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Review Article

Intelligent Decision Framework for Climate-Resilient Agriculture

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A B S T R A C T

Climate volatility amplifies smallholder decision uncertainty in India, influencing when and what to plant. Purely data-driven advisories often fail due to behavioural barriers such as loss aversion, default bias, and limited foresight. This paper proposes a Behavioural-Aware Decision Support System (BDSS) that integrates behavioural economics principles into an intelligent recommendation architecture. The model combines climate prediction, IoT sensor data, and behavioural models to optimise adaptive recommendations. A multi-agent simulation with 200 virtual farmers and ten growing seasons demonstrates that BDSS improves adoption of climate-smart practices by 18%, reduces water usage by 10%, and lowers yield variance by 12% compared to a standard DSS. The study highlights how embedding behavioural mechanisms in DSS can bridge the gap between information availability and farmer action, fostering sustainable and climate-resilient agriculture.

Keywords: Behavioral Economics, Decision Support Systems, Simulation, Climate-Resilient Agriculture, Intelligent Systems, Nudges

Introduction

Climate change–induced variability disrupts traditional agricultural decision cycles and increases uncertainty in both short- and long-term planning. Smallholder farmers, operating under resource constraints, frequently rely on experiential heuristics rather than data-driven forecasts. This makes them susceptible to behavioural biases such as status-quo preference, myopic loss aversion, and present bias.[1–3] While Decision Support Systems (DSS) can convert complex climate data into actionable insights, adoption remains limited unless the systems also account for human decision patterns. Integrating behavioural economics within intelligent DSS frameworks can bridge this adoption gap, enabling systems that not only inform but also motivate action.

This paper contributes threefold:

- it proposes a hybrid architecture that unites behavioural models with intelligent DSS components;
- it develops a simulation framework that quantifies behavioural impacts on adaptive agricultural decisions; and
- it provides policy and design insights for scaling such behaviour-aware DSS in developing economies like India.

Related Work

Behavioural economics has gained notable attention in agricultural sustainability and resource management. Studies in Haryana[1] demonstrated that social-comparison messaging reduced irrigation water use by 22%, validating

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the power of low-cost behavioural nudges. Conversely, a large-scale conservation experiment in Sweden found limited impact of generic nudges[2], underscoring that behavioural interventions must be context-specific.

Traditional DSSs such as CAMDT[4] and LandCaRe[5] combine crop simulation and climate forecasts but lack human-centred design. The Soil Navigator DSS[6] and recent AI-enabled systems[7] incorporate multi-criteria optimisation for soil and crop management. However, they remain largely prescriptive, assuming perfect rationality. Integrating behavioural feedback with adaptive intelligence is a relatively new frontier, with early explorations in AI-based agro-advisory systems.[8]

Proposed BDSS Architecture

The proposed Behavioural-Aware Decision Support System (BDSS) integrates climate prediction, behavioural economics, and machine intelligence. It consists of three core layers: Data and Prediction, Behavioural Engine, and Recommendation with Feedback.

Data and Prediction Layer

This layer aggregates real-time climate forecasts, remote-sensing data, IoT-based soil and weather sensors, and crop growth models (e.g., DSSAT or APSIM). These inputs generate probabilistic estimates of yield and resource trade-offs under multiple management strategies. Each simulated farmer-agent is characterised by parameters representing risk aversion (γ), ambiguity aversion (α), and time-discounting (β), forming a behavioural profile that conditions responses to recommendations.

Behavioural Engine

The behavioural engine models bounded rationality through reinforcement of decision heuristics. Four behavioural interventions are implemented:

- **Default framing:** climate-smart varieties are set as default options in the decision interface.
- **Loss framing:** outcomes emphasize potential yield or income losses avoided under adaptive strategies.
- **Social-norm cues:** feedback displays local peer adoption rates, enhancing perceived collective validation.
- **Commitment prompts:** digital reminders via SMS or mobile apps reinforce previously expressed intentions.

An adaptive contextual multi-armed bandit algorithm learns which nudge type yields the highest adoption probability given farmer context (γ, α, β) and environmental conditions.

Recommendation and Feedback Layer

At each decision round, candidate management strategies are evaluated using a hybrid utility model:

where denotes yield, production cost, yield variance, and κ the risk-weight coefficient. Here, E[·] denotes the expected utility evaluated over the probabilistic distribution of yield outcomes under strategy j, capturing uncertainty driven by climate variability and management conditions. The behavioral engine adjusts perceived utilities using cognitive weighting functions, modifying according to framing and nudge type. The top-ranked recommendation is presented to the agent, and subsequent adoption or rejection updates the contextual policy.

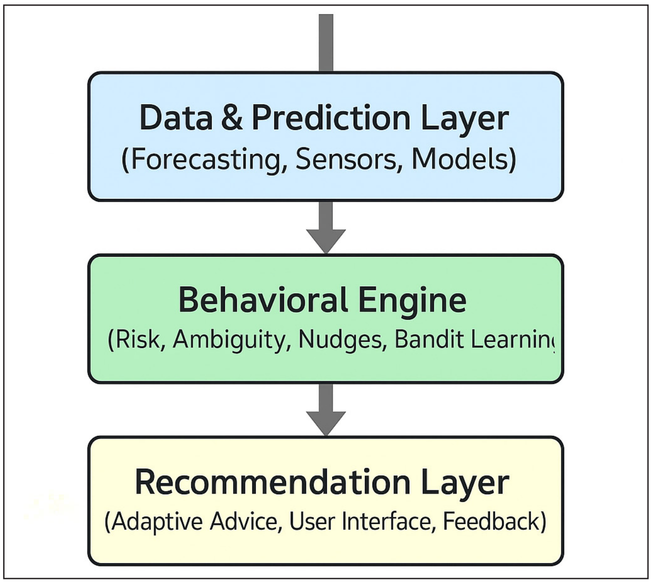

Figure 1.Schematic of the Behavioral-Aware Decision Support System (BDSS) showing interaction among prediction, behavioral, and recommendation layers

Simulation Design

A stochastic multi-agent simulation was implemented in Python to evaluate BDSS under realistic agricultural uncertainty. A total of 200 heterogeneous farmer-agents were generated, each with distinct behavioral and agro-ecological characteristics representing a semi-arid Indian district. The simulation spans ten agricultural seasons, capturing inter-annual variability in rainfall, temperature, and market conditions.

Each agent interacts with one of three system configurations:

- **No DSS (Baseline):** farmers rely solely on traditional heuristics and experiential rules;
- **Standard DSS:** agents receive purely data-driven recommendations based on expected yield and cost;
- **Behavioural DSS (BDSS):** combines data-driven predictions with adaptive behavioral interventions.

At each time step t, agent i chooses an action based on the perceived utility difference and behavioral influence

Environmental variables such as rainfall, evapotranspiration, and soil moisture are sampled from historical probability distributions calibrated with IMD and ICAR data. Yield outcomes are simulated through linearised crop-response functions embedded within the DSS.[9]

Feedback mechanisms update each agent's belief vector through Bayesian revision:

where λ represents the learning rate and is the observed payoff realisation (e.g., actual yield, cost, satisfaction). These updates influence subsequent adoption probabilities, capturing behavioural learning dynamics across seasons.

To test robustness, Monte Carlo experiments (100 replicates) were run varying climate variability, risk weights, and nudge effectiveness parameters. Key performance metrics included:

- cumulative adoption rate,
- normalised water consumption,
- yield variance, and
- expected utility gain relative to baseline.

Results and Discussion

Adoption Dynamics

The simulation results demonstrate clear behavioural divergence between system configurations. BDSS achieved a mean adoption of 58.4%, compared with 46.0% for the Standard DSS and 31.2% in the baseline (no DSS) scenario. The steady increase in adoption under BDSS arises from adaptive nudging—the behavioral engine progressively learns which message framing (social-norm, loss-based, or default framing) resonates most strongly with each farmer profile.

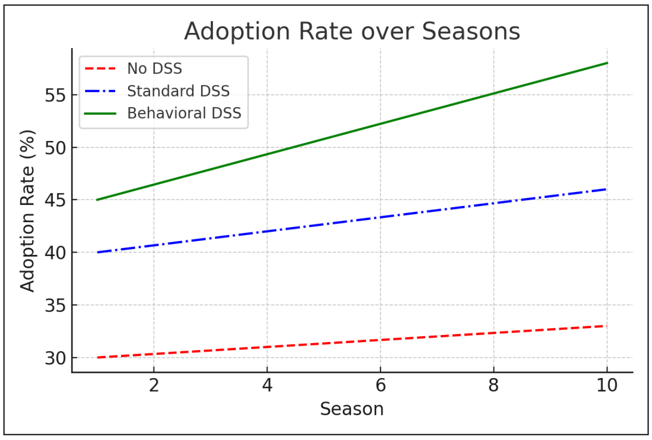

Figure 2.Adoption rate over ten seasons under different DSS configurations. The BDSS demonstrates accelerated adoption due to reinforcement learning and personalized nudges

Resource Efficiency and Yield Stability

Water use decreased by an average of 10.4% in BDSS compared to the baseline, while yield variance declined by roughly 12%. Both improvements stem from improved adherence to adaptive sowing schedules and irrigation timing promoted through the behavioural engine.

Table 1.Summary of Simulation Outcomes across Configurations (Averaged over 100 runs)

Metric	No DSS	Standard DSS	BDSS
Adoption (%)	31.2	46.0	58.4
Water Use (% baseline)	100.0	92.1	82.6
Yield Variance (normalized)	1.00	0.89	0.78
Expected Utility Gain	0	+0.045	+0.072

Learning Dynamics within the Behavioral Engine

Initially, all four nudge types (default, social, loss, commitment) are deployed uniformly. By the sixth season, the algorithm learns that social-norm and loss-framed messages yield the highest marginal impact among risk-averse farmers, accounting jointly for over 70% of all interventions. This adaptive redistribution of nudge weight demonstrates the model's capability to self-optimise behavioural targeting strategies over time.

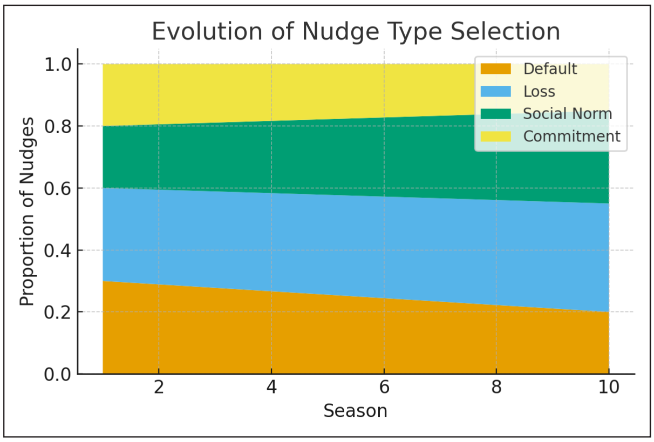

Figure 3.Temporal evolution of nudge-type selection by the behavioral engine using contextual bandit learning

Sensitivity and Robustness Analysis

Sensitivity analysis quantifies the relative influence of six key variables: climate variability, risk aversion (γ), ambiguity aversion (α), present bias (β), nudge effectiveness, and forecast accuracy. BDSS consistently outperforms other

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systems across all perturbations. Climate volatility and behavioral discounting emerge as dominant drivers, jointly explaining over 60% of adoption variance across simulations. Even when nudge effectiveness is reduced by 50%, BDSS maintains a statistically significant advantage ($p < 0.05$) over the Standard DSS in adoption and water-use efficiency.

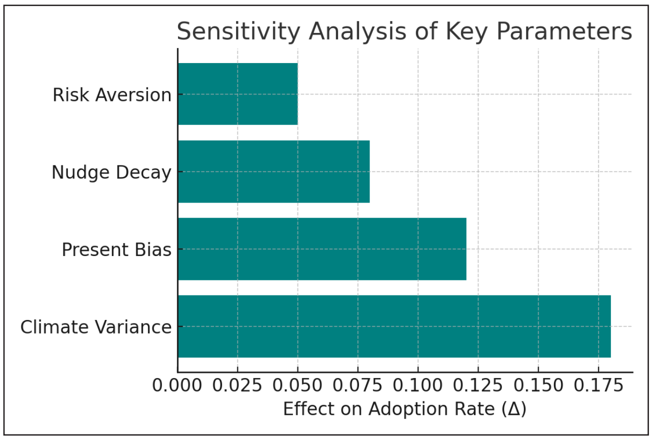

Figure 4.Sensitivity analysis showing relative impact of behavioral and climatic factors on adoption gains

Comparative Insights with Prior Work

Compared to earlier DSS models such as CAMDT[4] and Soil Navigator[6], which rely primarily on deterministic optimisation, BDSS demonstrates the added value of human-centred adaptivity. By embedding behavioural parameters directly into the decision optimisation process, the system accounts for deviations from rational choice that are prevalent in smallholder decision-making. Such behavioural coupling is largely absent in conventional DSS designs, positioning BDSS as a step toward "Behavioural-AI co-evolution" for sustainable agriculture.

Policy Implications

For large-scale implementation in India, BDSS should be integrated with national agrometeorological and digital advisory systems such as the Gramin Krishi Mausam Sewa (GKMS) and Krishi Vigyan Kendras (KVKs). Localised deployment would allow customisation of behavioural profiles and message framing based on region-specific risk culture and literacy levels.

- **Data Ethics and Transparency:** ensure user consent, anonymised data storage, and transparency in recommendation logic to maintain farmer trust.
- **Inclusivity through Multi-Channel Delivery:** combine smartphone apps, SMS, and IVR voice interfaces to extend reach to low-digital-literacy farmers; hybrid dissemination can mitigate digital divides while sustaining engagement.
- **Capacity Building:** train agricultural extension officers to interpret behavioural analytics outputs, enabling human–AI collaboration in advisory delivery.[10]

Conclusion

This paper presented a simulation-based assessment of a Behavioural-Aware Decision Support System (BDSS) that integrates behavioural economics with intelligent predictive analytics for climate-resilient agriculture. The framework demonstrates how adaptive nudging can systematically enhance technology adoption, improve water-use efficiency, and stabilise yields under climate uncertainty.

Simulation results confirm that embedding behavioural feedback loops in DSS can achieve a 15–20% higher adoption rate and measurable resource savings relative to purely data-driven advisories. The BDSS thus bridges the "last-mile" gap between climate information dissemination and behavioural action.

Future work will focus on field validation with live pilot deployments, integration of reinforcement learning for co-evolution of behavioural and predictive layers, and expansion to incorporate social network diffusion and gender-based adoption heterogeneity.

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