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ASSESSING THE ADOPTION AND INTENSITY OF PADDY TRANSPLANTING MACHINE SERVICES IN THANJAVUR DISTRICT OF TAMIL NADU: A DOUBLE HURDLE APPROACH

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ABSTRACT

This study examines the adoption and intensity of use of paddy transplanting machine services in the Cauvery Delta region of Tamil Nadu, one of the major rice-producing areas in India. Primary data were collected from 120 paddy farmers across selected blocks of Thanjavur district using a purposive-cum-random sampling technique. To capture the two-stage decision-making behaviour of farmers, Cragg's Double Hurdle model was employed, which allows the determinants of adoption and intensity of use to differ. The results indicate that a majority of farmers have adopted machine transplanting services, reflecting a growing shift towards mechanization in paddy cultivation. The econometric findings reveal that farm size, distance to service providers, and perceived yield improvement positively influence adoption, while age and availability of human labour have a significant negative effect. These results highlight the importance of resource endowment, accessibility, and labour dynamics in shaping adoption decisions. With respect to intensity of use, perceived time savings and affordability significantly increase the extent of utilization, suggesting that operational efficiency and cost considerations are key drivers of repeated use. In contrast, high rainfall conditions negatively affect intensity, indicating the influence of climatic factors on mechanization practices. The marginal effects further confirm the strong role of farm size and service accessibility in enhancing participation, while labour availability and adverse weather conditions act as major constraints. The study also identifies weather variability, water management issues, and field-related constraints as important challenges faced by farmers. The findings suggest that improving access to mechanization services, strengthening custom hiring centres, and promoting climate-resilient farming practices are essential for enhancing both adoption and effective utilization of paddy transplanting technologies.
***Keywords*:** Paddy Transplanting Machine Services, Agricultural Mechanization, Adoption and Utilization Intensity, Double Hurdle Model, Custom Hiring Services, Cauvery Delta.

Introduction

Mechanization in paddy cultivation has gained prominence in India due to increasing labour scarcity and rising wage costs, particularly during peak transplanting seasons, which create delays in operations and reduce crop yields (Gulati *et al*., 2019; Rajesh *et al*., 2022). Labour shortages in rice cultivation have become a critical constraint, especially in intensive rice-growing regions where timely transplanting is essential for optimal yields (Senthilkumar *et al*., 2016). This transformation has profoundly impacted modern agriculture by making operations more efficient, faster, and less physically demanding, while simultaneously addressing the challenges posed by declining rural labour availability and escalating wage rates (Kamali *et al*., 2023).

Farmers can today easily and efficiently cultivate larger areas of land through the inclusion of machinery throughout all stages of agricultural production, from soil preparation and planting to irrigation, plant protection, and harvesting (Banik *et al*., 2022). This has led to increased productivity and higher crop yields, which are essential to meet the rising food demands of a growing global population (Paudel *et al*., 2019). Among these technological advances, paddy cultivation has seen significant mechanization efforts, such as the use of paddy transplanters that improve planting accuracy and address labor shortages, especially in intensive rice-growing regions like Tamil Nadu (Anand & Amuthaselvi, 2021; Chithra, 2025). For smallholder farmers who cannot afford to buy machinery on their own, the use of mechanical rice transplanters through custom hire centres has become a practical solution (Senthilkumar & Naik, 2016).

Studies of machine transplantation in the Cauvery Delta report notable economic gains relative to conventional transplanting (Kamali *et al*., 2023). One such study indicates that using mat-nursery plus mechanical transplanting reduced production cost by about 59 per cent compared to conventional methods, owing to reduced labour, seed, and nursery expenses (Nirmala Devi *et al*., 2020). Economic analyses from various districts in Tamil Nadu have consistently demonstrated significant cost advantages and improved benefit-cost ratios from mechanical transplanting (Kavitha *et al*., 2018). Moreover, mechanized systems encourage precision farming practices by enabling accurate and timely operations such as irrigation, fertilization, and pest management (Nirmala Devi *et al*., 2020). Comparative studies between mechanical and manual transplanting have shown substantial reductions in labour requirements, improved field efficiency, and enhanced overall productivity (Chithra, 2025). This level of precision is crucial for enhancing crop quality and minimizing the waste of resources, ultimately supporting more sustainable agriculture (Castelein *et al*., 2022).

As technological advancements continue to drive innovation in agricultural machinery, mechanization is becoming increasingly sophisticated. Custom hiring services and machinery rental models have played a pivotal role in democratizing access to expensive agricultural equipment, particularly for smallholder farmers (Sharma *et al*., 2025). However, the adoption of these services faces several constraints including scheduling conflicts, maintenance issues, and service accessibility (Sharma *et al*., 2025). This continuous evolution is particularly crucial in addressing the issues faced by population expansion, climate variability, and declining rural labour supply (Paudel *et al*., 2019). By adopting advanced mechanized solutions, such as paddy transplanting machines, farming systems are better positioned to become more sustainable, efficient, and resilient ensuring food security for the future.

Against this backdrop, the current research examines the adoption and intensity of paddy transplanting machine services in Thanjavur district, a key rice-producing area in Tamil Nadu located in the Cauvery Delta region (Kamali *et al*., 2023). The district represents an ideal case study given its intensive triple-cropping pattern and the growing mechanization trends observed in the region. To fill this gap, econometric models that distinguish between these two stages (adoption vs intensity) are useful, the double-hurdle model is well suited for such analyses because it allows factors influencing the adoption decision to differ from those affecting intensity of use (Anjani *et al*., 2021; Cragg, 1971). While the double hurdle approach has been successfully applied to various agricultural technology adoption studies globally, its application to mechanical rice transplanting services remains limited (Dominic *et al*., 2023; Jules *et al*., 2023). Employing a double hurdle approach, the study aims to understand not only the decision to adopt these services but also the extent of their utilization, offering valuable insights into the factors that drive mechanization in regional paddy cultivation.

Materials and Methods

Study Area and Data Sources

The study was carried out in Thanjavur District, Tamil Nadu, one of the most productive rice-growing regions in southern India. Three key blocks Ammapettai, Orathanadu, and Thanjavur were purposively chosen for their prominence in paddy cultivation and varying levels of agricultural mechanization adoption. These blocks are strategically located within the Cauvery and Grand Anaicut (Kallanai) river irrigation belt, which provides abundant surface water resources and contributes to highly recharged groundwater levels throughout the year. This reliable water availability enables farmers in the region to practice an intensive triple cropping pattern (rice–rice–rice), distinguishing Thanjavur as one of the most productive rice belts in Tamil Nadu. This area is suitable for examining the adoption and level of use of new agricultural technologies, such as paddy transplanting machines, due to its favourable agroclimatic conditions and modern farming practices.

In total, 120 paddy farmers were chosen through a purposive-cum-random sampling method, with 40 respondents drawn from each of the three blocks, ensuring broad geographical representation across the study area. This sample size was deemed adequate for conducting robust econometric analysis while maintaining practical feasibility for primary data collection (Cohen *et al*., 1988). The questionnaire comprehensively covered various dimensions including farmer socioeconomic characteristics (age, education, farming experience), farm-related attributes (farm size, land ownership, cropping pattern), mechanization practices, access to agricultural services, and specific information regarding the adoption and use of paddy transplanting machine services (Rogers *et al*., 2003)Based on their responses to questions about machine transplanting usage during the most recent cropping season, farmers were categorized into two distinct groups: adopters (those who had used machine transplanting services at least once) and non-adopters (those who had not used such services), forming the basis for subsequent comparative and econometric analysis (Feder 1985).

Analytical Framework: Cragg's Double Hurdle Model

This study used Cragg's Double Hurdle Model, an econometric technique especially well-suited for circumstances where the decision to adopt a technology and the decision regarding the extent of its use may be influenced by different sets of factors, to examine the factors influencing farmers' adoption decisions and the intensity of machine transplanting use (Cragg, 1971). The Double Hurdle model comprehends that these two choices may be influenced by different underlying processes, contrary with standard single-equation models like the Tobit model, which presumes that the same mechanism produces both zero and positive outcomes with identical coefficients affecting both the probability of participation and the level of participation (Tobin, 1958). This adaptability is particularly important when it comes to the adoption of agricultural technology, where farmers first make a discrete choice about whether to try a new technology (influenced by factors such as awareness, accessibility, and initial risk perception), and subsequently, conditional on adoption, decide how intensively to use it (influenced by factors such as perceived benefits, operational constraints, and economic returns) (Foster *et al*., 2010)

The Double Hurdle model's theoretical foundations, initially set into practice by Cragg in 1971, are based on the idea that decisions about how much or how intensely to use a technology or participate in a market are independent of each other. According to the model used in this study, before we see positive use of machine transplanting services, a farmer has to successfully pass through two different hurdles. The adoption decision is the first hurdle, whether the farmer chooses to use machine transplanting at all while the second hurdle represents the intensity decision how many times the farmer uses the service during a cropping season, conditional on having adopted it (Burke, 2009). This two-stage conceptualization aligns closely with the actual decision-making process observed among smallholder farmers, who often exhibit cautious, incremental adoption behaviour when faced with new agricultural technologies (Sunding & Zilberman, 2001).

Model Specification

First Hurdle: Probit Model for Adoption Decision

The first stage of the Double Hurdle model employs a Probit specification to estimate the probability that a farmer adopts machine transplanting technology (Greene, W. H. 2018). In this framework, we assume that each farmer has a latent (unobserved) propensity to adopt, denoted as d_i, which is determined by a linear combination of explanatory variables and a random error term. The latent variable model can be expressed as:

$$d_i = X_i'\beta + u_i,$$

where X_i is a vector of explanatory variables affecting the adoption decision,

β is a vector of parameters to be estimated, and

u_i is an error term assumed to follow a standard normal distribution, $u_i \sim N(0,1)$ (Aldrich & Nelson, 1984).

The observed binary outcome d_i takes the value 1 if the latent propensity is positive ($d_i^* > 0$), indicating that the farmer is an adopter, and 0 otherwise ($d_i^* \leq 0$), indicating non-adoption. The probability of adoption, conditional on the explanatory variables, is given by

$$P(d_i = 1 \mid X_i) = \Phi(X_i'\beta),$$

where $\Phi(\cdot)$ represents the cumulative distribution function (CDF) of the standard normal distribution (Long & Freese, 2014).

The explanatory variables included in the first hurdle were carefully selected based on previous literature on agricultural technology adoption and preliminary exploratory analysis of the data (Adesina *et al*., 1995). These variables encompass farmer characteristics such as age (measured in years), which may capture both experience effects and potential resistance to change among older farmers; education level (measured in years of formal schooling), which is hypothesized as it enhances the ability of farmers to fully understand contemporary technological information and identify its potential benefits. Farm-related characteristics include farm size (in hectares), which may reflect both the scale of operations and the farmer's resource endowment; distance to the nearest service provider (in kilometers), which captures accessibility and transaction costs associated with obtaining machine transplanting services . Attitudinal and contextual variables include perceived affordability of the service (measured on a Likert scale), which reflects the farmer's subjective assessment of whether the service cost is reasonable relative to their budget constraints; availability of human labour (coded as a binary variable indicating adequate or inadequate), which captures the push factor that may drive mechanization adoption in response to labour scarcity. Additional variables include farming experience (measured in years), which may be distinct from age in capturing accumulated agricultural knowledge, and access to extension services (binary variable), which reflects exposure to information and technical guidance about modern agricultural practices (Anderson *et al*., 2007).

Second Hurdle: Truncated Regression for Intensity of Use

The second stage of the model focuses exclusively on farmers who have adopted machine transplanting (d_i = 1) and examines the factors that determine the intensity of use, measured as the number of times the farmer utilized machine transplanting services during the reference cropping season (Kahsay Gerezihar, 2014). This stage is modelled using a truncated regression framework, which is appropriate because we only observe positive values of the dependent variable for adopters, and the distribution is truncated at zero (Steven, 2004) (Amemiya, 1984). The latent intensity of use is specified as:

$$Y_i^* = Z_i'\gamma + \varepsilon_i,$$

where Y_i^* represents the desired or latent intensity of machine transplanting use,

Z_i is a vector of explanatory variables (which may overlap with but is not necessarily identical to X_i),

γ is a vector of parameters to be estimated, and

ε_i is an error term assumed to follow a normal distribution with mean zero and variance σ^2, $\varepsilon_i \sim N(0, \sigma^2)$ (Cameron, 2005)

The observed intensity Y_i equals Y_i^* when $Y_i^* > 0$, and the conditional distribution of Y_i given that it is positive can be expressed as:

$$f(Y_i \mid Y_i > 0, Z_i) = \varphi[(Y_i - Z_i'\gamma)/\sigma] / [\sigma\Phi(Z_i'\gamma/\sigma)],$$

where $\varphi(\cdot)$ is the probability density function (PDF) of the standard normal distribution.

The explanatory variables in the second hurdle were selected to capture factors that specifically influence the intensity of technology use among adopters (Newman, 2003). These include perceived affordability of the service, which may determine whether farmers use the service for all their plots or only selectively; perceived time savings compared to manual transplanting, which captures the operational efficiency gains that motivate repeated use; experience with high rainfall problems (binary variable), which may increase the urgency and frequency of using machine transplanting to complete operations within narrow weather windows (Takeshima *et al*., 2013). Perceived yield improvement (measured on a Likert scale) reflects the economic returns to technology use, which is expected to positively influence intensity of adoption (Doss, 2006). Additional variables include farm size, which may correlate with the number of transplanting operations needed; number of plots cultivated, which directly relates to the potential occasions for using the service; and access to credit facilities (binary variable), which may relax financial constraints and enable more frequent use of paid services.

Model Identification

For proper identification of the Double Hurdle model, it is generally recommended (though not strictly required) to include at least one variable in the first hurdle that is excluded from the second hurdle, or vice versa (Yen & Jones, 1997). In this study, variables such as "distance to service provider" and "availability of human labour" were hypothesized to primarily affect the initial adoption decision but have less direct influence on the intensity of use among adopters, since once a farmer has established a relationship with a service provider and committed to mechanization, these factors become less binding (Jack, 2013). Conversely, variables such as "perceived time savings" and "experience with high rainfall problems" were expected to more directly influence the intensity of use, as these factors relate to the operational benefits and situational urgency that drive repeated usage (Moser & Barrett, 2006). While the model can be estimated even with complete overlap in the variable sets for the two hurdles, the presence of some distinct variables enhances identification and facilitates interpretation of the separate decision processes.

Marginal Effects Analysis

To facilitate economic interpretation of the estimated coefficients, marginal effects were calculated for both hurdles (Little & Rubin, 2019). In nonlinear models such as Probit and truncated regression, the coefficients themselves do not directly represent the marginal effect of a change in an explanatory variable on the outcome of interest (Field, 2018). Therefore, marginal effects, which measure the change in the probability of adoption (first hurdle) or the change in expected intensity of use (second hurdle) resulting from a one-unit change in an explanatory variable, are essential for understanding the practical significance of the results (Kim, 2017).

For the Probit model in the first hurdle, the marginal effect of a continuous variable X_k on the probability of adoption is calculated as the partial derivative of the probability with respect to that variable, which yields:

$$\partial P(d_i = 1)/\partial X_k = \varphi(X_i'\beta) \cdot \beta_k,$$

where $\varphi(\cdot)$ is the standard normal probability density function evaluated at $X_i'\beta$.

This marginal effect varies across observations depending on the values of all explanatory variables, so it is common practice to report marginal effects evaluated at the mean values of all variables, providing a representative measure for the average farmer in the sample. For binary explanatory variables, the marginal effect is computed as the discrete change in probability when the variable changes from 0 to 1, holding all other variables constant:

$$\Delta P = \Phi(X_i'\beta \mid X_k = 1) - \Phi(X_i'\beta \mid X_k = 0).$$

For the truncated regression in the second hurdle, the marginal effect of a variable Z_k on the expected intensity of use, conditional on positive use, is more complex due to the truncation. The marginal effect must account for the fact that the distribution is truncated at zero, which is accomplished using the inverse Mills ratio, $\lambda(\cdot)$, defined as the ratio of the probability density function to the cumulative distribution function of the standard normal distribution [58]. The marginal effect is given by:

$$\partial E(Y_i \mid Y_i > 0)/\partial Z_k = \gamma_k \cdot [1 + (Z_i'\gamma/\sigma)\cdot\lambda(Z_i'\gamma/\sigma) - \lambda(Z_i'\gamma/\sigma)^2],$$

where $\lambda(Z_i'\gamma/\sigma) = \varphi(Z_i'\gamma/\sigma) / \Phi(Z_i'\gamma/\sigma)$.

This expression shows that the marginal effect in a truncated regression model is not simply equal to the coefficient γ_k, but is scaled by a factor that depends on the degree of truncation. As with the first hurdle, marginal effects for the second hurdle were computed at the mean values of all explanatory variables to provide a representative assessment of variable impacts for the average adopter in the sample.

Data Preparation and Variable Construction

Dependent Variables

The dependent variable for the first hurdle was constructed as a binary indicator taking the value 1 if the farmer reported having used machine transplanting services at least once during the most recent cropping season (adopter) and 0 if the farmer reported no use of such services (non-adopter) .This binary classification was based on farmers' self-reported responses to direct questions about their transplanting methods and their engagement with mechanized transplanting service providers. For the second hurdle, the dependent variable was constructed as a continuous measure representing the number of times the farmer utilized machine transplanting services during the reference cropping season, conditional on being an adopter. This intensity measure was obtained by asking adopters to recall the number of separate occasions on which they hired machine transplanting services, with each occasion potentially covering one or more plots depending on the service arrangement. The count data were treated as a continuous variable in the truncated regression framework, which is appropriate given the range of values observed and the flexibility of the normal distribution to approximate count distributions when the mean is reasonably large.

Results and Discussion

Frequency of adopters and non-adopters in paddy Transplanter

The results from the Figure 1 indicates that a majority of respondents are adopters, while non-adopters constitute 33 per cent of the total sample. This highlights a significant adoption rate, with a smaller but notable proportion still remaining as non-adopters.

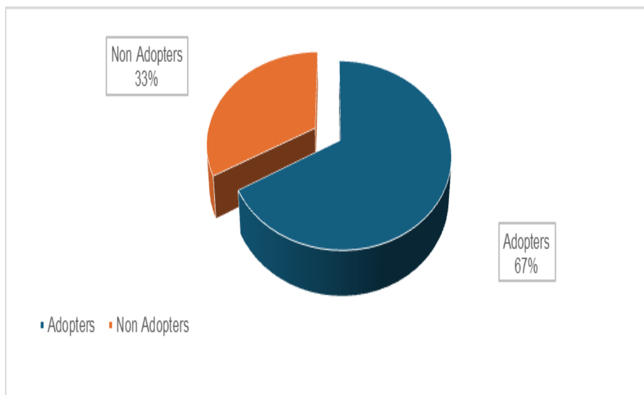

Fig. 1 : Frequency of adopters and non-adopters

Descriptive statistics of the variables

The table 1 presents descriptive statistics for adopters and non-adopters across five key variables. The results show that adopters are, on average, younger (42 years) compared to non-adopters (49.25 years). Family size is slightly larger for adopters (3.8) than non-adopters (3.5). Farm size is notably larger among adopters (8.9 acres) compared to non-adopters (5.1 acres). Similarly, adopters have marginally more farming experience (17.45 years) compared to non-adopters (16.3 years). However, the distance to service providers is shorter for adopters (3 km) than for non-adopters (4.4 km). This indicates that age, farm size, and access to services might influence adoption behavior.

Table 1 : Descriptive statistics of the variables

S. No	Variables	Adopters		Non-Adopters	
		Mean	Standard deviation	Mean	Standard deviation
1	Farmer's Age	42	10.13	49.25	10.66
2	Family size	3.8	1.44	3.5	1.02
3	Farm Size	8.9	4.9	5.1	2.59
4	Farming experience	17.45	9.91	16.3	8.37
5	Distance to Service Providers	3	1.05	4.4	1.2

The table 2 presents the socio-economic characteristics of adopters and non-adopters. Among adopters, 80 per cent are male and 20 per cent are female, while for non-adopters, males account for 70 per cent and females 30 per cent. Regarding marital status, 75 per cent of adopters are married compared to 100 per cent of non-adopters. In terms of education, 45 per cent of adopters are illiterate, 30 per cent have school education, and 25 per cent have college education, whereas for non-adopters, 60 per cent are illiterate, 30 per cent have school education, and only 10 per cent have college education.

With respect to land ownership, 55 per cent of adopters own land, 5 per cent are tenants, and 40 per cent have both owned and tenant land. In contrast, only 20 per cent of non-adopters own land, 60 per cent are tenants, and 20 per cent possess both types of land. These findings suggest that gender, education, and land ownership may play significant roles in influencing adoption decisions.

Table 2 : Socio-economic characteristics of adopters and non-adopters

S.No	Variables	Category	Adopters (N=80)	Non-Adopters (N=40)
1	Gender	Male	64 (80)	28 (70)
		Female	16 (20)	12 (30)
2	Marital Status	Single	32 (40)	0 (0)
		Married	48 (60)	40 (100)
3	Education	Illiterate	36 (45)	24 (60)
		School level	24 (30)	12 (30)
		College level	20 (25)	4 (10)
4	Land Ownership	Owned land	44 (55)	8 (20)
		Tenant land	4 (5)	24 (60)
		Both owned & tenant	32 (40)	8 (20)

*Figures in the parenthesis indicates the percentage

Econometric results of Adoption Decision and Intensity of Use paddy transplanting mechanization adoption model

The estimates from Cragg's Double Hurdle model, reported in Table 4, offer detailed insights into the factors influencing both the adoption and intensity of paddy transplanting machine services. The likelihood ratio statistic demonstrates that the model is highly significant (χ^2 = 126.77, p < 0.01), indicating a strong overall fit and explanatory power.

Table 3 : Results of Cragg's Double - Hurdle model

Variables	Adoption (Probit)		Intensity (Truncated)		Unconditional Effects (APE)		Conditional Effects (APE)	
	Coef.	Std.Err	Coef.	Std.Err	dy/dx	Std.Err	dy/dx	Std.Err
Age	-0.106***	0.012	—	—	-0.043***	0.006	-0.100***	0.011
Education	-0.262	0.180	—	—	-0.107	0.074	-0.246	0.170
Farm Size	0.163***	0.020	—	—	0.066***	0.009	0.153***	0.018
Distance to Service Providers	1.260***	0.134	—	—	0.513***	0.066	1.184***	0.115
Perceived Affordability	0.858***	0.213	-0.381	0.284	0.115	0.190	0.806***	0.196
Availability of Human Labour	-2.367***	0.252	—	—	-0.963***	0.126	-2.224***	0.221
Perceived Yield Improvement	0.711***	0.173	—	—	0.289***	0.073	0.668***	0.160
Perceived Time Savings	—	—	1.876***	0.350	1.154***	0.128	—	—
High Rainfall Problem	—	—	-1.633***	0.382	-1.004***	0.187	—	—
Field Constraints	—	—	0.449	0.315	0.276	0.188	—	—
Constant	1.998***	0.521	0.352	0.330	—	—	—	—

Adoption Decision

The Probit estimates indicate that age has a significant negative effect on adoption, suggesting that older farmers are less likely to adopt mechanized transplanting. Farm size shows a positive and statistically significant influence, implying that larger landholders are more inclined towards mechanization due to better resource endowment and economies of scale.

Distance to service providers is positively associated with adoption, reflecting the role of spatial clustering and accessibility of mechanization services. Perceived affordability also positively influences adoption decisions at the coefficient level, although its marginal effect is not statistically significant, indicating that affordability may shape perceptions rather than directly affecting adoption probability.

Availability of human labour exhibits a strong negative effect, confirming that mechanization acts as a substitute for labour. Farmers with adequate labour availability are less likely to adopt machine transplanting services.

Perceived yield improvement has a positive and significant influence on adoption, suggesting that farmers who expect higher productivity benefits are more likely to adopt mechanized transplanting.

Intensity of Use

The second hurdle results indicate that perceived time savings significantly increases the intensity of use, highlighting the importance of operational efficiency in repeated utilization. High rainfall conditions significantly reduce the intensity of use, indicating that climatic variability constrains mechanized operations.

Perceived affordability does not significantly influence adoption but plays a crucial role in determining the intensity of use, as reflected in its positive marginal effect. Farm size and distance to service providers also positively influence intensity, suggesting that larger farmers and those located in mechanization-intensive regions tend to use the services more frequently.

Availability of human labour negatively affects intensity, reinforcing the substitution effect between labour and mechanization even after adoption.

Field constraints do not exhibit a statistically significant effect on intensity; however, practical field conditions remain an important consideration in farmers' decision-making. Farmers with smaller landholdings and poor drainage facilities often hesitate to adopt machine transplanting across all seasons. During periods of heavy rainfall or monsoon disturbances, excess water can cause seedlings to become unstable or displaced, reducing the effectiveness of mechanical transplanting. Under such conditions, farmers tend to prefer manual transplanting, which allows for stronger and more stable placement of seedlings, ensuring better crop establishment.

Marginal Effects Interpretation

The marginal effects provide clearer economic interpretation of the results. Farm size increases overall participation by 6.6 per cent, while age reduces it by 4.3 per cent. Distance to service providers increases participation by 51.3 per cent, indicating the importance of service accessibility.

Availability of human labour reduces participation by 96.3 per cent, confirming its strong substitutive role. Perceived time savings significantly enhances participation, whereas high rainfall conditions reduce it.

Conditional marginal effects indicate that perceived affordability increases the intensity of use, while high rainfall reduces it. Farm size and distance to service providers continue to positively influence usage intensity, whereas labour availability exerts a negative effect.

Constraints Encountered by Sample Farmers

The Table 4.4 reveals the constraints encountered by sample farmers, ranked based on Garrett's scores. The most significant challenge identified is weather-related problems, with a Garrett's score of 65.93, suggesting that weather variability is the primary concern for farmers. Water management constraints follow closely with a score of 53.47, indicating that efficient irrigation and water use remain crucial issues. Field-related problems, with a score of 52.87, also present a notable challenge, highlighting the importance of maintaining and optimizing field conditions. Poorly maintained field boundaries 52.67 and scheduling conflicts 45.27 are additional concerns, although they are less impactful than the aforementioned issues. Overall, these results underscore the critical need for targeted interventions in weather forecasting, water management, and field maintenance to support farmers' productivity and sustainability.

Table 4 : Constraints Encountered by Sample Farmers

S.No	Constraints	Garrett's score
1	Weather problem	65.93
2	Water management constraints	53.47
3	Field problem	52.87
4	Poorly maintained field boundaries	52.67
5	Scheduling conflicts	45.27

Conclusion

The study provides comprehensive insights into the determinants of adoption and intensity of paddy transplanting machine services in Thanjavur District using Cragg's Double Hurdle Model. The findings clearly demonstrate that mechanization adoption is not a single decision but a two-stage process influenced by distinct socio-economic, farm-level, and perceptual factors.

The results reveal that a majority (67 per cent) of farmers have adopted machine transplanting, indicating a growing shift towards mechanized agriculture in the region. Adoption is significantly influenced by farm size and negatively affected by age and availability of human labour, confirming that mechanization primarily serves as a substitute for labour under conditions of scarcity. The positive influence of perceived yield improvement and accessibility to service providers further highlights the importance of both economic expectations and service availability in shaping adoption decisions.

The second-stage results emphasize that the intensity of use is largely driven by operational and economic considerations. Perceived time savings and affordability emerge as key drivers of repeated usage, indicating that farmers prioritize efficiency and cost-effectiveness over other factors. In contrast, high rainfall conditions significantly reduce the intensity of use, underscoring the vulnerability of mechanized operations to climatic variability. Labour availability continues to negatively influence intensity, reinforcing its substitutive role even after adoption.

Marginal effects analysis strengthens these findings by quantifying the magnitude of influence of key variables. Farm size and service accessibility significantly enhance participation, while labour availability and adverse weather conditions act as major deterrents. The results also highlight that practical considerations outweigh educational factors in influencing farmers' behaviour.

The constraint analysis further reveals that weather variability, water management issues, and field-related problems are the major barriers faced by farmers. These challenges limit both adoption and effective utilization of mechanized services, particularly under unstable climatic conditions.

Overall, the study concludes that promoting mechanization in paddy cultivation requires a multifaceted approach. Strengthening custom hiring centres, improving service accessibility, ensuring affordability, and addressing climatic and infrastructural constraints are essential to enhance both adoption and intensity of use. Policy interventions focusing on climate-resilient mechanization, improved water management, and timely service delivery can significantly accelerate the transition towards sustainable and efficient rice production systems.

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