**MARKET ANALYSIS FOR ARTIFICIAL INTELLIGENCE BASED GRAIN ANALYSER IN GUJARAT**

**ACHARYA GAURANG NIKUNJKUMAR MBA2025**

**ABSTRACT**

The India’s grain sector is vital to its agricultural economy, ensuring food security and supporting rural livelihoods. Gujarat is a leading grain-producing state, challenges like post-harvest losses, inefficient storage, and inconsistent quality assessment persist. Traditional manual inspection methods are increasingly inadequate to meet modern demands for speed and precision. In response, AI-based grain analysers have emerged as an innovative solution, offering rapid, objective, and standardized assessments of grain quality through advanced sensors, computer vision, and machine learning. This study, conducted across 10 districts in Gujarat with 50 respondents, highlights moderate awareness 38 percent of AI-based grain analysers. Factors influencing adoption include the perceived need, ease of use, and accuracy. However, barriers such as high costs, lack of skilled labor, and technical complexity hinder widespread implementation. The research also reveals a predominance of male respondents, limited higher education, and a reliance on small-scale mill operations handling paddy, wheat, and chickpeas. For broader adoption, efforts must focus on increasing awareness, improving affordability, and enhancing training and after-sales support. By addressing these challenges, AI grain analysers can revolutionize quality management in Gujarat’s grain sector, boosting efficiency, transparency, and global competitiveness.

***Keywords:*** *Grain analyser, Sensors, Machine learning, Artificial intelligence, Computer vision, Grain industry, Grain quality assessment*

1. **INTRODUCTION**

India is one of the world's largest agricultural producers, with agriculture playing a vital role in the country's economy and livelihood. Agriculture contributes approximately 18.3 percent to India's Gross Domestic Product (GDP) and employs nearly 46 percent of the country’s workforce (World Bank, 2024). The sector is highly diverse, encompassing food grains, fruits, vegetables, livestock, fisheries, and forestry. India's agricultural landscape is dominated by small and marginal farmers who operate on fragmented landholdings, leading to challenges in productivity and scalability (Roy *et al.,* 2020). Grains are essential to India's food security, with rice and wheat being the staples for millions of people, particularly in the northern and southern regions. Pulses, such as lentils and chickpeas, are also a critical part of the Indian diet, providing an important source of protein for the population. (FAO, 2022).

The grain industry in India is vital to both the economy and food security. While there is tremendous potential for growth, significant challenges remain in terms of grain quality, post-harvest losses, and storage. By adopting modern technologies, improving infrastructure, and implementing better practices across the agricultural value chain, India can overcome these hurdles. This will ensure a more sustainable and resilient grain industry, capable of supporting the country’s growing population and contributing to global food markets (Parwez, 2014).

The quality of grains is crucial not only for ensuring food security but also for maintaining the economic stability of the grain industry. Grains are fundamental to the global food system, serving as staple foods for billions of people. Ensuring that grains meet specific quality standards is essential for consumer safety, marketability, and long-term agricultural sustainability (Bishnoi *et al*., 2018). Grain quality is a multifaceted concept that includes several parameters, such as moisture content, impurity levels, size, shape, colour, and overall cleanliness. These factors play a significant role in the nutritional value, storage, processing, and economic value of the grains (Jena *et al*., 2023). While traditional methods of grain analysis, such as manual testing and physical inspection, have been useful in the past, they are increasingly inadequate in meeting the demands of modern agriculture (Sidnal *et al*., 2013).

The growing scale of production, the need for consistent and precise quality control, and the economic realities of large-scale operations necessitate the adoption of advanced technologies. These innovations in grain analysis will allow for quicker, more accurate, and more efficient quality assessments, ensuring that the grain industry can meet the needs of a growing global population (Jha *et al*., 2015).

AI-based grain analysers leverage advanced technologies such as computer vision, sensor technologies, and machine learning algorithms to assess grain quality efficiently and accurately. These systems use high-resolution imaging and spectroscopy to capture detailed visual and structural information about grains (Singh *et al*., 2024).

India, as one of the largest producers and consumers of grains, has been steadily adopting AI-based grain analysers to enhance agricultural efficiency and quality control. With government initiatives like "Digital India" and "Make in India," there is a strong push for integrating AI technologies into agriculture sector. The Food Corporation of India (FCI) and other regulatory bodies are encouraging the use of AI-based quality assessment tools to ensure better pricing and reduced post-harvest losses (Rai, 2023).

Gujarat, being a major hub for wheat, rice, and millet production, is witnessing a rise in the adoption of AI-driven grain analysers, especially in large-scale agribusinesses and cooperative sectors. The state is home to multiple agri-tech firms and research institutions investing in AI-based quality assessment technologies (Mishra, 2024).

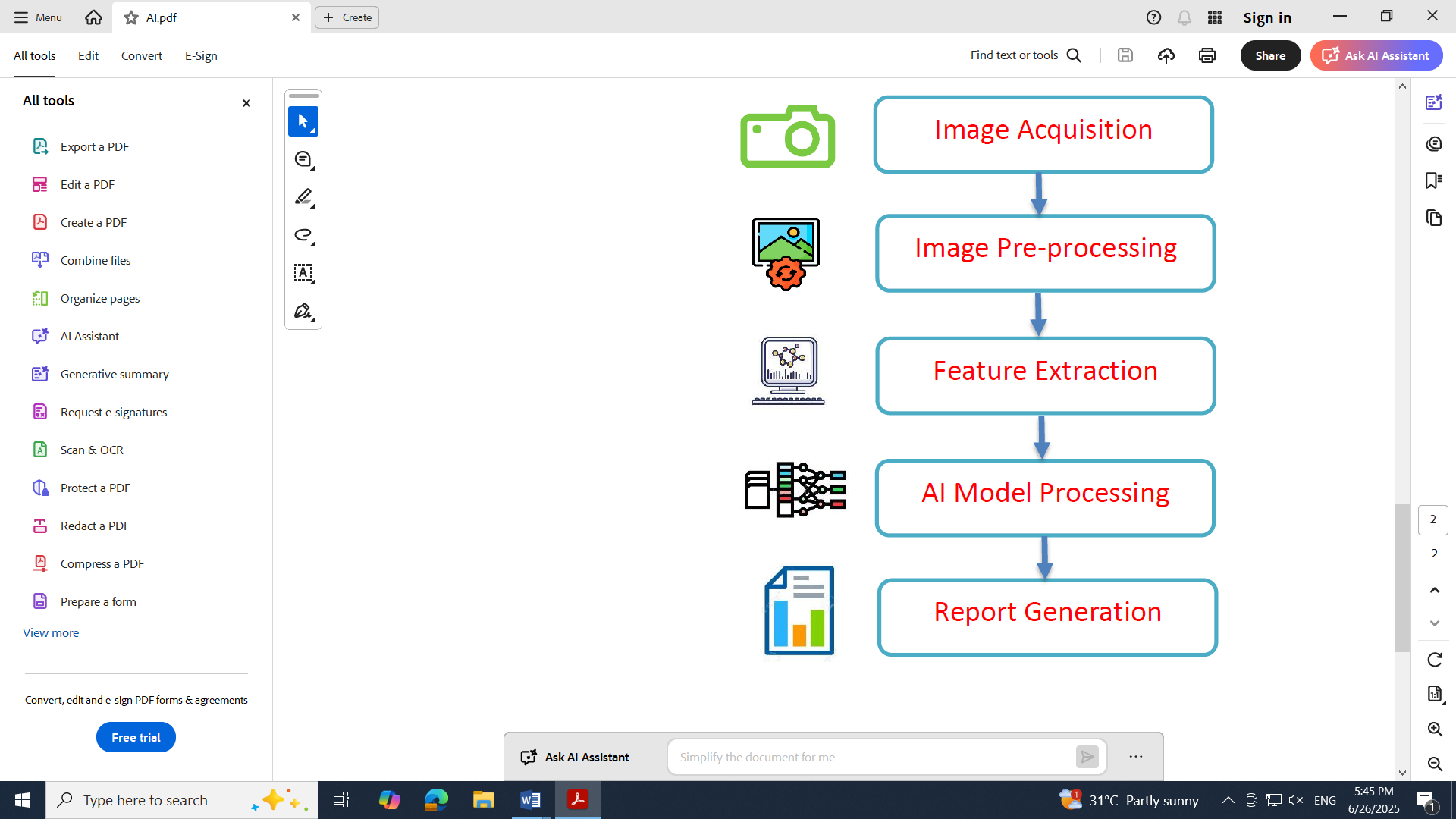
AI-based grain analysers are revolutionizing the agricultural industry by enhancing efficiency, accuracy, and decision-making in grain quality assessment. With continued advancements in AI, computer vision, and sensor technologies, the adoption of these analysers is expected to expand globally and within India, particularly in states like Gujarat. The implementation of AI in grain analysis is not only improving food quality but also ensuring better pricing, reducing wastage, and enhancing India's position in the global agricultural market. The future of AI-driven grain assessment looks promising as the technology continues to evolve and integrate deeper into the agricultural landscape (Kumar and Singh., 2021).

The study was conducted mainly to study the factors affecting buying decision of customer and the problems faced by the customer in quality assessment.

1. **ARTIFICIAL INTELLIGENCE BASED GRAIN ANALYSER**

AI-based grain analyser that leverages smartphone imaging, computer vision, and machine learning to deliver fast, accurate, and objective quality assessments of selected grains within few seconds. Users simply place grain samples on a scanning tray, ensuring consistent lighting and image clarity, and capture an image using a smartphone. The image is then pre-processed to enhance quality and remove background noise, after which advanced computer vision algorithms segment individual grains and extract various physical parameters such as size, shape, color, broken grains, discoloration, impurities, chalkiness, surface defects, etc. These parameters are analyzed by machine learning models trained on extensive datasets to classify the grains and assign a quality grade. The results are instantly displayed in a detailed and easy-to-understand digital report on dashboard, offering transparency, trust, and efficiency across the supply chain. Designed to be affordable and user-friendly, millers, traders, and procurement agencies to make rapid, data-driven decisions, minimizing reliance on manual inspection and ensuring consistent quality standards.

**AI Models**

AI-based grain analyzers are sophisticated systems that automate the inspection and classification of grains by utilizing high-resolution imaging, image processing, and artificial intelligence. These systems focus on evaluating external grain characteristics such as size, shape, color, texture, and the presence of impurities to ensure accurate and consistent quality assessment. Below fig 1 shows steps performed in AI-based grain analysis:

**Fig 1 : Steps for AI-based grain analysis**

1. **Image Acquisition:** It is the first and most critical step in any computer vision or image processing system, including AI-based grain analyzers. It refers to the process of capturing digital images of the grain samples—using imaging devices such as high-resolution cameras, scanners, or smartphone cameras.
2. **Image Pre-processing:** It is the second step in the image analysis workflow, and it involves enhancing the raw images captured during image acquisition to make them suitable for accurate analysis using AI algorithms. Noise reduction, color correction, contrast enhancement, background removal will be performed during this step.
3. **Feature Extraction:** It is the third step in the AI-based grain analysis process, where specific, measurable characteristics of each grain are identified and quantified from the pre-processed image. The grain characteristics includes size, shape, color, texture, broken edges, impurities, etc.
4. **AI Model Processing:** It is the fourth step in the grain analysis workflow, where the extracted features from each grain are analyzed by artificial intelligence algorithms to classify and grade the grains. It includes model selection, classification, model training, testing, improvement, etc.
5. **Report Generation:** It is the final step in the AI-based grain analysis process, where the system compiles the results of the analysis into a clear, detailed, and user-friendly format of report for decision-making.

The analysis begins with image acquisition under uniform lighting, followed by preprocessing steps like noise reduction and background removal. Computer vision techniques segment individual grains, and features such as length, width, color histograms, and texture metrics (e.g., GLCM) are extracted. These features are then analyzed using AI models—ranging from classical algorithms like SVM, Random Forest, and KNN to deep learning models like Convolutional Neural Networks (CNNs), which directly process raw images for classification into categories such as good, broken, defective, or chalky. The process concludes with the generation of a detailed report that quantifies defects and assigns an overall quality grade, significantly improving the speed, accuracy, and objectivity of grain inspection (Singh et al., 2024).

1. **METHODOLOGY**

**Research Methodology**

The study was conducted in the 10 districts of Gujarat. Primary data were collected with the help of a semi-structured schedule from the respondents. Secondary data were collected from government publications, multiple websites, journals, articles, etc. Research methodologies included surveys of rice and pulse miller. The sample were collected from Ahmedabad, Anand, Kheda, Gandhinagar, Surat, Vadodara, Valsad, Bharuch, Navsari and Dang districts of Gujarat. From every district 5 respondent were selected for the study. So, total 50 respondents were selected from the study area.

**Analytical Tools**

To accommodate the study's nature and ensure the reliability of gathered information, data were acquired through a semi-structured schedule from the respondents. Frequencies and percentage analysis were used to study the socio-economic profile of customer. Garrett’s ranking technique was used to rank the preferences indicated by the respondents on different factors. As per this method, respondents have been asked to assign a rank to all factors and the outcomes of such ranking have been converted into a score value.

Percentage position = (100 (Rij-0.5) ) / Nj

Where Rij = Rank given for the ith variable by jth respondent

Nj = Number of variables ranked by jth respondent

1. **RESULT AND DISCUSSION**

This section presents the key findings of the research in a clear and logical way. It interprets the data in relation to the research objectives and highlights the patterns, relationships, and trends observed. The results are discussed in alignment with the research goals, providing meaningful insights into the study’s outcomes.

**3.1 Socio-economic profile**

The socio-economic profile reflects their social and economic status, encompassing key factors such as age, education level, gender, etc. are essential resources. These elements play a crucial role in shaping of the study. The following table 1 shows the socio-economic profile of the customer.

**Table 1 : Socio-economic profile of customer**

|  |  |  |  |
| --- | --- | --- | --- |
| Sr. No. | Particular | No. of Respondents | Percentage |
| 1 | **Age** |  |  |
| 21-30 | 09 | 18.0 |
| 31-40 | 12 | 24.0 |
| 41-50 | 19 | 38.0 |
| >50 | 10 | 20.0 |
| **Total** | **50** | **100** |
| 2 | **Education** |  |  |
| Primary | 7 | 14.0 |
| Secondary | 13 | 26.0 |
| Higher Secondary | 17 | 34.0 |
| Graduate | 09 | 18.0 |
| Post Graduate | 04 | 8.0 |
| **Total** | **50** | **100** |
| 3 | **Gender** |  |  |
| Male | 50 | 100 |
| Female | 00 | 00 |
| **Total** | **50** | **100** |
| 4 | **Years in Business** |  |  |
| Below 5 Year | 12 | 24.0 |
| 5 to 10 Year | 17 | 34.0 |
| 10 to 15 Year | 16 | 32.0 |
| Above 15 Year | 5 | 10.0 |
| **Total** | **50** | **100** |
| 5 | **Type of Business** |  |  |
| B2B | 28 | 56.0 |
| B2C | 22 | 44.0 |
| **Total** | **50** | **100** |
| 6 | **Type of Work** |  |  |
| Seasonal | 20 | 40.0 |
| Yearly | 30 | 60.0 |
| **Total** | **50** | **100** |
| 7 | **Deal in Commodity** |  |  |
| Paddy | 45 | 90.0 |
| Wheat | 21 | 42.0 |
| Millet | 9 | 18.0 |
| Maize | 12 | 24.0 |
| Chickpea | 18 | 36.0 |
| 8 | **Source of Commodity** |  | **Out of 100 percent** |
| Farmer | 30 | 60.0 |
| APMC | 26 | 52.0 |
| FPO/FPC/COs | 12 | 24.0 |
| Online Platforms | 14 | 28.0 |
| Traders | 36 | 72.0 |
| 9 | **Production Capacity of Firm (T/day)** |  |  |
| Below 5 | 11 | 22.0 |
| 5-10 | 16 | 32.0 |
| 10-15 | 14 | 28.0 |
| More than 15 | 09 | 18.0 |
| **Total** | **50** | **100** |

(Source: Field Survey, 2025)

The socio-economic profile of 50 respondents, primarily rice millers, provides key insights into their age, education, experience, business practices, and operational scale. A substantial proportion 38% fall within the 41–50 age group, followed by 24% aged 31–40, and 20% above 50, indicating a predominantly middle-aged demographic. Only 18% were in the 21–30 age group, reflecting limited participation from younger entrepreneurs. In terms of education, 34% have completed higher secondary education, followed by 26% have secondary education. Only 18% were graduates and 8% were postgraduates, while 14% have only primary education, suggesting moderate educational attainment with room for improvement in higher education access. The entire respondent group comprises males. Business experience is fairly distributed, with 34% having 5–10 years, and 32% having 10–15 years of experience. Only 10% have more than 15 years in the field, suggesting a relatively young business landscape.

Most businesses operate in a B2B model 56%, with 44% engaged in B2C. A majority 60% run operations year-round, while 40% were operates only in seasonally. Paddy is the most commonly handled grain commodity 90%, followed by wheat, chickpea, maize, and millet. Commodity sourcing is primarily through traders 72% and farmers 60%, with additional procurement from APMCs, online platforms, and FPOs. Production capacity shows that 32% of firms process 5–10 tons per day, while 28% manage 10–15 tons per day. Only 18% handle more than 15 tons per day, and 22% operate below 5 tons per day, indicating that most businesses are small to mid-scale in terms of production. This profile reflects a predominantly male, middle-aged, moderately educated, and experienced group operating primarily B2B year-round businesses. The findings suggest opportunities for youth inclusion, gender diversification, and expansion of educational and institutional support to enhance sector efficiency.

* 1. **Factors affecting buying decision**

The various factors affect the buying decisions include awareness, product needs, easy to use, affordability, brands, etc. Following table 2 shows the different factors that affect the buying behaviour of the customers.

**Table 2 : Factors affecting buying decision of customer**

|  |  |  |  |
| --- | --- | --- | --- |
| Sr. No. | Particular | Respondents | Percentage |
| 1 | **Awareness about AI based grain analyser** | | |
| Yes | 19 | 38.0 |
| No | 31 | 62.0 |
| **Total** | **50** | **100** |
| 2 | **Factors affecting buying decision** | **Meam** | **Rank** |
| Need of product | 63.18 | 1 |
| Ease of use | 56.44 | 2 |
| Accuracy in results | 50.36 | 3 |
| Affordability | 47.32 | 4 |
| After-sales service | 43.84 | 5 |
| Brand reputation | 40.86 | 6 |

(Source: Field Survey, 2025)

The data revealed that awareness about the Artificial Intelligence-based grain analyser was relatively low among the respondents. Out of a total of 50 respondent 38% respondent were aware about AI based grain analyser. The majority 62% respondents reported that they were not aware of it. The Garrett’s Ranking analysis highlights that the primary factor influencing the purchase of AI-based grain analysers was the need for the product, reflecting buyers’ focus on utility and problem-solving capabilities. Ease of use ranked second, emphasizing the demand for user-friendly solutions, especially in sectors with limited access to skilled labor.

Accuracy of results was third, underlining the importance of reliable and consistent data in quality-sensitive operations. Affordability was also a major concern, showing that customers seek cost-effective solutions that do not compromise core functionalities. After-sales service ranked fifth, pointing to the value placed on technical support and maintenance, especially for complex technologies. Brand reputation had the least impact, suggesting that practical benefits outweigh brand recognition in influencing buying behavior. Overall, the findings reflect a customer base driven by functionality, efficiency, and support, rather than brand loyalty.

* 1. **Problems faced by customers**

The various problems faced by the customer in quality assessment. The following table 3 shows the different problems of customer in quality assessment.

**Table 3 : Problem faced by customer in quality assessment**

|  |  |  |  |
| --- | --- | --- | --- |
| Sr. No. | Particular | Mean | Rank |
| 1 | **Problem faced by customer in quality assessment** | | |
| Lack of skilled labour | 61.1 | 1 |
| Time-consuming manual process | 56.5 | 2 |
| Inaccuracy in results | 51.1 | 3 |
| High cost of assessment equipment | 47.1 | 4 |
| Difficulty in interpreting quality parameters | 40.2 | 5 |

(Source: Field Survey, 2025)

The Garrett’s Ranking analysis of problems in grain quality assessment reveals that the lack of skilled labour was the most critical issue, efficient use of assessment tools and leading to delays and unreliable results. Time-consuming manual processes was second, highlighting inefficiencies in traditional methods that affect productivity, especially in high-output environments. Inaccuracy in results was the third major concern, emphasizing the risks of financial loss and mistrust due to unreliable quality checks. The high cost of equipment ranks fourth, pointing to affordability as a barrier to adopting advanced technologies. Lastly, difficulty in interpreting quality parameters was the least pressing but still relevant, indicating a need for more intuitive tools.

Overall, the findings underscore the demand for cost-effective, accurate, and easy-to-use solutions that reduce reliance on skilled personnel and streamline the assessment process.

**4. CONCLUSION**

This study explores the market analysis for artificial intelligence-based grain analysers in Gujarat, focusing on rice and pulse millers. The study was conducted to evaluate the socio-economic background of customers, factors affecting their buying decisions, and the problems they face in assessing grain quality. Data were collected from 50 rice and pulse millers through purposive sampling using semi-structured schedules. Most respondents 38% were in the 41–50 years age group, and all participants were male. Educationally, 34% had completed higher secondary education, with only 8% holding postgraduate degrees. About 34% of millers had 5 to 10 years of experience, and 82% operated with production capacities below 15 tons per day. In terms of business type, 56 percent were involved in B2B, and 60% operated year-round rather than seasonally. Paddy was the most frequently handled commodity, followed by wheat and chickpeas. Traders and farmers were the primary sources of commodities, while procurement also occurred through APMCs and online platforms. A notable 38% of respondents were aware of AI-based grain analysers. The study identified the most influential factors affecting the purchasing decisions of customers. The need for the product ranked highest, followed by ease of use and accuracy in results. This indicated a preference for solutions that were practical, user-friendly, and performance-oriented. Affordability and after-sales service also played significant roles, while brand reputation was found to be the least influential. Problems in grain quality assessment were also analyzed. The most significant challenge was the lack of skilled labor, followed by time-consuming manual processes and inaccuracy in results. High equipment cost and difficulty in interpreting parameters were other important concerns. These findings highlight that while technological adoption is desired, it is often hindered by financial and operational constraints.

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