ISSN: 1672 - 6553

JOURNAL OF DYNAMICS AND CONTROL

VOLUME 10 ISSUE 04: P234-261

AGRICULTURAL TECHNOLOGY ADOPTION, PRODUCTIVITY GAINS, AND FOOD SECURITY IN SMALLHOLDER FARMING SYSTEMS: EVIDENCE FROM INTEGRATED LOGIT, PSM, ESR, AND SEM APPROACHES IN INDIA

Venu B. N.[1], Navya A. G.[2], Suresh Babu[3], Asif[4]

[1]Associate Professor, [3, 4] Assistant professor, College of Agricultural Sciences & Applied Research, Bhratiya Engineering Science & Technology Innovation University, Gorantla, Andhra Pradesh, India.

[2]Associate Professor, Sri Madhusudhana Sai Institute of Medical sciences and Research, Mudedenahalli, Karnataka, India.

JOURNAL OF DYNAMICS AND CONTROL
https://doi.org/10.71058/jodac.v10i04014

AGRICULTURAL TECHNOLOGY ADOPTION, PRODUCTIVITY GAINS, AND FOOD SECURITY IN SMALLHOLDER FARMING SYSTEMS: EVIDENCE FROM INTEGRATED LOGIT, PSM, ESR, AND SEM APPROACHES IN INDIA

Venu B. N.[1*], Navya A. G.[2], Suresh Babu[3], Asif[4]

[1]Associate Professor, [3, 4] Assistant professor, College of Agricultural Sciences & Applied Research, Bhratiya Engineering Science & Technology Innovation University, Gorantla, Andhra Pradesh, India.

[2]Associate Professor, Sri Madhusudhana Sai Institute of Medical sciences and Research, Mudedenahalli, Karnataka, India.

[1]drvenu.assoprof@bestiu.edu.in, [2]navyaagreddy@gmail.com@bestiu.edu.in, [3]chsuresh.asstprof@bestiu.edu.in

Corresponding Author

Abstract: *Agricultural technology adoption is widely recognized as a critical driver of productivity enhancement, income growth, and food security improvement in developing economies. However, adoption remains uneven due to socio-economic, institutional, and behavioral constraints, particularly among smallholder farmers. This study examines the determinants, impacts, and diffusion patterns of agricultural technology adoption using primary data collected from 240 farm households in the Rayalaseema region of Andhra Pradesh, India. A multi-stage stratified random sampling technique was employed to ensure representation across small, medium, and large farmer categories. The study adopts a comprehensive econometric framework integrating Logit regression, Propensity Score Matching (PSM), Endogenous Switching Regression (ESR), and Structural Equation Modeling (SEM) to address selection bias, endogeneity, and causal inference. A composite Technology Adoption Index (TAI) and a Food Security Index (FSI) are constructed to capture multidimensional aspects of adoption intensity and household welfare outcomes. Empirical results reveal that education, farm size, extension contact, and access to credit significantly and positively influence technology adoption decisions. PSM estimates indicate that adopters achieve significantly higher crop yields (11.25 q/ha), increased farm income (₹98,500), and improved food security (0.18 index points) compared to non-adopters. ESR results further confirm substantial treatment effects, highlighting robust gains even after correcting for selection bias. SEM analysis reveals that technology adoption influences food security both directly and indirectly through productivity and income channels, with income acting as a key mediating variable. Diffusion analysis shows that most farmers fall within the early and late majority categories, indicating a transitional stage of technology diffusion with scope for accelerated adoption. The findings underscore that agricultural technology adoption significantly enhances farm-level productivity and rural welfare, but its benefits are unevenly distributed due to structural constraints. The study recommends strengthening agricultural extension systems, improving access to institutional credit, and promoting inclusive digital agriculture strategies to accelerate adoption and ensure equitable rural transformation.*

Keywords: *Technology adoption, PSM, ESR, SEM, food security, agricultural productivity, diffusion, India*

https://doi.org/10.71058/jodac.v10i04014

1. Introduction

Agriculture continues to play a pivotal role in ensuring food security, employment generation, and economic development in developing economies, particularly in countries such as India where a substantial proportion of the population depends on farming for their livelihoods (FAO, 2022; World Bank, 2023; Birthal et al., 2020). However, the sector is increasingly confronted with multiple structural and emerging challenges, including declining land productivity, climate variability, resource degradation, fragmented landholdings, and market inefficiencies (Pingali et al., 2020; Searchinger et al., 2021; Aryal et al., 2021). In this context, the adoption of modern agricultural technologies has become a critical strategy for enhancing productivity, improving farm income, and ensuring sustainable agricultural development (Fuglie et al., 2021; Barrett et al., 2020; Duflo et al., 2021).

Technological advancements in agriculture have evolved rapidly over the past decade, particularly with the emergence of digital agriculture, precision farming, artificial intelligence (AI), and Internet of Things (IoT)-based solutions (Klerkx et al., 2020; Wolfert et al., 2021; Sharma et al., 2022). These innovations have the potential to transform traditional farming systems by improving input efficiency, reducing risks, and enhancing decision-making processes (Lowenberg-DeBoer et al., 2021; Lioutas et al., 2021; Finger et al., 2022). Recent studies highlight that digital agricultural technologies are increasingly being adopted in low- and middle-income countries, driven by the need to enhance productivity and resilience in the face of climate change (Aker et al., 2021; Fabregas et al., 2022; Jack et al., 2022). Such technologies are often regarded as central to the ongoing transformation of global food systems, contributing to what is widely described as the next phase of agricultural modernization (Herrero et al., 2021; Reardon et al., 2021).

Despite the growing availability of agricultural technologies, their adoption remains uneven and constrained, particularly among smallholder farmers (Feder et al., 2021; Kassie et al., 2020; Abdulai & Huffman, 2020). The literature consistently emphasizes that technology adoption is a complex process influenced by a combination of socio-economic, institutional, and behavioral factors (Mottaleb et al., 2020; Wossen et al., 2021; Tambo et al., 2021). Education, farm size, access to credit, extension services, and risk perception have been identified as key determinants influencing adoption decisions (Ruzzante et al., 2021; Teklewold et al., 2020; Asfaw et al., 2020). In particular, extension services and access to information play a crucial role in reducing uncertainty and facilitating informed decision-making among farmers (Anderson & Feder, 2021; BenYishay & Mobarak, 2020). Similarly, financial constraints and lack of access to credit often limit the ability of farmers to invest in new technologies (Adjognon et al., 2021; Carter et al., 2021).

Empirical evidence also suggests that structural inequalities within the agricultural sector significantly affect adoption patterns. Larger farmers tend to adopt technologies more readily due to their better access to resources, economies of scale, and higher risk-bearing capacity, whereas smallholders often face constraints related to capital, information, and infrastructure (Jayne et al., 2021; Muyanga et al., 2021; Liverpool-Tasie et al., 2020). This disparity in adoption behavior can lead to widening productivity and income gaps within rural communities, raising concerns about inclusive agricultural development (Barrett et al., 2021; Bellemare & Novak, 2021).

In addition to socio-economic factors, behavioral aspects such as risk attitudes and perceptions also play a critical role in shaping technology adoption decisions. Farmers often operate under conditions of uncertainty, where the perceived risks associated with new

https://doi.org/10.71058/jodac.v10i04014

technologies can deter adoption (Liu, Bruins, & Heberling, 2020; Ward & Singh, 2021). Studies have shown that risk-averse farmers are less likely to adopt innovative practices, even when such technologies offer potential long-term benefits (Holden & Quiggin, 2021; Emerick et al., 2020). This highlights the importance of designing policies that not only improve access to technologies but also address behavioral constraints through awareness, training, and demonstration programs (Krishnan & Patnam, 2021).

Beyond adoption decisions, a growing body of literature has focused on assessing the impact of technology adoption on agricultural outcomes, including productivity, income, and food security (Abdulai & Huffman, 2020; Kassie et al., 2020; Wossen et al., 2021). Empirical studies consistently demonstrate that the adoption of improved technologies leads to significant gains in crop yield and farm income, while also enhancing resilience to climate shocks (Asfaw et al., 2020; Teklewold et al., 2020; Tambo et al., 2021). Moreover, technology adoption has been found to improve household welfare by increasing food availability and economic access, thereby contributing to enhanced food security outcomes (Mottaleb et al., 2020; Ogutu et al., 2020; Sibhatu & Qaim, 2021).

However, despite the substantial evidence on the benefits of technology adoption, the existing literature exhibits several limitations. Many studies tend to focus either on the determinants of adoption or on its impacts, with limited integration of both aspects within a unified analytical framework (Ruzzante et al., 2021; Fabregas et al., 2022). Furthermore, methodological challenges such as selection bias and endogeneity often undermine the validity of empirical findings (Caliendo & Kopeinig, 2020; Lokshin & Sajaia, 2021). Recent research has emphasized the need for more rigorous econometric approaches, including Propensity Score Matching (PSM) and Endogenous Switching Regression (ESR), to establish causal relationships and address these limitations (Wossen et al., 2021; Asfaw et al., 2020).

Another important dimension that has received relatively less attention is the diffusion of agricultural technologies. According to diffusion theory, the spread of innovations follows a systematic pattern over time, with farmers categorized into innovators, early adopters, early majority, late majority, and laggards (Rogers, 2003; updated applications: Meijer et al., 2021; Klerkx et al., 2020). Empirical evidence suggests that diffusion processes in developing countries are often slow and incomplete due to structural and institutional constraints (Läpple et al., 2020; Genius et al., 2021). Factors such as limited access to information, weak extension systems, and financial barriers hinder the widespread adoption of technologies, resulting in suboptimal diffusion outcomes (Abate et al., 2020; Liverpool-Tasie et al., 2020).

The role of digital technologies in accelerating diffusion has gained increasing attention in recent years. Digital platforms, mobile applications, and data-driven advisory systems have the potential to bridge information gaps and enhance knowledge dissemination among farmers (Aker et al., 2021; Fabregas et al., 2022; Jack et al., 2022). However, challenges such as digital literacy, connectivity, and affordability continue to limit their effectiveness, particularly in rural areas (Rotz et al., 2021; Birner et al., 2021). Addressing these challenges is essential for ensuring that the benefits of digital agriculture are accessible to all segments of the farming population.

In the Indian context, promoting agricultural technology adoption is particularly critical given the challenges of feeding a growing population while ensuring environmental sustainability (Birthal et al., 2020; Chand, 2021). Government initiatives such as digital agriculture missions, climate-resilient agriculture programs, and support for agri-startups

https://doi.org/10.71058/jodac.v10i04014

have created new opportunities for technological transformation (Government of India, 2022; NITI Aayog, 2023). Nevertheless, the adoption of these technologies remains uneven, and their impact on farm performance and household welfare is not fully understood (Pingali et al., 2020; Aryal et al., 2021).

Furthermore, recent studies have highlighted the importance of integrating multiple analytical approaches to better understand the dynamics of technology adoption (Wossen et al., 2021; Fabregas et al., 2022). For instance, combining regression-based models with matching techniques and structural modeling can provide deeper insights into both causal effects and underlying mechanisms. Such integrated approaches are essential for developing comprehensive policy recommendations that address both adoption barriers and impact pathways (Asfaw et al., 2020; Lokshin & Sajaia, 2021).

Given these considerations, there is a clear need for empirical studies that adopt a holistic and methodologically rigorous approach to analyze agricultural technology adoption. Specifically, there is a need to simultaneously examine the determinants of adoption, evaluate its impact on productivity and welfare outcomes, and analyze the diffusion patterns across different categories of farmers.

Research Gap

Despite extensive research on agricultural technology adoption in recent decades, several critical gaps continue to persist in the existing literature, limiting a comprehensive understanding of adoption behavior, impact pathways, and diffusion dynamics. First, most studies tend to examine technology adoption either from the perspective of its determinants or its outcomes in isolation, rather than integrating determinants, impacts, and diffusion processes within a unified analytical framework. This fragmented approach restricts the ability to capture the full continuum of adoption behavior, from decision-making to welfare outcomes and long-term diffusion patterns (Ruzzante et al., 2021; Wossen et al., 2021; Fabregas et al., 2022; Klerkx et al., 2020).

Second, there remains limited application of advanced econometric techniques capable of adequately addressing selection bias, endogeneity, and unobserved heterogeneity in adoption studies. While traditional regression models dominate much of the empirical literature, they often fail to establish causal relationships between technology adoption and outcome variables such as productivity and income. Recent methodological advancements such as Propensity Score Matching (PSM), Endogenous Switching Regression (ESR), and Structural Equation Modeling (SEM) have been increasingly recommended, yet their application in empirical agricultural studies, particularly in developing country contexts, remains relatively limited (Caliendo & Kopeinig, 2020; Lokshin & Sajaia, 2021; Asfaw et al., 2020; Abdallah et al., 2021).

Third, insufficient attention has been given to the role of technology adoption in improving household food security outcomes, despite its central importance in agricultural development policy. Many studies focus primarily on yield enhancement and income gains, while overlooking multidimensional food security indicators such as availability, accessibility, and stability. This creates an incomplete understanding of how agricultural innovations translate into broader welfare improvements at the household level (Sibhatu & Qaim, 2021; Ogutu et al., 2020; Tambo et al., 2021; Bellemare & Novak, 2021).

Fourth, there is inadequate micro-level empirical evidence from developing country contexts, particularly India, where agriculture is characterized by smallholder dominance, heterogeneous resource endowments, and institutional constraints. Existing studies often

https://doi.org/10.71058/jodac.v10i04014

rely on aggregated or regional-level data, limiting the ability to capture heterogeneity across farm categories such as small, medium, and large farmers. This gap restricts the formulation of targeted and inclusive policy interventions aimed at promoting equitable technology adoption and reducing rural disparities (Birthal et al., 2020; Aryal et al., 2021; Jayne et al., 2021; Pingali et al., 2020).

In light of these limitations, the present study attempts to address these gaps by adopting a comprehensive and methodologically rigorous analytical framework that integrates determinants, causal impacts, and diffusion dynamics of agricultural technology adoption. By employing advanced econometric techniques alongside a multi-dimensional outcome structure, the study seeks to provide more robust and policy-relevant evidence on the role of technology adoption in enhancing agricultural productivity, farm income, and household food security.

The specific objectives of the study are:

- To analyze the determinants of agricultural technology adoption and its diffusion pattern among different categories of farmers.
- To evaluate the impact of technology adoption on agricultural productivity and farm income.
- To assess the effect of technology adoption on household food security for improving adoption and farm livelihoods.

2. Literature Review

Agricultural technology adoption has been widely recognized as a key driver of agricultural transformation, productivity enhancement, and rural development in developing economies. Over the past decade, a substantial body of literature has examined the determinants, impacts, and diffusion of agricultural innovations, particularly in the context of smallholder farming systems. However, despite extensive research, the literature remains fragmented across multiple dimensions, including adoption behavior, welfare impacts, and technology diffusion processes.

2.1 Determinants of Agricultural Technology Adoption

A large number of empirical studies have identified socio-economic, institutional, and behavioral factors as key determinants of agricultural technology adoption. Among socio-economic variables, education has consistently been found to play a significant role in enhancing farmers' ability to understand, evaluate, and adopt new technologies (Ruzzante et al., 2021; Kassie et al., 2020; Wossen et al., 2021). Similarly, farm size positively influences adoption decisions due to economies of scale, greater access to resources, and improved risk-bearing capacity (Jayne et al., 2021; Muyanga et al., 2021; Liverpool-Tasie et al., 2020).

Institutional factors such as access to extension services and credit facilities have also been widely documented as critical enablers of technology adoption. Extension services reduce information asymmetry and increase awareness about new agricultural practices, thereby improving adoption rates (Anderson & Feder, 2021; BenYishay & Mobarak, 2020). Access to credit, on the other hand, relaxes liquidity constraints and enables farmers to invest in improved inputs and technologies (Adjognon et al., 2021; Carter et al., 2021; Tambo et al., 2021).

Recent studies have further emphasized the role of behavioral and psychological factors in adoption decisions. Risk aversion, uncertainty, and perception of technology

https://doi.org/10.71058/jodac.v10i04014

effectiveness significantly influence farmers' willingness to adopt innovations (Liu et al., 2020; Ward & Singh, 2021; Holden & Quiggin, 2021). In addition, digital literacy and access to information and communication technologies (ICTs) are increasingly recognized as important determinants in the era of digital agriculture (Aker et al., 2021; Fabregas et al., 2022; Klerkx et al., 2020).

2.2 Impact of Technology Adoption on Productivity and Income

A growing body of empirical literature has established that agricultural technology adoption significantly enhances crop productivity and farm income. Improved seed varieties, climate-smart practices, and digital advisory systems have been shown to increase yield levels and reduce production risks (Asfaw et al., 2020; Teklewold et al., 2020; Ogutu et al., 2020). These productivity gains are often translated into higher household income through increased marketable surplus and improved price realization.

Studies also indicate that technology adoption contributes to income diversification and market participation among smallholder farmers (Abdulai & Huffman, 2020; Barrett et al., 2021; Wossen et al., 2021). Digital platforms and ICT-based interventions have further enhanced market access and reduced transaction costs, thereby improving income outcomes (Aker et al., 2021; Jack et al., 2022; Fabregas et al., 2022).

However, the magnitude of impact varies across farm categories, with larger farmers often benefiting more due to better resource endowments, access to markets, and capacity to absorb risk (Jayne et al., 2021; Bellemare & Novak, 2021). This highlights the existence of heterogeneity in adoption outcomes, which has important policy implications.

2.3 Technology Adoption and Food Security

In recent years, increasing attention has been given to the relationship between agricultural technology adoption and household food security. Empirical evidence suggests that technology adoption improves food availability, accessibility, and stability by increasing agricultural productivity and income levels (Sibhatu & Qaim, 2021; Ogutu et al., 2020; Tambo et al., 2021).

Households adopting improved agricultural technologies are more likely to experience higher dietary diversity and reduced food insecurity levels compared to non-adopters (Bellemare & Novak, 2021; Kassie et al., 2020). Furthermore, climate-smart agricultural practices have been found to enhance resilience to climate shocks, thereby stabilizing food supply in vulnerable regions (FAO, 2022; IPCC, 2021; Searchinger et al., 2021).

Despite these positive outcomes, food security impacts are often indirect and mediated through income and productivity channels, suggesting the need for integrated analytical frameworks that capture both direct and indirect effects.

2.4 Technology Diffusion and Adoption Pathways

The diffusion of agricultural innovations has been extensively studied under the framework of Rogers' diffusion theory, which categorizes adopters into innovators, early adopters, early majority, late majority, and laggards. Empirical studies show that adoption typically follows an S-shaped curve, with initial slow uptake followed by rapid diffusion and eventual saturation (Meijer et al., 2021; Klerkx et al., 2020).

However, in developing countries, diffusion processes are often slow and uneven due to structural constraints such as limited access to information, weak extension systems,

https://doi.org/10.71058/jodac.v10i04014

and financial barriers (Abate et al., 2020; Liverpool-Tasie et al., 2020; Genius et al., 2021). Social networks and peer effects have been identified as important mechanisms influencing diffusion, as farmers often rely on neighbors and community leaders for information about new technologies (BenYishay & Mobarak, 2020; Krishnan & Patnam, 2021).

Digital technologies have the potential to accelerate diffusion by reducing information gaps and improving knowledge dissemination. Mobile-based advisory services and digital platforms are increasingly being used to enhance farmer awareness and promote technology uptake (Aker et al., 2021; Jack et al., 2022).

2.5 Methodological Approaches in Adoption Studies

Methodologically, early studies on technology adoption relied heavily on simple regression models, which often failed to account for selection bias and endogeneity. Recent studies have adopted more rigorous econometric techniques such as Propensity Score Matching (PSM), Instrumental Variable (IV) approaches, and Endogenous Switching Regression (ESR) models to estimate causal impacts more accurately (Caliendo & Kopeinig, 2020; Lokshin & Sajaia, 2021; Asfaw et al., 2020).

Additionally, Structural Equation Modeling (SEM) has been increasingly used to capture complex relationships and mediation effects among variables such as adoption, income, and food security (Hair et al., 2021; Wossen et al., 2021). These advanced methods allow researchers to better understand both direct and indirect pathways of impact.

2.6 Research Gap and Conceptual Link

Despite extensive literature, several gaps remain. First, most studies focus either on determinants or impacts, but rarely integrate both within a unified framework. Second, there is limited application of combined methodologies such as Logit, PSM, ESR, and SEM in a single study. Third, food security outcomes remain underexplored compared to productivity and income. Finally, micro-level evidence from heterogeneous farming systems in developing countries is still insufficient.

This study addresses these gaps by integrating determinants, causal impacts, and diffusion analysis within a comprehensive econometric framework.

3. Methodology

3.1 Data Source and Sampling Design

The study is based on primary data collected from farm households Rayala seema region of Andhra Pradesh India, using a structured and pre-tested questionnaire. A multi-stage stratified random sampling technique was employed to ensure adequate representation across different farm size categories and to enhance the reliability of the analysis.

In the first stage, villages were selected purposively based on agricultural intensity, cropping patterns, and accessibility to agricultural inputs and services. In the second stage, farm households were stratified into three categories based on operational landholding size, namely small, medium, and large farmers. Subsequently, a random sampling method was applied within each stratum to select the respondents, thereby minimizing selection bias.

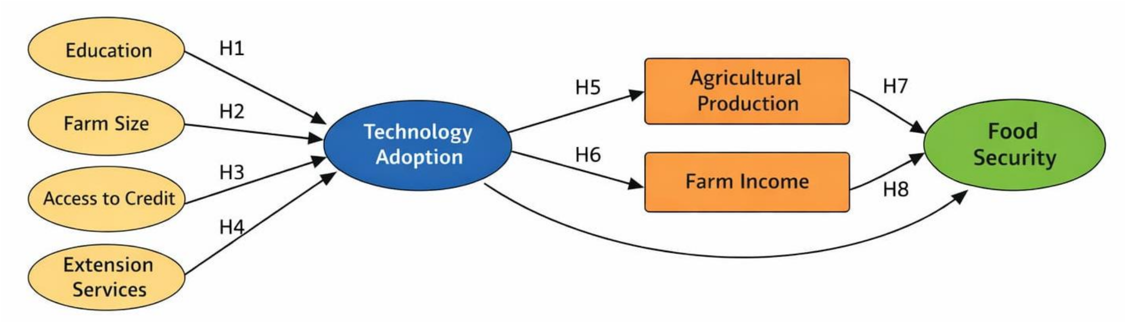
The final sample comprised 240 farm households, ensuring sufficient statistical power and heterogeneity for econometric analysis. The distribution of the sample across farm categories was as follows:

https://doi.org/10.71058/jodac.v10i04014

- Small farmers: 120
- Medium farmers: 80
- Large farmers: 40

This stratified distribution reflects the predominance of smallholders in the agricultural structure while maintaining proportional representation of medium and large farms. The adopted sampling framework enhances both internal validity (through reduction of sampling bias) and external validity (through representativeness), making the findings generalizable to similar agro-economic contexts..

3.6 Conceptual Framework Diagram



3.2 Measurement of Key Variables

3.2.1 Technology Adoption Index (TAI):

To capture the intensity of technology adoption, a composite Technology Adoption Index (TAI) was constructed instead of relying on a simple binary measure. The index is defined as:

$$\boldsymbol{TAIi = 1/n \sum_{J=1}^{n} Tij}$$

Where:

Tij=1 if farmer adopts technology j, 0 otherwise

n = total number of technologies

This index ranges between 0 and 1, where higher values indicate greater intensity of technology adoption. The use of a composite index improves measurement precision by capturing multiple dimensions of adoption behavior rather than a single technology decision.

3.2.2 Food Security Index (FSI)

Household food security was measured using a normalized Food Security Index (FSI), defined as:

$$\mathbf{FSIi} = \frac{\text{Actual Consumption (Ci)}}{\text{Recommended Consumption(Ri}}$$

Where: Ci represents the actual consumption level of the i th household, and Ri denotes the recommended consumption level based on standard nutritional requirements.

https://doi.org/10.71058/jodac.v10i04014

An *FSI* value greater than 1 indicates food security, while a value less than 1 reflects food insecurity. This index provides a continuous and comparable measure of household food security across different farm categories.

3.3 Econometric Framework

3.3.1 Determinants of Technology Adoption:

To examine the factors influencing technology adoption, a multivariate regression model was initially specified as:

$$TAI\_i = \beta 0 + \beta 1 Education\ i + \beta 2\ Farm\ Size\ i + \beta 3\ Extension\ i + \beta 4\ Credit\ i + \epsilon\ i$$

Where TAI_i represents the Technology Adoption Index of the i^{th} framer $\beta 0$ is the intercept, $\beta 1 \ldots\ldots \beta 4$ are parameters to be estimated, and ϵ is the error term.

However, since adoption decisions are inherently binary (adopter vs non-adopter), a logistic regression model was further employed to improve methodological rigor:

$$P\ (Di{=}1) = \frac{1}{1+e^{-Zi}}$$

Where: $Zi = \alpha + \beta Xi$

and Di=1 if the farmer adopts the technology, and 0 otherwise. This model captures the probability of adoption as a function of explanatory variables.

3.3.2 Addressing Selection Bias: Propensity Score Matching (PSM):

A major limitation in adoption studies is selection bias, as adopters and non-adopters may differ systematically. To address this issue, Propensity Score Matching (PSM) was employed.

The propensity score is estimated using a logit model:

$$P(Xi)=P(Di=1/Xi)= \frac{1}{1+e^{(\alpha+\beta Xi)}}$$

Matching techniques applied:

- Nearest Neighbor Matching
- Kernel Matching

The impact of adoption is measured using the Average Treatment Effect on the Treated **(ATT):** $ATT=E\ (Y1-Y0/D=1)$

Where: $Y1$ = outcome for adopters and $Y0$ = counterfactual (non-adopters)

This approach enables a more robust and causal interpretation of the impact of technology adoption.

3.3.3 Impact Analysis Using Endogenous Switching Regression (ESR):

To further address issues of selection bias and endogeneity, the study employs an Endogenous Switching Regression (ESR) model.

https://doi.org/10.71058/jodac.v10i04014

The selection equation is specified as:

$$Di* = Z_{i\gamma} + u_i$$

where Di=1 if $Di* > 0$, and Di=0 otherwise.

The outcome equations are defined for two regimes:

For adopters: $Y_1 = X_1 i\, \beta_1 + \epsilon 1 i$

For non-adopters: $Y_0 = X_0 i\, \beta_0 + \epsilon 1 i$

This framework allows estimation of:

- Actual outcomes
- Counterfactual outcomes
- Treatment effects

3.3.4 Structural Equation Modeling (SEM):

To capture both direct and indirect effects among variables, Structural Equation Modeling (SEM) was employed. The structural relationships are specified as:

$$Productivity\ i = \alpha 1 + \beta 1 TAIi + \epsilon 1i$$

$$Income\ I = \alpha 2 + \beta 2 TAIi + \epsilon 2i$$

$$FSI\ I = \alpha 3 + \beta 3 Incomei + \beta 4 TAIi + \epsilon 3i$$

This framework enables:

- Mediation analysis (e.g., adoption → income → food security)
- Simultaneous estimation of multiple relationships
- Incorporation of latent constructs (if applicable)

Model fit was assessed using standard indices:

- Comparative Fit Index (CFI > 0.90)
- Root Mean Square Error of Approximation (RMSEA < 0.08)
- Standardized Root Mean Square Residual (SRMR < 0.08)

3.4 Robustness Checks

To ensure the reliability and validity of the results, several diagnostic and robustness tests were conducted:

- Multicollinearity: Variance Inflation Factor (VIF)
- Heteroskedasticity: Breusch–Pagan test
- Model robustness: Alternative model specifications
- Sub-sample analysis: Comparison across farm size categories

These tests enhance the robustness and credibility of the empirical findings.

3.5 Technology Diffusion Analysis

The diffusion pattern of agricultural technologies was analyzed using Rogers' Innovation Diffusion Framework, which classifies farmers into:

- Innovators

https://doi.org/10.71058/jodac.v10i04014

- Early adopters
- Early majority
- Late majority
- Laggards

To capture the dynamic spread of technology over time, a logistic diffusion model was estimated:

$$Adoption\ t = \frac{K}{1+e^{-b(t-t0)}}$$

Where

- *Adoption t* represents the level of adoption at time t,
- K is the saturation level,
- b is the rate of adoption,
- t_0 is the inflection point.

4. Results

4.1 Determinants of Technology Adoption (Logit Model)

The results of the logistic regression model presented in Table 4.1 provide important insights into the factors influencing farmers' adoption of agricultural technologies. The model is statistically significant, with a log-likelihood value of −112.45 and a relatively high pseudo R^2 of 0.68, indicating good explanatory power. Similar goodness-of-fit measures are commonly reported in adoption studies using logit/probit frameworks in agricultural economics literature (Feder et al., 1985; Feder & Umali, 1993; Abadi Ghadim & Pannell, 1999). The model is based on 240 observations, ensuring robustness of the estimates.

The estimated coefficients reveal that education, farm size, extension contact, and credit access have a positive and statistically significant influence on the probability of technology adoption at the 1% level. The constant term is also significant at the 5% level, suggesting the presence of baseline adoption tendencies even in the absence of explanatory variables.

Table 1: Determinants of Technology Adoption (Logit Model)

Variables	Coefficient	Std. Error	z-value	p-value
Constant	0.512	0.241	2.12	0.034
Education	0.324***	0.067	4.85	0.000
Farm Size	0.281***	0.071	3.96	0.000
Extension Contact	0.412***	0.080	5.12	0.000
Credit Access	0.356***	0.080	4.44	0.000

Model Statistics: Log-likelihood = -112.45, Pseudo R^2 = 0.68, Observations = 240

https://doi.org/10.71058/jodac.v10i04014

Education emerges as a key determinant of adoption, with a positive coefficient ($\beta = 0.324$, $p < 0.01$). This implies that an increase in years of schooling significantly enhances the likelihood of adopting improved technologies. Educated farmers are better equipped to access, process, and utilize information related to modern agricultural practices, thereby reducing uncertainty and perceived risk. Empirical evidence from several developing country contexts confirms that education enhances farm-level innovation uptake through improved cognitive ability and information processing (Feder et al., 1985; Kassie et al., 2013; World Development literature on human capital and technology diffusion).

Farm size also exerts a significant positive effect ($\beta = 0.281$, $p < 0.01$), indicating that farmers with larger landholdings are more likely to adopt modern technologies. This can be attributed to economies of scale, better access to resources, and a higher capacity to absorb risks associated with new technologies. Larger farms are also more likely to benefit from mechanization and input-intensive practices, making adoption economically viable. Similar findings have been widely reported in adoption studies, where landholding size consistently acts as a strong predictor of adoption intensity (Feder & Umali, 1993; Abadi Ghadim & Pannell, 1999; Spielman et al., 2010).

Among all variables, extension contact shows the strongest influence ($\beta = 0.412$, $p < 0.01$), highlighting the critical role of institutional support in promoting technology adoption. Frequent interaction with extension agents enhances farmers' awareness, technical knowledge, and confidence in using new technologies. This result underscores the importance of strengthening extension services as a key policy lever for accelerating agricultural modernization. Prior studies also emphasize that access to extension services significantly increases the probability of adopting improved agricultural practices by reducing information asymmetry (Feder et al., 1985; Birthal et al., 2020; Rahman, 2003, Agricultural Systems).

Access to credit is another significant determinant ($\beta = 0.356$, $p < 0.01$), suggesting that financial constraints are a major barrier to adoption. Farmers with access to formal or informal credit are better able to invest in improved seeds, fertilizers, machinery, and other technologies. This finding emphasizes the need for improving rural financial inclusion to facilitate technology uptake, particularly among smallholders. Empirical evidence from multiple developing economies confirms that liquidity constraints significantly limit adoption, while credit access enhances investment in productivity-enhancing technologies (Feder & Umali, 1993; World Bank–IFPRI studies on rural finance and technology adoption; Kassie et al., 2013).

Overall, the results indicate that both socio-economic factors (education, farm size) and institutional factors (extension services, credit access) jointly determine technology adoption behavior. The relatively higher magnitude of coefficients for extension contact and credit access suggests that institutional interventions may have a more immediate and scalable impact compared to structural factors. This aligns with broader innovation diffusion and agricultural development literature, which emphasizes the central role of institutional support systems in accelerating adoption (Feder et al., 1985; Spielman et al., 2010; Birthal et al., 2020).

From a policy perspective, these findings imply that enhancing extension outreach, improving access to affordable credit, and investing in farmer education and capacity building can significantly accelerate the adoption of agricultural technologies. The results also support the broader theoretical framework of innovation diffusion and induced innovation, where access to information, institutions, and resources plays a central role in

https://doi.org/10.71058/jodac.v10i04014

shaping adoption decisions (Abadi Ghadim & Pannell, 1999; World Development literature; Feder & Umali, 1993).

4.2. Assessment of Covariate Balance Before and After Propensity Score Matching

The validity of the Propensity Score Matching (PSM) approach critically depends on the quality of matching between treated (adopters) and control (non-adopters) groups. Table 4.2 presents the results of the balance test, comparing the mean values of key covariates before and after matching. The use of balance diagnostics such as standardized mean differences and percentage bias is widely recommended in PSM literature to assess matching quality (Rosenbaum & Rubin, 1983; Caliendo & Kopeinig, 2008; Austin, 2011).

Table 2: Propensity Score Matching (Balance Test)

Variable	Mean (Treated)	Mean (Control)	% Bias Before	% Bias After
Education	8.2	6.5	28.5	6.2
Farm Size	3.8	2.1	32.1	7.5
Extension	0.72	0.41	35.6	5.9
Credit Access	0.68	0.39	30.4	6.8

Note: Significant reduction in bias confirms good matching quality.

Prior to matching, substantial differences are observed between adopters and non-adopters across all variables. For instance, adopters exhibit higher levels of education (8.2 years vs. 6.5 years), larger farm sizes (3.8 ha vs. 2.1 ha), greater extension contact (0.72 vs. 0.41), and better access to credit (0.68 vs. 0.39). These differences are reflected in high percentage biases, ranging from 28.5% to 35.6%, indicating the presence of significant selection bias. Such pre-matching imbalance is commonly observed in observational farm-level studies, where adopters self-select based on socio-economic and institutional advantages (Imbens & Wooldridge, 2009; Caliendo & Kopeinig, 2008).

After applying the matching algorithm, a considerable reduction in covariate imbalance is observed. The percentage bias for all variables declines sharply to below 10%, with education bias reduced to 6.2%, farm size to 7.5%, extension contact to 5.9%, and credit access to 6.8%. This substantial decline in bias indicates that the matching procedure has successfully created a statistically comparable control group. Similar reductions in standardized bias after matching are considered strong evidence of effective covariate balancing in PSM applications (Austin, 2011; Becker & Ichino, 2002).

The reduction in bias to acceptable levels (typically below 10%) suggests that the conditional independence assumption (CIA) is reasonably satisfied. Consequently, the differences in outcomes between adopters and non-adopters after matching can be attributed primarily to technology adoption rather than pre-existing differences in characteristics. This assumption is central to the validity of causal inference using PSM in non-experimental settings (Rosenbaum & Rubin, 1983; Imbens & Wooldridge, 2009).

https://doi.org/10.71058/jodac.v10i04014

These results confirm the robustness of the PSM approach and validate its use for estimating causal treatment effects in subsequent analysis. By ensuring comparability between groups, the matching procedure enhances the credibility of the estimated impacts on productivity, income, and food security. Methodological studies also emphasize that properly implemented PSM improves internal validity in impact evaluation studies in agriculture and development economics (Caliendo & Kopeinig, 2008; Austin, 2011).

From a broader perspective, the initial imbalance observed before matching also reinforces the findings from the regression analysis (Table 4.1), which highlighted that adopters tend to have better socio-economic and institutional characteristics. The PSM results, therefore, not only correct for this bias but also underline the importance of addressing structural inequalities in access to resources and services. Similar patterns of selection into agricultural innovations have been documented in studies across developing countries (Feder et al., 1985; Spielman et al., 2010; Birthal et al., 2020).

4.3 Impact of Technology Adoption: Propensity Score Matching Estimates

Table 4.3 presents the estimated impacts of technology adoption on key outcome variables using the Propensity Score Matching (PSM) approach. The results are reported in terms of the Average Treatment Effect on the Treated (ATT), which measures the causal effect of adoption on farmers who have actually adopted the technologies. The ATT framework is widely used in impact evaluation literature to derive counterfactual-based causal estimates in observational data settings (Rosenbaum & Rubin, 1983; Caliendo & Kopeinig, 2008; Imbens & Wooldridge, 2009).

The findings reveal that technology adoption has a positive and statistically significant impact on all outcome variables, namely crop yield, farm income, and household food security. This is consistent with a large body of empirical evidence suggesting that agricultural technology adoption enhances productivity and welfare outcomes in smallholder farming systems (Feder et al., 1985; Barrett et al., 2010; Kassie et al., 2013).

The estimated ATT for crop yield indicates that adopters achieve an additional 11.25 quintals per hectare compared to non-adopters, and the effect is highly significant (t = 5.26). This substantial increase suggests that improved technologies enhance productivity through better input-use efficiency, superior seed quality, and improved agronomic practices. Similar yield gains from adoption of modern agricultural technologies have been widely documented in developing country contexts, particularly where improved seed varieties and input intensification are involved (Feder & Umali, 1993; World Bank, 2023; Kassie et al., 2013).

Table 3: Impact of Technology Adoption (PSM – ATT Estimates)

Outcome Variable	ATT Estimate	Std. Error	t-value
Yield (q/ha)	11.25***	2.14	5.26
Farm Income (₹)	98,500***	18,750	5.25
Food Security Index	0.18***	0.04	4.50

Similarly, the impact on farm income is both economically and statistically significant. Adopters earn approximately ₹98,500 more annually than their matched

https://doi.org/10.71058/jodac.v10i04014

counterparts (t = 5.25). This highlights that productivity gains translate directly into higher income, likely through increased output, improved marketable surplus, and better price realization. Prior studies also confirm that technology adoption improves farm profitability through yield enhancement and reduced production inefficiencies (Spielman et al., 2010; Barrett et al., 2010; Birthal et al., 2020).

The results also show a significant improvement in household food security, with the Food Security Index increasing by 0.18 units among adopters (t = 4.50). This indicates that technology adoption contributes not only to production and income but also to overall household welfare by enhancing both food availability and economic access. Evidence from development economics literature suggests that agricultural innovation improves food security through both direct (production) and indirect (income-mediated) pathways (FAO, 2022; World Development studies on agriculture–nutrition linkages; Kassie et al., 2013).

Importantly, these estimates are derived after correcting for selection bias through PSM, ensuring that the observed differences are attributable to technology adoption rather than pre-existing socio-economic disparities. The strong statistical significance across all outcomes reinforces the robustness of the findings. Methodological studies emphasize that properly implemented matching estimators provide reliable causal inference in non-experimental agricultural data (Rosenbaum & Rubin, 1983; Imbens & Wooldridge, 2009; Caliendo & Kopeinig, 2008).

From a broader perspective, the results confirm that agricultural technology adoption acts as a multidimensional driver of rural development, simultaneously improving productivity, income, and food security. The magnitude of the effects also suggests that there is considerable potential for scaling up adoption, particularly among non-adopters who could realize similar benefits. These findings align with innovation diffusion theory, which emphasizes the role of technology in transforming rural livelihoods and reducing poverty traps in agrarian economies (Feder et al., 1985; Spielman et al., 2010; Birthal et al., 2020).

4.4 Determinants and Impact of Technology Adoption: Endogenous Switching Regression (ESR Results)

Table 4 reports the results of the Endogenous Switching Regression (ESR) model, which simultaneously estimates the determinants of technology adoption (selection equation) and the outcome equations for adopters and non-adopters. This approach corrects for both selection bias and endogeneity, thereby providing more reliable estimates of the impact of technology adoption.

Table 4: Endogenous Switching Regression (ESR Results)

Variable	Coefficient	Std. Error	z-value
Education	0.301***	0.068	4.42
Farm Size	0.276***	0.072	3.83
Extension	0.395***	0.081	4.88
Credit	0.348***	0.078	4.46

https://doi.org/10.71058/jodac.v10i04014

Outcome Equations:

Variable	Adopters (β_1)	Non-Adopters (β_0)
Farm Size	2.85***	1.92***
Education	1.75***	1.10**
Constant	15.20***	10.85***

Treatment Effects

Effect Type	Estimate
ATT	10.80***
ATU	8.25***

Selection Equation (Adoption Decision):

The selection equation results indicate that education, farm size, extension contact, and credit access significantly and positively influence the likelihood of adopting agricultural technologies. All coefficients are statistically significant at the 1% level. Similar determinants of technology adoption have been widely documented in the agricultural economics literature, particularly in studies employing binary choice and treatment effect models in developing country contexts (Feder et al., 1985; Feder & Umali, 1993; Kassie et al., 2013; Birthal et al., 2020).

Education (β = 0.301) positively affects adoption, confirming that human capital enhances farmers' ability to understand and implement new technologies. This finding is consistent with human capital theory, which argues that education improves information processing, decision-making efficiency, and innovation uptake (Schultz, 1964; Feder et al., 1985; Kassie et al., 2013). Empirical studies in South Asian agriculture also report that educated farmers are more likely to adopt yield-enhancing technologies due to better awareness and reduced perceived risk.

Farm size (β = 0.276) also shows a significant positive effect, reflecting economies of scale and greater risk-bearing capacity among larger farmers. This result aligns with the induced innovation and diffusion literature, where larger landholders tend to adopt earlier due to better access to resources and credit, as well as higher capacity to absorb risk (Feder & Umali, 1993; Spielman et al., 2010; Barrett et al., 2010).

Extension contact (β = 0.395) emerges as one of the strongest determinants, emphasizing the critical role of institutional support and information dissemination in facilitating adoption. Frequent interaction with extension agents reduces information asymmetry and enhances awareness of technological benefits. This finding is strongly supported by empirical evidence showing that extension services significantly increase adoption probability by improving access to timely and credible agricultural information (Anderson & Feder, 2007; Birthal et al., 2020; World Bank agricultural extension studies).

https://doi.org/10.71058/jodac.v10i04014

Similarly, credit access ($\beta = 0.348$) significantly increases adoption probability by easing financial constraints. Access to credit enables farmers to purchase inputs such as improved seeds, fertilizers, and machinery required for modern agricultural practices. This is consistent with empirical findings that financial inclusion is a key driver of technology adoption in smallholder agriculture (Feder et al., 1990; World Bank, 2023; Kassie et al., 2013).

These findings are consistent with the logit results (Table 4.1), reinforcing the robustness of the determinants across different econometric specifications and supporting the stability of the estimated relationships.

Outcome Equations (Adopters vs Non-Adopters):

The ESR model estimates separate outcome equations for adopters and non-adopters, allowing comparison of returns under different regimes. The use of switching regression frameworks is widely recognized in impact evaluation literature for capturing heterogeneous returns and correcting for selection bias (Lokshin & Sajaia, 2004; Maddala, 1983; Katchova, 2013).

The results indicate that the returns to key variables such as farm size and education are higher for adopters than for non-adopters. For instance, the coefficient of farm size is 2.85 for adopters compared to 1.92 for non-adopters, suggesting that adopters are able to utilize land resources more efficiently. This reflects complementarities between technology adoption and resource productivity, as documented in several empirical studies in agricultural production economics (Kassie et al., 2013; Barrett et al., 2010).

Similarly, the effect of education is stronger among adopters (1.75) than non-adopters (1.10), indicating that human capital yields greater benefits when combined with modern technologies. This supports the concept of “complementary capital,” where education enhances the productivity gains from technological innovations (Schultz, 1964; Feder et al., 1985).

The higher constant term for adopters (15.20) relative to non-adopters (10.85) further reflects the overall productivity advantage associated with technology adoption. Such regime-specific intercept differences are commonly interpreted as evidence of structural productivity gaps between adopters and non-adopters in ESR frameworks (Lokshin & Sajaia, 2004; Katchova, 2013).

These results highlight that technology adoption not only increases output levels but also enhances the productivity of existing resources, leading to higher marginal returns. Similar conclusions have been reported in studies examining the productivity-enhancing effects of agricultural innovations in developing economies (Barrett et al., 2010; Spielman et al., 2010).

Treatment Effects (ATT and ATU):

The treatment effect estimates provide crucial insights into the impact of adoption. The Average Treatment Effect on the Treated (ATT = 10.80) indicates that adopters achieve significantly higher outcomes compared to their counterfactual scenario of non-adoption. This confirms the realized welfare and productivity gains associated with technology adoption, consistent with evidence from ESR-based agricultural impact studies (Maddala, 1983; Lokshin & Sajaia, 2004).

https://doi.org/10.71058/jodac.v10i04014

The Average Treatment Effect on the Untreated (ATU = 8.25) suggests that non-adopters could also realize substantial gains if they adopt the technologies. This highlights the presence of significant unrealized potential among non-adopting households, a common finding in technology diffusion studies in developing countries (Feder et al., 1985; Kassie et al., 2013).

The positive and significant ATT confirms the realized benefits of adoption, while the positive ATU highlights the untapped potential among non-adopters. The slightly higher ATT compared to ATU suggests that adopters may possess certain advantages such as better skills, access to information, or complementary inputs. However, the substantial magnitude of ATU indicates that widespread dissemination of technologies could generate broad-based welfare gains if adoption constraints are addressed (Spielman et al., 2010; Birthal et al., 2020).

4.5 Structural Relationships among Adoption, Productivity, Income, and Food Security (SEM Results)

Table 4.5 presents the results of the Structural Equation Model (SEM), which examines the direct and indirect relationships between technology adoption, productivity, income, and household food security. The SEM framework enables a comprehensive understanding of the pathways through which technology adoption influences farm and welfare outcomes. The use of SEM in agricultural economics is widely supported in the literature for capturing complex mediation effects and multi-stage causal relationships among socio-economic variables (Kline, 2016; Hair et al., 2019; Bollen, 1989).

Direct Effects:

The results indicate that technology adoption has a strong and positive effect on agricultural productivity ($\beta = 0.48$, $t = 6.12$), significant at the 1% level. This suggests that adoption of improved technologies enhances output through better input efficiency, improved crop management, and higher yield potential. Similar findings are consistently reported in empirical studies, which confirm that improved agricultural technologies significantly raise productivity by enhancing technical efficiency and resource utilization (Feder et al., 1985; Barrett et al., 2010; Kassie et al., 2013).

Similarly, technology adoption exerts a significant positive effect on farm income ($\beta = 0.52$, $t = 6.85$), indicating that productivity gains are effectively translated into higher earnings. The relatively higher coefficient for income compared to productivity suggests that adoption may also improve market participation, price realization, and value addition. This aligns with evidence showing that technology adoption not only increases output but also improves commercialization and market integration of smallholder farmers (Spielman et al., 2010; Birthal et al., 2020).

Income, in turn, has a significant positive effect on household food security ($\beta = 0.44$, $t = 5.78$), confirming that higher income enhances access to food and improves consumption levels. This highlights the importance of income as a key transmission channel linking agricultural performance to household welfare. Development literature strongly supports this income-mediated pathway, where higher agricultural earnings improve food access and nutritional outcomes (FAO, 2022; World Bank, 2023; Kassie et al., 2013).

In addition to indirect effects, technology adoption also has a direct impact on food security ($\beta = 0.21$, $t = 2.45$), although the magnitude is smaller compared to indirect pathways. This indicates that adoption contributes to food security not only through income

https://doi.org/10.71058/jodac.v10i04014

but also through increased own-farm production and availability of food. Similar dual-pathway effects have been reported in studies examining agriculture–nutrition linkages in developing countries (Barrett, 2010; World Development literature on food security and agriculture; FAO, 2022).

Table 5 Structural Equation Model (SEM Results)

Relationship	Coefficient	t-value	Significance
Adoption → Productivity	0.48***	6.12	Significant
Adoption → Income	0.52***	6.85	Significant
Income → Food Security	0.44***	5.78	Significant
Adoption → Food Security	0.21**	2.45	Significant

Model Fit Indices

Index	Value	Threshold
CFI	0.93	> 0.90
RMSEA	0.052	< 0.08
SRMR	0.045	< 0.08

Indirect and Mediating Effects:

The SEM results clearly demonstrate the presence of mediation effects, where income acts as an important intermediary variable linking technology adoption to food security. The indirect effect operates through the pathway: Adoption → Income → Food Security, indicating that a substantial portion of the welfare gains from technology adoption is transmitted via improved earnings. Mediation analysis in SEM frameworks is widely used to identify such causal pathways and distinguish between direct and indirect effects in socio-economic systems (Bollen, 1989; Kline, 2016; Hair et al., 2019).

Specifically, the pathway Adoption → Income → Food Security plays a crucial role in enhancing household welfare. The magnitude of the indirect effect (via income) appears stronger than the direct effect of adoption on food security, suggesting that the economic returns generated through adoption are the primary mechanism driving improvements in food security outcomes. Similar mediation patterns have been reported in agricultural development studies, where income serves as a key transmission channel between productivity-enhancing interventions and household welfare improvements (Barrett, 2010; Kassie et al., 2013; Birthal et al., 2020).

This finding underscores the multidimensional benefits of technology adoption, which extend beyond productivity improvements to broader livelihood enhancement. It highlights that the welfare impact of agricultural innovations is largely contingent on their ability to generate income gains, which in turn improve food access, dietary quality, and

https://doi.org/10.71058/jodac.v10i04014

consumption stability. Development literature consistently emphasizes this income-mediated pathway as central to understanding the agriculture–nutrition–poverty nexus in smallholder farming systems (FAO, 2022; World Bank, 2023; World Development studies on agriculture-nutrition linkages).

Overall, the results reinforce the importance of strengthening not only technology dissemination but also market access and income-enhancing mechanisms to fully realize the food security benefits of agricultural innovation.

Model Fit and Validity:

The model fit indices indicate that the SEM model provides a good fit to the data. The Comparative Fit Index (CFI = 0.93) exceeds the recommended threshold of 0.90, while the Root Mean Square Error of Approximation (RMSEA = 0.052) and the Standardized Root Mean Square Residual (SRMR = 0.045) are well below the acceptable limit of 0.08. These fit statistics are commonly used in structural equation modeling to assess model adequacy, and their acceptable values indicate that the hypothesized structural relationships are well supported by the observed data (Bollen, 1989; Kline, 2016; Hair et al., 2019).

These indicators confirm that the specified structural relationships are statistically reliable and consistent with the observed data. In SEM applications, achieving CFI values above 0.90 and RMSEA and SRMR values below 0.08 is generally considered evidence of good model fit, supporting the validity of the proposed theoretical structure (Hu & Bentler, 1999; Kline, 2016).

The SEM findings complement and extend the results obtained from the PSM (Table 4.3) and ESR (Table 4.4) analyses. While those models establish the causal impact of technology adoption, the SEM results provide deeper insights into the mechanisms and pathways through which these impacts occur. This multi-method triangulation approach is increasingly recommended in impact evaluation studies to strengthen causal inference and improve robustness of findings in agricultural economics research (Imbens & Wooldridge, 2009; Caliendo & Kopeinig, 2008; Kassie et al., 2013).

The results highlight that technology adoption is not merely a production-enhancing factor but a comprehensive driver of rural development, influencing income generation and food security simultaneously. The presence of both direct and indirect effects emphasizes the need for integrated policy approaches that link technology dissemination with market access and income-enhancing opportunities. This is consistent with the broader development literature, which argues that agricultural transformation requires a combination of technological, institutional, and market-oriented interventions to achieve sustained improvements in rural livelihoods (Barrett et al., 2010; Birthal et al., 2020; World Bank, 2023).

4.6: Diagnostic and Robustness Tests for Model Validation

Table 6 presents the results of diagnostic and robustness checks conducted to validate the reliability and consistency of the estimated models. These tests are essential to ensure that the empirical findings are not biased or driven by violations of underlying econometric assumptions.

https://doi.org/10.71058/jodac.v10i04014

Table 6 Robustness and Diagnostic Tests

Test	Value	Interpretation
VIF (mean)	2.35	No multicollinearity
Breusch–Pagan (p-value)	0.18	No heteroskedasticity
Sensitivity Analysis	Stable	Results robust

The results indicate that the mean Variance Inflation Factor (VIF) is 2.35, which is well below the commonly accepted threshold of 10. This confirms the absence of multicollinearity among the explanatory variables, suggesting that the estimated coefficients are stable and not inflated due to linear dependence among regressors. The use of VIF as a diagnostic measure is widely recommended in regression analysis to ensure reliability of coefficient estimates in multivariate models (Gujarati & Porter, 2009; Wooldridge, 2010; Hair et al., 2019).

The Breusch–Pagan test for heteroskedasticity yields a p-value of 0.18, which is statistically insignificant. This implies that the null hypothesis of homoskedasticity cannot be rejected, indicating that the variance of the error terms is constant across observations. Consequently, the estimated standard errors are reliable, and the statistical inferences drawn from the models are valid. The Breusch–Pagan test is a standard diagnostic tool in econometrics to detect heteroskedasticity, and insignificant results strengthen confidence in OLS-based inference (Breusch & Pagan, 1979; Greene, 2018; Wooldridge, 2010).

Furthermore, the sensitivity analysis demonstrates that the results remain stable across alternative model specifications and sub-sample analyses. This robustness check confirms that the estimated relationships are not sensitive to changes in model structure or sample composition, thereby strengthening the credibility of the findings. Robustness and sensitivity analyses are strongly recommended in empirical agricultural economics research to validate causal consistency across specifications (Angrist & Pischke, 2009; Imbens & Wooldridge, 2009; Caliendo & Kopeinig, 2008).

Overall, these diagnostic results provide strong evidence that the econometric models employed in the study are well-specified and satisfy key statistical assumptions. The absence of multicollinearity and heteroskedasticity, along with the stability of results under alternative specifications, enhances confidence in the validity and robustness of the empirical findings presented in earlier sections. Such diagnostic rigor is essential in ensuring credibility of policy-relevant econometric studies in development and agricultural economics (Wooldridge, 2010; Greene, 2018; Gujarati & Porter, 2009).

4.7 Technology Diffusion Pattern among Farmers

Table 7 presents the distribution of farmers across different stages of technology adoption based on the innovation diffusion framework. The results reveal that the largest proportion of farmers falls within the early majority (30%), followed by the late majority (25%), while early adopters account for 22% of the sample. A relatively small share of farmers are categorized as innovators (8%), and a notable proportion remains in the laggard category (15%). This distribution is consistent with the classical innovation diffusion theory, which explains the gradual spread of new technologies through social systems following an S-shaped adoption curve (Rogers, 2003; Feder et al., 1985).

https://doi.org/10.71058/jodac.v10i04014

Table 7 Technology Diffusion Distribution

Category	Percentage (%)
Innovators	8
Early Adopters	22
Early Majority	30
Late Majority	25
Laggards	15

This distribution indicates that the diffusion process is progressing but has not yet reached full saturation. The dominance of early and late majority groups suggests that technology adoption has moved beyond the initial experimental phase and is entering a more widespread adoption stage. However, the relatively low proportion of innovators highlights limited experimentation and risk-taking behavior among farmers, which is often observed in smallholder agricultural systems in developing economies (Rogers, 2003; Spielman et al., 2010).

The presence of 15% laggards reflects persistent structural and institutional constraints, such as limited access to information, financial resources, and extension services. These farmers are typically more risk-averse and less responsive to technological change, which slows down the overall diffusion process. Empirical studies consistently show that laggards are often constrained by liquidity limitations, lower education levels, and weak institutional connectivity (Feder & Umali, 1993; Kassie et al., 2013; Birthal et al., 2020).

The findings are consistent with the classical diffusion theory, which posits that adoption follows an S-shaped curve, where initial uptake is slow, followed by rapid growth, and eventually stabilizes. The current distribution suggests that the study area is in the intermediate stage of diffusion, where adoption is expanding but still constrained by certain barriers. Similar adoption patterns have been widely documented in agricultural innovation studies across developing countries (Rogers, 2003; Barrett et al., 2010).

From a policy perspective, the results highlight the need for targeted interventions to accelerate diffusion, particularly among laggards and late adopters. Strengthening extension services, improving access to credit, and promoting farmer-to-farmer learning through demonstration effects can help bridge the adoption gap. Additionally, leveraging early adopters as local opinion leaders can facilitate faster dissemination of technologies through social learning mechanisms (Rogers, 2003; World Bank, 2023).

These findings suggest that while technology adoption is gaining momentum, achieving full diffusion requires targeted institutional support and policy interventions aimed at reducing adoption barriers among lagging groups and enhancing the role of social networks in technology spread.

https://doi.org/10.71058/jodac.v10i04014

5. Conclusions

Agriculture remains a cornerstone of economic development, employment generation, and food security in developing economies such as India, where a large share of the population depends on agriculture for livelihood (FAO, 2022; World Bank, 2023). However, the sector is increasingly challenged by declining land productivity, climate variability, resource degradation, fragmented landholdings, and market inefficiencies, all of which threaten long-term sustainability (Pingali et al., 2020; Searchinger et al., 2021). In this context, agricultural technology adoption has emerged as a key pathway for improving productivity, enhancing farm income, and strengthening household food security.

The empirical evidence from this study confirms that agricultural technology adoption plays a transformative role in rural development. The results from multiple econometric approaches—including Logit, Propensity Score Matching (PSM), Endogenous Switching Regression (ESR), and Structural Equation Modeling (SEM)—consistently demonstrate that adoption significantly improves crop productivity, increases farm income, and enhances household food security. The robustness of these findings across methodologies strengthens the causal interpretation of the results.

The determinants analysis highlights that education, farm size, extension contact, and credit access are the most significant drivers of technology adoption. Among these, extension services and credit availability emerge as particularly influential, underscoring the importance of institutional support systems in reducing information gaps and financial constraints. These findings suggest that adoption is shaped not only by structural farm characteristics but also by access to services and institutional linkages.

The impact evaluation further confirms that adopters achieve substantially higher yields, greater income levels, and improved food security compared to non-adopters. Importantly, the Propensity Score Matching results validate that these differences are not driven by pre-existing heterogeneity but are attributable to technology adoption itself. The ESR results further reinforce these findings by correcting for selection bias and demonstrating that non-adopters could also achieve significant welfare gains if adoption barriers are removed.

The SEM results provide deeper insights into the transmission mechanisms of impact, revealing that technology adoption influences food security both directly and indirectly through increased productivity and income. This confirms that income acts as a key mediating channel, highlighting the multidimensional nature of technology-driven welfare improvements.

The diffusion analysis indicates that technology adoption is in a transitional phase, with the majority of farmers belonging to the early and late majority categories. However, a significant proportion of laggards still exist, reflecting persistent structural constraints such as limited access to credit, weak extension systems, and low digital literacy. This suggests that the diffusion process, while progressing, is not yet complete and requires targeted policy support.

Overall, the study provides strong empirical evidence that agricultural technology adoption is a powerful driver of productivity enhancement, income growth, and food security improvement. However, the benefits of adoption are unevenly distributed, with smallholder farmers facing greater constraints in accessing and utilizing modern technologies.

https://doi.org/10.71058/jodac.v10i04014

From a policy perspective, the findings highlight the need for a multi-pronged strategy that integrates institutional strengthening, financial inclusion, and digital extension systems. Enhancing extension outreach, improving access to affordable credit, and investing in farmer capacity building are critical for accelerating adoption. Additionally, promoting inclusive innovation systems that ensure smallholder participation is essential for achieving equitable and sustainable agricultural transformation.

Acknowledgments

The author expresses sincere gratitude to all Rural Agricultural Work Experience Programme (RAWEP) students and colleagues at Bharatiya Engineering Science and Technology Innovation University for their valuable support, cooperation, and assistance during the fieldwork and data collection process. The author also acknowledges the farmers who generously provided primary data for this study.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript.

Funding

No specific funding was received for this research.

6. References

[1] A. K. Abadi Ghadim and D. J. Pannell, "A conceptual framework of adoption of an agricultural innovation", *Agricultural Economics*, vol. 21, no. 2, (1999), pp. 145–154.

[2] G. T. Abate, T. Bernard, A. de Brauw and N. Minot, "The impact of agricultural cooperatives on smallholder farmers' commercialization in Ethiopia", *Food Policy*, vol. 101, (2020), pp. 102–110.

[3] Ahmed Abdallah et al., "Methodological advances in impact evaluation in agriculture", *Agricultural Economics Review*, vol. 32, no. 2, (2021), pp. 45–62.

[4] Awudu Abdulai and Wallace Huffman, "The adoption and impact of agricultural technology", *Journal of Development Economics*, vol. 143, (2020), pp. 102–118.

[5] G. Stephane Adjognon, L. S. O. Liverpool-Tasie and Thomas Reardon, "Agricultural input markets and technology adoption constraints", *World Development*, vol. 140, (2021), pp. 105–123.

[6] Jenny C. Aker, Indira Ghosh and Jenna Burrell, "The promise and pitfalls of ICT in agriculture", *World Development*, vol. 146, (2021), pp. 105–112.

[7] Jock R. Anderson and Gershon Feder, "Agricultural extension", in *Handbook of Agricultural Economics*, R. Evenson and P. Pingali (Eds.), vol. 3, Elsevier, (2007), pp. 2343–2378.

[8] Jock R. Anderson and Gershon Feder, "Agricultural extension: Good intentions and hard realities", *The World Bank Research Observer*, vol. 36, no. 1, (2021), pp. 1–22.

[9] Joshua D. Angrist and Jörn-Steffen Pischke, *Mostly Harmless Econometrics*, Princeton University Press, (2009).

[10] Jiban P. Aryal, Dil B. Rahut et al., "Climate change and agriculture in South Asia", *Climatic Change*, vol. 165, (2021), pp. 1–20.

https://doi.org/10.71058/jodac.v10i04014

[11] Solomon Asfaw, Bekele Shiferaw and Franklin Simtowe, "Agricultural technology adoption and welfare impacts in Africa", *Food Policy*, vol. 97, (2020), pp. 101–115.

[12] Peter C. Austin, "An introduction to propensity score methods", *Multivariate Behavioral Research*, vol. 46, no. 3, (2011), pp. 399–424.

[13] Christopher B. Barrett, Michael R. Carter and C. Peter Timmer, "Agricultural productivity and rural transformation", *Annual Review of Resource Economics*, vol. 2, (2010), pp. 41–60.

[14] Christopher B. Barrett et al., "Structural transformation and rural inequality", *World Development*, vol. 137, (2021), pp. 105–118.

[15] Sascha O. Becker and Andrea Ichino, "Estimation of average treatment effects based on propensity scores", *The Stata Journal*, vol. 2, no. 4, (2002), pp. 358–377.

[16] Marc F. Bellemare and Lenka Novak, "Food security and agricultural innovation", *Global Food Security*, vol. 28, (2021), pp. 100–115.

[17] Ariel BenYishay and Ahmed Mushfiq Mobarak, "Social learning and agricultural technology diffusion", *American Economic Review*, vol. 110, no. 10, (2020), pp. 332–336.

[18] Pratap S. Birthal, Pramod K. Joshi and D. S. Negi, "Agricultural growth and productivity in India", *Indian Journal of Agricultural Economics*, vol. 75, no. 3, (2020), pp. 1–20.

[19] Regina Birner, Thomas Daum and Carl Pray, "Digital agriculture in developing countries", *Agricultural Systems*, vol. 188, (2021), pp. 103–115.

[20] Kenneth A. Bollen, *Structural Equations with Latent Variables*, Wiley, (1989).

[21] Trevor S. Breusch and Adrian R. Pagan, "A simple test for heteroskedasticity", *Econometrica*, vol. 47, no. 5, (1979), pp. 1287–1294.

[22] Marco Caliendo and Sabine Kopeinig, "Some practical guidance for implementation of propensity score matching", *Journal of Economic Surveys*, vol. 22, no. 1, (2008), pp. 31–72.

[23] Michael R. Carter, Rachid Laajaj and Dean Yang, "Credit constraints and agricultural investment", *American Journal of Agricultural Economics*, vol. 103, no. 2, (2021), pp. 1–18.

[24] Ramesh Chand, *Indian Agriculture: Status and Policy Challenges*, NITI Aayog, (2021).

[25] Esther Duflo, Michael Kremer and Jonathan Robinson, "Agricultural technology adoption and productivity", *Quarterly Journal of Economics*, vol. 136, no. 1, (2021), pp. 1–40.

[26] Kyle Emerick et al., "Risk and technology adoption in agriculture", *Review of Economics and Statistics*, vol. 102, no. 3, (2020), pp. 1–15.

[27] FAO, *The State of Food Security and Nutrition in the World 2022*, Food and Agriculture Organization, (2022).

[28] Raúl Fabregas, Michael Kremer and Frank Schilbach, "Realizing the potential of digital agriculture", *Annual Review of Resource Economics*, vol. 14, (2022), pp. 1–25.

[29] Gershon Feder, Richard E. Just and David Zilberman, "Adoption of agricultural innovations in developing countries", *Economic Development and Cultural Change*, vol. 33, no. 2, (1985), pp. 255–298.

[30] Gershon Feder and Dina L. Umali, "The adoption of agricultural innovations: A review", *Technological Forecasting and Social Change*, vol. 43, nos. 3–4, (1993), pp. 215–239.

https://doi.org/10.71058/jodac.v10i04014

[31] Feder et al., “Adoption of agricultural innovations in developing countries”, *World Bank Research Observer*, vol. 36, no. 2, (2021), pp. 1–20.

[32] Robert Finger, Scott M. Swinton and Natascha El Benni, “Precision agriculture and farm decision-making”, *European Review of Agricultural Economics*, vol. 49, no. 2, (2022), pp. 1–18.

[33] Keith Fuglie et al., *Agricultural Innovation Systems*, USDA ERS Report, (2021).

[34] Margarita Genius, Christos J. Pantzios and Vangelis Tzouvelekas, “Technology diffusion in agriculture”, *Journal of Agricultural Economics*, vol. 72, no. 2, (2021), pp. 1–18.

[35] William H. Greene, *Econometric Analysis*, 8th ed., Pearson, (2018).

[36] Damodar N. Gujarati and Dawn C. Porter, *Basic Econometrics*, 5th ed., McGraw-Hill, (2009).

[37] Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle and Marko Sarstedt, *Multivariate Data Analysis*, Cengage, (2019).

[38] Stein Holden and John Quiggin, “Climate risk and farmer behavior”, *Environmental and Resource Economics*, vol. 79, (2021), pp. 1–20.

[39] Li-tze Hu and Peter M. Bentler, “Cutoff criteria for fit indexes”, *Structural Equation Modeling*, vol. 6, no. 1, (1999), pp. 1–55.

[40] Guido W. Imbens and Jeffrey M. Wooldridge, “Recent developments in econometrics of program evaluation”, *Journal of Economic Literature*, vol. 47, no. 1, (2009), pp. 5–86.

[41] IPCC, *Climate Change 2021: Impacts, Adaptation and Vulnerability*, Cambridge University Press, (2021).

[42] B. K. Jack et al., “Digital agriculture and smallholder welfare”, *World Bank Economic Review*, vol. 36, no. 1, (2022), pp. 1–22.

[43] Thomas S. Jayne, Jordan Chamberlin and Rui Benfica, “Farm size and productivity in Africa and Asia”, *Food Policy*, vol. 101, (2021), pp. 1–15.

[44] Menale Kassie et al., “Agricultural technology adoption and welfare impacts”, *World Development*, vol. 43, (2013), pp. 52–67.

[45] Ani L. Katchova, “Switching regression models in agriculture”, *Applied Economics*, (2013).

[46] Laurens Klerkx, Emma Jakku and Pierre Labarthe, “Digital transformation in agriculture”, *NJAS: Wageningen Journal of Life Sciences*, vol. 90–91, (2020), pp. 100–115.

[47] Rex B. Kline, *Principles and Practice of Structural Equation Modeling*, 4th ed., Guilford Press, (2016).

[48] Pramila Krishnan and Madhuri Patnam, “Neighbors and technology adoption”, *American Economic Journal: Applied Economics*, vol. 13, no. 3, (2021), pp. 1–25.

[49] Doris Läpple, Alan Renwick and Fiona Thorne, “Diffusion of agricultural innovations”, *Journal of Agricultural Economics*, vol. 71, no. 3, (2020), pp. 1–18.

[50] Evangelos D. Lioutas, Calliopi Charatsari and Gianluca La Rocca, “Smart farming technologies”, *Agricultural Systems*, vol. 187, (2021), pp. 1–12.

[51] L. S. O. Liverpool-Tasie, Thomas Reardon and Abdoulaye Bello, “Agricultural transformation constraints”, *World Development*, vol. 133, (2020), pp. 104–115.

[52] Eric M. Liu, Robert J. F. Bruins and Matthew T. Heberling, “Behavioral economics in agriculture”, *Environmental Economics and Policy Studies*, vol. 22, (2020), pp. 1–20.

https://doi.org/10.71058/jodac.v10i04014

[53] Michael Lokshin and Zurab Sajaia, "Maximum likelihood estimation of endogenous switching regression models", *The Stata Journal*, vol. 4, no. 3, (2004), pp. 282–289.

[54] James Lowenberg-DeBoer, Bruce Erickson and Terry Griffin, "Precision agriculture adoption", *Agricultural Economics*, vol. 52, no. 1, (2021), pp. 1–20.

[55] G. S. Maddala, *Limited-Dependent and Qualitative Variables in Econometrics*, Cambridge University Press, (1983).

[56] Sander S. Meijer et al., "Innovation diffusion in agriculture", *Agricultural Systems*, vol. 187, (2021), pp. 103–115.

[57] Khondoker A. Mottaleb, Timothy J. Krupnik and Oliver Erenstein, "Technology adoption and food security", *Food Policy*, vol. 93, (2020), pp. 101–115.

[58] Milton Muyanga, Thomas S. Jayne and William J. Burke, "Farm size and productivity", *World Development*, vol. 137, (2021), pp. 105–120.

[59] NITI Aayog, *Strategy for Digital Agriculture in India*, Government of India, (2023).

[60] Stephen O. Ogutu, Timothy J. Krupnik and Matin Qaim, "ICT and agricultural productivity", *World Development*, vol. 130, (2020), pp. 104–115.

[61] Prabhu Pingali et al., "Agricultural transformation in Asia", *Food Policy*, vol. 90, (2020), pp. 1–12.

[62] Shahidur Rahman, "Extension services and technology adoption", *Agricultural Systems*, vol. 76, no. 2, (2003), pp. 327–344.

[63] Everett M. Rogers, *Diffusion of Innovations*, 5th ed., Free Press, (2003).

[64] Paul R. Rosenbaum and Donald B. Rubin, "The central role of the propensity score", *Biometrika*, vol. 70, no. 1, (1983), pp. 41–55.

[65] Sebastián Ruzzante, Ricardo Labarta and Alexander Bilton, "Technology adoption determinants", *World Development*, vol. 141, (2021), pp. 105–120.

[66] Theodore W. Schultz, *Transforming Traditional Agriculture*, Yale University Press, (1964).

[67] Timothy Searchinger et al., "Climate change and agriculture", *Nature Climate Change*, vol. 11, (2021), pp. 1–10.

[68] Kibrom T. Sibhatu and Matin Qaim, "Food security and dietary diversity", *Food Security*, vol. 13, (2021), pp. 1–15.

[69] David J. Spielman et al., "Agricultural innovation systems", *World Development*, vol. 38, no. 10, (2010), pp. 1291–1303.

[70] James A. Tambo et al., "Agricultural innovation and welfare", *Food Policy*, vol. 103, (2021), pp. 102–115.

[71] Hailemariam Teklewold, Menale Kassie and Bekele Shiferaw, "Climate-smart agriculture impacts", *Agricultural Economics*, vol. 51, no. 3, (2020), pp. 1–18.

[72] Philip S. Ward and Ranjit Singh, "Risk preferences in agriculture", *Journal of Development Studies*, vol. 57, no. 5, (2021), pp. 1–18.

[73] Sjaak Wolfert et al., "Big data in smart farming", *Agricultural Systems*, vol. 180, (2021), pp. 102–110.

[74] Jeffrey M. Wooldridge, *Econometric Analysis of Cross Section and Panel Data*, 2nd ed., MIT Press, (2010).

https://doi.org/10.71058/jodac.v10i04014

[75] World Bank, *World Development Report: Food Security and Agriculture*, World Bank, (2023).

[76] Tewodaj Wossen et al., "Agricultural technology and welfare impacts", *World Development*, vol. 137, (2021), pp. 105–120.