

# Determinants of Green Technology Adoption among Malaysian Paddy Farmers: Evidence from Northwest Selangor

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## ABSTRACT

Adopting sustainable practices is becoming increasingly vital to enhancing the sustainability and resilience of rice production. In Malaysia, efforts such as the Malaysian Good Agricultural Practices (myGAP) and Integrated Pest Management (IPM) have been promoted to foster more environmentally friendly paddy farming. Nonetheless, adoption rates among farmers are inconsistent, and evidence on the socioeconomic, farm, and institutional factors influencing adoption remains limited. This study investigates the socioeconomic, farm, and institutional determinants of green technology adoption among Malaysian paddy farmers, focusing specifically on the roles of farmer training, land tenure, and farm management practices. Data were collected from 457 paddy farmers in the Integrated Agricultural Development Area (IADA) Barat Laut Selangor, including 252 conventional farmers and 205 adopting green technology. Green technology adoption was defined as implementing myGAP and IPM. A binary logistic regression with heteroskedasticity-robust standard errors assessed the relationship between adoption and various socioeconomic, farm, and institutional factors. Results indicate that training participation is the strongest positive predictor of adoption, followed by planting method, which also has a significant positive effect. Conversely, gender and rented land tenure were significant negative predictors. Age, formal education, main occupation, land type, irrigation, loans, government assistance, and organic fertiliser use were not statistically significant at the 5% level. The findings suggest that green technology adoption among Malaysian paddy farmers is more closely linked to experiential learning, farm management practices, and land tenure than to formal education. Enhancing farmer training and extension services, improving institutional support for tenant farmers, and promoting practical learning opportunities could help expand the adoption of sustainable rice-farming practices.

**Keywords:** Green Technology Adoption; Paddy Farmers; myGAP; Integrated Pest Management (IPM); Logistic Regression; IADA Barat Laut Selangor

## INTRODUCTION

Sustainable agriculture has become crucial for tackling global challenges like food insecurity, environmental damage, and climate change. As part of the Sustainable Development Goals (SDGs), efforts are increasing to transition from traditional farming to practices that emphasise sustainable resource use and environmental conservation. In this framework, sustainable rice farming is particularly important, especially in developing nations where rice is a main dietary staple and vital for rural communities.

The Malaysian paddy sector remains vital for national food security, despite accounting for a small share of the economy. Local rice production falls short of meeting domestic needs, with self-sufficiency at about 52.9% in 2024, leading Malaysia to continue importing rice [1]. Although its economic impact is limited, the sector remains politically and socially important by ensuring staple food availability and supporting rural areas. The government aims to raise rice self-sufficiency to 80% by 2030, focusing on sustainable, technology-based practices [2]. However, the industry still faces challenges such as slow productivity growth, rising input costs, and weather-related risks.

Policy initiatives are increasingly emphasising productivity improvements through green technologies, eco-friendly practices, and better farm management. However, intensive paddy farming raises concerns about agrochemical use, resource management, environmental harm, and climate change impacts. These issues underscore the need for agricultural methods that balance high productivity with environmental sustainability. Consequently, research and focus on green technologies and sustainable agricultural practices are growing.

Among Malaysian paddy farmers, Malaysian Good Agricultural Practices (myGAP) and Integrated Pest Management (IPM) are key strategies for encouraging sustainable farming. myGAP certification offers a structured approach to good practices, encompassing production management, food safety, environmental practices, and farm management. Meanwhile, IPM emphasises efficient, environmentally friendly pest control. IPM is a required part of the myGAP standard, making its adoption a crucial step toward sustainable rice cultivation. These practices go beyond buying specific inputs; they involve changing production routines, building technical knowledge, maintaining proper farm-management practices, and, for certified farms, following standard operating procedures (SOPs). IPM requires skills in pest identification, monitoring, and intervention, while myGAP covers comprehensive farm management related to production, environmental care, and compliance. Implementing GAP and IPM enables farmers to reduce production costs by optimising chemical and pesticide use [15]. Moreover, previous research often focuses on specific farming practices rather than viewing green technology adoption as part of overall farm-level decision-making.

Therefore, farmers' adoption of technologies likely depends on their ability to access and utilise knowledge, their farm features, and the institutional setting of their production. However, simply providing and promoting sustainable technologies does not guarantee adoption, as farmers vary in their access to information, training, resources, land security, institutional backing, and farm management experience. Previous research highlights socioeconomic factors, farm characteristics, and institutional support as key influences on farmers' adoption decisions. However, the impact and direction of these factors differ by production system and region.

However, the presence of sustainable technologies alone does not ensure their adoption. Research indicates that farmers' adoption decisions are influenced by a mix of economic, behavioural, social, farm-specific, and institutional factors [8,9,10,11]. Likewise, studies have highlighted that knowledge, perceptions, access to information, institutional involvement, and economic factors play crucial roles in farmers' transition to sustainable production methods [12,13,14,17]. Although several studies have investigated technology adoption among Malaysian farmers [12,13,14], evidence on the adoption of green technologies such as myGAP and IPM by paddy farmers remains limited.

Despite increasing policy attention to sustainable rice production in Malaysia, empirical evidence on the determinants of farmers' adoption of green agricultural technologies remains limited and fragmented. Previous studies have examined specific practices such as green fertiliser, IPM, and sustainable farming management. Still, their findings on the roles of education, age, farm characteristics, institutional support, and financial incentives remain mixed [7,11,12,17,18]. Moreover, relatively limited attention has been given to the adoption of green technology as a combined practice involving myGAP and IPM among Malaysian paddy farmers. Therefore, this study investigates the socioeconomic, farm-related, and institutional determinants that influence green technology adoption among Malaysian paddy farmers.

This study addresses this gap by examining the socioeconomic, farm and institutional characteristics associated with green technology adoption among 457 paddy farmers in Northwest Selangor. A binary logistic regression model with robust standard errors estimates the association between farmer characteristics and the probability of adopting green technology. The study contributes empirical evidence on the relative importance of farmer training, land tenure, planting method and other socioeconomic and institutional characteristics in explaining green technology adoption in Malaysian rice farming.

## LITERATURE REVIEW

Farmers' adoption of sustainable agricultural technologies is influenced by a mix of socioeconomic traits, farm conditions, and institutional backing, rather than one single factor. Nonetheless, evidence remains variable across technologies, farming systems, and countries, showing that adoption drivers depend heavily on context [7,11,31]. This is especially true for green technologies like myGAP and IPM, which demand not just financial investment but also specific knowledge, behavioural changes, and institutional support.

### Socioeconomics

Socioeconomic traits shape farmers' ability to access information, evaluate innovations, and navigate adoption risks [9,17], but these influences vary. For instance, age can promote adoption through experience and knowledge but may also lead older farmers to resist changing established routines. Kamaruddin and Abd. Rashid [18] identified a negative link between age and sustainable farm management, while Begho et al. [11] observed mixed effects across different studies. Therefore, age alone does not fully explain adoption behaviour. Similarly, gender impacts adoption not through inherent differences but via disparities in resource access, information, extension services, and decision-making. Begho et al. [11] and Rahman [17] noted diverse gender effects on sustainable practices, emphasising that gender should be understood within the broader context of institutional and household influences on farming decisions. Female farmers tend to show stronger environmental stewardship and participate more in conservation practices when supported by gender-sensitive institutional and extension programs [11,19].

Education is generally believed to promote technology adoption by enhancing farmers' capacity to understand technical information [7,20,30]. Studies by Adnan et al. [12] and Rahman [17] showed positive links between education and the adoption of sustainable technologies or IPM. However, Tan et al. [20] found that education level did not significantly influence knowledge about insecticides, pests, and arthropod pests related to IPM awareness. While formal education reflects overall human capital, technologies like IPM and myGAP require specific practical knowledge. Rahman [17] emphasised that understanding the complexity of IPM practices means formal education alone may not guarantee successful adoption.

### Farm Characteristic

Farm characteristics impact adoption by affecting production conditions, resource needs, and farmer incentives. Larger farms might better handle adoption costs and risks. Rahman [17] observed a positive link between farm size and IPM adoption, while Chang et al. [7] also pointed out farm size as a key factor in several sustainable rice-farming studies. Conversely, Kamaruddin and Abd. Rashid [18] found that cultivated land size did not significantly influence Malaysian paddy farmers. These mixed results suggest that farm size does not universally predict the adoption of sustainable technologies.

Meanwhile, land tenure may offer a clearer explanation because sustainable practices often require investments that benefit more than one production cycle [21]. Secure land control can motivate farmers to invest in new management methods, while rented land may limit long-term planning and reduce motivation for additional learning, record-keeping, or certification. Nkomoki et al. [22] showed that land-tenure arrangements affected adoption of sustainable agricultural practices in Zambia. Nonetheless, tenure effects vary by context since farmers' incentives depend on land-access arrangements and institutional factors. For Malaysian paddy farming, this distinction matters, given the structured irrigation and institutional systems involved. Therefore, this study

differentiates between own, rented, and other land types, instead of simply categorising tenure as secure or insecure, offering a more context-aware view of how land arrangements influence green technology adoption.

Other farm characteristics might also impact adoption. While irrigation influences production conditions and could determine whether certain practices are compatible, its effect on myGAP and IPM adoption remains theoretically uncertain because having access to irrigation doesn't necessarily alter technology-specific incentives. Similarly, planting methods may reflect differences in mechanisation, labour needs, and overall farm-management approaches. According to the Diffusion of Innovations framework, factors like compatibility with existing practices and perceived benefits play a role in adopting innovations [20]. Evidence from Tu et al. [25] and Chang et al. [7] suggests that production practices can influence the adoption of sustainable rice technologies. However, planting method should be seen as an associated farm trait rather than a direct causal factor.

### **Institutional supports**

Institutional factors shape adoption by providing access to knowledge, technical assistance, financial resources, and agricultural networks. Key mechanisms such as extension services, training, communication channels, and farmer organisations support the implementation of sustainable agricultural technologies [7,12]. Additionally, credit and government grants can help lower financial barriers and costs [11]. However, institutional support alone does not guarantee adoption. Kamaruddin and Abd. Rashid [18] observed that some institutional variables were not significant, despite earlier evidence of positive effects. Rahman [17] also found that participation in training did not always lead to a significant increase in adoption. A recent study indicated that environmental awareness was not a significant factor for sustainable practices among Malaysian paddy farmers, though effective institutional support through training did promote adoption [26, 27]. These results suggest that the quality, relevance, and proper targeting of institutional support may matter more than its mere presence.

Research shows significant variability in what influences the adoption of sustainable agricultural technologies. Factors like education and farm size matter in some studies but not in others, and the impacts of age, gender, training, and institutional support differ by context [7,11]. For example, Rahman [17] highlights that education and farm size correlate with IPM adoption, whereas training, despite higher participation among high adopters, was not statistically significant. This suggests that adoption determinants depend on technology features, institutional support, and measurement methods. Consequently, training should be treated as a separate factor because it provides technology-specific knowledge and practical skills that can reduce adoption uncertainty. Many studies identify training and extension services as crucial for promoting sustainable agriculture [7,9,11]. Haque et al. [24] confirmed a positive link between training and IPM adoption, but evidence remains mixed. Rahman [17] found that training was not statistically significant in the adoption model, even though more high adopters had received training. This implies that participation alone does not guarantee effective knowledge transfer; instead, the quality, intensity, and practical relevance of training drive its success.

Rogers' (2003) Diffusion of Innovations theory provides the primary theoretical basis for understanding adoption as a decision influenced by farmers' exposure to information, their perceptions of an innovation's compatibility, and their capacity to implement it. Ajzen's (1991) Theory of Planned Behaviour complements this perspective by recognising that perceived behavioural control and social conditions can influence adoption behaviour. In the present study, these theoretical perspectives are operationalised through observable socioeconomic, farm and institutional characteristics that may shape farmers' capacity and opportunity to adopt green technology. Empirical research points to various factors influencing adoption, such as socioeconomic status, risk perception, economic incentives, farm characteristics, social networks, and institutional support [7,17,25,33]. In Malaysia, studies show that adoption rates are less linked to formal education and more influenced by targeted training, institutional involvement, and market incentives, especially for smallholder farmers [13].

This literature identifies three key gaps. Firstly, it mostly focuses on individual technologies like green fertiliser, IPM, or organic practices, with limited exploration of their combined use, such as myGAP and IPM in Malaysian paddy farming. Second, studies often examine socioeconomic, farm, and institutional factors separately, limiting understanding of their combined impact. Third, findings on education, age, gender, land tenure, and institutional support are inconsistent, highlighting the need for context-specific empirical research rather than assuming universal adoption patterns.

The present study addresses these gaps by examining the socioeconomic, farm, and institutional determinants of green technology adoption among Malaysian paddy farmers using a farmer-level Logit model. By focusing directly on the adoption decision, the study identifies which characteristics remain associated with adoption after controlling for multiple dimensions simultaneously. This provides a more integrated explanation of green technology adoption and offers evidence to inform targeted interventions to support sustainable rice production.

## METHODOLOGY

### Study area

The study was conducted in the Northwest Selangor Integrated Agricultural Development Area (IADA Barat Laut Selangor - IADA BLS), Selangor, Malaysia. Established in 1978, IADA BLS covers the districts of Kuala Selangor and Sabak Bernam and aims to support agricultural development and improve the socioeconomic well-being of the target population. The area spans almost 18,784 hectares dedicated to paddy cultivation. It is divided into nine main blocks to facilitate agricultural management and development programs. IADA BLS was selected as the study area because it is one of Malaysia's major rice granary areas and has been the second-largest contributor to national rice production, underscoring its importance to national food security. Its irrigation system is among the better-developed in Malaysia's rice granary areas, providing favourable conditions for efficient and sustainable rice production. In addition, IADA BLS accommodates both conventional and sustainable rice production systems, including myGAP and IPM practices, which farmers continue to practice under relatively similar agroecological and institutional conditions.

### Sampling and data collection

The study involved both conventional and green technology farmers. Green technology encompasses sustainable practices that produce eco-friendly products or utilise environmentally conscious production methods that protect the environment. In this research, green technology practices were identified as paddy fields with myGAP certification or those implementing IPM practices. The sampling frame was built from farmer lists provided by IADA BLS and the Department of Agriculture (DOA). The overall population included 9,754 paddy farmers, with 9,226 conventional and 528 engaged in green technology practices. A stratified random sampling approach was used to select respondents, which is suitable for capturing diverse strata within the population [28]. IPM farmers were chosen using both stratified random and purposive sampling, since IPM projects are restricted to three blocks: Sabak Bernam, Sungai Nipah, and Sawah Sempadan. The final green technology group consisted of farmers who met at least one study criterion, either myGAP certification or IPM participation. The differing sampling methods reflect the structure of each sampling frame. Therefore, the results should be viewed as demonstrating associations within the sample, not as statistically representative of all Malaysian paddy farmers.

This study uses a quantitative research approach and cross-sectional data collected through a field survey. A structured questionnaire collected information on socioeconomic, farm, and institutional characteristics, as well as green technology adoption. After screening, 457 valid observations remained, comprising 252 conventional farmers and 205 green technology adopters. Given the non-probability selection of part of the adopter group, interpret the results as sample-specific associations rather than causal effects, and consider their generalizability beyond the study area with caution.

## Data analysis

We analysed the collected data using descriptive statistics and binary logistic regression. Descriptive statistics summarised farmers' socioeconomic and farm characteristics, as well as institutional support. Chi-square tests examined whether the distribution of categorical socioeconomic, farm, and institutional characteristics differed significantly between conventional and green technology farmers. These bivariate analyses provided preliminary evidence of group differences before estimating the binary logistic regression model, which identified key factors influencing green technology adoption among paddy farmers.

## Logistic Model Specification

Green technology adoption was specified as a binary dependent variable, coded as 1 if a farmer adopted myGAP or IPM, and 0 if the farmer adopted neither practice. A binary logistic regression model was then estimated to examine the association between farmers' socioeconomic, farm and institutional characteristics and the probability of green technology adoption. The logistic regression model was specified as:

$$\ln\left(\frac{P_i}{1 - P_i}\right) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i$$

where  $P_i$  represents the probability that a farmer  $i$  adopts green technology,  $1 - P_i$  represents the probability of non-adoption,  $\beta_0$  is the intercept,  $\beta_k$  represents the estimated coefficient of each explanatory variable, and  $\varepsilon_i$  is the error term. We selected the explanatory variables based on the literature on agricultural technology adoption and grouped them into socioeconomic, farm characteristics, and institutional supports, as shown in Table 1. The hypothesised signs indicate the expected direction of association with the probability of green technology adoption. For variables for which the theoretical and empirical direction is context-dependent, an ambiguous ( $\pm$ ) sign is specified. We estimated model coefficients using maximum likelihood and reported heteroskedasticity-robust standard errors to provide more reliable statistical inference for the cross-sectional farmer-level data. We presented the results as regression coefficients ( $\beta$ ), odds ratios, and marginal effects. We assessed statistical significance at the 1%, 5%, and 10% levels.

## Model Diagnostic Tests

Several diagnostic tests assessed the adequacy and robustness of the logistic regression model. Model specification was examined using the link test, where a significant fitted-value term ( $\hat{\mu}$ ) and an insignificant squared fitted-value term ( $\hat{\mu}^2$ ) indicate an adequately specified model [34]. Multicollinearity was assessed using variance inflation factor (VIF) and tolerance statistics. VIF values below 5 and tolerance values above 0.10 were considered indicative of no serious multicollinearity [35]. The Hosmer-Lemeshow goodness-of-fit test assessed agreement between observed and predicted probabilities; a non-significant result indicated adequate model fit [36]. The model's discriminatory performance was further evaluated using receiver operating characteristic (ROC) analysis and the area under the curve (AUC). An AUC above 0.50 indicates performance better than random classification, with higher values reflecting stronger discriminatory ability [37].

Finally, robust standard errors were employed in the final logistic regression estimation to account for potential heteroskedasticity in the cross-sectional data [38]. These diagnostic procedures were used collectively to assess model specification, multicollinearity, goodness-of-fit and predictive discrimination before interpreting the estimated determinants of green technology adoption. The Pseudo R-squared indicates the model's explanatory power, though it is not directly comparable to the R-squared in linear regression. The -2 Log-Likelihood statistic assesses overall model fit, with lower values indicating better fit. In addition, we use the percentage of correctly classified observations to evaluate the model's predictive accuracy.

Table 1: Explanatory variables, measurements and hypothesised direction of green technology adoption

| Category                      | Variables          | Definition / Measurement                                                                                                                                         | Expected Sign |
|-------------------------------|--------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------|
| Socioeconomic characteristics | Age                | Age of farmer (years); represents farming experience and may influence risk preference and openness to new technologies                                          | ±             |
|                               | Gender             | Dummy (1 = Male, 0 = Female); captures potential differences in access to information, resources and farm decision-making.                                       | ±             |
|                               | Education          | Years of formal schooling: a proxy for human capital and information processing ability                                                                          | +             |
|                               | Main occupation    | Dummy variable (1 = Farming is the main occupation, 0 = otherwise); reflects farmers' degree of dependence on and engagement with farming                        | +             |
| Farm characteristics          | Own land           | Dummy variable (1 = Own land, 0 = otherwise); reflects land-tenure security and farmers' control over production decisions                                       | ±             |
|                               | Rental land        | Dummy variable (1 = Rental land, 0 = otherwise); reflects tenure arrangements and potentially shorter planning horizons                                          | -             |
|                               | Irrigation         | Dummy variable (1 = Canal irrigation, 0 = other irrigation arrangement); represents access to and control over water resources                                   | ±             |
|                               | Planting method    | Dummy variable (1 = Direct seeding, 0 = Mechanical transplanting); captures differences in production and farm-management practices                              | ±             |
|                               | Soil type          | Dummy variable (1 = Clay soil, 0 = other soil types); represents differences in land and soil conditions                                                         | ±             |
| Institutional supports        | Training           | Dummy variable (1 = Participated in agricultural training, 0 = otherwise); proxy for extension exposure and technology-specific knowledge                        | +             |
|                               | Access to credit   | Dummy variable (1 = Access to agricultural credit, 0 = otherwise); represents farmers' access to financial resources for farm operations and technology adoption | +             |
|                               | Government grants  | Dummy variable (1 = Received government grants/assistance, 0 = otherwise); represents institutional and financial support for farm activities                    | +             |
|                               | Organic fertilizer | Dummy variable (1 = Received organic fertilizer, 0 = otherwise); represents input support for fertilization                                                      | +             |

## RESULTS AND DISCUSSION

### Profile of respondents

The survey covered 457 paddy farmers, comprising 252 non-adopters (conventional) and 205 adopters of green technology. Table 2 shows that adopters generally differ from non-adopters in age, education level, and experience, but the differences between groups are not significant. For gender, the Chi-square test indicated a statistically significant association with green-technology adoption ( $\chi^2 = 6.272$ ,  $p = 0.012$ ). Female farmers represented 9.8% of the green technology group compared with 3.6% of the conventional group, whereas male farmers represented 90.2% and 96.4%, respectively. This pattern suggests that female farmers were relatively more represented among green technology adopters than conventional farmers.

Table 2: Profile of respondents by adopters and non-adopters

| Variables       | Scale              | Non-adopters | Adopters   | Statistical Analyses |         |
|-----------------|--------------------|--------------|------------|----------------------|---------|
|                 |                    | n (%)        | n (%)      | Chi-Square           | p-value |
| Age             | <31                | 15 (6.0)     | 9 (4.4)    | 2.333                | 0.675   |
|                 | 31 - 40            | 42 (16.7)    | 31 (15.1)  |                      |         |
|                 | 41 - 50            | 57 (22.6)    | 57 (27.8)  |                      |         |
|                 | 51 - 60            | 93 (36.9)    | 69 (33.7)  |                      |         |
|                 | > 60               | 45 (17.9)    | 39 (19.0)  |                      |         |
| Gender          | Male               | 243 (96.4)   | 185 (90.2) | 6.272                | 0.012** |
|                 | Female             | 9 (3.6)      | 20 (9.8)   |                      |         |
| Education       | Primary school     | 37 (14.7)    | 25 (12.2)  | 7.325                | 0.198   |
|                 | Secondary 1        | 47 (18.7)    | 49 (23.9)  |                      |         |
|                 | Secondary 2        | 148 (58.7)   | 111 (54.1) |                      |         |
|                 | Diploma            | 14 (5.6)     | 11 (5.4)   |                      |         |
|                 | Degree and above   | 5 (2.0)      | 3 (1.5)    |                      |         |
|                 | Others             | 1 (0.4)      | 6 (2.9)    |                      |         |
| Main occupation | Paddy farmer       | 226 (89.7)   | 180 (87.8) | 5.307                | 0.380   |
|                 | Others farmer      | 5 (2.0)      | 10 (4.9)   |                      |         |
|                 | Business           | 5 (2.0)      | 4 (2.0)    |                      |         |
|                 | Government servant | 8 (3.2)      | 6 (2.9)    |                      |         |
|                 | Private company    | 3 (1.2)      | 4 (2.0)    |                      |         |
|                 | Others             | 5 (2.0)      | 1 (0.5)    |                      |         |

Note: Total Respondents (N) = 457; non-adopters n = 252; adopters n = 205; \*\* denotes significance at the 5% level.

Source: Survey data 2022.

Table 3 presents the distribution of paddy field characteristics by farming practice, along with the results of the Chi-square test of independence. The analysis shows that land rental status and planting method are significantly associated with green technology adoption. Specifically, green technology adopters are less likely to operate on rented land (57.1%) than conventional farmers (71.8%), indicating that land tenure arrangements influence adoption decisions ( $\chi^2 = 10.844$ ,  $p < 0.01$ ). In addition, a significantly higher proportion of adopters practice direct seeding (63.9%) than conventional farmers (44.4%), suggesting that planting method is closely linked to adopting sustainable practices ( $\chi^2 = 17.189$ ,  $p < 0.01$ ). In contrast, own land, soil type, and irrigation do not differ significantly between the two groups ( $p > 0.05$ ). This indicates that these factors are relatively homogeneous across the study area and do not distinguish between the groups in adoption behaviour.

Table 3: Farm Characteristics and Institutional Support by Adopters and Non-adopters

| Variables                                                              | Non-adopters | Adopters   | Statistical Analyses |          |
|------------------------------------------------------------------------|--------------|------------|----------------------|----------|
|                                                                        | n (%)        | n (%)      | Chi-Square           | p-value  |
| Own land<br>(1 = Own land, 0 = otherwise)                              | 146 (57.9)   | 131(63.9)  | 1.685                | 0.194    |
|                                                                        | 106 (42.1)   | 74 (36.1)  |                      |          |
| Rental land<br>(1 = Rental land, 0 = otherwise)                        | 181 (71.8)   | 117 (57.1) | 10.844               | 0.001*** |
|                                                                        | 71 (28.2)    | 88 (42.9)  |                      |          |
| Soil type<br>(1 = Clay soil, 0 = other soil types)                     | 165 (65.5)   | 135 (65.9) | 0.007                | 0.933    |
|                                                                        | 87 (34.5)    | 70 (34.1)  |                      |          |
| Irrigation<br>(1 = Canal irrigation, 0 = other irrigation arrangement) | 243 (96.4)   | 194 (94.6) | 0.870                | 0.351    |
|                                                                        | 9 (3.6)      | 11 (5.4)   |                      |          |

|                                                                        |            |            |        |          |
|------------------------------------------------------------------------|------------|------------|--------|----------|
| Planting method<br>(1 = Direct seeding, 0 = Mechanical transplanting)  | 112 (44.4) | 131 (63.9) | 17.189 | 0.000*** |
|                                                                        | 140 (55.6) | 74 (36.1)  |        |          |
| Training<br>(1 = Participated in agricultural training, 0 = otherwise) | 51 (20.2)  | 96 (46.8)  | 35.424 | 0.001*** |
|                                                                        | 201 979.8) | 109 (53.2) |        |          |
| Access to credit<br>(1 = Access to agricultural credit, 0 = otherwise) | 13 (5.2)   | 12 (5.9)   | 0.106  | 0.745    |
|                                                                        | 239 (94.8) | 193 (94.1) |        |          |
| Government grants<br>(1 = Received government grants, 0 = otherwise)   | 4 (1.6)    | 6 (2.9)    | 0.948  | 0.330    |
|                                                                        | 248 (98.4) | 199 (94.1) |        |          |
| Organic fertilizer<br>(1 = Received organic fertilizer, 0 = otherwise) | 18 (7.2)   | 13 (6.3)   | 0.023  | 0.879    |
|                                                                        | 234 (92.8) | 192 (93.7) |        |          |

Note: Total respondents (N) = 457; Conventional n = 252; Green Technology n = 205.

Significance levels: \*\*\* and \*\* denote significance at the 1% and 5% levels, respectively.

Source: Survey data 2022.

### Model Diagnostics and Robustness Checks

Several diagnostic tests were conducted to assess the adequacy and robustness of the logistic regression model. The link test was employed to assess potential model specification error. The fitted-value term ( $\hat{\mu}$ ) was statistically significant ( $p < 0.001$ ), whereas the squared fitted-value term ( $\hat{\mu}^2$ ) was insignificant ( $p = 0.512$ ), indicating no evidence of major specification error [34]. Multicollinearity was assessed using variance inflation factor (VIF) and tolerance statistics. The VIF values ranged from 1.04 to 1.36, while tolerance values ranged from 0.734 to 0.959, indicating no evidence of serious multicollinearity [35]. The Hosmer–Lemeshow goodness-of-fit test was insignificant ( $\chi^2(8) = 7.73$ ,  $p = 0.460$ ), suggesting no statistically significant difference between the observed and model-predicted outcomes and, therefore, an adequate model fit [36]. In addition, the receiver operating characteristic (ROC) analysis produced an area under the curve (AUC) of 0.733, indicating acceptable discriminatory ability in distinguishing green technology adopters from conventional farmers [37]. Finally, heteroskedasticity-robust standard errors were employed in the final Logit estimation to obtain more reliable statistical inference in the presence of potential heteroskedasticity [38]. Collectively, these diagnostic results indicate that the specified logistic regression model has adequate specification, no serious multicollinearity, satisfactory goodness-of-fit and acceptable discriminatory performance.

### Determinants of green technology adoption among rice farmers

A binary logistic regression model was estimated to examine the socioeconomic, farm, and institutional factors associated with green technology adoption among Malaysian paddy farmers. Table 4 presents the results of the binary logistic regression model estimating the determinants of green technology adoption among paddy farmers.

Table 4: Binary Logistic Regression Estimates of green technology adoption

| Variables                   | Coefficients ( $\beta$ ) | Robust Standard Error ( $\epsilon$ ) | z        | Odd Ratio | Marginal Effect |
|-----------------------------|--------------------------|--------------------------------------|----------|-----------|-----------------|
| <b>Socioeconomics</b>       |                          |                                      |          |           |                 |
| Age                         | 0.005                    | 0.010                                | 0.52     | 1.005     | 0.001           |
| Gender                      | -1.549                   | 0.473                                | -3.27*** | 0.212     | -0.353          |
| Education                   | -0.015                   | 0.052                                | -0.29    | 0.985     | -0.004          |
| Main occupation             | -0.093                   | 0.114                                | -0.82    | 0.911     | -0.023          |
| <b>Farm characteristics</b> |                          |                                      |          |           |                 |
| Own land                    | -0.451                   | 0.242                                | -1.86*   | 0.637     | -0.111          |

|                               |        |       |          |       |        |
|-------------------------------|--------|-------|----------|-------|--------|
| Rental land                   | -0.730 | 0.251 | -2.91*** | 0.481 | -0.180 |
| Soil Type                     | -0.047 | 0.232 | -0.20    | 0.954 | 0.011  |
| Irrigation                    | -0.914 | 0.525 | -1.74*   | 0.400 | -0.152 |
| Planting method               | 1.017  | 0.229 | 4.44***  | 2.764 | 0.223  |
| <b>Institutional supports</b> |        |       |          |       |        |
| Training                      | 1.531  | 0.228 | 6.72***  | 4.625 | 0.365  |
| Access to credit              | 0.246  | 0.470 | 0.52     | 1.278 | 0.061  |
| Government Grant              | 0.489  | 0.745 | 0.66     | 1.632 | 0.122  |
| Organic fertilizer            | -0.545 | 0.407 | -1.34    | 0.579 | -0.128 |
| Constant                      | 1.852  | 1.149 | 1.61     | 6.376 |        |

Note: Robust standard errors are reported. \*, \*\*, \*\*\* significant at  $\alpha < 10\%$ , 5% and 1%.

The logistic regression model is statistically significant overall, with a Wald  $\chi^2$  of 70.54 (13 df,  $p < 0.001$ ), indicating that the explanatory variables collectively provide meaningful information about green technology adoption. The model's Pseudo  $R^2$  is 0.1346. Given the cross-sectional data and binary outcome, this Pseudo  $R^2$  reflects model fit rather than variance explained. The model correctly predicted 44.4% of cases. We also used robust standard errors to address heteroskedasticity.

### Socioeconomic

Among socioeconomic variables, gender was negatively associated with green technology adoption ( $\beta = -1.549$ ,  $p = 0.001$ ), indicating a lower predicted probability of adoption among male farmers relative to female farmers, holding other covariates constant. This means females have a higher probability of adopting green technology, with a 35% marginal effect. Although gender was significantly associated with adoption, interpret the finding cautiously because female farmers constituted a relatively small proportion of the sample. The observed association may reflect differences in participation, access to information, or involvement in particular green-technology programs rather than a direct gender effect. Therefore, the finding should be regarded as an association specific to the study sample rather than evidence of a general gender effect. Begho et al. [11] reported both positive and negative gender effects across studies. Similarly, Chang et al. [7] highlighted heterogeneous effects of socioeconomic and demographic characteristics. This finding suggests that gender may capture differences in access to information, institutional networks, decision-making authority, and participation in agricultural programs, rather than differences in environmental attitudes per se.

Age was not a significant factor ( $\beta = 0.005$ ,  $p = 0.601$ ), indicating no systematic difference between younger and older farmers after accounting for other variables. This aligns with the mixed evidence reported by Begho et al. [11]. The findings support the idea that adoption should not be automatically linked to younger farmers being more innovative or older farmers being more experienced; access to relevant knowledge and institutional exposure may matter more. Occupation status, defined as agriculture being the main occupation, does not significantly affect adoption. Education level shows a negative but statistically insignificant relationship with adoption. The non-significant education coefficient contrasts with Rahman [17] and some previous adoption studies. However, this finding does not necessarily imply that knowledge is unimportant. Rather, it suggests that general formal education may be less directly relevant than technology-specific knowledge acquired through agricultural training.

### Farm characteristics

Farm characteristics significantly influence adoption behaviour. Although landownership has a slight, statistically insignificant negative coefficient, rental land status shows a notable negative effect ( $\beta = -0.731$ ,  $p = 0.004$ , OR = 0.482). This indicates that farmers on rented land have about 51.8% lower odds of adopting green technology than those with other land tenures, after accounting for other factors. Soil type and irrigation system do not significantly affect adoption, suggesting these factors do not systematically influence green technology

adoption. Conversely, the planting method is a strong indicator ( $\beta = 1.016$ ,  $p < 0.001$ ; OR = 2.76), with farmers using a particular method having roughly 2.76 times higher odds of adopting green technology than the baseline, highlighting it as a useful farm-management indicator rather than a direct driver of technology adoption.

Land rental was negatively associated with green technology adoption relative to farmers operating under other arrangements. This finding is consistent with the broader argument that land-tenure arrangements can shape incentives to undertake sustainable farm investments [22]. However, the result should not be interpreted as evidence that ownership itself necessarily promotes adoption, since own-land status was only marginally significant. Instead, the findings suggest that different land-access arrangements may generate different incentives and levels of control over farm-management decisions.

The planting method was also a significant positive predictor ( $\beta = 1.017$ ,  $p < 0.001$ ; OR  $\approx$  2.76). Farmers categorised as 1 had about 2.76 times higher odds of adoption compared to the reference group. This indicates that current production-management practices could be linked to farmers' willingness to adopt broader sustainable technologies. In line with Chang et al. [7], farm-management traits might be more revealing than demographic factors alone. However, planting method should not be viewed as a direct causal factor without additional evidence, as it may partly reflect a modern or structured farm-management approach.

Irrigation showed a slight negative link with adoption, but this was only marginally significant ( $\beta = -0.914$ ,  $p = 0.082$ ). Since it does not reach the standard 5% significance level, this result is weak evidence. Although Begho et al. [11] found irrigation significant in several adoption studies, this discrepancy may reflect differences in how irrigation is measured and the more structured irrigation system of IADA Barat Laut Selangor. Therefore, this finding should not be taken as proof that irrigation infrastructure deters green technology adoption.

### **Institutional supports**

The strongest association was observed for training, which was significant at the 1% level ( $\beta = 1.531$ ,  $p < 0.001$ ; OR = 4.63). This finding supports the argument that technology-specific knowledge and practical exposure are important for sustainable agricultural adoption [7,11]. It also contrasts interestingly with Rahman [17], who found that training was not statistically significant in the ordered adoption model despite a higher proportion of high IPM adopters having received training. This difference suggests that training effectiveness may depend on its content, intensity, and institutional delivery. In the Malaysian paddy context, training specifically related to myGAP and IPM may provide practical knowledge more directly relevant to adoption than general formal education. This result supports findings from Haque et al. [24] and Begho et al. [11], who reviewed 133 studies and identified extension and training as key drivers for sustainable technology adoption. This also concurs with Singh et al. [29], who reported that formal IPM training through farmer field schools effectively promotes adoption, and with Md Nordin et al. [14] and Adnan et al. [12,13], who stressed the importance of knowledge, information, communication, and behaviour in Malaysian paddy farmers' adoption of sustainable practices. Additionally, Harun et al. [26] agree that social capital via training, peer learning, and advisory access improves sustainable rice farming in Malaysia.

Contrary to expectations and some previous studies [7,11], credit and government grants were not significantly associated with green technology adoption. This suggests that financial access alone may not be the primary constraint to adopting myGAP and IPM. These technologies require substantial knowledge, management, and compliance, implying that technical assistance and extension support may be more directly relevant than general financial assistance. This, in turn, suggests that financial support alone may be insufficient if capability and knowledge gaps remain. Similarly, the lack of significance for organic fertiliser use shows that adopting one environmentally friendly practice doesn't automatically lead to broader green technology adoption. Farmers tend to adopt practices selectively, based on perceived costs, benefits, familiarity, and technical demands. Therefore, green technology adoption should be viewed as a practice-specific, multidimensional decision rather than a uniform reaction to environmental concerns.

The findings show that farmers' demographic traits alone do not account for their adoption of green technology. Key factors included training, gender, planting method, and land tenure, while land ownership and irrigation played a minor role at the 10% significance level. Conversely, age, education, occupation, land type, credit, government grants, and organic fertiliser use were not statistically significant at the typical 5% level. This indicates that technology-specific skills and farm-related conditions influence adoption more than traditional socioeconomic factors.

This finding provides a more precise contribution: training proved significant, while formal education did not. This suggests that specific technological knowledge and practical experience may matter more than overall educational levels. Green technologies like IPM and myGAP require farmers to adapt their routines, grasp technical details, and apply knowledge in practice. Therefore, the results suggest a shift from a broad human-capital focus to a technology-specific learning approach. This interpretation is consistent with Chang et al. [7], who highlighted behavioural and institutional factors as key yet varied influences on sustainable rice-farming practices in Southeast Asia.

Overall, the results both confirm and challenge earlier evidence. Rahman [17], for instance, found positive impacts of education and farm size on IPM adoption, while Kamaruddin and Abd. Rashid [18] reported that cultivated land size was not a significant factor in explaining sustainable farm management among Malaysian paddy farmers. The notable training effect observed in this study also contrasts with Rahman's [17] findings of an insignificant training impact, despite higher training participation among high IPM adopters. These variations suggest that adoption depends on context and technology, shaped by differences in complexity, institutional support, and socioeconomic conditions.

This study broadens current research by showing that adoption of green technology among Malaysian paddy farmers depends less on traditional demographic factors and more on targeted training programs, farm-management focus, and land tenure conditions. It advocates shifting from a technology-focused strategy to a capability-based policy that emphasises hands-on training, experiential learning, and institutional support, along with initiatives that motivate farmers to invest in sustainable practices.

### **Conclusion and Policy implication**

This study examined the socioeconomic, farm, and institutional characteristics associated with green technology adoption among 457 Malaysian paddy farmers in IADA BLS. The results indicate that training, planting method, gender, and land tenure arrangements are the main variables associated with adoption. In contrast, age, formal education, occupation, soil type, credit, grants, and organic fertiliser use are not statistically significant.

Training is the strongest policy-relevant finding, underscoring the importance of practical, technology-specific extension. Agricultural agencies should therefore strengthen ongoing, field-based training in IPM, myGAP compliance, pest monitoring, and sustainable farm management. The negative association between rental tenure and adoption also suggests the need for more inclusive extension and certification support for tenant farmers. Because credit and grants were not significant, financial assistance should be complemented by technical and institutional support rather than treated as a stand-alone adoption instrument.

These findings should be interpreted as associations due to the cross-sectional design and purposive sampling among adopters. The cross-sectional design limits the ability to establish temporal or causal relationships between the explanatory variables and technology adoption. Therefore, interpret the estimated coefficients as associations rather than causal effects. Future research using probability-based, longitudinal data would provide stronger evidence on the temporal and behavioural mechanisms underlying green technology adoption. Further research could also incorporate behavioural variables such as perceived benefits, environmental awareness, risk attitudes, and perceived behavioural control.

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**Availability of data and material:** The data set used/or analyzed for this study is available from the corresponding author upon reasonable request.

## Declarations

**Conflicts of interest/Competing interests:** The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

**Ethics approval:** Ethics approval was not required for data collection. The study involved a questionnaire survey as a low-risk activity involving adult participants and non-identifiable, non-sensitive data, so institutional ethics approval was not sought. The Director of the Integrated Agricultural Development Area (IADA) Barat Laut Selangor granted administrative approval via an official letter dated 27 December 2021. Participation was voluntary, with informed consent obtained from all participants, and responses were collected anonymously and kept confidential.

**Consent to participate:** Before each interview, participants were informed of the study's objectives, the voluntary nature of participation, and the confidentiality of their responses. Verbal informed consent was obtained from all participants before administering the questionnaire. Only those who agreed to participate were allowed to continue and complete the survey. Participants were also informed that they could decline to participate or withdraw from the survey at any time without any consequences.

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