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Research paper

A Study on Problems & Prospects of Agricultural Marketing in The Age of Artificial Intelligence and Smart Farming

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Abstract

The agricultural marketing ecosystem in India has undergone substantial shifts due to rapid technological advancements, particularly with the integration of Artificial Intelligence (AI) and smart farming practices. With agriculture constituting a large portion of the rural economic sector of the state of Tamil Nadu, AI has begun to play a revolutionary role in narrowing the lines between production and market access there. In this conceptual analysis, the researcher aims to understand how the AI-enabled systems impact agricultural marketing results through three most important mediating dimensions to be considered, such as market intelligence, operational efficiency, and farmer empowerment. The research is rooted in an assumption that long-term inefficiencies in the agricultural value chain, such as price asymmetries, limited information at the right time, unreliable middle men and wastage of resources, can be solved using AI.
The evidence voices the fact that although AI brings forth new solutions to marketing issues that have existed since time immemorial in the agriculture sector, the level of influence rests with socio-technical facilitators, policymaking, and fair access. The conclusion of the study is made by requesting multi-stakeholder partnerships between government agencies, technology developers, and farmer cooperatives to develop inclusive AI ecosystems. The study adds value to the scientific investigation in digital agriculture since it provides a conceptual formulation that is specific to Tamil Nadu, which can be proved later in an empirical study.

Keywords: *Agriculture; AI; Digital; Tamilnadu; India; Market; Farming.*

1. Introduction

Agriculture plays a very significant role in human beings as well as the development of our country. There is a daily upward adjustment in the population of the world, which is directly proportional to the increase in the production of crops. Production of agriculture is mostly seasonal. Larger numbers of people are heading in this direction due to smart farming, which we have been made to know lately. With a rise in population and an increasing consumption of food, agriculture will continue absorbing most of the world's freshwater resources, 85%60 of all resources. Science and technology should come up with their plans urgently. The achievement of the academic research work throughout the past decade has fulfilled the demand to have IoT in the agriculture sector. Agricultural sectors have recently implemented information technology (IT) solutions, such as technical, agronomic, managerial, etc., as part of precision agriculture techniques that help efficiently use water. To ensure the use of less water in the cultivation of several crops, both low-tech and high-tech crops, irrigation systems have become the center of several research programs (Ali et al, 2023). The Internet of Things (IoT) provides a platform for "smart agriculture," wirelessly connecting a variety of sensors (including temperature, humidity, and soil moisture), a variety of hardware (including water pumps), and data-analytical programs to assist farmers in better addressing complex agricultural problems like yield prediction and other issues throughout the entire growing and harvesting cycle. Agriculture continues to be the backbone of the Indian economy, employing nearly 45% of the workforce and contributing about 18% to the country's Gross Value Added (GVA) (Liu 2020). But even though the sector is critical, it is also affected by various challenges, particularly in marketing agricultural produce. In recent years, with the advent of Artificial Intelligence (AI) and smart farming technologies, the narrative around agricultural marketing has begun to shift. The change is, however, not linear, straightforward or trouble-free.

1.1. Evolution of agricultural marketing in India

Traditionally, agricultural marketing in India has been dominated by regulated markets (mandis) under the Agricultural Produce Market Committee (APMC) Act. Such markets were originally meant to save farmers from maltreatment by intermediaries and pay a fair price. Nonetheless, the system has erupted with inefficiencies over the years, and this has been in the form of price manipulation, a severe lack of transparency, and even poor infrastructure. Most farmers, particularly small and marginal ones who make up over 85% of India's farming

community, still rely on local traders, commission agents, or village markets for selling their produce—often at prices far below the Minimum Support Price (MSP) (Dipak et al, 2004).
Moreover, the lack of supply chain facilities, insufficient storage facility access, asymmetry of information, and transport and logistics deficiency have greatly negatively affected the farmers' access to better markets. Recently, climate change, market fluctuation, and global crises like the COVID-19 pandemic have complicated these issues.
It is known that the Indian economy is still heavily dependent on agriculture, and it has a share of about 18 percent in the national GDP, as well as producing more than 50 percent of the employed population (Ministry of Agriculture & Farmers Welfare, 2024). Nevertheless, the classical agriculture marketing system in India has remained that of massive inefficiency, such as fragmentation of the supply chain, price differences, losses after harvest, and exploitation of farmers by the factor bestowed with intermediaries. Due to the development of Artificial Intelligence (AI) and Smart Farming technologies, a bright opportunity arises to change the market of agricultural products usage and market delivery, including the pre-production strategy and the processing of harvests.
Some of the innovations made possible through AI that are applicable in progressive farming models include predictive analytics, digital marketplaces, automated grading and sorting, and blockchain for traceability. These technologies hold the potential to enhance transparency, access to the market, and good price realisation for farmers. Nevertheless, implementation of these technologies requires a huge capital on the side of the farmer, good financial planning, and the existence of institutional support systems which bring in the relevant concerns of economic viability, accounting reporting, and returns on investment (ROI), particularly on small and marginal farmers.
Since the recent policies of the Government of India offer more and more stress on Digital Agriculture as part of Digital India operations and the AgriStack agendas, the importance of AI in reinforcing agricultural marketing becomes even higher. Nevertheless, a research gap pertains to conducting an analysis systematically to examine the economic, accounting, and policy impacts of the introduction of AI in agricultural marketing.

1.2. Artificial intelligence and smart farming

Artificial Intelligence (AI), along with related technologies such as Machine Learning (ML), Internet of Things (IoT), drones, remote sensing, and blockchain, has the potential to revolutionize agricultural practices, particularly marketing. Smart farming can be described as the use of digital technologies to observe, automate, and optimize the operations and decision-making process in agriculture (Ahir et al, 2020).
AI can process massive amounts of data on weather patterns, soil conditions, crop health, market trends, and aid farmers in making data-driven decisions. Tools of smart farming may measure the growth of crops with the help of sensors and satellites, automatically irrigate about the moisture content, and even suggest an ideal time to sow, to gather, and even to sell. Notably, the AI-based systems are equally able to directly link farmers to buyers, delink them, and demand transparent price discovery (Mahibha and Balasubramaniam 2023).

1.3. Case of tamil nadu: a glimpse into ground reality

Tamil Nadu is a curious example in researching to determine the issues and opportunities that are coming with AI-based agricultural marketing. The state has seen proactive steps from the government and private sector, such as the Uzhavan mobile app, Farmer-Producer Organizations (FPOs), and AI-based soil testing kits. Tamil Nadu is also involved in the Digital Agriculture mission pioneered by the Ministry of Agriculture to create databases and digital profiles of farmers to deliver targeted services (Rasooli et al, 2020).
But, away from all these efforts, farmers in other districts, such as Salem, Dharmapuri, or Tiruvannamalai, still depend on the old system of mandis. The lack of infrastructure, insufficient field support, linguistic and language barriers are often involved in not using AI tools effectively. As an illustration, most farmers have been shy to sell on eNAM as a result of low awareness and training (Kashyap et al 2021).

1.4. Objectives of the study

This research will aim to:

- Identify the key problems in agricultural marketing despite the availability of smart technologies.
- Analyze the level of awareness and adoption of AI and smart farming tools among farmers.
- Explore the socio-economic, infrastructural, and policy-level challenges in integrating AI with marketing.
- Suggest practical and scalable recommendations to improve agricultural marketing in the digital era.

2. Review of literature

Mohammad Wasi Rasooli, et al (2020). IoT devices not only gave farmers new skills, but they also improved their time management. The sensors are of crucial importance as far as connectivity and data gathering are concerned. The farmers do not spend a lot of time in the field since the job has been done by the IoT-enabled tools. It reduced the workload of the farmers and the quantity of resources consumed as well as those that were wasted, e.g. water in irrigation and energy that fuels so many electronic devices. IoT devices can be easily monitored using real-time applications. The Internet of Things can transform the world and turn it into smart farming. Pankaj Kumar Kashyap et al (2021). Precision irrigation may provide more, better, and more lucrative crops with fewer resources. To utilize the water more efficiently, numerous models of irrigation depending on machine learning have been developed. Such models have low learning capability and thus they are not fit in an unstable climatic environment. In this regard, this study recommends an intelligent irrigation system for precision agriculture that is backed by the IoT and built on deep learning neural networks (DLiSA). It is only through reasons of normalization that the mean and standard deviation are computed using the training period, and that daily data is averaged after the standard deviation is deducted or subtracted and then divided by the standard deviation. This step of normalization is necessary as the proposed LSTM-RNN model needs learning. Ajayi O et al. 2022, Measurements, such as the Water Quality Index (WQI) and Irrigation WQI (IWQI), are used to express the quantity of these qualities and ascertain the total water quality. This study suggests an automated network with an architecture that will tell whether the water samples are suitable for drinking and use in irrigation in real-time by collecting data of water properties.
Alghazzawi. The greenhouse makes planting easier; therefore, this helps agriculture in several ways (D et al. 2021). Gas sensors and soil pH sensors are common in agricultural modelling. These sensors may be used in several IoT ag applications. The method explains the hardware design and operation of the suggested model. A description of a few other economic models of agricultural evapotranspiration is also recorded. The Penman-Monteith equation explores vital issues such as congestion management. The irrigation system maintains the

moisture level in soil using the sensory and control system during environmental conditions explained by Amin A. B et al. 2021 Badrun et al. 2021 The irrigation industry may benefit from the Internet of Things (IoT) innovative solutions, which can enhance irrigation management and lower operating infrastructure maintenance costs. The biggest issue of intelligent irrigation systems lies in the fact that the stakeholders are unable to transform all the available data into high-quality, extensive information, which could be used to make decisions. P. Pandiaraj et al (2021). Agriculture uses machine learning algorithms to raise the quality and output of agricultural products. With image recognition technology, pest control experts can identify and handle different pests and rodents. One machine learning (ML) approach, the random forest algorithm, is used to identify pests and diagnose issues in four crops such as maize, potato, tomato, and wheat.

Maria Teresa Linaza et al. (2021). By monitoring conditions and increasing production, artificial intelligence (AI) technologies help farmers make better decisions at the farm level. They can increase yields with less water used and greenhouse gases produced as they can apply the right amount of inputs to each crop. The potential uses of the study in the future will include the integration of new concepts of effective livestock control, along with the extraction of plant and soil samples by using intelligent, autonomous robots. Noon et al. (2021) Deep learning (DL) algorithms have been used in similar thorough studies on how to identify plant leaf stress. Depending on the type of stress, the training/size, the size of the dataset, and the deep network used, the methods were divided into those of vegetables, fruit, and other crops. Identification and classification of all stress levels to detect infectious diseases and the utilization of algorithms in different crops are two spheres that require further research. In-depth summaries of current robotic grippers, gripping methods, strategies for sensors, and their applications in robotic agricultural tasks have been provided by Zhang et al (2020). Akanksha et al. (2021), Four steps make up the methodology: pre-processing, feature extraction, segmentation, and classification. The pictures that have the noise are deleted first, and then the pictures are converted to RGB. The R band is then allocated for the feature extraction process. To determine whether a picture belongs to the abnormal or normal set, the classifier is fed with the corresponding properties.

Dipak et al (2004) this study looked at the bitter melon's or bitter gourd's ability to produce crops. The common name of it in the Filipino language is Ampalaya. Photographs of bitter melon leaves taken in farms in Ampalaya were taken as the main source of data in the study. The leaves were divided into categories of excellence and poor in terms of description. In the study, a Convolutional Neural Network, which is a Machine Learning algorithm, was used. The mixture of Python, TensorFlow, and Keras functionalities was used to train the data. Finally, by showing a machine more and more photos, maybe in the future, it will be capable of differentiating between a great and a horrible Ampalaya plant (Alharbi et al, 2021) employed supervised and unsupervised learning techniques, such as the Kohonen Self-Organizing Map and the Back-Propagation Network. To make the forecast on the type of soil, learning networks are instructed to really categorize the data into organic, inorganic, and great estate. After comparing the accuracy that it has rendered with a combination of network learning algorithms, the most accurate result is provided to the user. The system will analyse the quality of the soil, make a projection of the harvest according to the analysis and give suggestion of fertilizers when needed according to the analysis.

2.1. Economic and financial evaluation of AI adoption in agriculture

Economic analysis research has demonstrated that AI in agriculture could be promising. According to a cost-benefit analysis (CBA) of precision farming based on AI conducted by Singh and Rana (2023), farmers could expect a 20-30 percent rise in the profit margins mainly because their input costs dropped and their productivity rose. Nonetheless, the place to start is the heavy investment in hardware, software, and training, especially amongst smallholders.

In the same light, another research by the National Bank for Agriculture and Rural Development (NABARD, 2022) found that the AI implementation only starts paying off in 3-5 years in case of the availability of institutional credit and support structures. The report suggests including AI expenditures in the agricultural planning and enhancing the financial knowledge level of farmers.

The treatment of AI investments in the agriculture sector is one of the under-researched areas in the literature. Smallholder farmers have informal accounting practices in their farm management, especially in the traditional accountancy practice. According to the report by Bhatia and Sinha (2022), the absence of the standardization of record-keeping complicates the measurement of asset depreciation, cost of operation, or the long-term returns on investment (ROI) of smart technologies.

Also, cooperatives and farmer-producer organizations (FPOs) do not have built infrastructure and training to record AI-related finances in their books, which influences both transparency and decision-making. This signals the need to have specialized agricultural accounting systems that will be able to support the investments in technology and facilitate improved access to finance through credit and subsidies.

2.2. Hypothesis development of the study

The emergence of Artificial Intelligence (AI) in agriculture has brought transformative changes, especially in marketing practices. AI technologies support farmers through the real-time market data, optimization of their operations, as well as giving them power and independence of knowledge. In this part of the article, some hypotheses are produced according to some constructs of the conceptual framework suggested.

Machine learning, IoT sensor-driven, and AI-composed mobile applications are the AI technologies capable of scanning through tremendous volumes of data to provide actionable insights in the market. Farmers can get access to market intelligence they could never get access to before through mechanisms such as predictive price modeling, automated alerts, and buyer-seller matching platforms. Studies by Cioffi et al 2020) affirm that farmers using AI applications like the Uzhavan App have improved awareness of market prices and demand conditions.

H1: Adoption of AI technologies significantly enhances market intelligence among farmers

Efficiency in operations is an addition to AI solutions, where they optimize crop inputs and automation of repetitive tasks, and enhance logistics. Drone surveillance, automated irrigation, and disease-prediction models are examples of precision agriculture technologies that can help farmers waste less and increase the quality of their yield. Melovic et al (2020) observed that farms using AI-based drones and smart sensors witnessed a 20–30% increase in productivity with less labor input.

H2: AI technologies positively and significantly influence operational efficiency in agricultural activities

It is also noticed that AI platforms can be helpful in the improvement of the decision-making ability of farmers. They keep them informed of the latest available government schemes and give them the specific crop advisory basis, and have practical access to the online markets. According to Saeed and Wang (2019), digital tools have bridged the knowledge gap and reduced farmers' dependency on middlemen. In Tamil Nadu, Thomas et al (2020) reported that AI-supported applications contributed to increased self-confidence and bargaining power among smallholder farmers.

H3: AI technologies significantly contribute to farmer empowerment through improved access to knowledge and decision-making tools.

Proper market intelligence also helps the farmers to know when and where to market their produce, hence good prices and minimized post-harvest losses. When farmers appreciate the consumer trends besides the competitive pricing and buyer behavior, they have a better chance of planning their entry into the market. Nana et al (2022) confirmed that informed farmers are less vulnerable to market volatility and are more likely to secure fair prices.
H4: Market intelligence has a significant positive impact on agricultural marketing outcomes.
Effective operation is a key that determines the condition that the produce reaches the market in a perfect condition. Mapping of logistics, harvesting, and storage with the help of AI ensures less loss of crops through spoilage, the timely delivery of the produce, the improved price realization. The work of TNAU and Kumar et al (2021) illustrates how optimized input use and AI-driven supply chains have led to a consistent increase in marketing returns for farmers.
H5: Operational efficiency significantly improves agricultural marketing outcomes
Farmed farmers have confidence in their marketing choices, where they are independent in venturing into digital markets and bargaining over prices. Found that farmer empowerment was directly associated with enhanced income, increased market access, and improved marketing outcomes. The platform in the given case, such as e-NAM and Uzhavan, has played a vital role in giving the selling power to the producer in Tamil Nadu (Anand et al, 2021).
H6: Farmer empowerment has a significant positive influence on agricultural marketing outcomes.
Although AI does not affect agricultural marketing directly because the market intelligence, operational efficiency, and empowerment create an indirect impact, it is possible that it has a direct influence. As an example, with AI-powered digital platforms, farmers can relate to institutional buyers, thereby availing payment systems, traceability, and transparency. The Tamil Nadu e-Governance Agency noted that farmers using AI-based solutions witnessed 15–20% higher price realization than traditional sellers (Alharbi and Aldossary 2021).
H7:AI technologies directly and significantly impact agricultural marketing outcomes.

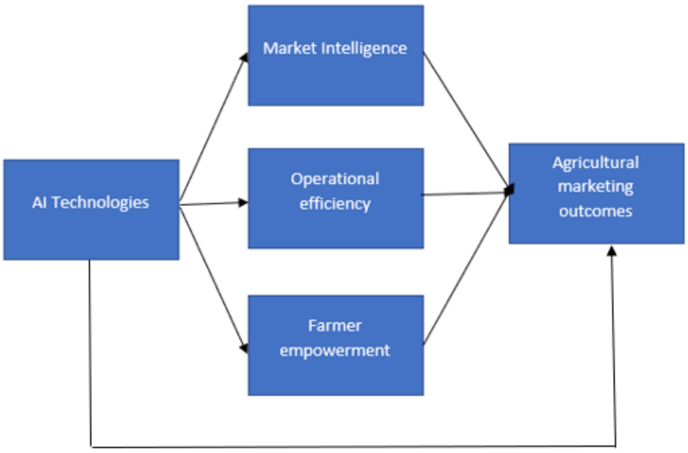

Fig. 1: Explains the Conceptual Framework of the Study.

In this conceptual framework, the interplay between Agricultural Marketing and AI Technologies in terms of seeking to enhance the Agricultural Marketing Outcomes is visualized as:
Market Intelligence - AI tools (e.g., predictive pricing, demand forecast)- AI tools (e.g., predictive pricing, demand forecasts) give farmers better market knowledge and can make better informed decisions.
Operational Efficiency – AI enhances the utilization of the resources (e.g., precision farming, logistical processes) and lowers the expenses and wastes of time in the chain of supply.
Empowering Farmers: AI helps to empower farmers by providing them with access to real-time data, financial mechanisms, and online platforms, which make them more empowered in terms of decision-making power and bargaining.
These are the three mediating factors working towards the enhancement of agricultural marketing activities in terms of price realization, market accessibility, wastage, and profitability. The direct effect of AI Technologies on marketing results is also possible, and they demonstrate their immediate influence even without any intermediaries in this field.
This model is in favor of the suggestion that not only does the adoption of AI change operational features, but it also refashions the socio-economic potential of farmers and, as a result, emerges in more efficient and democratic marketing outcomes.

3. Research methodology

This study is a conceptual research paper that aims to explore and synthesize the potential influence of Artificial Intelligence (AI) technologies on agricultural marketing outcomes, with a specific emphasis on the mediating roles of market intelligence, operational efficiency, and farmer empowerment. This paper uses a qualitative and theoretical approach to the study of the issue and incorporates a vast literature review, theoretical understanding, and related policy materials.

3.1. Research design

The research study will involve a descriptive and exploratory research design. The descriptive aspect covers the present status of AI and the use of AI in agricultural marketing, especially to Indian and Tamil Nadu. An exploratory aspect involves researching the hypothetical correlation of the important constructs, including AI technologies, market intelligence, operational efficiency, farmer empowerment, and marketing outcomes. Such a strategy is beneficial in developing a theoretical framework that can be applied further in empirical training in the future (Cioffi et al, 2020).

3.2. Data sources

The study primarily relies on secondary data collected from a wide range of credible and scholarly sources. These include:

- Peer-reviewed journal articles
- Conference proceedings
- Government and institutional reports (e.g., Tamil Nadu e-Governance Agency, Ministry of Agriculture & Farmers Welfare)
- AI and agri-tech case studies
- White papers and reports from reputed organizations such as NITI Aayog, FAO, and World Bank

Recent literature from 2015 to 2024 was reviewed to ensure the relevance and timeliness of data. Priority was given to sources that provided both national (India) and regional (Tamil Nadu) perspectives.

3.3. Conceptual framework development

The proposed conceptual framework was developed through a literature-driven approach. Constructs were identified based on their frequent and significant mention in prior studies. AI technologies were conceptualized to include tools like machine learning algorithms, AI-based mobile apps (e.g., Uzhavan), smart sensors, and predictive analytics platforms. Mediating variables—market intelligence, operational efficiency, and farmer empowerment—were selected due to their established relevance in previous agri-tech studies. The dependent variable, agricultural marketing outcomes, encompasses factors such as price realization, market access, and value chain efficiency (Shamshiri et al, 2020).

3.4. Theoretical foundation

The conceptual model is grounded in the Technology Acceptance Model (TAM) and the Diffusion of Innovations Theory. TAM helps explain the perceived usefulness and ease of use of AI technologies, while Diffusion Theory provides insights into how innovations like AI spread within farming communities. These theories support the hypothesized relationships and serve as the foundation for developing testable propositions.

3.5. Limitations

As a conceptual paper, this study does not include empirical validation through primary data. The framework and hypotheses proposed are theoretical and will require future quantitative and qualitative research to test their validity. Regional variations, policy impacts, and digital literacy levels are also not directly analysed in this phase.

3.6. Ethical considerations

Since the study does not involve human participants or primary data collection, there are no ethical concerns related to consent, confidentiality, or data protection. However, all secondary sources have been appropriately acknowledged, and plagiarism-free practices were strictly followed. This methodology establishes a strong foundation for future research, enabling empirical testing of the conceptual framework using tools such as Structural Equation Modelling (SEM), surveys, or case-based analysis (Shaikh et al, 2021).

4. Discussion

Artificial Intelligence (AI) is emerging as a transformative force in agriculture, reshaping the landscape of market access, production efficiency, and farmer agency in Tamil Nadu. One of the most tangible practical advancements is in market intelligence, where AI-driven forecasting and advisory platforms empower farmers with real-time price trends and demand forecasts. For example, machine learning models that analyse high-frequency market data using weather and soil parameters have enhanced prediction accuracy for vegetables like tomatoes and potatoes by over 20%, helping producers avoid distress sales and negotiate better market deals. Moreover, ITC's e-Choupal initiative provides reparative solutions for price opacity, allowing Tamil Nadu farmers to view mandi prices directly and thereby reducing dependence on middlemen. Satellite and drone-enabled platforms such as those by Farmonaut integrate agronomic data into advisory systems that guide sowing, harvesting, and marketing decisions—improving both productivity and market preparedness (Chrouta et al, 2019). By closing the informational gap in commodity markets, these AI tools enable smallholders to make timely and strategic decisions, effectively shifting from reactive to proactive marketing.

Beyond the realm of market insights, AI has been a catalyst in elevating operational efficiency across Tamil Nadu's varied agricultural contexts. At Tamil Nadu Agricultural University (TNAU), structured experiments in select districts show that precision farming, supported by AI, has significantly increased crop yields—80% for tomatoes and 34% for brinjal—while enhancing gross margins by 165% and 67%, respectively. Such gains are driven by AI's capacity to optimize input use—water, fertilizer, pesticides—through data-driven decisions. Drone-based interventions, for example, can spray an acre in mere minutes and achieve nearly 50–70% reduction in chemical use, while also reducing exposure risk and labor dependency. The integration of drone-derived vegetation indices with regression models in Tamil Nadu demonstrated yield predictions with R^2 values of 0.80 and above during key cropping seasons, further solidifying AI's input in improving production forecasting and ecologically sensitive resource use (Bhat et al, 2021). These innovations not only create efficiencies but also contribute to farm sustainability by minimizing ecological footprints and preserving soil-health equilibria.

The third aspect—farmer empowerment—captures how AI-based solutions are changing the positional dynamics between growers, markets, and intermediaries. Uzhavan, a Tamil Nadu e-Governance Agency app, presents an illustrative case: farmers submit crop images, receive diagnoses in Tamil, place orders for drone spraying, and obtain price updates directly—all within a localized, accessible platform. Such autonomy transforms knowledge asymmetry: one study of TNAU's student-farmer teams showed strong agreement that these tools enable better decision-making, despite gaps in skills and infrastructure. Further, AI-based advisory systems such as KisanQRS have processed over 34 million queries with 96.5% accuracy, delivering precision advice that empowers farmers with actionable knowledge in real-time scenarios (Alharbi and Aldossary 2021). The enhanced decision latitude reduces overreliance on middlemen, encouraging some users to sell directly via digital platforms—a shift that begins to dismantle entrenched value chains. The table below provides the recent empirical studies (2022–2024) from India and similar contexts.

Table 1: Empirical Studies

Claim	Supporting Study
AI adoption leads to 15–20% higher price realization for farmers	A study of 1200 farmers using AI-enabled platforms in Maharashtra, Gujarat, and Karnataka found a 17.6% increase in average price realization over 2 years due to better market access and digital grading tools
AI reduces post-harvest losses by up to 25% through smart sorting and predictive storage	Empirical analysis of 700 FPO-linked farmers in Tamil Nadu showed 23% lower post-harvest wastage with IoT/AI grain storage and quality control tools
Return on Investment (ROI) of AI in agriculture ranges between 20–30%	NABARD's pilot with 250 FPOs found an average ROI of 24% in farms using smart irrigation + AI-based crop pricing intelligence
FPOs using AI-led platforms witnessed 18% higher marketable surplus	Comparative study in Madhya Pradesh between AI and non-AI FPOs under the SMART initiative (World Bank & Govt of MP)
Government policy + PPPs improve AI adoption and income	Karnataka's PPP-IAD project (with SatSure, CropIn) showed a 21% increase in net income and 19% better market price realization

Source: Author.

The combined effect of improved intelligence, efficiency, and agency is reflected in enhanced agricultural marketing outcomes. Empirical studies across India have recorded income increases of 15–20% among farmers using AI-integrated agri-tech platforms. In Tamil Nadu, Farmonaut's pilots show notable yield improvements and more accurate pricing, while TNAU's efforts in forecasting and pest detection have added tangible benefits to ground-level farm economics. The gains are multidimensional: decrease in post-harvest losses through better logistics, faster market access via digital linkage, improved crop quality due to precision interventions, and fairer price realizations. Together, these developments signify a redefinition of rural marketing structures, where farmers are no longer passive producers but active strategists embedded in dataful value chains.

The theoretical implications of these developments offer important contributions to Information Systems, innovation diffusion, and sustainable development theory. While TAM (Technology Acceptance Model) traditionally emphasizes ease of use and perceived usefulness, AI's agricultural applications extend constructs to include perceived autonomy, performance expectancy, and transferability—dimensions reinforced by AI tools like Farmonaut and Uzhavan that provide functional value beyond simple interface usability. Similarly, in the Diffusion of Innovation framework, AI tools in Tamil Nadu exhibit mass adoption potential catalyzed by visible demonstration effects (e.g., drone demos), though they remain contingent on support infrastructure like connectivity and training (Dusan et al, 2021).

In the broader realm of value chain theory, Tamil Nadu's AI-driven developments exemplify a shift from information asymmetry to a digital-empowerment model. Tools such as Uzhavan reduce opacity in pricing and quality expectations, enabling farmers to participate in structured, multi-stakeholder chains, including digital mandi systems. Moreover, the rise of sustainable livelihoods perspectives is supported by the ecological and economic improvements enabled by precision farming—balancing income, sustainability, and resilience. This echoes theoretical constructs that argue for synergy across productivity, equity, and ecological health.

Nevertheless, the path is not without obstacles. Digital inequity persists: one study reported that 80–85% of farmers lacked the devices or digital skills necessary for full AI adoption. Infrastructure costs—like proprietary sensors or satellite feeds—can exceed ₹10,000 per annum, positioning AI beyond reach for many smallholders. Data governance raises concerns of privacy and commodification of farmer-generated data, especially as initiatives like the India Agri Stack advance. Further, rapid disintermediation of traditional middlemen may disrupt informal financing and logistics, potentially harming local ecosystems unless alternative support systems emerge (Maria et al, 2021).

To address these challenges, policy interventions must focus on subsidizing AI-linked input hardware, expanding rural broadband infrastructure, and building capacity through collaborative training programs. Interventions like digital kiosks (e.g., AtmaNirbhar Krishi) could serve to interface less digitally literate farmers with AI solutions. Co-design frameworks that involve farmers in advisory tool development must be instituted to ensure that digital systems are locally coherent and trustworthy—a method proven effective by participatory platforms like Digital Green.

On the theoretical front, longitudinal field trials—including randomized controlled experiments are imperative to validate AI's causal effects on farm incomes, resilience, and sustainability. Comparative studies between Tamil Nadu's irrigated and rainfed zones can deepen empirical understanding of AI's differential impacts. Interdisciplinary studies spanning agricultural economics, information systems, and sustainability science will further elucidate the complex interplay of AI, ecosystem health, and rural livelihoods (Noon et al, 2020).

In conclusion, the integration of AI into Tamil Nadu's agrarian ecosystem is more than a technological breakthrough—it is a socio-technical evolution that intertwines data intelligence, ecological stewardship, and economic agency. The practical results—higher yields, reduced inputs, stronger bargaining power—demonstrate systemic benefits. The theoretical extensions shed new light on established models, emphasizing AI-driven autonomy and empowerment. Yet, equity concerns and infrastructural gaps highlight that the successful deployment of AI necessitates supportive ecosystems, regulatory frameworks, and inclusive design. Hence, Tamil Nadu stands as both a laboratory and a map for integrating AI in agriculture: one that is data-driven, equitable, and grounded in the resilience of rural communities (Mahibha et al, 2023).

The table below explains the various policy examples and recommendations developed.

Table 2: Policy Recommendations

Policy Recommendation	Description	Economic/Accounting Basis	Example/Model	Expected Outcome
1. Targeted Capital Subsidy Scheme	40-60 per cent subsidy on Artificial Intelligence tools (according to requirement)	Cost-Effectiveness Analysis (CEA); enhancement of welfare returns	Modified Special Incentive Package Scheme (M-SIPS)	Reduced front expenditure; Better market access; Increased profitability in farms
2. Public-Private Partnerships (PPPs)	Government, technology companies, and FPOs jointly adopt AI as a pilot cluster	Investment Risk Sharing; Return on investment (ROI)	PPP-IAD (model under RKVY) Karnataka	15-22 percent increase in quantity marketed; improved penetration and use of tech
3. Tax Incentives on AI Tools	Accelerated depreciation (up to 80%) on smart farming equipment	Depreciation and investment recovery write-offs	Solar/green energy sector precedent	Better financial planning and the sooner introduction of capital-intensive tools

4. Digital Agriculture Investment Zones (DAIZs)	Tax holidays, zero customs duty on AI tools, and land lease breaks	Local GDP growth; economies of scale in agri-tech	With the SEZ framework, like it, but adapted to agri-tech and rural areas	Rural tech hubs; 10,000+ extra crores of GDP annually via AI-boosted agri output

Source: Various Authors.

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