Indian Journal of Agricultural Economics 80: 3 (2025):650-670
DOI:10.63040/25827510.2025.03.008

Digital Inclusion for Rural Transformation: A Double Hurdle Analysis of IoT Sensor Adoption among Grape Farmers in India

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ABSTRACT

Digital inclusion is vital for equitable rural transformation, especially in high-value horticulture. This study uses a Cragg Double Hurdle model to analyze both the decision to adopt and the extent of use of IoT-based sensors among 225 grape farmers in India. In the adoption stage, structured training ($\beta = 2.80$, $p < 0.001$) and farming experience ($\beta = 0.048$, $p < 0.01$) increase uptake, while younger age ($\beta = -0.036$, $p < 0.05$) and cooperative membership ($\beta = -0.716$, $p < 0.01$) have negative effects. In the usage stage, education ($dy/dx = 0.0063$, $p < 0.001$) and training ($dy/dx = 0.0408$, $p < 0.001$) expand sensor coverage, whereas larger farm size (–0.0171, $p < 0.001$), higher income (–0.0373, $p < 0.001$), and greater distance to information services (–0.0014, $p < 0.001$) limit use. Higher per-acre costs (0.0691, $p < 0.001$) correlate with deeper investment by commercial growers. A significant residual-income term (1.002, $p < 0.001$) confirms endogeneity, addressed via a two-stage residual inclusion method. Findings support Rogers' Diffusion of Innovations and Lenton's tipping point framework suggest integrated policies localized training hubs, tiered subsidies, cooperative reforms, and village-level helplines to overcome barriers to tipping towards sustainable digital transformation in Indian viticulture.

Keywords: Digital inclusion, IoT sensors, Cragg Double Hurdle model, rural transformation, precision agriculture

JEL codes: O33, Q12, Q16, Q55, R11

I

INTRODUCTION

The Indian agriculture is the cornerstone of the nation's economy, supporting livelihood of around 58 per cent of the population (FAO, 2022), on the grounds 85 per cent of them are having farm-size less than 2 acres and contributing about 14 per cent to the GDP. The sector face challenges such as stagnant agricultural growth (Pandey & Suganthi, 2014; Nadkarni, 2022), declining crop productivity (Bhagat & Jadhav, 2021), rising production costs, limited resources (Ballabh and Batra, 2016), environmental challenges (Katke, 2019; The State of Food Security and Nutrition in the World 2024, 2024), and farmer indebtedness leading to suicides (Balla & Batra, 2016; Vasavi, 2009; Merriott, 2016). Hence, to address these obstacles moving away from traditional methods toward modern technologies and sustainable practices are paramount. Smart Agriculture and Precision Agriculture (PA) are recognized as effective ways to leverage technology for higher productivity, resilience, and reduced environmental impact (Barnes et al., 2018).

The Internet of Things (IoT) plays a pivotal role by integrating smart sensors with digital platforms for continuous monitoring of soil, water usage, crop health, and

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environmental factors, aiding in optimizing irrigation, pest detection, and input application (Soussi et al., 2024; Ammoniaci et al., 2021: Ayaz et al., 2019). Current research suggests that the anticipated technological advancements in farming in developing countries are not aligning with the actual situation for small-scale farmers. These farmers mainly rely on simple tools like phones and radios due to the high cost of advanced technologies. This creates disparities favoring wealthier farmers and marginalizing others (Somkuwar, 2018; Thuijsmanet al., 2022).

In India, numerous initiatives have spurred the interest of Agri-tech startups in offering technological solutions for agriculture (Chatterjee, 2018). However, despite these efforts, the uptake of smart farming practices low and faces significant challenges. Currently, there is a lack of information regarding how farmers employ precision farming (PF) technologies for decision-making and the specific costs and benefits associated with these technologies at the farm level (Klerkx et al., 2019; Rajak et al., 2023). Therefore, further research is imperative to investigate the adoption, application, and potential advantages of PF technologies. Understanding the factors influencing the adoption and deterrent of smart farming practices is crucial. This study aims to address this gap by examining the adoption of high-investment, information-intensive Precision Agriculture (PA) technologies like IoT sensors in Indian horticulture.

II

LITERATURE REVIEW

2.1 Concept

Precision agriculture leverages advanced technologies such as IoT, GIS, drones, and remote sensing to improve farm productivity, optimize inputs, and enhance environmental sustainability (Ramesh et al., 2022; lo et al., 2023). Among these, IoT systems are particularly effective in providing real-time data on soil, crop, and climate conditions, allowing for timely, site-specific interventions (Fondaj et al., 2024; Loddo et al., 2020). These features are especially valuable in viticulture, which is highly sensitive to micro-climatic variation and terroir. Viticulture encompasses complex cultivation practices including canopy management, irrigation scheduling, and disease control require precision to maximize grape quality and yield (Smart & Robinson, 1991; van Leeuwen et al., 2004). While precision viticulture has gained momentum in advanced economies, its adoption among smallholders in developing regions remains underexplored. Precision Agriculture (PA): Site-specific management using spatial data and technologies to improve efficiency and productivity (Sishodia et al., 2020; Mazzetto et al., 2020; Bolfe et al., 2020). Digital Agriculture: An integrated ecosystem using data analytics, AI, cloud computing, and IoT for strategic decision-making (Klerkx et al., 2019; Dhal et al., 2024; Sott et al., 2021). Internet of Things (IoT): Network of interconnected devices (e.g., sensors, actuators) that collect, transmit, and act on real-time data (Ahmed et al., 2018; Khanna & Kaur, 2019; Saranya et al., 2023). IoT Sensors: Hardware components that monitor physical farm variables like soil moisture, temperature, and nutrients (Mazzetto et al., 2020; Moraes et al., 2020; Symeonaki et al., 2020). Viticulture is the science of grapevine cultivation, involving canopy, irrigation, and pest management to optimize yield and quality (Jackson, 2020). Due to its sensitivity to environmental (Harish, 2024) and management variables, it demands high precision (Smart & Robinson, 1991). This makes viticulture an ideal setting for IoT-based smart technologies to enhance data-driven decision-making (van Leeuwen et al., 2004).

2.2 Adoption Dynamics of Digital Technologies

IoT adoption in agriculture offers notable economic and environmental benefits, including yield improvements, cost reductions, and market access through traceability, but smallholder uptake in contexts like India remains constrained by financial, institutional, and cognitive barriers (Balaceanu et al., 2021; Rajak et al., 2023). Empirical evidence highlights that adoption is shaped by a combination of demographic, socioeconomic, and farm-level factors, often interacting nonlinearly across adoption stages. Age exhibits mixed effects: older farmers may resist some innovations yet adopt others, suggesting quadratic modeling for stage-specific impacts (Yue et al., 2023; Workie & Tasew, 2023). Education generally enhances adoption likelihood by improving information processing, particularly for participation decisions, though effects on intensity (Isgin et al., 2008; Siyum et al., 2022). Farming experience, similarly, can either reinforce inertia or promote learning, with U-shaped relationships observed in some service-based adoptions (Kamau et al., 2024; Yue et al., 2023).

Farm size consistently predicts adoption, with larger holdings favoring equipment ownership, whereas smaller farms may prefer service-based access (Isgin et al., 2008; Yue et al., 2023). Household income, credit access, and cost of technology strongly influence both probability and intensity, though effects vary by context, liquidity, and delivery mechanisms (Tang et al., 2022; Yue et al., 2023). Off-farm income and distance to markets or information sources show context-dependent effects, emphasizing the need to model interactions with farm size and information channels (Kamau et al., 2024). Overall, the literature underscores the necessity of stage-specific, nonlinear, and interaction-aware frameworks to accurately capture adoption dynamics among smallholders, integrating behavioral, institutional, and technological dimensions.

2.3 Theoretical Positioning of technology Adoption

Technology adoption in agriculture has traditionally been explained through linear frameworks such as the Diffusion of Innovations (DOI) theory, Neo-classical models, and institutional perspectives. The DOI model emphasizes innovation attributes relative advantage, compatibility, and observability along with the influence of communication networks and social systems (Rogers, 2003; Looney et al., 2022; Feder et al., 2004; Sangeetha et al., 2023). Neo-classical models explain adoption as a rational economic choice, driven by benefits exceeding costs and risks (Feder et al., 1985; Abdulai & Huffman, 2005; Koundouri et al., 2006; Ghadim et al., 2005). Institutional theories further highlight the importance of formal mechanisms such as subsidies and credit, and informal norms such as trust and collective behavior (Eastwood et al., 2017; Anderson & Feder, 2007; Asfaw et al., 2012; Genius et al., 2014; Garcia et al., 2024). However, these approaches often assume a gradual, additive process of adoption. In contrast, Positive Tipping Point (PTP) theory (a et al., 2021) introduces a non-linear systems perspective, suggesting that once enabling conditions like access to credit, training, and supportive networks reach a critical threshold, adoption can accelerate rapidly through reinforcing feedback loops. This research aims to fill these research gaps by employing a double-hurdle model to examine access and usage impediments faced by grape cultivators in India.

III

METHODOLOGY

3.1 Research Design and Sampling

This study adopts a mixed-methods approach integrating qualitative classification with quantitative computation to evaluate the adoption and intensity of use of IoT-enabled precision agriculture technologies in grape farming. The study employed a stratified sampling approach with purposive selection of respondents across two major grape-producing regions. A structured questionnaire was administered to a sample of 225 grape farmers across two major grape growing districts Nashik (Maharashtra) and Vijayapura (Karnataka). Respondents were categorized into adopters and non-adopters based on their use of IoT sensors and drip irrigation technologies. Stratified purposive sampling ensured a balanced representation of adopters and non-adopters. From Nashik, 75 adopters and 50 non-adopters were sampled from Vijayapura, 50 adopters and 50 non-adopters were selected. This study is based on primary data collected through a structured household survey conducted between October 2023 and March 2024, the survey timeline was aligned with post-harvest and pre-pruning periods to ensure data accuracy and farmer availability.

3.2 Rationale for Commodity and Region Selection

Limited technology adoption is evident in various commercial crops such as pomegranate, grapes, Chilli, banana apple, Chilli tomato, orange etc., but scattered around India in different states. Grapes were selected due to their high commercial value and sensitivity to environmental conditions, making them ideal candidates for precision agriculture also a greater number of technology adopters can be evident in grape compare to other crops. India exports over 1.6 lakh tons of grapes annually, predominantly from Maharashtra and Karnataka (APEDA, 2024). These regions are also focal points for Agri-tech pilot projects, hosting innovations by firms such as Fyllo, Fasal, Crop In, and Sensartics. The agro-climatic diversity between Nashik's loamy, semi-tropical soils and Vijayapura's black cotton soils under semi-arid conditions allows for robust testing of IoT technology effectiveness.

3.3 Analytical Framework

Integrating PTP with the double-hurdle model allows the study to capture both the decision to adopt (first hurdle) and the intensity of adoption (second hurdle), showing how micro-level decisions and institutional supports can interact to trigger transformative, self-sustaining digital inclusion among grape farmers in India. The study follows descriptive statistics to summarize socio-economic and farm-level variables, disaggregated by adopter status and farm size. To assess group differences, independent t-tests were conducted on continuous variables such as years of experience and distance to extension, while chi-square (χ^2) tests were used for categorical variables like education, caste, training, and credit access.

3.4 Model Specification

3.4.1 Model Overview

The econometric model used to identify the determinants of adoption is a double hurdle model, as formulated by Cragg (1971). The model assumes that two separate hurdles must be passed before adoption of technology. The Double Hurdle framework separates the adoption process into two distinct stages: (1) the decision to adopt the technology (extensive margin), and (2) the proportion of land where the technology is applied (intensive margin). This approach accounts for both non-adoption and partial adoption and full adoption. The Cragg Double Hurdle model was selected for this study due to its ability to distinguish between two separate stages in the adoption process of IoT-based smart sensor technologies: the binary decision to adopt and the continuous intensity of use among adopters. Unlike the Tobit model, which assumes that zero and positive outcomes are generated by a single underlying process, the double hurdle approach allows for a more flexible framework in which non- adoption and limited adoption are treated as outcomes of distinct decision-making processes (Cragg, 1971; Wooldridge, 2010). This distinction is especially relevant in agricultural technology adoption, where some farmers may not adopt due to lack of awareness or institutional access, while others may adopt only partially due to financial or operational constraints (Nichola, 1996; Yu, Nin-Pratt, Funes, & Asenso-Okyere, 2011; Aristei & Perali, 2010). Moreover, the model permits different explanatory variables in each hurdle, enabling a richer and more accurate representation of real-world decision-making (Burke, 2009). Given the prevalence of zero observations and the theoretical justification for modeling adoption and intensity separately, the Cragg Double Hurdle model offers a more appropriate econometric framework than standard Probit, Logit, or Tobit specifications for understanding technology uptake behavior in Indian viticulture.

Stage 1: Adoption Decision (Probit Selection Model)

Let A*_i be the latent propensity for farmer i to adopt IoT sensors. The adoption decision is modeled as:

$$A_i^* = Z_i^{\prime} + u_i$$

Where,

A_i is unobserved adoption utility

Z_i is a vector of explanatory variables (e.g., training, education, experience, age)

γ is a vector of parameters to be estimated

ε_i is the error term assumed to follow a standard normal distribution

The observed decision is:

$$A_i = \begin{cases} 1, & if\ A_i^* > 0\ (adopt) \\ 0, & \text{otherwise} \end{cases}$$

Stage 2: Intensity of Use (Truncated Regression)

Conditional on adoption (A_i= 1), the extent of adoption (e.g., proportion of land using IoT) is modeled as:

$$Y_i \ = X_i^{\prime}\beta + \varepsilon_i$$

Where,

Y_i is the proportion of land under IoT use

X_i is a vector of explanatory variables (e.g., cost, farm size, income, distance)

β is a vector of parameters to be estimated

ε_i is the error term, assumed to follow a normal distribution with constant variance This equation is truncated at zero, accounting for the fact that non-adopters do not report usage levels.

3.4.2 Multicollinearity, Endogeneity and heteroskedasticity correction

To verify the stability of the model estimates, we checked for multicollinearity among explanatory variables using the Variance Inflation Factor (VIF) (Gujarati & Porter, 2009). VIF values were computed separately for each set of covariates in the selection and outcome equations. All VIFs were below the critical threshold of 10, suggesting no significant multicollinearity. Given the potential endogeneity of farm income, we implemented a Two-Stage Residual Inclusion (2SRI) approach (Terza, Basu, & Rathouz, 2008; Wooldridge, 2015). In the first stage, log-transformed farm income was regressed on valid instruments such as land ownership and household structure. The residuals from this regression were then included in the second-stage truncated regression alongside the original income variable. A statistically significant residual term indicated the presence of endogeneity. To ensure robust inference, all models were estimated with heteroskedasticity-consistent standard errors using the vce(robust) option in Stata (White, 1980). All econometric analyses were conducted using Stata 17.0.

3.4.3. Final Specification

The model jointly estimates:

- A probit model for the probability of adoption
- A truncated normal regression for the intensity of adoption (conditional on adoption) Variables include:
- Demographic: Years of education, age, experience
- Institutional: Access to training, extension, credit
- Economic: farm income, cost of tech per acre, farm size
- Instrumental: Residual farm income prediction

IV

RESULTS AND DISCUSSION

4.1 Farmer Classification and Demographics

The adoption of agricultural technologies by grape growers in India displays a mix of advancements and ongoing limitations. According to data presented in Table 1 and Figure 1 using Rogers' Diffusion of Innovations model, farmers are categorized into

TABLE 1. CATEGORIZATION OF FARMERS BASED ON TECHNOLOGY ADOPTION LEVELS

Category	Percentage of population (%)	Freq.	Description
Innovator	2.5	4	First movers, risk-takers with early access to innovations
Early Adopter	13.5	17	Opinion leaders, influence others, adopt after innovators
Early Majority	34	42	Thoughtful adopters, adopt before the average person
Late Majority	34	43	Skeptical group, adopt due to necessity or peer pressure
Laggard	16	19	Conservative, tradition-bound, last to adopt
Not Adopted	0	100	Farmers who have not adopted the innovation

Source: Author's calculation based on primary survey data (2023-24)
Note: Year of adoption is base for categorical classification

innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%), and laggards (16%). This distribution indicates a gradual adoption trend, consistent with the non-linear dynamics proposed by the Positive Tipping Point theory (Lenton et al., 2021). The acceleration of cumulative adoption occurs after a critical threshold of facilitating factors such as credit accessibility, training, and social networks is met. Spatially, most cultivated land falls within the early and late majority categories, with a minority remaining under laggard management (Figures 2 and 3).

Factors such as education, training, and institutional connections significantly influence adoption rates. Access to extension services, participation in cooperatives, and training programs demonstrate a substantial impact on adoption. These outcomes align with diffusion and institutional theories, emphasizing the role of social proximity to knowledge systems and institutional resources in driving adoption (Looney et al., 2022; Eastwood et al., 2017). Additionally, disparities linked to caste and land ownership highlight systemic inequalities affecting technology adoption (Table 2).

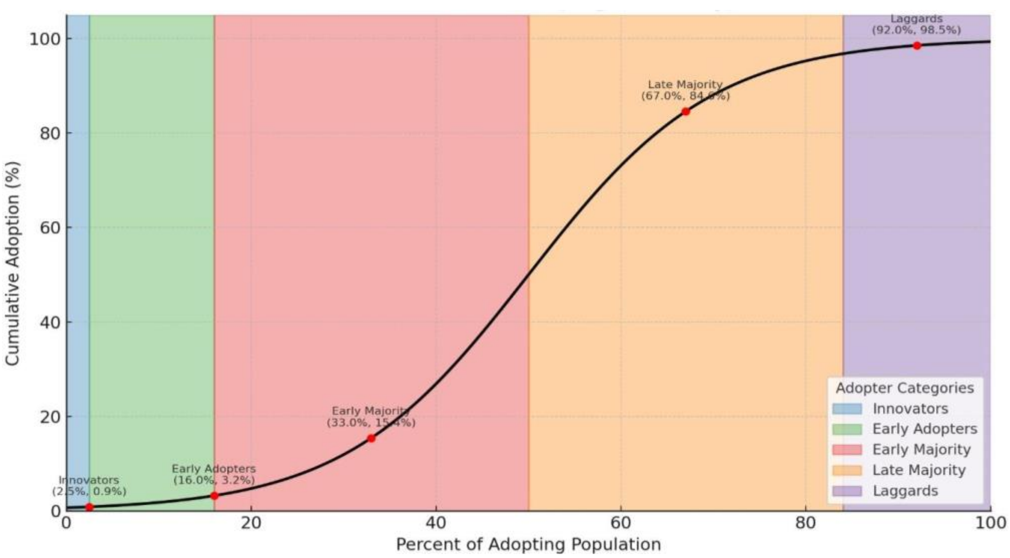

FIGURE 1. S CURVE OF INNOVATION

4.2 Adoption Intensity and Technology Costs

Further analyses on adoption intensity and economic aspects reveal that a considerable proportion of farmers do not adopt (44.44%), with a majority exhibiting low adoption intensity (41.33%). Larger adopters, managing more land (5.17–7.15 acres), experience economies of scale with lower per-acre costs (Rs. 10,621-12,612). Conversely, marginal adopters face higher per-acre costs (Rs. 13,845), indicating

TABLE 2. DEMOGRAPHIC PROFILE OF THE SELECTED FARMERS (% OF HOUSEHOLDS)

Characteristics		Adopters (n=125)				Non-adopters (n=100)			
		Marginal	Small	Medium	Large	Marginal	Small	Medium	Large
Years of farming experience		22.71	23.97	23.65	23.93	21.33	21.90	20.75	23.43
Distance to information***		41.93	22.11	20.29	25.12	76.20	53.66	46.25	38.57
Average number of working persons**		2.64	2.11	2.12	2.59	2.40	2.71	2.74	2.43
Average Age		40.75	40.8	46.27	44.9	41.3	41.73	43.09	48.29
Training (%)	No	13.51	17.57	2.70	16.22	7.65	29.08	9.69	3.57
	Yes	2.27	13.07	18.18	16.48	0.00	25.00	25.00	0.00
Education (%) ***	Primary	30.00	0.00	10.00	10.00	10.00	30.00	10.00	0.00
	Secondary	10.00	20.00	8.00	12.00	12.50	25.00	7.81	4.69
	Higher Secondary	3.03	12.12	15.15	19.70	9.09	36.36	4.55	0.00
	Under graduate	2.44	17.07	14.63	15.85	0.00	28.85	15.38	5.77
	Postgraduate & above	4.76	9.52	16.67	19.05	0.00	20.00	20.00	10.00
Caste (% of households)	SC	7.69	23.08	7.69	11.54	4.55	36.36	4.55	4.55
	ST	14.29	14.29	21.43	0.00	4.17	45.83	0.00	0.00
	OBC	4.88	13.41	15.85	15.85	8.70	21.74	13.04	6.52
	General	4.69	13.28	12.50	19.53	8.33	26.85	12.04	2.78
Credit availability (% of households)	No	7.35	10.29	14.71	17.65	7.69	25.00	13.46	3.85
	Yes	4.95	15.93	13.19	15.93	7.43	30.41	8.78	3.38
Primary Occupation (%)	Non-agriculture	5.26	5.26	21.05	18.42	10.53	26.32	10.53	2.63
	Agriculture	5.66	16.04	12.26	16.04	6.79	29.63	9.88	3.70
Membership in organization (%)**	Yes	9.21	25	35.53	30.26	14.89	48.94	23.4	12.77
	No	14.29	34.69	14.29	36.73	15.09	66.04	16.98	1.89

Source: Author's calculation based on primary survey data (2023-24) (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

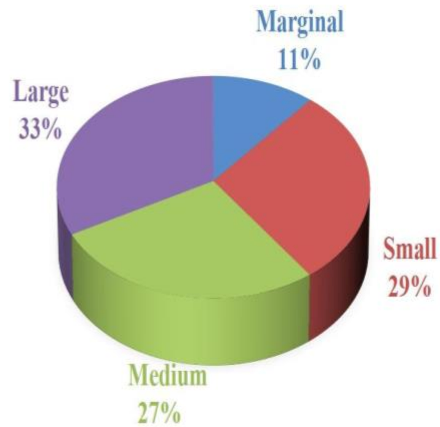

FIGURE 2. ADOPTER CLASSIFICATION AS PERCENTAGE OF NET OPERATED AREA

financial and capacity constraints. Adoption intensity does not linearly increase with farm size, suggesting that broader coverage may compromise depth of implementation (Tables 3 and 4). These outcomes are concordant with previous research (Isgin et al., 2008; Siyum et al., 2022; Kamau et al., 2024), indicating that adoption is influenced by various socio-economic, behavioral, and institutional factors. The results emphasize the gradual, uneven, and scale-dependent nature of

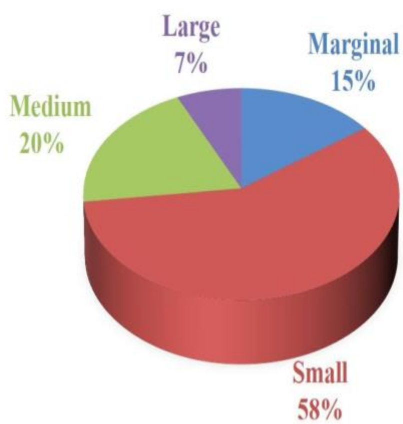

FIGURE 3. NON-ADOPTER CLASSIFICATION AS PERCENTAGE OF NET OPERATED AREA

technology adoption and underscore the need for interventions tailored to different stages and scales of adoption. Early adopters should be encouraged to enhance peer influence, low-intensity adopters require technical support and incentives, while laggard-managed areas need concrete evidence and institutional backing to overcome resistance. In summary, technology adoption is portrayed as a socially mediated, non-linear process influenced by individual capacity, resource availability, and supportive institutional environments.

TABLE 3. DISTRIBUTION OF FARMERS BASED ON TECHNOLOGY ADOPTION INTENSITY

Adoption Intensity	Freq.	Percent
Low	93	41.33
Medium	32	14.22
None	100	44.44

TABLE 4. AREA UNDER TECHNOLOGY, ADOPTION INTENSITY, AND PER ACRE TECHNOLOGY COSTS IN GRAPE CULTIVATION OF ADOPTERS (n=125)

Variable	Marginal	Small	Medium	Large	Total
Area under technology (acre)	1.90	3.41	5.17	7.15	4.95
Adoption Intensity	1.43	1.22	1.17	1.31	1.26
Total technology cost (Rs)	24678.57	29513.89	54664.71	57558.05	45011.84
Technology cost (Rs./Acre)	13845.24	10290.78	12612.05	10621	11428.58

Source: Author's calculation based on primary survey data (2023-24)

4.3 Cragg Double Hurdle Model Results

The Cragg Double Hurdle model's findings shed light on the factors influencing the adoption and usage intensity of IoT technology among grape growers, differentiating between the decision to adopt and the level of usage, and emphasizing stage-specific factors like information, economic, and structural elements. The model showed a strong overall fit, as evidenced by the log-likelihood value (188.53), AIC (-339.06), and BIC (-274.24). These metrics indicate that the model effectively accounts for variations in farmer behaviour across both decision-making stages (Table 5). Economic and cost factors have diverse effects. Notably, higher technology costs per acre were linked to increased usage intensity ($p < 0.001$), suggesting that profit-oriented farmers invest more in quality or market demand. In contrast, larger farm income and size negatively affected usage intensity ($p < 0.001$), possibly due to diversification, logistical challenges, or diminishing returns in large-scale operations. Proximity to information sources negatively influenced usage intensity ($p < 0.001$), underscoring the importance of access to advisory services, aligning with Eastwood et al. (2017). Training (Baig, 2005) emerged as the most significant and reliable factor affecting both hurdles ($p < 0.001$). Familiarity with digital tools helps farmers overcome initial hesitance, improves technical skills, and encourages ongoing use. This aligns with Rogers' (2003) "knowledge" and "persuasion" stages, supported by Asfaw et al. (2012), highlighting training's role in reducing uncertainty in precision agriculture. While education did not affect engagement, it significantly enhanced usage intensity ($p < 0.001$), indicating that formal education enhances the ability to effectively use complex technologies post-adoption. This supports Feder et al. (1985), who stressed the importance of human capital in managing technical information. Experience significantly increased the likelihood of technology adoption ($p = 0.003$) but had little effect on usage intensity. Older age negatively impacted adoption ($p =$

TABLE 5. CRAGG DOUBLE HURDLE MODEL RESULTS (MODEL FIT STATISTICS)

Statistic	Value
Observations (N)	225
Log Likelihood	188.53
Degrees of Freedom	19
AIC	–339.06
BIC	–274.24
Pseudo R^2	2.03

0.044), highlighting generational differences in risk tolerance and openness to innovation according to Rogers' adopter categories. Surprisingly, group membership negatively affected adoption ($p = 0.009$). This suggests exclusion, lack of focus on technology, or misalignment, contrasting with previous studies that emphasized group benefits. Interventions are necessary to enhance the role of social networks in digital adoption. Non-significant variables, such as off-farm income and experience in usage intensity, suggest context-specific effects or influences from other factors. A significant residual income term ($p < 0.001$) indicates that unobserved economic and behavioural factors, such as risk tolerance, time allocation, or unmeasured access constraints, also influence intensity decisions. These findings align with Rogers' DOI theory and the positive tipping point framework, indicating that adoption is sensitive to knowledge and liquidity constraints, with structural barriers impeding uptake. Interventions that combine training, credit access, and proximity to advisory services, along with tailored strategies for farm size and group engagement, are likely to accelerate both adoption and sustained use, helping grape technology diffusion reach its tipping point.

V

POLICY IMPLICATIONS

The empirical evidence from our Double Hurdle analysis underscores the multifaceted barriers to IoT sensor adoption and sustained use among grape farmers in India. To translate these findings into concrete action, we propose an integrated policy framework comprising six interrelated strategies.

1. **Enhance Capacity Building through Localized Training:** Technology hubs within agricultural extension centres can effectively mitigate information gaps by conducting practical workshops focused on sensor installation and data interpretation. Mobile units equipped with IoT kits should be deployed to reach remote areas. Implementing a "train-the-trainer" model will certify farmers and officers as educators, thereby facilitating knowledge dissemination and promoting digital integration.
2. **Integrate Digital Literacy into Rural Education:** Education plays a crucial role in enhancing IoT utilization. State agricultural universities and NGOs should develop adult education programs that focus on data management and sensor adjustment. Online platforms offering courses in local languages will expand access. These strategies ensure that technical guidance is both accessible and context-specific.
3. **Reform Cooperative Governance to Support Innovation:** Despite the presence of cooperatives, the adoption of digital technology remains limited. Farmer Producer Organizations (FPOs) and cooperatives should introduce a "Digital Innovation Mandate" to initiate pilot projects and training programs. Establishing an "Innovation Committee" within each institution can oversee technology assessment and facilitate group purchases.
4. **Develop Equitable Financial Instruments:** For smallholders facing financial constraints, a tiered subsidy system can incentivize adoption. Collaborate with rural banks to offer agriculture-specific loans. "Sensor-as-a-service" payment models can reduce initial financial barriers.
5. **Implement Continuous Monitoring and Adaptive Management:** A dashboard managed by the state agriculture department can display adoption rates and yield improvements. Integrating data with farmer feedback will enable policymakers to refine training and service delivery strategies. This comprehensive approach addresses the challenges of achieving digital inclusion and sustainable rural development in India's viticulture sector.

VI

CONCLUSION

This study utilized a Cragg double-hurdle model to analyse the factors influencing both the decision to adopt IoT-based smart sensors and the intensity of their use among grape farmers in India. This study explores the integration of IoT sensors in rural agricultural settings through the lens of Roger's Innovation Lenton's Tipping Point framework. Our findings indicate that capacity-building initiatives, particularly structured training, are the most significant drivers of enhanced adoption and sustained application of precision agriculture technologies. Education further amplifies usage intensity, whereas farming experience increases the likelihood of adoption. Conversely, age and membership in traditional cooperatives dampen initial uptake, suggesting that older cohorts and existing institutional arrangements may require targeted interventions to overcome inertia or misalignment with digital innovation. Economic constraints play a nuanced role in this regard. Although higher per-acre technology costs correlate with greater intensity of use, likely reflecting commitment on the part of commercial operators, farm income and larger farm size are negatively associated with the usage scale, possibly indicating that wealthier or larger producers diversify their investments or face logistical challenges in sensor deployment. Importantly, physical distance from information services emerged as a significant barrier to sustained use, underscoring the need to enhance proximity to extension support. Finally, the significant residual income term validates our approach to addressing endogeneity and highlights the influence of unobserved economic factors on adoption behaviour. Collectively, these results emphasize that digital inclusion in rural high-value agriculture depends not only on making technologies available but also on building human capital, reforming institutional frameworks, and designing equitable financial instruments to support farmers. Achieving digital inclusion in precision agriculture requires perceiving technology adoption as a systemic transformation, rather than a straightforward progression. When enabling conditions are synchronized, they can catalyze pivotal moments and expedite equitable rural advancement. Therefore, policy frameworks should combine localized, hands-on training programs with tiered subsidies and flexible financing while reforming cooperative governance to incentivize innovation and establish village-level information outposts or helplines. Future research should adopt longitudinal designs across multiple crops and geographies to capture dynamic adoption trajectories and allow causal inference. Integrating precise geospatial measures and variables, such as risk attitudes, market access, and intra-household decision-making, will further enrich our understanding. By addressing both informational and structural barriers to IoT uptake, stakeholders can foster an inclusive digital transformation that benefits both smallholders and commercial growers, thereby advancing equitable rural development and sustainable viticulture in India. This study examines IoT adoption in Indian grape farming, with broader relevance to high-value crops such as apples, mangoes, and vegetables in smallholder agriculture in Asia, Africa, and Latin America. Integrating a double-hurdle model with Rogers' diffusion theory and Lenton's tipping point framework offers a transferable method for analyzing impediments to access and utilization. These outcomes underscore the pivotal role of systemic facilitating factors, such as infrastructure, cost-effectiveness, and communal confidence, in instigating nonlinear adoption trends, presenting practical implications for policymakers, agricultural extension services, and technology suppliers in analogous rural environments.

Our study offers invaluable insights, yet it is crucial to acknowledge its limitations to enhance its impact. By focusing exclusively on grape growers in select locales, we inadvertently narrowed our scope, limiting the study's applicability across diverse agricultural landscapes. This focus, while insightful, restricts the broader resonance of our findings. Furthermore, the absence of critical factors such as risk inclination, market accessibility, and gender roles may skew our results, underscoring the need for a more comprehensive approach. Additionally, relying on self-reported travel times instead of precise geospatial data introduces potential inaccuracies. To truly enrich our understanding of adoption trends, future research must expand its scope, adopt longitudinal methodologies, and incorporate precise geographical and comprehensive variable datasets. By doing so, we can create a more robust and universally applicable tapestry of insights.

Acknowledgments: We express our appreciation to the Indian Council of Social Science Research (ICSSR) for the Doctoral Fellowship to Bhuvaneshwari, special thanks to ISEC for facilitating this study. We also wish to acknowledge Sumit Sheoran and Sudhanshu Rai, founders of Fyllo, for their assistance in connecting us with farmers and supporting data collection. Our sincere thanks go to Prof. Kaliappa Kalirajan and Dr. Manjunatha A.V. for their valuable feedback, which significantly improved the manuscript. Additionally, we are grateful to Akshay S. Deshmukh for his continuous support and insightful discussions throughout the research process.

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APPENDICES

TABLE A1. LAND CLASSIFICATION

Land Category	Landholding Size (in Acres)
Marginal	Less than 2.5 acres
Small	2.5 – 5 acres
Medium	5 – 10 acres
Large	More than 10 acres

TABLE A2. MEAN VALUES OF KEY VARIABLES BY ADOPTION STATUS

Adoption Status	Years of Education	Farmer's Age (Years)	Farming Experience (Years)	Distance to Extension (km)
Non-Adopter	11.36	42.58	21.69	54.5
Adopter	13.00	44.26	23.73	24.82
Total	12.27	43.52	22.82	38.01

TABLE A3. EDUCATION CLASSIFICATION

Category	Years of Education
No Schooling	0
Primary	1–7
Upper Primary/Secondary	8–10
Higher Secondary	11–12
Undergraduate/Diploma	13–15
Postgraduate & Above	>15

TABLE A4. CROSS-TABULATIONS BY ADOPTION STATUS FOR CATEGORICAL VARIABLE

Variable	Non-Adopters (%)	Adopters (%)
Training (No)	72.59	27.41
Training (Yes)	2.22	97.78
Social - SC	45.83	54.17
Social - ST	63.16	36.84
Social - OBC	35.94	64.06
Social - General	45.76	54.24
Credit - No	43.33	56.67
Credit - Yes	44.85	55.15
Member - No	51.96	48.04
Member - Yes	38.21	61.79
Land - Marginal	51.72	48.28
Land - Small	68.18	31.82
Land - Medium	40.24	59.76
Land - Large	14.58	85.42

TABLE A5. ADOPTION INTENSITY CLASSIFICATION

Code	Category	Interpretation
0	None	No technology adopted
1	Low	Adoption of 1 technology
2	Medium	Adoption of 2 technologies
3	High	Adoption of 3 or more technologies

TABLE A6. RESULTS OF T-TEST AND CHI-SQUARE TEST

Characteristics	t-test/ Chi square (df)	P value
Years of farming experience	-1.26 (223)	0.210
Distance to information***	7.12	<0.001
Average number of working persons **	2.11	0.036
Age	-1.10	0.273
Training	108.3 (1)	<0.001
Education***	-4.21	<0.001
Caste	4.67(3)	0.197
Credit availability	0.04(1)	0.840
Primary Occupation	0.57(1)	0.450
Membership in organization**	4.27(1)	0.039

Note: chisquare used for only Categorical variables- Training, primary occupation, Credit availability, Membership in organization, Caste. Significance : * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$

TABLE A7. VARIANCE INFLATION FACTORS (VIF) FOR DOUBLE HURDLE MODEL

Variable	Stage 1		Stage 2	
	VIF	1/VIF	VIF	1/VIF
Years Education	1.35	0.741	1.27	0.789
Training (Yes)	1.35	0.739	1.61	0.623
Credit Facilities (yes)	1.05	0.953	1.06	0.940
Exp Farming	1.19	0.838	2.76	0.362
Distance to information	1.23	0.816	-	-
Cost Tech Acre	1.16	0.861	-	-
Farm size	1.33	0.753	-	-
Farm Income	1.82	0.548	1.17	0.852
Off Farm Income	-	-	1.10	0.906
Age	-	-	2.82	0.355
Member Dummy	-	-	1.51	0.661
Mean VIF	1.31		1.66	

Farmers were classified into adopter categories based on Rogers' Diffusion of Innovations theory (2003), which posits that the spread of new technologies follows a bell-shaped curve. According to this framework, the population was divided as follows:

- Innovators: First 2.5% to adopt
- Early Adopters: Next 13.5%
- Early Majority: Next 34%
- Late Majority: Next 34%
- Laggards: Last 16%