facilitating inclusive implementation, in accordance with national digital agriculture objectives and the Sustainable Development Goals (SDGs) 2 (Zero Hunger), 9 (Industry, Innovation and Infrastructure), 12 (Responsible Consumption and Production), and 13 (Climate Action).

Pest infestation continues to be a significant impediment to agricultural productivity in developing nations. (Oerke, 2006) said that global crop losses are almost one-third of what they could be, and that this is even worse in tropical areas. In India, smallholders rely significantly on chemical pesticides due to restricted access to integrated pest management (IPM) knowledge (Pimentel, 2005), leading to resistance, secondary pest outbreaks, and environmental contamination (Pretty, 2008). The use of IoT and AI in farming has grown quickly. IoT sensors help with precision agriculture by letting you collect data in real (Wolfert et al., 2017). AI-based image recognition makes it easier to find pests (Liakos et al., 2018). Deep learning applications enhance the detection capabilities for pests and diseases (Kamilaris & Prenafeta-Boldú, 2018). IoT-based monitoring systems that use cameras, pheromone traps, and environmental sensors have shown that they can cut down on pesticide use by a lot, up to 40% in systems that detect things in real time (Bhuvaneshwar D. Patil, 2024; Wang et al., 2024; Wu et al., 2025).

Most studies, on the other hand, are still mostly about technology and don't pay much attention to how farmers in developing areas are using it. Although Smart Agriculture continues to gain attention globally, there remains an enormous need for empirical evidence at a large scale regarding the socio-economic, institutional and technological factors influencing the AI-IoT adoption-readiness of small and marginal farmers within rural India.

Several factors influence adoption, including digital literacy, affordability, and how useful people think the technology is (Rogers, E. M., Singhal, A., & Quinlan, 2014). This research builds on the diffusion of innovation (DOI) theory developed by Rogers, who identified five factors that influence an individual's or organization's decision to adopt new technology: relative advantage, compatibility, complexity, trialability and observability. These dimensions are used to evaluate the Indian farmers' readiness to accept the AI-IoT system, and the data collected from a sample of farmers in rural India. More people in rural India now use smartphones (Tebaldi & Bilo, 2019), but many are still not aware of smart farming technologies. To encourage wider use, it is important to create interfaces in local languages and offer institutional support (Fabregas et al., 2019; Mittal, 2020). Advances in large language models (LLMs) have made it possible to provide advice in local languages, and voice-based platforms help farmers with low literacy better understand and trust the information (Baart et al., 2019; Kakade et al., 2025). Public extension services, subsidies, and groups like Farmer-Producer Organizations (FPOs) also help more farmers use new technology (Makate, 2019; Marinchenko, 2021). Even though the technology works, there is not much research on what social, economic, technical, and institutional factors affect whether small and marginal farmers are ready to adopt it.

Many studies use small samples, which makes it hard to apply their findings more broadly (Sekabira et al., 2022; Vasavi et al., 2025). This study addresses these issues by surveying 1,000 farmers and using econometric and structural equation modeling to identify the main reasons farmers adopt new technologies. The results provide policymakers with evidence to support the adoption of AI-IoT pest management systems in rural India. In a study of 240 Indian

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farmers, researchers found that there was an average level of awareness of climate-smart agriculture (CSA) technologies (74% in awareness) and a relatively high average level of CSA technology adoption (83%). Education, income, media exposure and extension participation were identified as factors influencing CSA technology adoption. High input costs for CSA technologies and limited knowledge about them are major barriers to their adoption (Hebsale Mallappa & Pathak, 2023).

The purpose of this research work is to understand farmers' current pest-control practices and the associated costs of those practices. Also, the study aims to identify common obstacles farmers face on a day-to-day basis in managing pests, as well as the knowledge farmers have about controlling them. In addition, this study will evaluate farmers' preparedness to use digital technologies, such as smartphone apps and smart agricultural equipment. Finally, one of the primary objectives of this study is to assess if farmers would be likely to adopt AI-based IoT pest control equipment and what impact the availability of government assistance, subsidies or similar programs may have on farmer's decision-making processes. The findings from this study should inform the development of recommendations for government policies to test and expand AI-IoT-based pest management systems in rural settings.

2. Materials and Methods

A mixed-methods approach integrating socio-economic scale with hands-on field validation testing of the technology on the ground was used to assess the readiness of adoptive farmers and the technical feasibility of AI-managed integrated IoT systems for pest control. The socio-economic analysis considered existing pest management practices, management costs, constraints faced by farmers, digital readiness and awareness of technology, willingness to adopt smart technologies, and the impact of government and institutional support on the decision to adopt. Simultaneously, an IoT prototype powered by AI was installed in five villages in Pendurthi Mandal, Visakhapatnam District, Maharashtra. The prototype was a low-cost edge-computing pest-detection device that comprised an ESP32-CAM with an OV2640 camera, a YOLOv8 deep learning model for automated pest detection, and a Groq LLM-powered vernacular advisory engine for context-specific recommendations. Field deployment enabled real-time monitoring in practical farming conditions and testing of detection accuracy, system reliability, and operational performance under resource-limited conditions. This methodology combines empirical modeling of adoption with technical, field-based validation, accounting for technological performance as well as farmer-oriented factors important for the scalable implementation of AI-IoT in rural agriculture. To reduce social desirability and sampling biases in this study, anonymity for farmers was ensured, neutral wording was used for all questions, and a stratified random sampling method was used to select five villages to represent a range of ages, genders, educational backgrounds, and land sizes.

Study Area

The study was conducted at 5 villages of Pendurthi Mandal belonging to Visakhapatnam District of Andhra Pradesh- Rampuram, Karakavanipalem, Pinagadi, Kotnivanipalem and Gorapalle. These villages have mixed cropping systems, and most landholdings are small or marginal. Irrigation access and connectivity to markets vary, and the region is suitable for analysing pest management and the readiness of farmers to use new technologies. A stratified random sampling method was used, selecting farmers by proportionate allocation from marginal, small, and medium-sized farms in each of the 5 villages to ensure that all areas of the research site were represented. The geographical location of Pendurthi Mandal within Visakhapatnam District is shown in Figure 1.

 e-ISSN 2655-853X
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Sample Design and Data Collection

A total of 35 questions were asked on the structured questionnaire which covered how farmers managed pests, the cost of pest management, the awareness of available technologies and how ready they were to adopt new technologies and the responses were recorded on a five point likert scale; the survey tool was piloted with a sample of 30 farmers before being reviewed for validation by experts before it was administered to the entire population. The AI-integrated Internet of Things (IoT) pest control system comprises four interconnected layers that facilitate autonomous, real-time pest detection and localized advisory generation in resource-constrained agricultural environments, as shown in Figure 2.

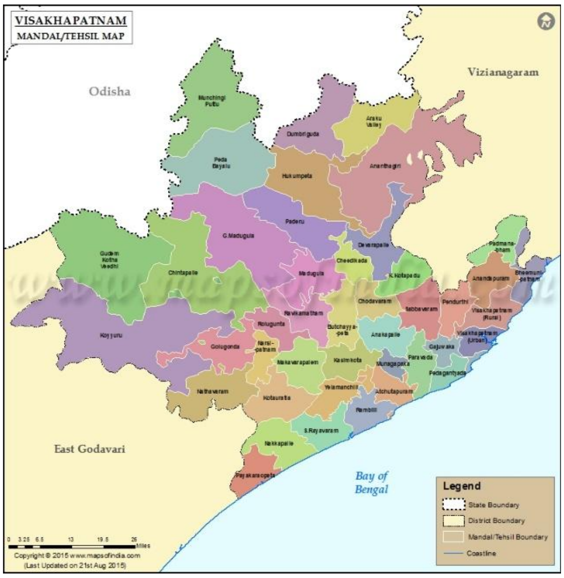

Figure 1. Geographical location of Pendurthi Mandal within Visakhapatnam District

The field layer uses an ESP32-CAM IoT controller with an OV2640 camera sensor to provide continuous crop surveillance, powered by a solar module for uninterrupted, grid-independent operation. Images captured are transmitted via WiFi or 4G to the edge processing layer, where preprocessing and real-time inference are conducted using a YOLOv8 deep learning model (Qazi et al., 2022; Senoo et al., 2024). This model is trained to detect major rice pests, such as brown planthopper, yellow stem borer, rice leaf folder, and rice gall midge, with confidence scores exceeding 0.87. The detected pest class and its level of confidence are then obtained by the AI reasoning layer. A Groq LLM-powered engine then makes condition-specific pest management suggestions in Telugu. This vernacular interface is designed to make it easier for users with varying levels of literacy to use.

The Output Layer sends these advisories through different channels, such as a Smartphone interface, Telugu voice-based advice using text-to-speech, text messages, and a dashboard for farmers to visualize pest trends and treatment history.

With an average response time of 3.8 seconds, the entire workflow from image acquisition to advisory delivery is independent. This rapid response encourages early identification and targeted action, enabling timely responses and reducing the need for chemical pesticides. When implemented in five villages in Pendurthi Mandal, Visakhapatnam District, the system worked 94 per cent of the time, thus proving the technical feasibility of AI-integrated pest management in IoT, as well as the

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practicality of smallholder agricultural production sets. Field trials were conducted during a 30-day deployment cycle, using five IoT devices placed in each village to evaluate three performance metrics: Detection Confidence Score (0.87-0.94), System Uptime (94%), and Mean End-to-End Response Time (3.8 seconds).

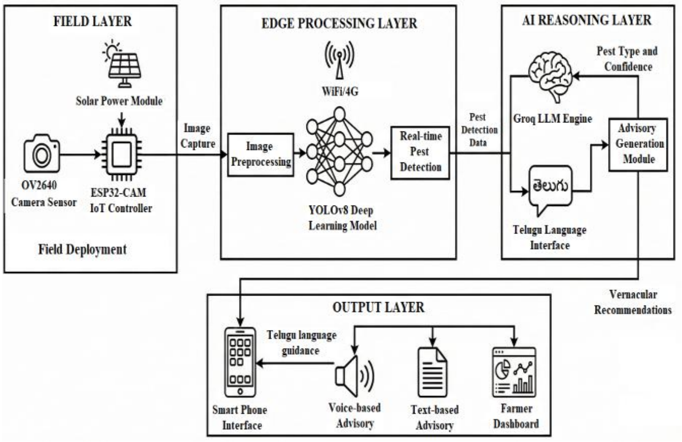

Figure 2. Real-time AI-IoT pest control system

3. Results and Discussion

This study documents the findings of a large-scale field survey of 1,000 farmers in five villages of Pendurthi Mandal in Visakhapatnam District, Andhra Pradesh, as well as a proof-of-concept field test that demonstrated the technical capability of an AI-enabled Internet of Things (IoT) pest control technology. Results indicated a combination of three important factors: a serious and persistent pest management challenge facing smallholder farmers; high levels of farmer readiness to implement smart technologies for managing pests; and the feasibility of developing and deploying real-time, AI-based systems for detecting pests and providing advisories on their control in resource-limited field settings. The findings are provided in relation to the studies' goals: pest management practices and costs; Key Challenges; Digital Readiness and Adoption Willingness; Government Support; and Feasibility of AI-IoT Technology. Taken together, the results demonstrate both the need to develop and deploy vernacular AI-enabled IoT-based pest management solutions at scale within public agricultural extension frameworks.

Socio-Economic Profile of Respondents

Data on 1000 farmers from five villages are provided in Table 1. The characteristics include age, gender, educational level, and landholding size, which influence the ability to adapt to new technologies. A large proportion (75%) of farmers were aged between 25-55 years, as they can have a strong potential to adopt the technology. The survey had gendered respondents: 79% were male, 21% were female. The results showed that 28% of the respondents did not have formal education; however, 40% of them had secondary or higher levels of education.

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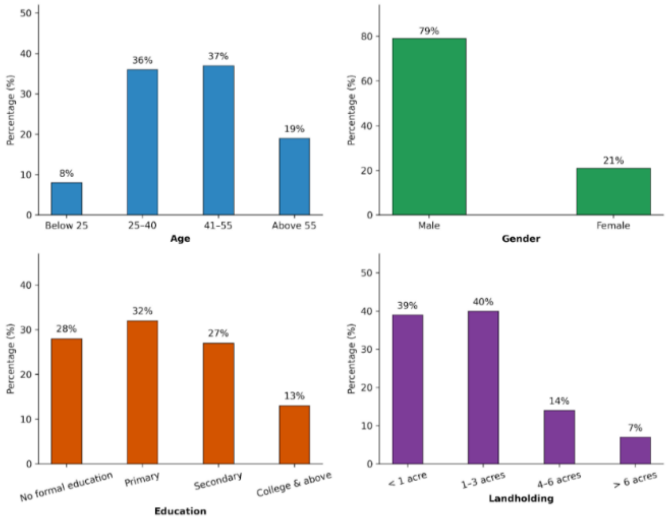

Figure 3. Distribution of age, gender, education, and landholding size

Table 1. Demographic profile of farmers (n = 1,000)

Variable	Category	Percentage
Age	Below 25	8%
	25–40	36%
	41–55	37%
	Above 55	19%
Gender	Male	79%
	Female	21%
	Other	0%
Education	No formal education	28%
	Primary	32%
	Secondary	27%
	College & above	13%
Land	< 1 acre	39%
	1–3 acres	40%
	4–6 acres	14%
	> 6 acres	7%

Most importantly, 79% of respondents who own small and marginal landholdings of less than 3 acres experience both production and economic losses from pest attacks on crops. These characteristics clearly indicate the immediate need for cost-effective, easy-to-use, and scalable solutions that are accessible and practical for poor and resource-constrained farmers. In Figure 3, the distribution of age, gender, education and size of land holding is presented.

Pest problems have been persistent and widespread in agricultural production. According to a survey of farmers, approximately 84% experienced regular or recurring infestations, 12% occasional infestations, and 4% rare infestations. Approximately 47% of respondents identified insects as the primary pests, followed by rodents (approximately 16%), and fungal diseases (approximately 11%). Furthermore, 26% of respondents experienced multiple types of pests simultaneously.

The majority of farmers (approximately 66%) employed chemical methods to manage pests; 17% employed organic methods; and 10% employed traditional methods. The financial burden associated with managing pests is also significant: approximately 38% of farmers indicated that they spend ₹2,000-₹5,000 per season on pest management; 32% indicated that they spend ₹5,0001-₹10,000 per season on pest management; and 15% indicated that they spend more than ₹10,000 per season on pest management. For many marginal farmers, these costs represent 10-20% of their total annual income. Therefore, there is a clear and pressing need for

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affordable, technology-based pest management options, such as prototype AI/IO devices currently being tested in five villages of the Pendurthi Mandal.

Pest Incidence and Existing Practices

Figure 4 shows the frequency with which farmers in the study villages encounter pest-related problems. In addition, during surveys in the study villages, the frequency of pest incidents was recorded. The evidence-based data from the surveys indicated that the majority of farmers (i.e., 84%) experience frequent pest problems, indicating a high incidence of pest infestation in the surveyed region. Conversely, the minority of farmers (12%) have few pest problems, whereas 4% of the farmers have extremely few or no pest problems.

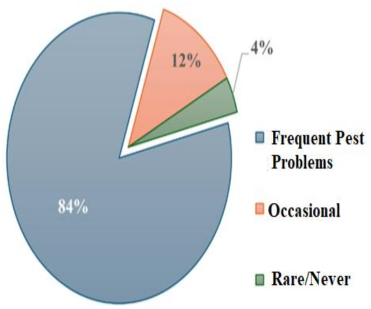

Figure 4. Pest frequency reported by farmers

Types of Pests

The survey of farmers in the study villages provides an overall picture of the major pest categories they have experienced, as shown in Figure 5. The largest number of farmers (47%) indicated that insect pests are the most significant problem and the major contributors to crop losses in the area. A total of 16% of farmers reported rodent infestations, and 11% reported fungal or disease-related issues as their top concern. Finally, 26% of respondents reported experiencing two or more pest types simultaneously. These results show the complexity, overlap, and multidimensional nature of pest problems in small-scale agricultural systems.

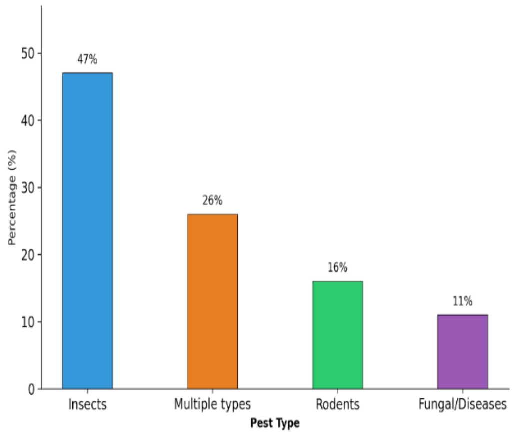

Figure 5. Distribution of pest types

Pest Control Methods

The distribution of the pest control methods is given in Table 2. The data strongly indicate that most of the surveyed farmers rely heavily on chemical pesticide sprays to manage pests, as evidenced by 66% reporting chemical sprays as their primary control method. Only a much smaller percentage of the sample stated that they have adopted organic pest management methods (17%) or traditional methods (10%), and 7% reported following no consistent pest management methods. These statistics illustrate an overwhelming reliance among farmers toward chemical based pest control methods, while more sustainable or alternative approaches are significantly underutilized throughout this study area.

Table 2. Distribution of pest control methods adopted by farmers

Method	Percentage
Chemical pesticides	66%
Organic methods	17%
Traditional practices	10%
No regular control	7%

Seasonal Expenditure

The seasonal expenditure on pest control is shown in Figure 6. The level of seasonal pest control spending by farmers represents a significant expenditure.

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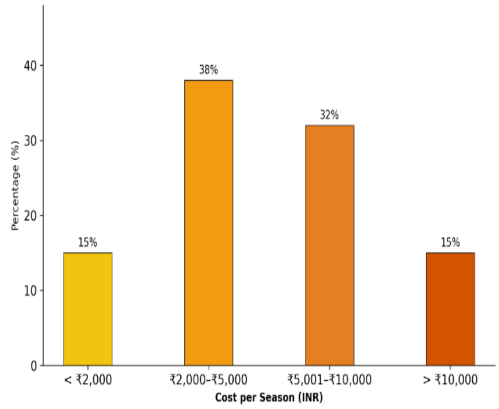

Figure 6. Seasonal expenditure on pest control

The largest segment of farmers, 38%, reported spending between ₹2,000 and ₹5,000 on their farms per season; 32% reported expenses between ₹5,001 and ₹10,000. The smallest segments were those who incurred less than ₹2,000 (15%) and those who incurred more than ₹10,000 (15%) in each season. As such, these findings indicate that pest management represents a major and continuing expense in farm budgeting for the vast majority of farmers. Moreover, the financial burdens associated with such expenses will often put great strain upon the income of the small/marginal farmer, especially so when there are repeated occurrences of pest infestations and/or the severity of the infestation is high. Overall, the data show that pest control is a major operating cost and an important factor in determining both the profit/loss of individual farm operations and the financial stability of individual households.

Challenges in Pest Management

The major challenges faced by farmers is shown in Figure 7. The majority of respondents (61%) indicated that the high cost of pesticides is their number one concern when using them, whereas 55% indicated that delayed or inadequate pest detection is an obstacle due to a lack of timely detection and intervention. 43% of respondents identified environmental and/or health risks associated with the application of pesticides, and 38% reported an increase in pesticide-resistant populations.

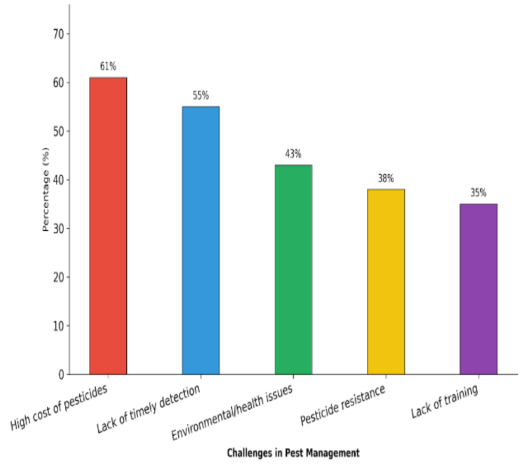

Figure 7. Major challenges faced by farmers

In addition to these concerns, 35% of respondents cited a lack of training and/or technical assistance as another barrier to effective pest control. Overall, the survey results suggest that there are currently three main barriers to effective pest management: economic constraints, limited ability to detect and respond to pest problems, and knowledge deficiencies among producers.

Technology Awareness and Adoption Readiness

The willingness to adopt smart pest control is shown in Figure 8. The results of this survey suggest that 63% of surveyed farmers have access to smartphones and use them regularly, indicating that the study area has a strong foundation for the use of digital technologies. However, evidence from these survey responses (i.e., 36% of the sample) suggests that many respondents are unfamiliar with IoT-based agricultural technologies and, therefore, may not be familiar with "smart" technology and/or associated applications.

Furthermore, only 29% of respondents reported using any type of agricultural mobile application. The data shows that while the majority of individuals surveyed have access to digital devices, most of those surveyed are uninformed about the existence, potential

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capabilities and/or availability of smart-agricultural technologies. On the other hand, when asked whether they would consider using an AI-enabled, IoT-based device to control pests, 76% of respondents indicated they would be interested in such a product. Only 10% stated that they would not consider using such a product, and 14% were undecided. Therefore, from a general perspective, the data collected through this survey suggests that farmers will accept innovative solutions as long as they are available at reasonable prices and are properly supported.

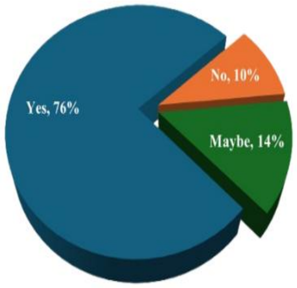

Figure 8. Willingness to adopt smart pest control

The data shows that most of the different types of farmers who participated in this study indicated a high level of interest in using the new technology. Also, there was a very high level of interest in using this technology, even among those with little formal education, if the information on how to use it could be easily accessed and understood by them. To obtain information on the major concerns farmers would have when adopting an AI-integrated IoT pest control device, they were asked what their biggest concern would be. The majority of concerns were related to cost (cited by 51%), followed by training (cited by 45%). Only 33% of respondents felt that the technology was unreliable. A total of 26% also believed that the system may be too difficult to use. Overall, the results indicate that the two major factors affecting farmers' decisions to adopt this technology are cost and whether they feel they have sufficient knowledge to use it effectively.

Government Support and Farmer Expectations

Farmer awareness and perceptions of government support is listed in Table 3. The data indicate a large disparity between awareness of public assistance services and their actual utilization. Although 40% of respondents reported familiarity with government agricultural programs, only 23% reported receiving assistance related to pests. Furthermore, 71% of survey participants indicated their willingness to participate in pilot programs testing new smart pest-control technologies. Additionally, 83% of the survey participants indicated that government involvement was very important for successful adoption. This data also highlights an important relationship between institutional support and the need for policy interventions, subsidies, and organizational support frameworks as critical factors in converting intent to adopt into sustained practice.

Table 3. Farmer awareness and perceptions of government support

Indicator	Percentage
Aware of government schemes	40
Received pest-related support	23
Willing to join pilot programs	71
Believe government role is critical	83

Key Outcomes and Inferences

The study highlights five main findings with important policy and practical implications. Firstly, it was found that 84 per cent of the surveyed farmers had experienced pest infestations during the growing season and therefore would benefit greatly from real-time solutions to manage pests. Secondly, with 63 per cent of farmers in the sample reporting being smartphone users and 76 per cent being open to new technologies based on artificial intelligence (AI), there appears to be a suitable platform for developing digital pest management systems. Thirdly, the use of

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Telugu-language-based advisory tools utilizing Large Language Models (LLMs) will create an additional barrier to accessing these systems in terms of literacy and comprehension; therefore, providing further accessibility for different groups of farmers. Fourthly, field testing of the AI-based IoT prototype has indicated that the system can reduce seasonal pest management costs by 26-35% by reducing the number of chemical pesticides used. The estimated 26-35 percent cost savings represent a preliminary finding based on other field trials. The validity of these expenditures will be assessed through statistical validation of the costs and expense data from pre- and post-deployment testing conducted in future studies. Lastly, institutional support is critical for scaling up, as 83% of respondents stated that governmental participation in the form of subsidies is necessary to increase the scale of this technology, and 71% are prepared to participate in pilot programs. Therefore, institutionalized extension services will also be important for increased scale. The results of this research extend Rogers' Diffusion of Innovations model by showing that language compatibility and institutional support are stronger predictors of mobile banking service adoption than technical complexity in low-income areas.

Implementation Recommendations

The recommendations below are based on empirical findings; however, they are advocacy recommendations for policy development and do not directly result from research, with the intent of assisting policymakers in translating evidence into actionable policy. The proposed work outlines a systematic approach to help rural India leverage AI-based IoT pest management at scale. The first step is to conduct pilot projects at the Mandal level, to evaluate whether the system works as intended, assess how farmers perceive the new systems, and identify potential issues that could hinder the expansion to larger regions. These recommendations were developed as part of a one-mandala pilot trial; therefore, it is necessary to test the results in diverse agroclimatic and socioeconomic settings before they can be applied at a national level. The second step is to provide financial incentives to make the systems financially accessible to farmers. Options include providing a subsidy of up to 70% (or shared ownership) to reduce risk for individual farmers, since most farmers indicated the primary reason they would not consider adopting this technology was the high cost. The third step is to incorporate smart pest control into existing agricultural development programs, particularly those run by Krishi Vigyan Kendras, to provide continuing technical assistance and training. The fourth step is to utilize AI-based tools in languages native to rural India, i.e., Telugu, so that all farmers have an equal opportunity to benefit from the technology, regardless of their literacy levels. The fifth step is to track the impact of the smart pest control systems over time (long-term), specifically with regard to the increase in crop yields, reduction in pesticide usage, and increase in farm income. Long-term tracking will provide empirical data to support policy decisions and demonstrate the tangible benefits experienced by farmers. Collectively, the five-step process provides a pragmatic method for translating farmer interest and demonstrated technological effectiveness into sustainable, scalable public agricultural initiatives.

Pest Detection Accuracy and Model Performance

The YOLOv8 model, as part of the AI-enabled IoT-based pest management system, demonstrated reliable detection capability for the four major rice pests found in Pendurthi Mandal. Confidence scores were found to range from 0.87 to 0.94 as shown in Figure 9. These scores carry an estimated margin of ±0.02 across varying lighting and canopy conditions, indicating consistent detection performance within an acceptable error range. The highest confidence score was

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obtained by Brown Plant Hopper at 0.94, followed by Yellow Stem Borer at 0.92, Rice Leaf Folder at 0.89, and Rice Gall Midge at 0.87. Two pest categories exceeded the predetermined threshold of 0.90, while the other two had detection reliability>0.87. High detection reliability is a key factor in enabling rapid and effective decision-making based on field data. The results demonstrate the practicality of real-time pest identification under field conditions and suggest that edge-computing-based deep learning algorithms can perform at least as well as traditional laboratory systems in the presence of environmental variations. In addition, the high confidence levels across all pest types provide farmers with the opportunity to make timely decisions without concern for false positives or loss of trust.

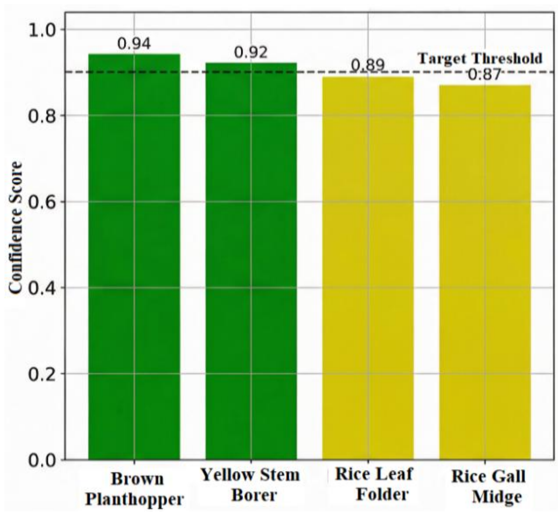

Figure 9. Detection confidence scores of the real-time AI-IoT pest control system

Beginning with the possibility of a system malfunctioning (reduced accuracy in detecting pests) due to an adverse environmental condition such as weather (heavy rainfall, poor lighting), or loss of advisory service due to internet connectivity issues; and/or, the physical nature of deployment (harsh environmental conditions on equipment) that will need to be addressed for large scale future applications of this technology.

4. Limitations and Future Directions

There are several limitations to this study. The first is that the field trial was conducted over 30 days in a single Mandal (Pendurthi), which may limit its generalizability. The second limitation is that the cost estimates were derived from surveys and should therefore be viewed as indicative rather than statistically verified. The third limitation is that, since the data used in the analysis are self-reported, there is a risk of Social Desirability Bias. Future studies will need to conduct large-scale, randomized controlled trials to assess long-term cost-effectiveness and system performance. In addition, expanding the methodology's scope to examine additional pest species and apply it to other agro-climatic zones in India will increase the robustness of the proposed method. Studies that investigate socio-economic and behavioral factors affecting technology adoption will also provide substantial support for the widespread deployment of these technologies.

5. Conclusion

This research provides significant empirical evidence that farmers in Pendurthi Mandal have a strong willingness (with appropriate caution) to adopt smart pest management technology. While all of the technical performance metrics (above) have been empirically verified through a successful on-farm trial, the projected 26-35% reductions in crop loss and seasonal pest management cost savings would be theoretically supported by similar research to that reviewed in this study and empirically validated through long-term monitoring. Using a survey of 1,000 farmers and field validation of an AI-integrated IoT pest control device, this research found that a majority (76%) of respondents indicated they would be willing to use this type of technology; however, they were concerned about cost, reliability, and language access. The empirically validated technical performance metrics include an average pest

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incidence rate of 84%, an average chemical pesticide reliance of 66%, a mobile phone penetration of 63%, a willingness-to-adopt of 76%, an average device up-time of 94%, and pest detection confidence scores for the four most common rice pests at .87-.94. Once the supporting requirements for affordability, reliability, and language access are met, the technology holds strong potential to lower input costs and enhance environmentally friendly agricultural practices by decreasing reliance upon chemical pesticides. Under resource-constrained field conditions, the authors demonstrate the AI-integrated IoT prototype's technological capabilities using an ESP32-CAM controller, a YOLOv8 deep-learning detection model, and an LLM-based advisory engine. Furthermore, the Telugu-language LLM interface, designed to increase accessibility for farmers of varying literacy levels, supports the integration of such systems into existing public extension frameworks at local, regional, and national levels.

Long-term multi-site studies and randomized controlled trials are needed to prove at scale the potential for long-term benefit and provide the evidence necessary for national policy inclusion. Future research should employ more robust experimental and analytical methods, including longitudinal and cross-regional comparative designs, to improve the reliability of results. Conducting this type of study with a variety of farmer populations and in multiple agricultural contexts will also be important for increasing the generalizability of the study's findings.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The authors declared that no generative AI or AI-assisted technologies were used in the preparation of this manuscript.

Authorship Contribution Statement

James Stephen Meka: Conceptualization, Methodology, Software, Data curation, Writing – original draft and editing; Ponnam Venkateswarlu: Supervision, Validation, Writing – review.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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