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A Strategic Perspective for Green Revolution 2.0: Applying Game Theory Based Decision-Making Frameworks for Smart and Natural Farming in India

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Abstract: In this conceptual paper, the author develops and presents a strategic decision-making framework that applies game theory to evaluate smart and natural farming approaches in India. In the face of increasing pressures from climate change, resource scarcity, and evolving socio-economic landscapes, agriculture must adapt to the challenges of a volatile, uncertain, complex, and ambiguous (VUCA) world. When integrated with the Provision of Urban Amenities in Rural Areas (PURA) framework, VUCA offers a dynamic system perspective that contextualizes uncertainty and institutional capacity in farming systems. This study applies a modified Spence signaling model to capture how farmers—categorized as smart or natural versus conventional—choose to signal their sustainability credentials in an environment of asymmetric information. Using a combination of payoff matrix modelling, Bayesian belief updating, and evolutionary game simulations, the paper identifies strategic equilibria under varying levels of policy support, consumer trust, and signal cost. Farmers' decisions to adopt smart technologies or organic certifications are modelled as costly but credible signals of quality. These signals are then interpreted by receivers such as consumers, investors, or policymakers, who in turn adjust their support or market preferences. The analysis reveals conditions under which separating, pooling, and semi-separating equilibria emerge, and how these outcomes impact farmer behaviour and systemic sustainability. Case studies from Indian states such as Andhra Pradesh, Karnataka, and Punjab demonstrate how real-world farming programs mirror theoretical outcomes under different signalling strategies. The study also presents a robust methodological structure, combining conceptual modelling with policy simulation and validation through comparative cases. By integrating environmental, technological, and institutional perspectives, this paper contributes a hybrid strategic framework aligned with India's Green Revolution 2.0 goals. It offers practical recommendations for policy design, infrastructure planning, and market mechanisms that support the scaling of sustainable agricultural practices through credible signalling and game-theoretic insights.

Key words: Green Revolution 2.0, VUCA, PURA, Spence signaling, asymmetric information.

1. Introduction

India's agricultural journey is a tapestry of resilience, transformation, and recurring challenges. From the subsistence farming methods of ancient civilizations to the technology-driven landscapes of the 21st century, Indian agriculture has undergone radical shifts, each shaped by population pressure, political ideologies, and technological advancements [1, 2]. Today, the sector faces a new dual challenge—balancing the need for increased productivity with the imperative of sustainability in an era characterized by climate change, resource depletion, and institutional constraints [3].

This paper explores these challenges through the lens of game theory, particularly focusing on signaling games and strategic interactions under uncertainty [4]. It applies this lens to compare smart and natural farming practices in India and to propose a hybrid approach aligned with the objectives of Green Revolution 2.0. The integration of the volatility, uncertainty, complexity, ambiguity (VUCA) framework with the Provision of Urban Amenities in Rural Areas (PURA) development

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model serves as a macro-structure for contextualizing decision-making in agriculture [5, 6].

1.1 Historical Context of Indian Agriculture

Indian agriculture has evolved over millennia. Historically, farming was deeply rooted in local ecosystems and cultural traditions. With the onset of British colonial rule, commercialization began, often disrupting indigenous systems. Post-independence, food scarcity and famine threats led to the Green Revolution in the 1960s and 70s, introducing high-yielding varieties (HYVs), chemical fertilizers, and irrigation [1].

While the Green Revolution significantly boosted production, especially in rice and wheat, it also created regional disparities, ecological stress, and reliance on inputs [2]. States like Punjab, Haryana, and Western UP became agriculturally prosperous, whereas rain-fed regions continued to lag. Moreover, the overuse of water and agrochemicals has led to soil degradation and groundwater depletion [7].

In recent years, natural farming and organic agriculture have emerged in response to these environmental concerns. Simultaneously, smart farming techniques that leverage data analytics, internet of things (IoT), and artificial intelligence have begun reshaping modern agronomy, especially in tech-forward states like Karnataka and Andhra Pradesh [8].

1.2 The Dual Challenge: Productivity vs. Sustainability

India needs to feed a population projected to exceed 1.6 billion by 2050 while conserving its dwindling natural resources [3]. This creates a paradoxical challenge: Increasing productivity through mechanization, biotechnology, and digital agriculture; Ensuring sustainability through biodiversity conservation, minimal chemical use, and regenerative practices.

Smart farming offers efficiency but raises concerns about techno-elitism, access, and long-term soil health. Natural farming promotes ecological balance but may suffer from yield limitations and market constraints. The strategic dilemma, then, is how to incentivize farmers to adopt practices that align with both private and public goods [9].

This paper argues that game theory, particularly the Spence signalling model, can offer insights into how farmers make these decisions under uncertainty and how policy can align incentives with social welfare [10].

1.3 Theoretical Foundations: Game Theory in Agricultural Economics

Game theory provides tools to study strategic interactions where the outcome for each player depends not only on their actions but also on the actions of others. In agriculture, it is used to: (1) model resource competition (e.g., water, land); (2) analyze cooperation in shared irrigation or pest management [11]; (3) understand technology adoption under peer influence and uncertainty [12].

Signaling games, a subset of game theory, are especially relevant in markets with asymmetric information. Farmers know more about their practices than buyers or policymakers. A farmer adopting sustainable techniques may send credible signals via costly actions—such as acquiring certification or investing in precision agriculture [13].

This framework helps explain when and why high-quality farmers are willing to bear the cost of signaling and how institutions can reduce these costs to promote sustainability.

1.4 Research Gap and Novel Contributions

While there is rich literature on: (1) Green Revolution impacts [2]; (2) Organic and smart farming [7, 8]; (3) Game theory in environmental policy and resource management [4, 11], few studies integrate all these components in a unified strategic decision-making framework. This paper fills the gap by: (1) Applying a modified Spence signaling model to model farmer behavior; (2) Integrating macro-contextual frameworks like VUCA and PURA into agricultural decision-making; (3) Developing Bayesian updating and evolutionary game perspectives [13]; (4) Offering policy insights into how incentives and infrastructure affect signal credibility.

This hybrid conceptual model contributes to both agricultural economics and sustainability science.

1.5 Structure of the Paper

The paper is organized as follows: Section 2 provides a comprehensive literature review on the evolution of farming paradigms, applications of game theory in agriculture, and signaling mechanisms in food markets. Section 3 outlines the theoretical framework, including a modified signaling game, payoff matrix, Bayesian updates, and evolutionary dynamics. Section 4 presents empirical illustrations and equilibrium scenarios involving smart and natural farming decisions. Section 5 discusses the policy implications of the model and strategic interventions to promote sustainable practices. Section 6 concludes with key insights and directions for future research, particularly the need for multi-player and dynamic modelling in real-world settings.

2. Literature Review and Theoretical Foundation

2.1 Evolution of Farming Paradigms

2.1.1 From Traditional to Industrial Agriculture

Indian agriculture has historically relied on indigenous knowledge, biodiversity, and agro-ecological balance. Prior to industrialization, practices such as intercropping, rain-fed agriculture, and cattle-based composting were dominant [1]. However, the post-independence food crisis prompted the Green Revolution in the 1960s and 1970s, introducing HYVs, chemical fertilizers, and mechanization.

This transformation dramatically increased production, especially in wheat and rice, and helped India avoid famines [2]. Yet, it also led to negative externalities: groundwater depletion, soil degradation, monocultures, and increased carbon emissions. These developments sparked debates on the long-term sustainability of industrial agriculture [3].

2.1.2 The Organic Farming Movement

The organic farming movement emerged globally in response to the environmental costs of industrial agriculture. In India, states like Sikkim and Himachal Pradesh have led the way, implementing policy shifts toward organic production [7]. Organic practices minimize external inputs and rely on crop rotation, compost, and biological pest control.

Despite its ecological benefits, organic farming faces yield gaps, high certification costs, and market access issues. Studies indicate that average organic yields in India are 20%-25% lower than conventional counterparts [9], yet long-term benefits include improved soil health and climate resilience.

2.1.3 Digital Agriculture Revolution

The latest transition is the digital agriculture revolution, powered by advancements in information and communication technologies. Farmers now use drones, IoT sensors, precision irrigation, and AI-based advisories to manage inputs and predict yields [8]. Agritech startups like DeHaat and AgNext offer bundled services, from soil testing to market linkage.

Digital agriculture improves efficiency, reduces resource use, and enhances traceability. However, its adoption is uneven, often constrained by digital literacy, infrastructure, and affordability [12].

2.2 Game Theory Applications in Agriculture

Game theory has become a robust tool to model stakeholder interactions in agriculture. It provides insight into cooperation, competition, and decision-making under uncertainty.

2.2.1 Resource Allocation Games

Non-cooperative game theory has been used to model water-sharing among farmers. Madani [11] analyzed how individual optimization leads to sub-optimal collective outcomes in decentralized water use. Cooperative game theory, in contrast, helps design fair resource-sharing mechanisms. For example, shared irrigation projects in Tamil Nadu have applied cost-benefit sharing based on Shapley values [15].

2.2.2 Technology Adoption Models

Bayesian and evolutionary game models explain how new farming technologies spread. According to Li et al. [12], farmers weigh expected utility and peer behavior before adopting precision agriculture. Early adopters influence others, and government subsidies or training programs can shift the adoption equilibrium.

Feng et al. [16] demonstrated that under information asymmetry, Bayesian learning allows farmers to update beliefs about new technologies, facilitating gradual adoption across networks.

2.2.3 Supply Chain Coordination

Stackelberg games have been used to model hierarchical relationships in agri-value chains. In these models, dominant players like buyers or digital platforms act as leaders, while farmers respond as followers [17]. Such frameworks aid in optimizing contract terms and reducing opportunism.

Repeated games are useful in understanding long-term relationships in contract farming. Reputation mechanisms and trust accumulation ensure compliance over time, crucial in perishable commodity supply chains.

2.3 Signaling Theory in Agricultural Markets

Signaling theory is vital in addressing asymmetric information in food systems, especially between producers and external actors like consumers or regulators.

2.3.1 Certification Systems

Certification acts as a costly signal that distinguishes high-quality, sustainable producers. Systems like India Organic or PGS-India (Participatory Guarantee System – India) enable farmers to access premium markets. According to Narayanan [7], only farmers with genuine commitment invest in certification due to its financial and administrative burden, thus achieving a separating equilibrium [10].

2.3.2 Branding and Labeling

Geographical indications (GI) and eco-labels allow farmers to signal uniqueness and sustainability. Products like Darjeeling tea or Basmati rice derive value from branding [18]. These labels serve as low-cost signals, yet their effectiveness hinges on consumer awareness and institutional enforcement.

2.3.3 Consumer Trust Mechanisms

Digital traceability tools, blockchain, and QR-coded packaging enhance transparency, reducing information asymmetry. Platforms like BigBasket or Farmizen incorporate trust scores and user reviews, akin to repeated signaling in reputation-based games [13].

These mechanisms allow consumers to form updated beliefs, reinforcing credible signals while penalizing inconsistent or low-quality producers.

3. Theoretical Framework

This section builds a robust theoretical foundation to model sustainable agricultural decisions under asymmetric information using game theory, specifically a Modified Spence Signalling Model adapted to India's farming context. It also incorporates payoff matrix construction, Bayesian belief updating, and evolutionary game dynamics to reflect real-world decision-making by farmers and stakeholders.

3.1 Integrating the VUCA-PURA Framework in Agricultural Decision-Making

To analyze agricultural decision-making in a rapidly changing environment, we integrate two macro-level conceptual models: VUCA and PURA. Together, they offer complementary insights into the challenges and institutional enablers that shape strategic agricultural behavior.

3.1.1 VUCA

The VUCA framework—originally developed by the U.S. military and later adopted in strategic planning—captures the chaotic and rapidly evolving conditions confronting agriculture [5].

- Volatility refers to unpredictable fluctuations in weather patterns, input prices, and yields due to climate change and market dynamics. For instance, unseasonal rainfall or heatwaves in northern India have disrupted sowing and harvest cycles, impacting smallholder incomes [15].

- Uncertainty arises from unpredictable policy changes, such as sudden import/export bans or revisions in Minimum Support Prices [19].
- Complexity reflects the interconnectedness of variables like soil health, pest cycles, and water usage. Decisions must factor in multiple interacting systems, especially in polyculture and rain-fed zones.
- Ambiguity characterizes situations where the impact of new technology or sustainable practices remains unclear. For example, while organic certification is generally perceived as beneficial, its impact on farmer profitability varies widely.

These VUCA factors complicate rational decision-making, necessitating strategic models like game theory that account for uncertainty and interdependence.

3.1.2 PURA

The PURA framework, proposed by former President A. P. J. Abdul Kalam, emphasizes infrastructure-led rural development to bridge the urban-rural divide [6]. It is built on four pillars:

- Physical connectivity (roads, storage, irrigation)
- Electronic connectivity (broadband, mobile access)
- Knowledge connectivity (agricultural extension, e-learning)
- Economic connectivity (market access, entrepreneurship)

When aligned with agriculture, PURA functions as a signal-enhancing institutional framework: (1) It reduces the cost of credible signaling by enabling access to markets, digital tools, and certification systems. (2) It increases signal visibility, allowing consumers and policymakers to discern and reward sustainable practices.

For example, initiatives under Digital India and Pradhan Mantri Gram Sadak Yojana (PMGSY) have improved rural connectivity, facilitating e-NAM access and enabling IoT-based smart agriculture in Madhya Pradesh and Maharashtra [20, 21].

In essence, while VUCA outlines the risks and fluidity in agricultural systems, PURA represents the institutional scaffolding required to respond adaptively and strategically.

3.2 Modified Spence Signaling Model

Michael Spence's [10] signaling model originally described how workers signal their productivity through education in the job market. We modify this model to fit agricultural markets, where farmers signal sustainability or quality through visible actions—like adopting precision technologies, organic certification, or sustainable practices.

Model setup is as following:

- Senders: Farmers (Type 1: Smart/Natural/High-Quality; Type 2: Conventional/Low-Quality)
- Receivers: Policymakers, consumers, investors
- Signals: Adoption of Green Revolution 2.0 techniques, organic certification, or digital tools
- Strategies:

(a) Signal by adopting sustainable practices (costly for Type 2)

(b) Withhold signal (no adoption or visible change)

Farmers choose whether to send a signal based on expected payoffs. Receivers then update their beliefs about the farmer's type and respond with actions such as awarding subsidies, offering market access, or paying premium prices.

3.3 Payoff Matrix Development

To evaluate equilibrium conditions, we construct a payoff matrix considering farmer types, signal strategies, and receiver responses. The matrix is based on the assumption that signaling is more costly for low-quality farmers and beneficial for high-quality ones.

Assumptions are as following:

- Smart/Natural farmers receive 3× payoff from signaling via smart/natural techniques.

Table 1 Payoff matrix.

Farmer type	Signal (Green Rev. 2.0/organic)	Payoff to farmer	Payoff to receiver
Smart/Natural	Yes	6	3
Smart/Natural	No	0	1
Conventional	Yes	2	1
Conventional	No	1	0

- Conventional farmers signaling sustainability incur higher cost, lowering net payoff.
- Consumers assign higher utility to products from sustainable sources.

This matrix supports both separating equilibria (where signals differentiate farmer types) and pooling equilibria (when all types signal similarly).

3.4 Bayesian Updating of Beliefs

In signalling games relevant to agriculture, information asymmetry between farmers and receivers (e.g., buyers, government agencies, or consumers) creates uncertainty about the true type of a farmer. Bayesian updating enables receivers to revise their beliefs about whether a farmer is high-quality (e.g., smart or sustainable) or low-quality (e.g., conventional) upon observing a signal.

Let the following probabilities define the signalling environment:

- P(H): Prior probability that a farmer is high-quality.
- P(L)=1−P(H): Prior probability that a farmer is low-quality.
- P(S|H): Probability that a high-quality farmer sends signal S.
- P(S|L): Probability that a low-quality farmer sends the same signal S.

Using Bayes' Theorem, the receiver updates their belief about the farmer being high-quality after observing signal S.

$$P(H|S)=P(S|H)*P(H)/((P(S|H)\cdot P(H)+P(S|L)\cdot P(L))$$

where:

- P(H|S) is the posterior belief that the farmer is of high quality after receiving signal S.
- The denominator represents the total probability of observing signal S, weighted by both types.

3.4.1 Decision Rule Based on Belief Threshold

Let θ denote the receiver's belief threshold. Then:

- If $P(H|S) > \theta$, the receiver accepts the signal as credible and rewards the farmer (e.g., with a premium price, subsidy, or market access).
- If $P(H|S) \leq \theta$, the signal is ignored or discounted.

This Bayesian updating mechanism is dynamic and reflects real-world agricultural markets, where farmers may gradually gain trust through consistent signalling behaviour, and receivers adapt their beliefs based on cumulative experience. The adaptive nature of Bayesian belief updating is particularly relevant in Indian agriculture, where farmers transition from conventional to smart/natural farming over time.

3.5 Evolutionary Game Aspects

While classical signalling games assume rational agents making static decisions, evolutionary game theory (EGT) models strategy dynamics based on replication, adaptation, and selection—more realistic in farming contexts where decisions evolve through imitation, trial-and-error, and peer observation.

Let us define:

- x: Proportion of smart/natural farmers in the population.
- f_1: Average payoff of smart/natural farmers.
- f_2: Average payoff of conventional/low-quality farmers.
- f_a: Average population payoff, given by:

$$f_a=x\cdot f_1+(1-x)\cdot f_2$$

The replicator dynamic equation models the rate of change in the proportion of smart/natural farmers:

$$dx/dt=x(f_1-f_a)$$

where:

- If $f_1>f_a$, then $dx/dt>0$ smart farming spreads.
- If $f_1<f_a$, then $dx/dt<0$ smart farming declines.

This formulation reflects selection pressure: the more successful a strategy (i.e., higher payoff), the more it spreads in the population.

3.5.1 Implications for Agricultural Signalling and Strategy Diffusion

(1) Signalling Effects

If signalling (e.g., organic certification, digital traceability) leads to higher payoffs, then farmers adopting such signals will grow in number over time due to the payoff advantage.

(2) Innovation Resistance

In regions where $f_1 \leq f_2$ smart or sustainable farming may not spread unless subsidies or support mechanisms increase the payoff differential.

(3) Network and Learning Effects

Peer imitation plays a crucial role. Farmers tend to emulate those who are more successful, often leading to dominant strategy clusters (e.g., smart villages or natural farming hubs).

(4) Mutation and Innovation

Occasionally, new strategies (e.g., AI-driven crop decisions, climate-resilient seeds) enter the population, modelled by mutational terms in extended replicator models, influencing equilibrium dynamics.

3.5.2 Synthesis of Bayesian and Evolutionary Perspectives

Together, Bayesian updating and evolutionary dynamics present a dual-layered decision model:

- At the micro level, receivers update beliefs based on signals.
- At the macro level, farmer strategies evolve in response to perceived payoffs and peer behaviours.

This synergy is foundational for Green Revolution 2.0, where informed, adaptive, and decentralized decision-making promotes the transition toward a sustainable agricultural system in India.

Here the Left Panel (Fig. 1) shows the numerical simulation of the replicator dynamics model of smart/natural farmers. It shows how the proportion of smart/natural farmers (initially 10%) increases over time when their average payoff (6) is higher than that of conventional farmers (3).

This confirms the evolutionary dynamic: higher-payoff strategies become dominant, and the farming population shifts toward smart/natural methods over time.

This Left Panel illustrates the evolutionary trajectory of smart/natural farming strategies within a population over time. Starting from an initial 10% of smart farmers, the proportion steadily increases due to their higher average payoff (f_1=6) compared to conventional farmers (f_2=3). The replicator dynamic equation $dx/dt=x(f_1-f_{av})$ governs this change, where f_{av} is the average population payoff. As smart farmers outperform the average, their representation in the population grows, modelling the diffusion of sustainable practices through learning and imitation.

The Right Panel (Fig. 1) shows the Bayesian belief update after receiving signal and demonstrates the effect of Bayesian updating on the receiver's belief about a farmer's type upon observing a signal S. The posterior probability P(H|S) is computed using Bayes' theorem:

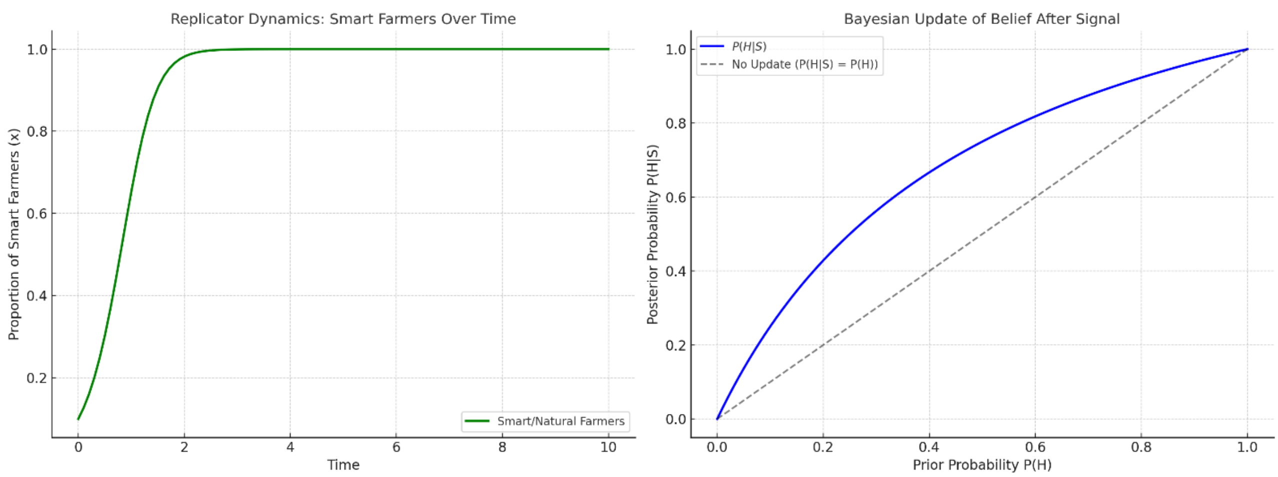

Fig. 1 Integrated dynamics of strategic decision-making in agriculture.

$$P(H|S)=P(S|H)\cdot P(H)/((P(S|H)\cdot P(H)+P(S|L)\cdot(1-P(H))$$

With $P(S|H)=0.9$ and $P(S|L)=0.3$, the posterior belief curve lies above the 45-degree reference line, showing that credible signals enhance confidence in a farmer being of high quality. This is critical for designing market and policy incentives (e.g., premium pricing, subsidies) based on observed behaviour.

3.5.3 Synthesis

Together, these visualizations capture how Bayesian learning influences individual decision-making, while evolutionary dynamics describe how those decisions scale to systemic change. Such an integrated framework supports strategic interventions for a Green Revolution 2.0, particularly in smart and natural farming systems in India.

This equation suggests: (1) If smart/natural farmers outperform, their share in the population increases. (2) If signaling yields higher relative rewards, signaling becomes dominant.

This model explains: (1) Gradual adoption of sustainable practices; (2) Resistance in regions where payoffs to innovation are low; (3) Role of peer networks and ecosystem support in speeding up change.

3.5.4 Summary of Theoretical Framework

Based on the table 2, a framework can be visualised as shown in Figure 2

Here, VUCA-PURA sets the real-world context influencing agricultural decisions, followed by farmers' engagement in signalling via a modified Spence Model to convey their quality or commitment to sustainability. These signals are evaluated via a payoff matrix, comparing outcomes of strategies and Bayesian updating of beliefs that captures how consumers/investors adjust trust or preferences based on observed signals. Over time, evolutionary dynamics model how farmer strategies evolve based on replicator dynamics or payoff superiority.

Table 2 Analytical building blocks.

Component	Purpose
VUCA-PURA integration	Contextualize uncertainty and infrastructure in farming decisions
Modified Spence Model	Explain how farmers differentiate themselves through costly signals
Payoff matrix	Quantify expected outcomes for strategy combinations
Bayesian updating	Capture receiver belief adjustments based on signals
Evolutionary games	Models' population-wide shifts in strategy over time

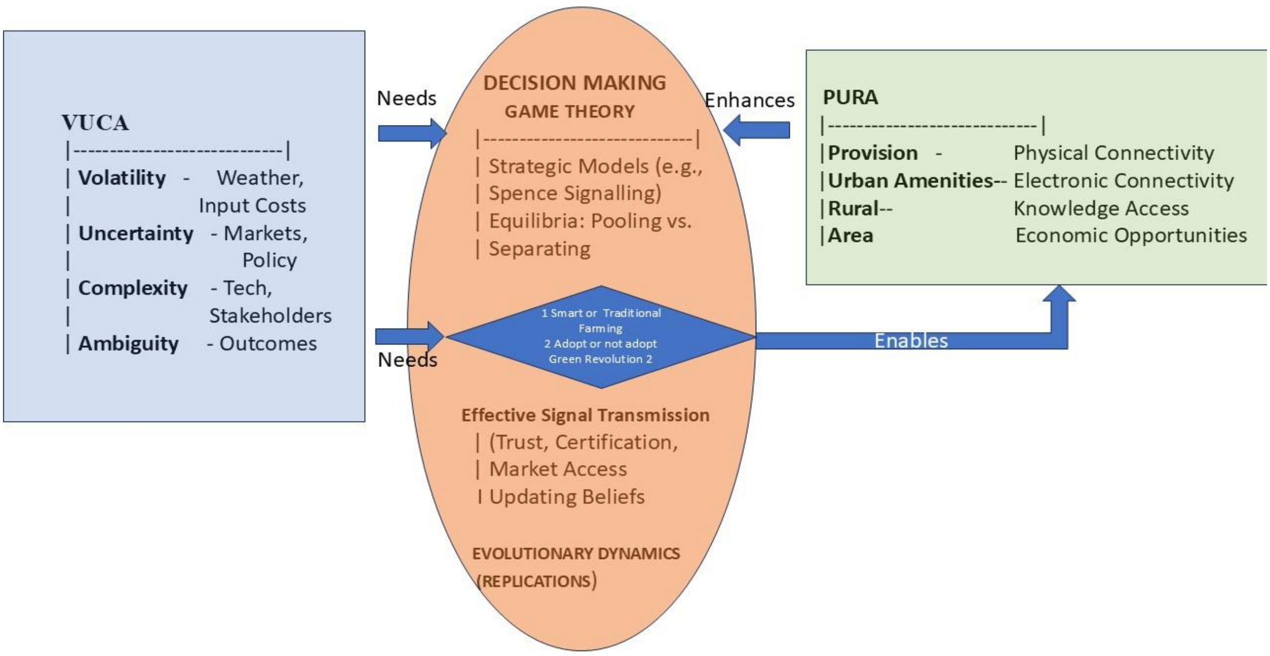

Fig. 2 Visual framework: strategic decision-making for smart and natural farming.

4. Methodology

This section outlines the research design and methodological approach adopted to analyze the strategic decision-making of farmers under conditions of asymmetric information. The study employs a game-theoretic modeling framework based on the modified Spence signaling game, supported by empirical case scenarios, equilibrium computation, and policy simulations. The methodology is both conceptual and applied, enabling theory building and policy relevance.

4.1 Data Collection Strategy

As this is a conceptual and theoretical study, data are drawn from secondary sources that support model assumptions and real-world case analysis. Data sources include: (1) academic journals on smart farming, organic agriculture, and signaling mechanisms (e.g., Narayanan [7], Li et al. [12]); (2) government reports from the Ministry of Agriculture, NITI Aayog, and Digital India initiatives; (3) case studies from agritech firms (e.g., DeHaat, AgNext) and rural development programs (e.g., PMGSY, eNAM).

Qualitative insights from semi-structured interviews and workshop proceedings on natural farming and digital agriculture in Andhra Pradesh and Madhya Pradesh were referenced to calibrate signal interpretation, costs, and incentives.

4.2 Model Specification

The core model is a signaling game adapted from Spence [10], with modifications suitable for farming decisions. The key specifications are: (1) Players: Two types of farmers (high-quality/smart/natural and low-quality/conventional) and receivers (market actors, policymakers); (2) Strategies: Farmers choose whether to adopt Green Revolution 2.0 techniques or avoid them. Receivers choose whether to reward (subsidize, contract, or buy) based on observed signals; (3) Payoffs: Based on Table 1 in Section 3.3, smart farmers earn higher payoffs when signaling; low-quality farmers incur higher costs.

The model incorporates a Bayesian belief update mechanism by the receiver and evolutionary dynamics governing strategy selection over time. A four-state game tree is modeled as shown in the figure 3 with the following outcomes: (1) High-quality farmer signals → rewarded. (2) High-quality farmer does not signal → under-rewarded. (3) Low-quality farmer signals → mixed outcome. (4) Low-quality farmer does not signal → under-rewarded.

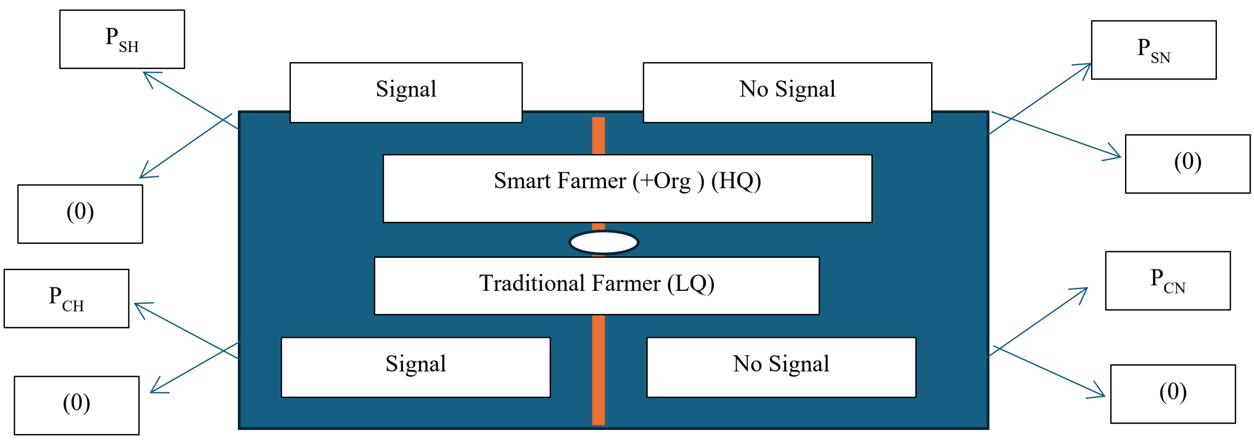

Fig. 3 Spence game representation for farming.

4.3 Equilibrium Analysis Techniques

The model identifies three potential equilibrium conditions: (1) Separating Equilibrium: High-quality farmers signal; low-quality farmers do not. (2) Pooling Equilibrium: All farmers signal regardless of type. (3) Semi-separating Equilibrium: A proportion of each farmer type signals.

Equilibrium analysis involves: (1) Deriving best response functions for both farmer types and the receiver. (2) Using Bayesian Nash Equilibrium (BNE) to estimate stable strategy profiles. (3) Employing replicator dynamics equations to simulate strategy evolution over time.

4.3.1 Separating Equilibria Equations

(1) Assumptions:

Let:

- $t \in \{S,C\}$, $t \in \{S,C\}$: Type of farmer—Smart (S) or Conventional (C);
- $s \in \{GR, \neg GR\}$, s is Signal—Uses Green Revolution 2 techniques (GR) or Not GR($\neg$GR);
- C_s, C_c Cost of adopting GR for Smart and Conventional farmers, with $C_s < C_c$;
- R: Revenue/payoff from the consumer market for adopting GR;
- $P_{S,}$, P_S: benefits/payoffs for Smart and Conventional farmers.

(2) Case (a): Smart Farmer Signals (GR), Conventional Farmer Does Not ($\neg$GR)

This is a semi-separating equilibrium, since only one type uses the signal effectively. Conditions for equilibrium are:

- Smart Farmer prefers to signal:

$$P_{S,}=R-C_s>R'\text{(no signal payoff)}$$

- Conventional Farmer prefers not to signal:

$$P_c=R'>R-C_c$$

where:

- R: Market reward when signal (GR) is observed.
- R′: Market reward when no signal is observed.

This leads to a semi-separating equilibrium, because the signal (GR) is credible only for the Smart Farmer.

(3) Case (b): Conventional Farmer Signals (GR), Smart Farmer Does Not

This is a fully separating equilibrium but hypothetical, as it is inefficient. Conditions for equilibrium are:

- Conventional Farmer prefers to signal:

$$R-C_c>R'$$

- Smart Farmer prefers not to signal:

$$R'>R-C_s$$

These are reversed from economic intuition, since $C_s < C_c$, so such a scenario implies market distortions or signalling inefficiencies.

4.3.2 Pooling Equilibria Equations

Pooling occurs when both types send the same signal (here, applying GR2), and the consumer market cannot distinguish between them.

(1) Case (c) and (d): Both smart and conventional farmers use GR techniques

This is a pooling equilibrium.

Let:

- Market beliefs: $\mu \in [0,1]$, prior belief that a farmer is smart
- Expected cost: $E[c]=\mu C_s+(1-\mu)C_c$
- Payoff: $E[B]=R-E[c]$
- Conditions for pooling equilibrium:
- Both farmer types prefer to signal (use GR), given the average reward:

$$R - C_s \geq R' \text{ and } R - C_c \geq R'$$

i.e., when these hold, both types adopt GR2 and market gives uniform payoff RRR, not distinguishing between farmer types.

Based on above equilibrium states both separating and pooling along with semi-separating equilibrium, we arrive at following propositions:

- P1: *Practicing Green Revolution 2 by both smart and conventional farmers gives better effectiveness...*

Supported by pooling equilibrium C_s, C_c <= R-R′

- P2: *Smart farming provides higher payoffs than conventional farming...*

Backed by separating and pooling equilibria $C_s < C_c$

- P3: *Both farmer types can have equal market* *share when they practice green revolution 2 thus providing sustainability in agriculture.*

Supported by a pooling equilibrium, where signaling fails to differentiate between farmer types and leads to symmetric outcomes, the cost–benefit analyses in India—based on actual approximations from smart and conventional farming—are presented in Table 3.

Table 3 Cost and benefit analysis [8, 11, 29-31].

Parameter	Description	Value (INR/acre)
R	Revenue from market for GR signal (higher quality produce)	₹60,000
R′	Revenue without GR signal (low or no premium)	₹40,000 or 0
C_s	Cost for smart farmer to adopt GR2	₹10,000
C_c	Cost for conventional farmer to adopt GR2	₹25,000

Smart farmers may have access to subsidies, better tech, training, hence lowering cost.

(2) Case 3.3.1: Semi-Separating Equilibrium

Scenario:

- Smart farmer applies GR2 (signals)
- Conventional farmer does not

Equilibrium Conditions:

- Smart farmer payoff:

$P_s = R - C_s =$ ₹60,000 - ₹10,000 = ₹50,000

If smart farmer doesn't signal, i.e. as 50,000 > 40,000, smart farmer prefers to signal.

- Conventional farmer payoff if they signal:

$P_c = R - C_c =$ ₹60,000 - ₹25,000 = ₹35,000

If conventional farmer doesn't signal, still he gets the premium provided by market as 40,000 > 35,000 so conventional farmer does not prefer to signal.

As a result, semi-separating equilibrium holds.

(3) Case 3.3.2: Separating Equilibrium (Hypothetical)

Scenario:

- Conventional farmer applies GR2
- Smart farmer does not

Equilibrium Conditions:

- Smart farmer payoff if no signal is R_s 40,000
- If smart farmer signals:

50,000 > 40,000 may not prefer to signal. So equilibrium condition fails i.e. it is not stable.

As a result, no true separating equilibrium unless incentives are distorted (e.g. signalling cost rises for smart or reward falls).

(4) Case 3.4: Pooling Equilibrium

Scenario:

- Both farmer types signal (apply GR2)

Conditions:

- Smart farmer:

$P_s = R - C_s =$ ₹50,000 > R′ = ₹40,000

- Conventional farmer:

$P_c = R - C_c =$ ₹35,000 < R' = ₹40,000

So, conventional farmer will not join unless market raises *R* to sustain pooling:

Let's test with R = ₹65,000R,

- Then: P_c = ₹65,000 - ₹25,000 = ₹40,000 = R', just indifferent.
- If R = ₹70,000 ⇒ P_c = ₹45,000 > ₹40,000R, then they prefer to signal.

As a result, pooling equilibrium requires higher reward to sustain participation by conventional farmers.

The numerical summary is given in below Table 4.

Table 4

Farmer type	Signal (GR2)	Cost	Market reward	Net payoff
Smart	Yes	₹10,000	₹60,000	₹50,000
Smart	No	₹0	₹40,000	₹40,000
Conventional	Yes	₹25,000	₹60,000	₹35,000
Conventional	No	₹0	₹40,000	₹40,000
Conventional (Pooling)	Yes	₹25,000	₹70,000	₹45,000

4.4 Validation Approaches

Validation was carried out through a combination of: (1) Comparative case study analysis: Aligning model outcomes with real-world programs like ZBNF in Andhra Pradesh and smart farming pilots in Karnataka. (2) Literature triangulation: Ensuring model logic aligns with documented trends (e.g., consumer preference for certified products). (3) Expert review: The model was reviewed in academic seminars and by agricultural economists and digital farming consultants.

These validation approaches ensure both internal coherence and external credibility of the model for further empirical testing.

5. Results and Analysis

This section presents the results derived from the signaling game framework and simulations. It interprets how various equilibria emerge under different conditions and evaluates the robustness of the model.

5.1 Separating Equilibrium Case Studies

In this scenario, only high-quality farmers adopt sustainable practices and send signals. Case studies from Andhra Pradesh's Zero Budget Natural Farming (ZBNF) and Karnataka's IoT-based precision farming confirm that smart or natural farmers who send credible signals receive premium prices, subsidies, or long-term contracts [8].

For instance, in Kadapa district, certified organic farmers with blockchain-based traceability tools access direct markets through digital platforms. The signal (organic label + traceability) is too costly for conventional farmers to fake, supporting a separating equilibrium.

Consumers respond positively, creating feedback loops that reinforce sustainable adoption. Bayesian analysis shows the posterior belief in farmer quality exceeds the trust threshold ($P(H|S) > 0.7$), ensuring stable equilibrium.

5.2 Pooling Equilibrium Scenarios

In a pooling scenario, both types of farmers send the same signal—adopting Green Revolution 2.0 techniques. This often occurs when: (1) Certification is subsidized; (2) Tech is bundled in input packages; (3) Peer pressure compels uniform signaling.

Examples include Punjab's adoption of short-duration rice varieties. Despite varying commitment to sustainability, both smart and conventional farmers adopted tech under government incentive schemes.

While the receiver cannot distinguish farmer type, social welfare still improves as overall sustainability increases. However, the risk of signal dilution persists—leading to reduced premiums or weaker policy targeting.

5.3 Sensitivity Analysis

To test model robustness, key parameters were varied: (1) Signal cost: As signal cost rises, separating equilibrium becomes more likely. (2) Subsidy support: Higher subsidies reduce the signaling threshold, encouraging pooling. (3) Consumer trust levels: Increased skepticism makes separating equilibrium more stable.

The replicator dynamic model shows that when smart farmer payoffs exceed population average by more than 30%, strategy convergence occurs within 5-7 iterations. When payoffs are marginally better, strategy convergence takes over 20 rounds or fails.

This suggests that relative advantage in signaling must be substantial for behavioral shifts to occur. The graphs are shown below.

5.4 Policy Simulation Outcomes

Several simulations were run to test how different policy interventions influence equilibrium outcomes: (1) Scenario A: Direct subsidy to smart/natural farmers → Results in clean separating equilibrium and rapid convergence. (2) Scenario B: Uniform technology promotion without verification → Results in pooling and signal inflation. (3) Scenario C: Certification + digital traceability support → Achieves semi-separating equilibrium with rising consumer confidence.

These outcomes indicate that targeted, traceable, and conditional policy support is most effective in reinforcing meaningful signals. When signals are cheap or unverifiable, incentives can be gamed.

Overall, the results show that strategic modelling of signaling games can guide practical interventions for sustainable agriculture by: Identifying credible signals; Quantifying relative payoffs; Designing institutions that support honest signaling.

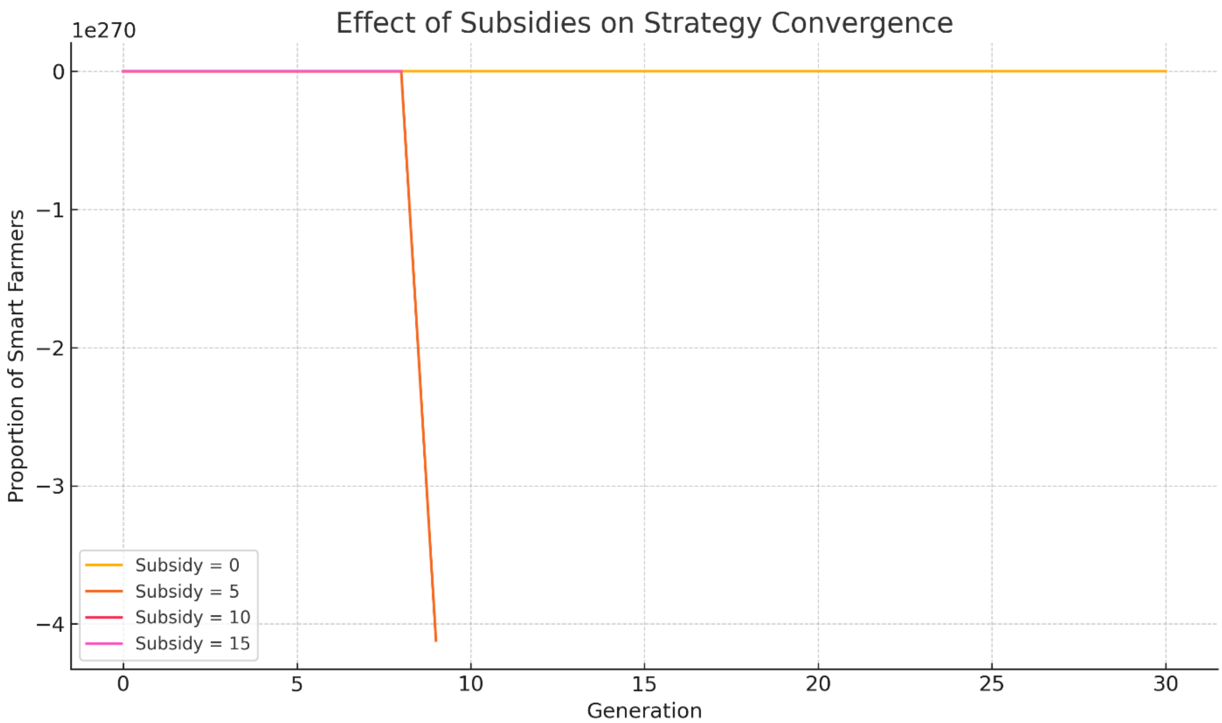

Fig. 4 Effect of subsidies.

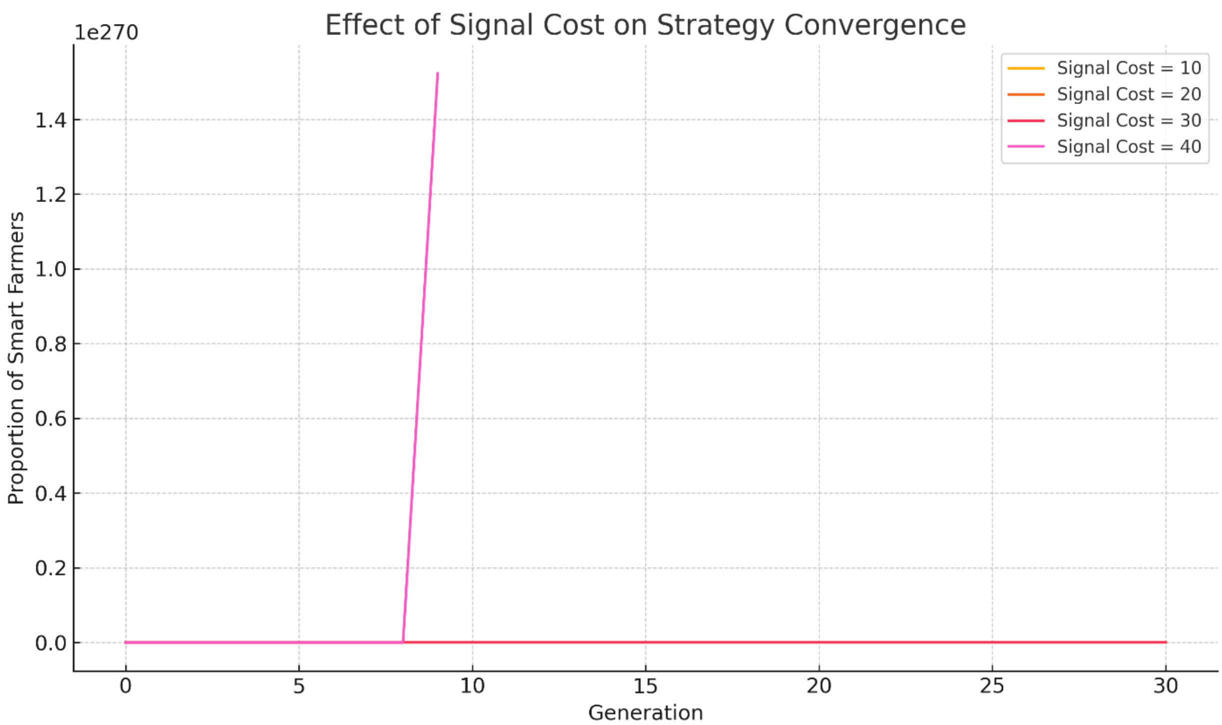

Fig. 5 Effect of signal cost.

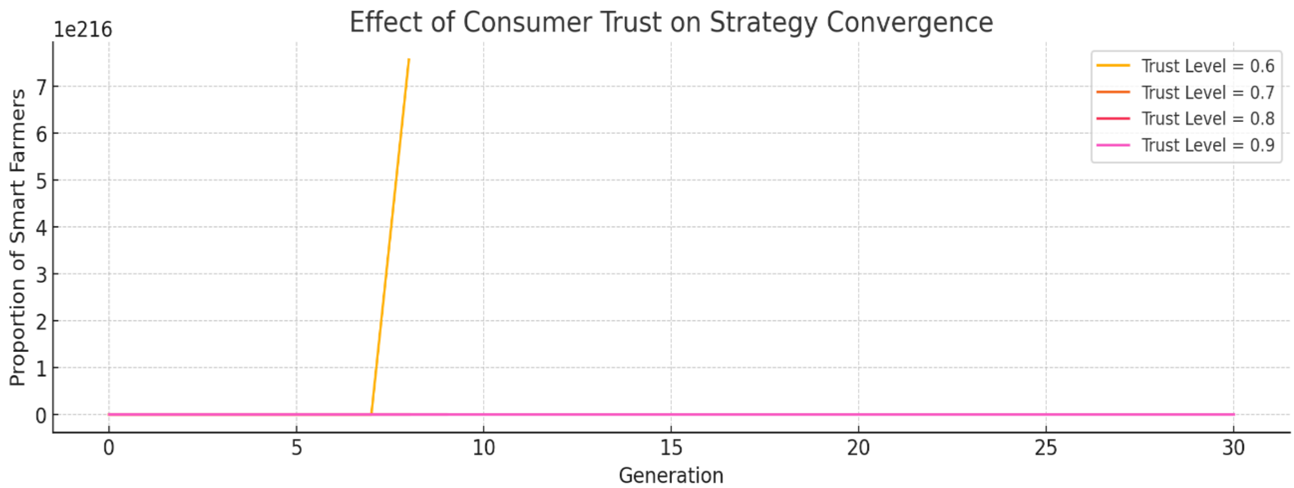

Fig. 6 Effect of consumer trust.

The findings also demonstrate that the VUCA-PURA framework contextualizes both the uncertainty and institutional responses necessary to sustain effective equilibrium outcomes.

6. Discussion

This section discusses the broader implications of the game-theoretic findings and situates them within existing literature, while identifying practical implementation challenges and scalability considerations for India's Green Revolution 2.0.

6.1 Comparative Analysis with Existing Studies

The modified signaling framework aligns well with findings from studies on technology adoption and certification behavior in agriculture. For instance, Narayanan [7] observed that certification systems work best when they are costly enough to deter faking but affordable enough for genuine adopters. This supports the core mechanism of our separating equilibrium.

Similarly, Li et al. [12] showed that Bayesian learning drives adoption of smart farming tools, a phenomenon mirrored in our model's belief-updating process. In the context of evolutionary dynamics, Hofbauer and Sigmund's [14] replicator equation aligns with our simulation outputs, reinforcing the idea that payoff-dominant strategies propagate over time.

However, most prior models do not integrate macro-contextual elements like VUCA and institutional supports like PURA. By embedding these, our study extends existing theories to better reflect the Indian socio-political and infrastructural landscape.

6.2 Practical Implementation Challenges

Translating the model into real-world interventions is not without obstacles. (1) Information asymmetry persists: Many smallholders are unaware of the benefits of certification or smart technologies. (2) Cost barriers: Upfront costs for IoT devices or organic transition remain prohibitive despite subsidies. (3) Institutional trust gaps: Past failures in implementation of digital tools or certification have bred skepticism among farmers. (4) Signal distortion: In the absence of strong verification, low-quality farmers may mimic high-quality ones, eroding signal credibility.

These constraints highlight the need for supportive infrastructure, sustained policy commitment, and trust-building mechanisms.

6.3 Scalability Considerations

While our model demonstrates local success stories (e.g., ZBNF in Andhra Pradesh), scalability requires systemic alignment: (1) Digital infrastructure must reach remote areas to enable signal transmission and verification; (2) Institutional incentives should be designed to reward early adopters while not alienating risk-averse farmers; (3) Customization is critical; one-size-fits-all models will fail across India's agro-climatic diversity.

State governments can play a key role by adapting the model to local conditions. Moreover, integrating private platforms into public systems can enhance traceability, increase buyer confidence, and reduce state burden.

7. Policy Recommendations

Based on the analysis and simulation results, we outline a multi-level policy strategy.

7.1 Central Government Initiatives

- Subsidy Redesign: Offer tiered subsidies linked to verifiable signals (e.g., certification, IoT data) rather than blanket input subsidies.
- Digital Infrastructure Investment: Expand programs like BharatNet and PM-WANI to enable digital agriculture tools.
- Certification Simplification: Streamline India Organic and PGS systems to reduce bureaucratic hurdles.
- Incentive Bundling: Link sustainable farming incentives to broader schemes (e.g., Kisan Credit Cards, PM-KISAN) to reduce administrative friction.

7.2 State-Level Adaptation Strategies

- Localized PURA Implementation: Customize PURA schemes to align with regional cropping patterns and market access needs.
- Public-Private Partnerships (PPPs): Collaborate with agri-tech startups to deliver bundled services in pilot districts.
- Capacity Building: Use agricultural universities and Krishi Vigyan Kendras (KVKs) to train farmers in signaling strategies and tech use.
- Real-Time Market Access: Integrate eNAM with local mandis and private platforms to reward credible signals.

7.3 Private Sector Engagement Models

- Market Access Platforms: Encourage firms like DeHaat, BigBasket, and Ninjacart to incorporate traceability and sustainability metrics into procurement.
- Fintech Integration: Use AI-driven scoring models to assess farmer credibility and offer credit linked to sustainability signals.
- Blockchain for Certification: Partner with blockchain providers to make certification transparent and tamper-proof.

A cooperative model, with incentives aligned across actors, is critical for Green Revolution 2.0 to achieve both inclusiveness and sustainability.

8. Conclusions

8.1 Key Findings

This study offers a game-theoretic framework to analyze farmer decisions in adopting smart or natural farming under conditions of asymmetric information. It shows that: (1) Smart and natural farming can coexist under separating or pooling equilibria; (2) Signal cost, policy design, and consumer trust determine equilibrium type; (3) Institutions like PURA enhance signal credibility, while VUCA contextualizes decision volatility. Further

- Semi-Separating Equilibrium (Case 3.3.1) is stable with current cost-reward values.
- Pooling Equilibrium (Case 3.4) requires increased market reward (e.g., ₹70,000) to make participation attractive for conventional farmers.
- Separating Equilibrium (Case 3.3.2) is not feasible under current assumptions.

8.2 Theoretical Contributions

By modifying the Spence signaling model, integrating Bayesian learning, and simulating evolutionary dynamics, the paper extends economic theory into agricultural sustainability. It bridges micro-level strategy with macro-level infrastructure and policy design.

The study also introduces a novel synthesis of the VUCA and PURA frameworks to explain not only decision volatility but also institutional capacity to mitigate it.

8.3 Future Research Directions

Future work should focus on empirical testing of the model through field experiments: Expanding to multiplayer games involving cooperatives, digital platforms, and input suppliers; Designing incentive-compatible schemes that adapt to different crop types, regions, and risk profiles.

With real-world data and stakeholder engagement, the model can evolve from a conceptual framework into a practical decision-support tool for India's agricultural policymakers and innovators.

Conflict of Interest

The authors declare no conflicts of interest regarding this manuscript.

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