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Research Article

Unlocking Value in Agricultural Value Chains: How AI-Driven Decision Intelligence Improves Value Realisation Across Stakeholders, with a Tur Dal Pilot in Kalaburagi

Tarak Dhurjati*

Whale Tank BioCatalysts, Hyderabad, India

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India's agricultural value chains remain fragmented and inefficient, characterised by information asymmetry, weak price discovery, excessive post-harvest losses, and poor coordination among farmers, traders, processors, and retailers. These structural inefficiencies result in a large price spread between farm gate and consumer, with farmers capturing a disproportionately small share of final value while consumers face high and volatile prices. This paper hypothesizes on how artificial intelligence (AI), deployed as a value-chain-wide decision intelligence platform, can significantly improve value realisation for all stakeholders. By integrating soil, weather, crop, price, demand, quality, and logistics data, AI can enable demand-aligned production, transparent quality-based price discovery, reduced processing losses, and optimised distribution. The paper elaborates four dimensions of AI intervention—production, procurement and price discovery, processing and value addition, and distribution and consumption—and illustrates the hypothesis through a tur dal (pigeon pea) pilot in Kalaburagi district, Karnataka. The analysis demonstrates that AI can compress the price spread by 20–25%, reduce processing losses from 10–15% to 9%-11%, increase farmer price realisation, and improve consumer affordability. The paper concludes with policy and institutional implications for scaling AI-enabled value chains in India.

Keywords

Artificial Intelligence, Agricultural Value Chains, Price Discovery, Transaction Costs, Pulses, INDIA

1. Introduction

Despite significant gains in agricultural production, India's agricultural value chains remain structurally weak. For most commodities—particularly pulses, oilseeds, and horticulture—value chains are discontinuous, fragmented, and opaque. Farmers make production decisions with limited information on future demand, prices, or quality requirements. Post-harvest handling is constrained by inadequate warehousing and logistics, while price discovery remains largely trader-driven and detached from quality parameters. The outcome is a wide divergence between farm-gate and retail prices, with substantial losses and inefficiencies absorbed in the middle of the chain.

From a microeconomic perspective, this is not merely an infrastructure deficit; it is fundamentally a decision lag or a decision failure. Farmers, traders, processors, and retailers operate with incomplete, delayed, or asymmetric information,

*Correspondence: Tarak Dhurjati (tarak@whaletank.in)

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leading to sub-optimal choices at every stage of the value chain. Farmers decide what to produce based on convenience, risk aversion, or minimum support price (MSP) signals rather than market demand. Traders rely on anecdotal assessments rather than systematic quality grading, despite the presence of a quality evaluation framework which is used only with a low rigour. Processors face volatile input quality and high processing losses, while distributors struggle with demand uncertainty and inventory risk.

Artificial intelligence (AI) withs its exponential power for analysis of large number of diverse datasets and structuring solutions as per logical patterns, can act an excellent decision intelligence layer as a rather than a narrow automation tool, offers a pathway to address these failures. AI systems can integrate heterogeneous agriculture data sources—soil, weather, satellite imagery, mandi arrivals, prices, retail demand, logistics costs, and quality parameters—into predictive and prescriptive insights. In doing so, AI reduces information asymmetry, lowers transaction costs, and improves coordination across the value chain.

This paper advances the proposition that AI should be understood as an institutional and economic enabler, not merely a technological upgrade. By improving decision quality across four dimensions of the agricultural value chain—production, procurement and price discovery, processing and value addition, and distribution and consumption—AI can unlock shared value and improve welfare outcomes. Further this paper provides a conceptual framework for design of pilots in specific crop hot spots and processing clusters to validate the gains by use of AI based decision intelligence tools. Various case studies have alreadt demonstrated on how AI can be successfully integrated to increase agricultural productivity [7]. The below hypothesis extends to a specific case simulation for Tur Dal (Red gram), an important part of Indian diet.

The hypothesis applies well to perishable agricultural commodities like Tomato and other vegetables and localized commodities spanning across an agro-climatic region or a few districts aggregated across a homogenous area of edaphic and climatic conditions. This paper provides an illustrated through a case study of the Tur dal (red gram) value chain in Kalaburagi district, Karnataka, one of India's largest pulse-producing regions. The case demonstrates how AI-driven decision intelligence can compress price spreads, reduce processing losses, and redistribute value more equitably among stakeholders. The prices considered are indicative and only to provide an example for further research as a part of a "live action case" involving various stakeholders to demonstrate decision points which can open opportunities to optimize value and distribute proportionately among the value chain participants.

2. Conceptual Framework: AI as Decision Intelligence in Agricultural Value Chains

Traditional agricultural digital interventions have focused on isolated functions—weather advisories, market price dissemination, or mechanisation. Artificial intelligence (AI) is transforming agriculture by offering innovative solutions to persistent challenges [1] While useful, these interventions often fail to address the systemic coordination problem across the value chain. AI-driven decision intelligence differs in that it connects decisions across stages, aligning incentives and outcomes. AI can support the decision-making process leading to an increase in productivity, efficiency, product quality and cost reduction [2]. The decision intelligence is applicable and required by various stakeholders at different points of the value chain.

From an agricultural economics standpoint, the primary contributions of AI lie in:

1) Reducing information asymmetry: Farmers and small traders gain access to predictive market and quality signals previously monopolised by larger intermediaries.
2) Lowering transaction costs: Better forecasting reduces search, negotiation, and risk-management costs.
3) Improving price discovery: Quality-based, transparent pricing replaces ad hoc bargaining.
4) Enhancing allocative efficiency: Production, processing, and distribution decisions are aligned with consumption demand.

AI thus functions as a coordination mechanism, enabling decentralized actors to make better decisions using shared intelligence. Empirical examples and case studies in the recent years, demonstrate the advantages of AI-driven supply chain optimization, encompassing enhanced resource allocation, diminished costs, and augmented sustainability [3].

Also the existing agricultural policy treats production, marketing, processing, and trade as sequential stages. In reality, commodities function as economic assets whose value depends on timing, quality, storage, processing, finance, and market access. Automated harvesting, predictive crop modeling, pest and disease detection, intelligent irrigation, supply chain optimization, and quality control are some of the applications deployed using AI-driven solutions, which have successfully demonstrated improving traceability, reducing waste, and enabling data-driven decision-making across the food system [4]. The paper also conceptualises agriculture as a commodity orchestration system, comprising:

1) Land and crop planning
2) Production and surplus emergence
3) Aggregation and procurement
4) Processing and value addition
5) Storage and logistics
6) Finance and insurance
7) Domestic and export consumption
8) Governance and dispute resolution

AI's value lies in managing the interfaces between these nodes, rather than optimising isolated processes, AI enables system-wide coordination by converting fragmented data into actionable intelligence. AI's role can be particularly realized in upstream decision-making, midstream logistics and storage optimization, and downstream market intelligence and traceability, resulting in significant gains in efficiency, sustainability, and supply chain resilience. However, realizing AI's full potential requires attention to data interoperability, governance, access, and context-sensitive design [5]. In fact the acronym AI can be changed as "actionable intelligence", which is more appropriate, given its ability to enable actionable and measurable decisions. Further the AI tools function not in isolation but as part of a dynamic, interconnected system where data, insights, and decisions flow across functional boundaries [6].

2.1. Hypothesis Development

Grounded in agricultural economics and transaction cost theory, this study advances the following testable hypotheses:

H1: AI adoption increases farm-gate price realisation- Farmers exposed to AI-driven price and quality intelligence receive significantly higher farm-gate prices compared to non-exposed farmers.

Rationale:

Reduced information asymmetry and better timing decisions improve bargaining position and sale outcomes.

H2: AI adoption reduces processing losses and unit processing costs- AI-enabled quality grading and process optimization reduce processing loss percentages and operating costs per unit of output.

Rationale:

Predictive control improves recovery rates and machine efficiency.

H3: AI adoption compresses the farm-to-retail price spread- Commodities traded through AI-enabled value chains exhibit a significantly lower price spread between farm gate and retail prices.

Rationale:

Improved coordination reduces mid-chain rent and inefficiencies.

H4: AI adoption reduces price volatility at wholesale and retail levels- AI-enabled demand forecasting and inventory management reduce inter-temporal price volatility.

Rationale:

Better matching of supply and demand smoothens seasonal price swings.

H5: AI adoption improves consumer welfare- Retail prices in AI-enabled value chains are lower and more stable, increasing consumer surplus.

2.2. Empirical Strategy

2.2.1. Data Sources

1) Farm-gate prices (APMC, field surveys)
2) Processing loss and cost data (dal mills)
3) Wholesale and retail prices (state market intelligence, CPI data)
4) Weather, soil, and satellite data
5) AI adoption indicators (pilot participation)

2.2.2. Econometric Model (Difference-in-Differences)

A quasi-experimental Difference-in-Differences (DiD) framework is proposed:

$$Y_{it} = \alpha + \beta_1 AI_i + \beta_2 Post_t + \beta_3 (AI_i \times Post_t) + \gamma X_{it} + \epsilon_{it}$$

Where:

1) Y_{it}: Outcome variable (price, loss %, spread, volatility)
2) AI_i: Binary indicator for AI-enabled participants
3) $Post_t$: Post-intervention period
4) X_{it}: Control variables (rainfall, acreage, MSP, seasonality)
5) β_3: Causal impact of AI adoption

2.2.3. Outcome Variables

1) Farm-gate price (₹/quintal)
2) Processing loss (%)
3) Farm–retail price spread (₹/quintal)
4) Retail price volatility (CV or SD)

2.2.4. Robustness Checks

1) Propensity score matching (PSM)
2) Placebo tests using non-pulse crops
3) District fixed effects
4) Weather shock controls

3. AI-Enabled Decision Intelligence Across Four Value Chain Dimensions

The Commodity value chain can be structured across four dimensions as below. At the production stage, farmers function as micro-enterprises making decisions on crop choice, input use, and timing of operations. Traditionally, these decisions are weakly linked to market demand. By providing forward-looking price and demand signals, AI allows farmers to shift from subsistence or convenience-driven cropping to market-aligned production. This transition improves expected returns without necessarily increasing physical output. AI systems enable demand-oriented production by:

1) Matching block-level agro-climatic conditions with regional and national demand trends.
2) Forecasting relative profitability across competing crops.
3) Recommending optimal sowing windows, varieties, and input regimes using soil and weather data.

In a highly integrated value chain driven by one or more of anchor participants in each dimensions, decision are made as per prior agreement and a contract with service levels. But such value chains form a miniscule of the total of commodity trade. The difference between highly integrated value chain and a disintegrated and mis-integrated value chains is the *adhoc* nature in which decisions are taken either based on tradition or trust and based on expeditious conditions. Artificial intelligence tools can be applied at each of these dimensions to unlock latent value to the deserving value chain participants, as explained below.

3.1. Production: Empowering Farmers as a "Firm"

At the production stage, farmers act as micro-enterprises making decisions on crop choice, input intensity, and timing. However, these decisions are often backward-looking, based on last year's prices or informal advice.

3.1.1. What to Produce and for Whom

AI models integrate agro-climatic suitability (soil type, rainfall, temperature) with demand forecasts, price trends, and export opportunities. By comparing expected profitability across crops, AI can recommend demand-aligned crop choices. For instance, in districts with strong and growing demand for tur dal, AI can suggest shifting area from lower-value or over-supplied crops to pulses.

This represents a shift from supply-driven to demand-driven agriculture, improving expected returns without necessarily increasing cultivated area.

3.1.2. How and Where to Produce

AI combines soil health card data, historical yield records, and weather forecasts to provide location-specific agronomic recommendations. These include optimal sowing windows, varietal selection, nutrient management, and integrated pest management (IPM). Precision recommendations reduce input waste, lower risk, and improve both yield and quality.

3.1.3. When to Sell, How Much to Store

Perhaps the most significant impact of AI at the farm level lies in post-harvest decisions. By forecasting mandi arrivals, price trends, and seasonal demand cycles, AI enables farmers to decide whether to sell at harvest, store produce in warehouses or FPO facilities, or enter forward contracts with processors. This reduces distress sales and improves price realisation.

Collectively, these interventions allow farmers to operate more like informed firms rather than passive price takers.

3.2. Post-Production to Procurement: Transparent Price Discovery

The procurement stage is traditionally dominated by traders and commission agents, creating a classic case of information asymmetry.

3.2.1. Quality-Based Price Discovery

AI systems integrate mandi prices with quality parameters such as moisture content, grain size, colour, and protein levels. Using sensors and computer vision, produce can be graded into quality slabs, each linked to a transparent price. This replaces subjective bargaining with rule-based pricing, improving trust and efficiency.

3.2.2. Optimised Procurement and Warehousing

AI forecasts arrival patterns across mandis and estimates storage costs and price risks. Traders and warehouses can thus plan procurement volumes and timing more efficiently, avoiding over-procurement during peak harvests and shortages during lean periods.

3.2.3. Logistics Optimisation

Route optimisation algorithms identify the lowest-cost transport options and enable shared aggregation. Reduced logistics costs directly contribute to lower consumer prices or higher farmer realisation.

3.3. Processing and Value Addition

Processing is a critical value-adding stage but is often plagued by high losses and variability.

3.3.1. Reducing Processing Losses

In Tur dal milling, processing losses typically range from 10–15%. AI predicts expected recovery rates based on grain characteristics and recommends optimal machine settings. Even a 1–3 percentage point reduction in loss translates into significant value gains.

3.3.2. Predictive Maintenance

AI-based monitoring of machine performance reduces downtime and ensures consistent quality, lowering operating costs per unit.

3.3.3. Demand-Driven Processing

By integrating retail and export demand forecasts, AI helps processors plan production schedules, product mix, and inventory levels. This reduces overproduction, stockouts, and working capital stress.

3.4. Distribution and Consumption

In the final stage, inefficiencies arise from poor demand forecasting and high last-mile costs.

3.4.1. Micro-Market Demand Forecasting

AI models use retail sales data, festival calendars, and socio-economic indicators to predict demand at district or town level. This enables optimal stocking and reduces wastage.

3.4.2. Dynamic Pricing and Promotion

AI supports dynamic pricing strategies based on inventory levels, competitor actions, and consumer price sensitivity, balancing margins and volumes.

3.4.3. Route Optimisation

Optimised delivery routes reduce fuel consumption and delivery times, lowering costs and emissions.

4. Platform Architecture and Design Principles

4.1. Federated Data Ingestion Layer

The platform ingests data from land records, satellite imagery, weather systems, APMC (Agricultural Produce Marketing Committee) markets, processors, warehouses, logistics providers, banks, insurers, and export agencies. Data ownership remains decentralised, with interoperability ensured through APIs (Application Programming interface).

4.2. Data Harmonisation and Trust Layer

Incoming data is standardised, geo-tagged, and commodity-tagged. Consent mechanisms, access controls, combination of heterogeneous datasets [8] and audit trails establish trust without centralising data ownership [9].

4.3. AI and Decision Intelligence Core (DIC)

To start with the DIC using the current LLMs (Large Language Models), Regression, Association Analysis and Clustering Models [10] and Machine learning models can generate the following information for undertaking decisions in a contractual mode.

1) Crop classification and yield forecasts
2) District-level surplus estimates
3) Price discovery and volatility forecasts
4) Processing and storage optimisation
5) Credit risk and collateral valuation
6) Insurance trigger models

These models continuously improve through feedback loops.

4.4. Commodity Orchestration Layer

AI insights are translated into coordinated workflows across procurement, processing, storage, logistics, finance, and exports. Intermediaries are integrated rather than eliminated, improving transparency and predictability.

4.5. Functional Impact Across the Value Chain

AI-enabled land intelligence improves crop planning and procurement readiness. District-level surplus mapping reduces distress sales and aligns storage deployment. Processing clusters are planned based on real surplus and demand, increasing farmer realisation and rural employment.

Commodity-backed finance becomes viable through AI-verified warehousing and cold-chain systems, reducing credit costs and price volatility. Export and specialty markets benefit from compliance-by-design production, traceability, and demand forecasting.

4.6. Addressing Legacy IT Fragmentation

Existing agri-commodity IT systems in India digitise records but do not enable decision coordination. They operate vertically within departments, forcing policymakers and markets to rely on delayed and incomplete information. Technologies of AI era including blockchain, swarm intelligence, big data, machine learning, deep learning, IoT, cyber physical systems, robotics and autonomous systems, generative adversarial networks, and cloud-edge-fog-computing, etc, now can both seamlessly and discretely integrate with legacy systems to generate desired decision outcomes [11].

Such AI integrated platforms overlays these systems, enabling horizontal data flows across the value chain. Static databases are transformed into a living intelligence network, allowing anticipatory governance rather than reactive intervention. This approach improves efficiency without dismantling existing institutional structures.

5. Case Study: Tur Dal Value Chain in Kalaburagi

Kalaburagi district, often referred to as the “Tur Bowl of Karnataka,” accounts for a substantial share of India’s tur production. Despite this, the value chain exhibits severe inefficiencies.

5.1. Existing Price Structure

Farm-gate prices range from ₹6,250-6,500 per quintal, while retail prices reach ₹13,000-16,500 per quintal. Farmers capture only about 40-45% of final value.

Table 1. *Decision Failures and AI Interventions Across the Agricultural Value Chain.*

Value Chain Stage	Traditional Decision Failure	AI-Based Intervention	Economic Impact
Production	Crop choice driven by convenience/	Demand-aligned crop planning	Higher expected farm income

Value Chain Stage	Traditional Decision Failure	AI-Based Intervention	Economic Impact
	MSP (Minimum Support Price)		
Post-harvest	Distress sale at harvest	Price forecasting & storage advice	Improved price realisation
Procurement	Ad hoc quality assessment	AI-based quality grading	Transparent price discovery
Processing	High loss & downtime	Predictive process control	Lower unit processing cost
Distribution	Overstocking/shortages	Demand forecasting & routing	Lower wastage, stable prices

5.2. AI-Enabled Interventions

An AI platform integrating district-level crop data, soil and weather information, mandi prices, logistics costs, and demand indicators can:

1) Improve crop planning and quality at the farm level
2) Enable transparent, quality-based procurement
3) Reduce processing losses from 12–13% to 10–11%
4) Optimise distribution and retail pricing

Table 2. Tur Dal Price Formation: Baseline vs. AI-Optimised Chain (Kalaburagi).

Stage	Baseline Price (₹/quintal)	AI-Optimised Price (₹/quintal)	Change
Farm gate (tur whole)	6,250-6,500	7,200-7,400	+700 to +900
Processor effective cost	7,900-8,600	7,600-7,900	-300 to -700
Processor → distributor	9,500-10,500	9,000-9,800	-500 to -700
Wholesale	12,500-13,500	11,800-12,500	-700 to -1,000
Retail	15,000-16,500	13,800-14,500	-1,200 to -1,700

5.3. Impact on Value Distribution

Simulation results indicate:

1) Farmer price realisation increases by ₹700–900 per quintal
2) Processor costs decline by ₹400–700 per quintal
3) Retail prices fall by ₹1,200–1,700 per quintal

Overall, the price spread compresses by 20–25%, benefiting all stakeholders.

Table 3. Welfare Effects of AI Adoption Across Stakeholders.

Stakeholder	Mechanism	Welfare Impact
Farmers	Higher price realisation, lower distress sales	Income ↑, risk ↓
Processors	Lower loss, stable input quality	Margin stability ↑
Traders/Logistics	Optimised procurement & routing	Cost ↓
Retailers	Lean inventory, dynamic pricing	Working capital ↓
Consumers	Lower and stable prices	Consumer surplus ↑

6. Policy and Implementation Implications

Technological reform alone is insufficient. Agricultural commodities function simultaneously as farm outputs, industrial inputs, trade goods, and consumer essentials. Governance remains fragmented across ministries and Departments in Governments at both Central and State level [12]. Agriculture being a State subject, the Central Government should create new operating structures, information governance models, standards setting & regulatory bodies and handhold State Governments to develop a homogenous regulation which is uniform across the country. To scale AI-enabled value chains, institutional support is essential. Key recommendations include:

1) Establishing a multi-disciplinary Department of Value Chains to coordinate data and policy
2) Leveraging existing digital assets such as Soil Health Cards and e-NAM (electronic-National Agricultural Market)
3) Developing commodity-specific AI models for major crops
4) Deploying multi-stakeholder platforms accessible to farmers, traders, and retailers
5) Creating ease of access to high-performance hardware (GPUs, ASICs) and infrastructure required to train, deploy, and run large-scale AI models and open source software for benefit of Researchers and students [14].

At the core of the entire Agri-value chains from crop planning to sowing to crop production & protection to harvesting and further towards processing into consumer products, multiple decisions need to be made by the producer in a timely manner, amidst uncertainties of agriculture as an economic activity and additional risks ushered into by climate change and dynamic markets.

Well curated and trained AI models [13] have immense potential to unlock significant value, to each of the value chain participant in Agriculture, starting from farmer to the trader, to the processor and finally to the end-consumer. The proportion of value captured and redistributed may vary contextually, but certainly value is unlocked. The paper provides simulation around the concept of AI decision intelligence framework and the results should not over-interpreted, without proper empirical evidence based on primary data [15].

To enable the same, there is a need to conduct multiple pilots across various production-processing clusters to validate the improvement in market efficiencies and thereafter, standardize the AI driven interventions to further scaleup and establish a sustainable business model. As it is multidisciplinary, the Agricultural policy should transform into commodity specific value chain policy with clear risk and benefits management.

7. Conclusion

AI-driven decision intelligence offers a transformative pathway for Indian agriculture. By reducing information asymmetry, improving coordination, and aligning production with demand, AI can convert fragmented value chains into integrated systems of shared value. The Kalaburagi Tur dal case demonstrates that such transformation is not speculative but achievable with existing data and technology. This paper is a conceptual model and is not based on any direct primary research on the ground for collection of data and has been developed to enable generation of a series of pilot projects to start with to deploy AI in Agricultural commodity management system. The above is only one use case focused on price discovery and distribution. However AI interventions and use cases in warehouse management especially using robotics in stock movement, scheduling and logistics, precision agriculture, soil health management, plant breeding and new variety development, commodity quality assessment, etc., integrated with commodity procurement and distribution systems will further augment efficiency across the agricultural supply chains. Scaling this approach could significantly enhance farmer incomes, processor efficiency, and consumer welfare across India's agricultural economy.

Abbreviations

e-NAM	e-National Agriculture Market
APMC	Agricultural Produce Marketing Committee
GPU	Graphic Processing Units
ASIC	Application Specific Integrated Circuits

Author Contributions

Tarak Dhurjati: Conceptualization, Writing – original draft, Writing – review & editing

Conflicts of Interest

The author declares no conflicts of interest.

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