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Ordinal regression of rice technology adoption in Pinrang, Indonesia

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[3]Department of Socio-economics of Agriculture, Faculty of Agriculture, Universitas Hasanuddin. Jl. Perintis Kemerdekaan No. Km. 10. Tamalanrea Indah, Tamalanrea, Makassar City 90245, South Sulawesi, Indonesia
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Abstract. *Hasnal, BDR MF, Akhsan, Jamil MH, Baba S. 2026. Ordinal regression of rice technology adoption in Pinrang, Indonesia. Asian J Agric 10 (1): g100146. https://doi.org/10.13057/asianjagric/g100146.* The agricultural sector continues to play a vital role in sustaining livelihoods in Indonesia, contributing significantly to national food security and rural economic development, with rice as the staple food. However, the decline in rice cultivation area and productivity in Pinrang District highlights the need to enhance the adoption of agricultural technology. Optimizing rice production requires intensive management, including the use of modern equipment, high-yielding varieties, and the implementation of sustainable agricultural practices. This study examines the socioeconomic factors influencing the adoption of rice farming technology amid increasing agricultural digitalisation. The results indicate that most farmers are at a moderate level of technology adoption, suggesting uneven diffusion across farmer groups. Formal education, distance from home to farmland, extension intensity, and household income emerged as key positive predictors of adoption. In contrast, participation in non-formal education had a negative effect, particularly among farmers who had never attended non-formal training. These findings provide important insights for policymakers and stakeholders in designing targeted interventions, strengthening extension services, and improving access to education and resources to promote wider adoption of agricultural technologies and ultimately enhance rice productivity and farmers' welfare.

Keywords: Agricultural extension, ordinal regression, rice farming, South Sulawesi, technology adoption

INTRODUCTION

The agricultural sector plays a strategic role in ensuring global food security and serves as one of the main pillars of Indonesia's economy (Sagrim 2022; Siregar et al. 2024; Kadir et al. 2025; Widyastutik et al. 2025). In 2023, it contributed 13.7% to the national Gross Domestic Product (GDP) (Badan Pusat Statistik (BPS) Indonesia 2025). Rice (*Oryza sativa*), as the staple food for nearly 90% of the population (Saragih 2001), remains a vital commodity for maintaining national food security. Optimizing rice production requires intensive management, including the use of modern equipment, high-yielding varieties, and the implementation of sustainable agricultural practices (Deng et al. 2026). To support these efforts, the government enacted Indonesian Minister of Agriculture Regulation No. 19 of 2017, which strengthens the institutional role of the Agricultural Technology Assessment Agency (BPTP) in accelerating the adoption of agricultural technologies.

Despite these efforts, rice-producing regions outside Java, particularly South Sulawesi, have experienced fluctuations in production. Although the province was the largest rice producer outside Java in 2022 and was recognized for its strong food security performance from 2018 to 2020 (Dinas Komunikasi dan Informasi Sulawesi Selatan 2021), several key districts such as Pinrang, Wajo, and Bone recorded production declines in 2023 (BPS Sulawesi Selatan 2024). Java Island continues to dominate more than half of national production, with East Java, Central Java, and West Java as the primary contributors, while provinces such as South Sulawesi, South Sumatra, and Lampung also play a critical role in ensuring rice availability across the country.

Pinrang District has shown a consistent downward trend in harvested area and production in recent years. The rice harvest area and production in Pinrang District showed a significant downward trend until 2023, with a recorded harvest area of 77,790 hectares and production of 453,510.7 tonnes in that year, marking a decrease of 11,110 hectares and 93.97 thousand tonnes from the previous year, as well as a more drastic decline compared to 2019. Rice productivity also fluctuated, reaching 5.83 tonnes per hectare in 2023, though it was lower in 2020 (BPS Pinrang 2020, 2022, 2024). This decline is likely influenced by various factors, including the efficiency of input allocation in production, the adoption of agricultural technology in the digitalisation era, and the need for more sustainable agricultural sector development to achieve stable growth (Sinabang et al. 2021).

Technology diffusion plays a pivotal role in advancing agricultural development and improving farmers' welfare. Prior studies have demonstrated that technology adoption can optimize crop yields (Sisay et al. 2018; Rahayu et al. 2019), enhance capital and labor efficiency (Sunaryono et al. 2021), strengthen the capacity of young farmers (Qudrotulloh et al. 2022), and improve the quality, quantity, and speed of cultivation processes (Budiman et al. 2022). Moreover, technology facilitates better resource management, such as irrigation during the dry season (Shofi et al. 2023), and promotes efficiency through smart farming applications (Jain and Kumar 2017; Tjhin and Riantini 2022; Wulakada et al. 2025).

Numerous studies have explored factors influencing the adoption of agricultural technologies across diverse settings. (Selan et al. 2019) examined the adoption of Integrated Crop Management (PTT) rice technologies using a binary outcome (adopted vs. not adopted), emphasizing the role of age, experience, education, and access to information. Intiaz et al. (2022) focused on the adoption of combine harvesters, while Wulandari et al. (2024) analyzed the *jajar legowo* planting system. Miine et al. (2023) studied the adoption of digital agricultural services such as drones, and Vihi et al. (2024) analyzed farmer characteristics and institutional support in Nigeria. Other relevant contributions include Bananiek and Abidin (2013), and Riasa et al. (2020), which addressed various types of technology and socio-economic dimensions in different regional contexts.

Among these, the studies by Selan et al. (2019), Intiaz et al. (2022), Miine et al. (2023), and Vihi et al. (2024) offer valuable insights but remain limited in scope. For example, Selan et al. (2019), categorized adoption using a binary classification, failing to capture variations in adoption intensity. Similarly, Intiaz et al. (2022) focused on specific technologies but did not address progressive stages of adoption. Miine et al. (2023) assessed the use of drones but did not examine their degree of utilization. Vihi et al. (2024) explored determinants of adoption in Nigeria without employing an ordinal analytical framework. Overall, these studies have not fully examined the multi-level nature of adoption across multiple technologies within a unified model.

This study fills that gap by applying an ordinal logistic regression model to investigate the adoption levels - categorized as low, medium, and high- of seven rice cultivation technologies: tractors, transplanters, drones, electric sprayers, certified seeds, the *jajar legowo* system, and combine harvesters. Conducted in Pinrang District, South Sulawesi, a key rice-producing region with distinct agroecological and socio-economic characteristics, the study incorporates nine explanatory variables, including age, education, farming experience, income, non-formal education, land area, access to information, distance to farmland, and extension intensity. By shifting from binary to ordinal classification, this research provides a more nuanced and comprehensive analysis of adoption behavior, generating more precise insights to inform agricultural policy and technology dissemination strategies.

MATERIALS AND METHODS

Research framework

Based on an extensive literature review, this study developed a framework to investigate the factors influencing the adoption of rice farming technology. The hypothesized determinants included: education, farming experience, age, access to information sources, land area, extension intensity, distance from home to farm location, non-formal education, and income.

Study area and period

This study was conducted in Pinrang District, South Sulawesi Province, Indonesia (Figure 1). Three sub-districts were purposively selected as the study sites: Patampanua, Tiroang, and Matiro Bulu. Pinrang District was chosen due to its status as one of the major rice-producing centres in South Sulawesi. Within each sub-district, three villages were sampled: Tonyamang, Teppo, and Meccerinna in Patampanua; Mattiro Deceng, Marawi, and Pammase in Tiroang; and Padaidi, Manarang, and Pananrang in Matiro Bulu. Data collection was conducted from August 2024 to February 2025.

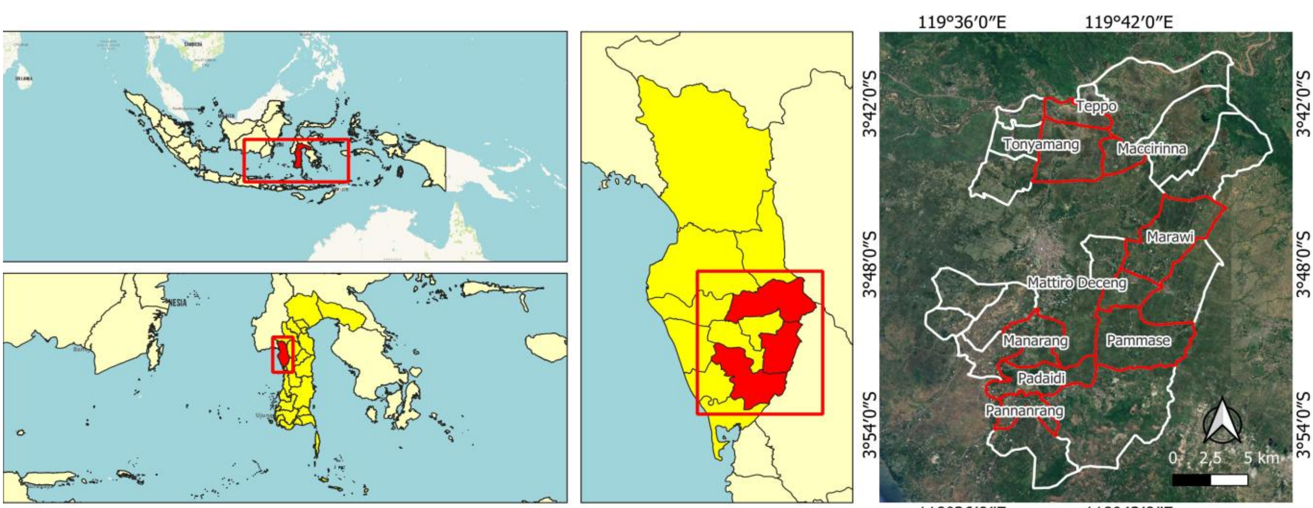

Figure 1. Research location map in Pinrang District, South Sulawesi Province, Indonesia

Population and sample

The study population consisted of 11,123 rice farmers from three sub-districts that produce rice in Pinrang District. The sampling technique employed was the Slovin formula (Slovin 1960), which determines the minimum sample size based on population size and desired precision level. Using a 10% margin of error, the calculated minimum sample size was 99 respondents. To ensure adequate representation and account for potential non-responses, the researchers surveyed 108 rice farmers, exceeding the minimum requirement by 9%.

Data type and sources

This study utilized both primary and secondary data. Primary data were collected through structured interviews using a validated questionnaire administered to rice farmers in Pinrang District between August 2024 and February 2025. The questionnaire captured quantitative information on farmer characteristics, technology adoption practices, and socioeconomic variables. Secondary data were obtained from the Central Bureau of Statistics (BPS) of Pinrang District and included agricultural production statistics, demographic information, and regional agricultural development reports. Prior to fieldwork, the questionnaire was pre-tested with 10 farmers to ensure clarity and reliability of the instrument.

Data analysis

Measuring the level of adoption of rice paddy technology

The level of rice cultivation technology adoption was measured based on the cumulative score of seven types of technologies: tractors, transplanters, drones, electric sprayers, certified seeds, the *jajar legowo* planting system, and combine harvesters. For each technology, farmers were assigned a score based on their adoption status: 1 (not adopted) 2 (partially adopted), or 3 (fully adopted). The total adoption score thus ranged from 7 to 21.

The adoption level was subsequently classified into three categories using equal-interval classification: low (score 7-11), medium (score 12-16), and high (score 17-21). The class interval was calculated using the formula $C = (X_n - X_i) / K$, where the maximum score is 21, the minimum score is 7, and the number of classes is 3, yielding an interval width of 4.67, which was rounded to 5 for practical classification. Detailed calculations are presented in Appendix A. Table 1 presents the scoring criteria for each technology, while Table 2 summarizes the classification thresholds for overall adoption levels.

Ordinal logistic regression analysis

Ordinal logistic regression is a statistical technique used to analyze the relationship between an ordinal response variable and one or more predictor variables. This model is particularly appropriate when the response categories follow a natural order, such as "low," "medium," and "high" (Agresti 2010). Among the various modeling approaches, the cumulative logit model is the most commonly used due to its ability to handle the ordered structure of the outcome through the calculation of cumulative probabilities (Hosmer et al. 2013).

In this context, the cumulative probability of being in category r or below, $P(Y \leq r \mid x)$, is modeled as a function of the predictor variables using the logit transformation. Parameter estimation is conducted using the Maximum Likelihood Estimation (MLE) method, which aims to maximize the likelihood function based on the observed data (Utari et al. 2023). Since the likelihood function involves non-linear derivatives, numerical methods such as the Newton-Raphson iteration are employed to obtain parameter estimates (Setyawati et al. 2020).

This model also adopts the proportional odds assumption, in which the regression coefficients (β) are assumed to be constant across the different thresholds of the response categories, while the intercepts may vary. This means that a single set of β coefficients is applied to all cumulative logit equations, reflecting consistent effects of predictors across response levels (Lahens et al. 2024).

Research model specifications

In this study, the dependent variable is the level of rice cultivation technology adoption (TAT), which is categorized into three ordinal levels: low (1), medium (2), and high (3). The nine predictor variables include: years of formal education (LP), farming experience in years (PP), age in years (U), number of information sources (JSI), land area in hectares (LL), frequency of agricultural extension visits (IP), distance from home to farmland in kilometers (JRU), non-formal education participation (PNF), and annual household income in Indonesian Rupiah (P). The operational definitions and measurement scales of these variables are presented in Table 3.

Table 1. Indicators of adoption rate of paddy rice technology

Indicator	Criteria
Farmers use ploughing technology in the form of tractors in the process of wet rice farming Farmers use planter technology in the form of rice transplanter in the process of rice paddy farming. Farmers use sprayers in the form of drones in the process of farming paddy rice. Farmers use sprayers in the form of electric hand sprayers in the process of farming paddy rice. Farmers use a harvester in the form of a combine harvester in the process of farming rice paddies. Farmers use certified rice seeds in paddy rice farming. Farmers use the jajar legowo planting system in paddy rice farming.	Full use of technology (3), Not full use of technology (2), Not using technology (1)

Table 2. Categories of adoption level of paddy rice technology

Category	Class interval
Low	7-11
Medium	12-16
High	17-21

Note: Data processed by researchers in 2024

Table 3. Variable definitions and measurements

Independent variable	Dependent variable: Y = Adoption rate of rice technology), Where: 1: Low adoption; 2: Medium adoption; 3: High adoption				
Variable name	**Unit of measurement**	**Type of data**	**Hypothesis**	**Expected hypothesis /Significance results[b]**	**Reference**
Duration of Education (LP)	Year	Continuous	H_O: No effect H_1: There is an effect	+/SIG	(Khanal 2019; Ullah et al. 2022; Vihi et al. 2024; Oli et al. 2025)
Experience (P)	Year	Continuous	H_O: No effect H_1: There is an effect	+/SIG	(Bananiek and Abidin 2013)
Age (U)	Year	Continuous	H_O: No effect H_1: There is an effect	+/SIG	(Akudugu et al. 2012; Bananiek and Abidin 2013; Vihi et al. 2024)
Number of Information Sources (JSI)	Total	Continuous	H_O: No effect H_1: There is an effect	+/SIG	(Jamal et al. 2014; Caffaro et al. 2020; Wulandari et al. 2024; Du et al. 2025)
Land Size (LL)	Ha	Continuous	H_O: No effect H_1: There is an effect	+/SIG	(Bananiek and Abidin 2013; Vihi et al. 2024)
Intensity of agricultural extension (IP)	Frequency	Continuous	H_O: No effect H_1: There is an effect	+/SIG	(Cook et al. 2021; Miine et al. 2023; Wulandari et al. 2024)
Distance from Home to Farm Location (JRU)	Km	Continuous	H_O: No effect H_1: There is an effect	+/SIG	(Abdulai et al. 2021; Arizka et al. 2021; Zhichkin et al. 2023; Nagaraja et al. 2024)
Non Formal Education (PNF)	1= ever followed 0= never followed	Dischotomos	H_O: No effect H_1: There is an effect	+/SIG	(Duveskog et al. 2011; Khanal 2019; Mariyono et al. 2021; Miine et al. 2023)
Revenue (P)	Rp	Continuous	H_O: No effect H_1: There is an effect	+/SIG	(Bananiek and Abidin 2013; Ullah et al. 2022; Vihi et al. 2024)

$$\text{logit}[P(TAT \leq 1|x)] = \beta_{01} + \beta_1 LP + \beta_2 PP + \beta_3 U + \beta_4 JSI + \beta_5 LL + \beta_6 IP + \beta_7 JRU + \beta_8 PNF + \beta_9 P$$

$$\text{logit}[P(TAT \leq 2|x)] = \beta_{02} + \beta_1 LP + \beta_2 PP + \beta_3 U + \beta_4 JSI + \beta_5 LL + \beta_6 IP + \beta_7 JRU + \beta_8 PNF + \beta_9 P$$

Where, β_{01} and β_{02} are the threshold parameters (intercepts) for categories 1 and 2, respectively, $\beta_1, \beta_2, ..., \beta_9$ are the regression coefficients assumed constant across categories (proportional odds assumption) and x represents the vector of predictor variables

Model evaluation and interpretation

Simultaneous (global) testing in ordinal logistic regression is used to evaluate whether all independent variables collectively have a significant effect on the dependent variable by comparing a full model (with predictors) to a null model (without predictors). The model is considered statistically significant if the log-likelihood decreases substantially, as indicated by a p-value less than the significance level (α) or if the G^2 test statistic exceeds the critical value of the chi-square distribution at the specified degrees of freedom (Pradhan et al. 2013; Setyawati et al. 2020; Tafhamin and Indawati 2022). The G^2 statistic follows a chi-square distribution with degrees of freedom equal to the number of predictors. Additionally, to assess the overall contribution of the independent variables, this study uses pseudo R^2 measures, which include Cox and Snell R^2, Nagelkerke R^2, and McFadden R^2. A higher pseudo R^2 value indicates a stronger collective influence of the independent variables on the response variable (Salam et al. 2024; Sholikah et al. 2024).

Partial testing uses the Wald test statistic to assess the significance of individual regression coefficients (Setyawati et al. 2020). A coefficient is considered statistically significant if its p**-value is less than the predetermined significance level ($\alpha = 0.05$ in this study). **The overall model fit is evaluated using the goodness-of-fit test based on deviance. A p-value > α indicates that the model adequately fits the observed data (Hosmer et al. 2013).

Interpretation of the odds ratio is used to determine the direction and strength of each predictor's effect. An odds ratio less than 1 indicates a negative relationship, whereas a value greater than 1 indicates a positive relationship -that is, an increased likelihood of being in higher adoption categories (Tafhamin and Indawati 2022). An odds ratio equal to 1 suggests no effect of the predictor on the outcome.

RESULTS AND DISCUSSION

Distribution of rice cultivation technology adoption levels

The distribution of rice cultivation technology adoption levels among farmers in Pinrang District is presented in Figure 2. The results reveal that the majority of respondents (69 farmers, 63.9%) demonstrated moderate adoption levels, indicating that these farmers have integrated several, but not all, technological components into their farming practices. A notable proportion (26 farmers, 24.1%) achieved high adoption levels, suggesting successful and comprehensive implementation of the seven technologies examined in this study. Conversely, 13 farmers (12.0%) remained at low adoption levels, reflecting limited engagement with modern agricultural technologies.These findings indicate that while technology dissemination efforts in Pinrang District have achieved considerable success, with nearly 88% of farmers adopting technologies at moderate to high levels, there remains room for improvement. The presence of 12% of farmers with low adoption rates suggests that technology diffusion has not been uniform across the district. This heterogeneity may be attributed to various factors, including limited access to financial resources, insufficient extension services, socioeconomic constraints, or differences in farm characteristics. The predominance of moderate adoption suggests that many farmers are in a transitional phase and may benefit from additional support to achieve comprehensive technology integration.

Factors determinants of rice cultivation technology adoption

Multicollinearity test

Multicollinearity among independent variables was evaluated using the Variance Inflation Factor (VIF) and tolerance statistics. Threshold criteria of VIF < 10 (Pradhan 2016) and tolerance > 0.10 were applied to assess acceptable independence among predictors. As presented in Table 4, all variables satisfied these criteria, indicating the absence of problematic multicollinearity in the model.

Ordinal logistic regression analysis

Pseudo R-Square test

Table 4 shows a Nagelkerke R-Square value of 0.961, indicating that the nine independent variables collectively explain approximately 96.1% of the variation in the level of rice paddy technology adoption. The remaining 3.9% may be attributed to other unobserved factors outside the model. According to Sholikah et al. (2024), a higher Pseudo R-Square value reflects a stronger joint influence of independent variables on the dependent variable.

Simultaneous test

Table 4 shows a substantial decrease in the -2 Log Likelihood value, from 190.924 in the intercept-only model to 18.711 in the final model. This reduction yields a Chi-square value of 172.213 (df = 9, p < 0.001), which substantially exceeds the critical value of 16.919 at α = 0.05 [or 14.684 at α = 0.10]. These results indicate that the final model, which includes all nine independent variables, significantly improves model fit compared to the null model. Therefore, the null hypothesis (H_0) that the independent variables have no collective effect on the dependent variable is rejected, confirming that the independent variables collectively have a significant effect on rice cultivation technology adoption levels.

Partial test

Table 5 presents the parameter estimates and Wald test results for each independent variable. Six of the nine variables demonstrated statistically significant effects on rice cultivation technology adoption. At the 95% confidence level (α = 0.05), four variables were significant: number of information sources (JSI), distance from home to farmland (JRU), non-formal education (PNF), and household income (P), with Wald statistics exceeding the critical χ^2 value of 3.841 and p-values < 0.05. Two additional variables, duration of education (LP) and intensity of extension (IP), were significant at the 90% confidence level (α = 0.10), with Wald statistics greater than 2.706 and p-values < 0.10.

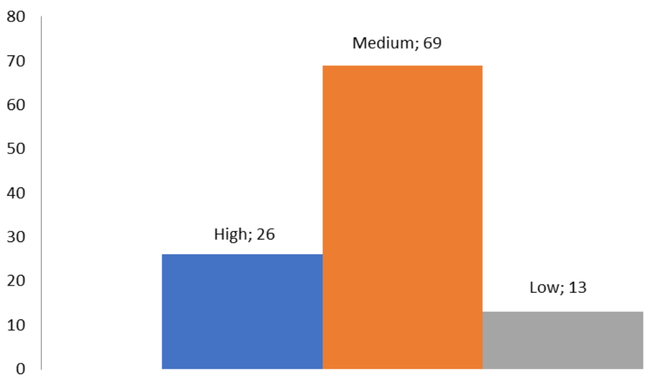

Figure 2. Distribution of rice cultivation technology adoption levels among farmers in Pinrang District, South Sulawesi Province, Indonesia (n=108)

Table 4. Results of multicollinearity test, pseudo R-square, and simultaneous test

Coefficients[a]	**Collinearity statistics**		**Pseudo R-square**		**Model fitting information**		
Model	**Tolerance**	**VIF**			**Model**	**Intercept only**	**Final**
Duration of Education (LP)	0.514	1.947	Cox and Snell	0.797	-2 Log Likelihood	190.924	18.711
Farmer Experience (PP)	0.322	3.107	Nagelkerke	0.961	Chi-square		172.213
Age (U)	0.346	2.887	McFadden	0.902	Df		9
Number of Information Sources (JSI)	0.550	1.819			Sig.		0.000
Land Size (LL)	0.834	1.200					
Intensity of agricultural extension (IP)	0.605	1.653					
Distance from Home to Farm Location (JRU)	0.591	1.692					
Non-Formal Education (PNF)	0.734	1.363					
Revenue (P)	0.584	1.714					

Note: [a]: Dependent variable: Level of rice paddy technology adoption

Table 5. Parameter estimates for ordinal logistic regression model

		Parameter estimates					
Variable		**Estimate**	**Std. Error**	**Wald**	**Df**	**Sig.**	**Exp (β)**
Threshold	[TAT=1] Low adoption level	27.444	11.884	5.333	1	0.022	-
	[TAT=2] Medium adoption level	46.702	17.162	7.405	1	0.007	
Location	Length of Education (LP)	0.865	0.447	3.748	1	0.053*	2.374
	Farmer Experience (PP)	0.216	0.146	2.176	1	0.140	1.241
	Age (U)	-0.061	0.158	0.149	1	0.700	0.941
	Number of Information Sources (JSI)	2.768	1.361	4.138	1	0.042**	15.929
	Land Size (LL)	0.077	1.649	0.002	1	0.963	1.080
	Intensity of agricultural extension (IP)	1.209	0.716	2.850	1	0.091*	3.350
	Distance from Home to Farm Location (JRU)	2.693	1.196	5.069	1	0.024**	14.780
	Revenue (P)	0.582	0.255	5.227	1	0.022**	1.790
	Non-Formal Education (PNF=0)	-4.726	2.090	5.110	1	0.024**	0.009
	Non-Formal Education (PNF=1)	0[a]	-	-	0	-	-

Note: **: Significant at $\alpha = 0.05$, *: Significant at $\alpha = 0.10$, [a]: Reference category, -: Not applicable

Conversely, three variables-farming experience (PP), age (U), and land area (LL)-did not show significant effects, as their Wald statistics were below the critical values and their p-values exceeded 0.10. Therefore, for these three variables, the null hypothesis (H_0) of no effect was retained.

The estimated ordinal logistic regression model is expressed as:

For low adoption level (TAT ≤ 1):

logit[P(TAT ≤ 1|x)] = 27.444 + 0.865(LP) + 0.216(PP) - 0.061(U) + 2.768(JSI) + 0.077(LL) + 1.209(IP) + 2.693(JRU) - 4.726(PNF) + 0.582(P)

For medium adoption level (TAT ≤ 2):

logit[P(TAT ≤ 2|x)] = 46.702 + 0.865(LP) + 0.216(PP) - 0.061(U) + 2.768(JSI) + 0.077(LL) + 1.209(IP) + 2.693(JRU) - 4.726(PNF) + 0.582(P)

Where, the coefficients remain constant across categories (proportional odds assumption), and only the threshold parameters (27.444 and 46.702) differ between the two models.

Duration of formal education (LP)

The duration of formal education (LP) demonstrated a statistically significant positive effect on rice cultivation technology adoption at the 90% confidence level (β = 0.865, p = 0.053, OR = 2.374). This finding indicates that farmers with longer years of formal education are 2.374 times more likely to progress to higher adoption categories compared to those with shorter education duration, holding other factors constant. Higher education enhances cognitive abilities, enabling farmers to better understand extension materials, assess the benefits of innovations, and make informed adoption decisions. This finding is consistent with previous studies (Khanal 2019; Ruzzante et al. 2021; Oli et al. 2025), which confirm that education plays a vital role in shaping learning attitudes, increasing technological literacy, and strengthening farmers' capacity to identify problems and adopt innovative solutions. Therefore, formal education emerges as a key driver of agricultural technology adoption in rice farming systems.

Access to information sources (JSI)

The number of information sources (JSI) had a statistically significant positive effect on technology adoption at the 95% confidence level (β = 2.768, p = 0.042, OR = 15.929). Farmers who access a greater diversity of information sources are substantially more likely to adopt rice cultivation technologies comprehensively. The notably high odds ratio suggests that each additional information source dramatically increases the likelihood of higher adoption. Broader access to information enhances farmers' understanding and confidence in new technologies, which in turn facilitates adoption decisions. Both informal channels (social media, peer networks) and formal sources (extension workers, farmer organizations) play crucial roles in expanding knowledge and shaping perceptions (Jamal et al. 2014; Caffaro et al. 2020). Reliable and credible sources are especially important for conveying information about the benefits, applications, and potential risks of agricultural technologies (Wulandari et al. 2024). As emphasized by Du et al. (2025), information literacy significantly influences farmers' readiness and capacity to adopt new technologies.

Frequency of extension contact (IP)

The intensity of agricultural extension (IP) demonstrated a significant positive effect on technology adoption at the 90% confidence level (β = 1.209, p = 0.091, OR = 3.350). Farmers who participate more frequently in extension activities are 3.350 times more likely to adopt rice cultivation technologies at higher levels. Regular extension contact through diverse methods provides farmers with essential knowledge, raises awareness, and builds confidence to adopt innovations such as certified seeds, mechanized equipment, or improved planting systems like *jajar legowo*. As emphasized in previous studies (Cook et al. 2021), the frequency of extension visits positively affects technology adoption and utilization. Furthermore, repeated exposure to information through extension services helps reduce uncertainty, strengthen understanding of benefits, and guide farmers in the practical application of technologies (Miine et al. 2023; Wulandari et al. 2024; Joka et al. 2025), thereby accelerating adoption and enhancing decision-making capacity.

Distance from home to farmland (JRU)

Distance from home to farm location (JRU) exhibited a statistically significant positive effect on rice technology adoption at the 95% confidence level ($\beta = 2.693$, $p = 0.024$; OR = 14.780). The positive coefficient indicates that greater distance between residence and farmland is associated with higher odds of technology adoption. Substantively, the odds ratio suggests a strong increase in adoption likelihood with increasing distance; however, the magnitude should be interpreted cautiously given the scale of the distance variable and the contextual specificity of the study area.

This finding contrasts with much of the existing literature (Aakjaer 2014; Abdulai et al. 2021), which generally reports that greater distance reduces adoption due to higher transportation costs and monitoring constraints. In the present context, however, the relationship may reflect adaptive behavior: farmers managing more distant plots may prioritize labor-saving and time-efficient technologies to reduce travel frequency and operational delays (Zhichkin et al. 2023; Nagaraja et al. 2024).

In addition, local infrastructure conditions may partly explain the observed pattern. Field observations indicate that agricultural machinery service units-providing access to equipment such as drones and transplanters-are concentrated in Tiroang Sub-district. Where farmland is located near these service facilities, access to rental services, demonstrations, and technical support may offset the disadvantages of residential distance. Thus, in this setting, proximity to technology providers at the farm site may exert stronger influence on adoption decisions than the distance between the farmer's home and the land itself (Arizka et al. 2021).

Nevertheless, given the magnitude of the estimated odds ratio and its divergence from prevailing empirical findings, the result should be interpreted within the specific infrastructural and geographic configuration of the study area rather than generalized broadly. Further research incorporating interaction effects, spatial accessibility measures, and alternative model specifications would help clarify the robustness and mechanism of this relationship.

Participation in non-formal education (PNF=0)

Non-formal education participation (PNF) had a statistically significant effect on technology adoption at the 95% confidence level ($\beta = -4.726$, $p = 0.024$, OR = 0.009 for PNF=0). The negative coefficient and odds ratio below 1 indicate that farmers who have never participated in non-formal education (PNF=0) are significantly less likely to adopt technologies compared to those who have participated (PNF=1, reference category). Specifically, non-participants have only 0.9% of the odds of adoption compared to participants, highlighting the critical importance of non-formal education programs.

This finding highlights the crucial role of non-formal education-such as agricultural training, workshops, and farmer field schools-in providing practical knowledge, skills, and confidence necessary for technology adoption. These programs offer hands-on learning experiences that help farmers understand the proper application of technologies, including certified seeds, mechanized tools, and efficient planting systems, while also addressing concerns about potential risks. Previous studies have consistently shown that participation in non-formal education increases awareness, reduces uncertainty, improves technical competence, and enhances farmers' decision-making capacity regarding agricultural innovations (Duveskog et al. 2011; Khanal 2019; Mariyono et al. 2021). Thus, expanding access to non-formal education should be prioritized in agricultural development policies aimed at accelerating technology diffusion.

Revenue (P)

Household income (P) demonstrated a significant positive effect on technology adoption at the 95% confidence level ($\beta = 0.582$, $p = 0.022$, OR = 1.790). Farmers with higher incomes are 1.790 times more likely to achieve higher levels of technology adoption. This relationship can be attributed to reduced financial constraints, enabling farmers to make initial investments in costly technologies such as tractors, transplanters, drones, electric sprayers, and combine harvesters, while also affording the ongoing operational costs associated with these technologies. Additionally, higher-income farmers typically have greater risk-bearing capacity and are more willing to experiment with innovations, including certified seeds and improved planting systems like *jajar legowo*. Income thus serves as both an enabler of technology access and a facilitator of sustained technology use across multiple stages of rice production-from land preparation through harvesting. This finding aligns with previous studies demonstrating that household income positively influences agricultural technology adoption (Riasa et al. 2020; Ullah et al. 2022; Miine et al. 2023; Vihi et al. 2024).

Model adequacy

The goodness-of-fit of the ordinal logistic regression model was assessed using the deviance statistic (Table 6). The deviance test yielded a Chi-square value of 18.711 with 205 degrees of freedom ($p = 1.000$). Since the p-value substantially exceeds the significance level of 0.10 ($p > \alpha$), the null hypothesis that the model fits the data adequately is accepted.

Table 6. Goodness-of-fit statistics for the ordinal logistic regression model (p-values > 0.10 indicate adequate model fit)

	Goodness-of-fit		
	Chi-square	**Df**	**p-value**
Pearson	21.655	205	1.000
Deviance	18.711	205	1.000

Additionally, the calculated Chi-square value (18.711) is considerably smaller than the critical value of 231.340 ($\chi^2_{0.10,205}$). Both criteria confirm that there is no significant difference between the observed data and the model predictions, indicating that the ordinal logistic regression model is appropriate for explaining and predicting rice cultivation technology adoption levels among farmers in Pinrang District. The Pearson goodness-of-fit test (χ^2 = 21.655, df = 205, p = 1.000) similarly supports adequate model fit.

In conclusion, this study examined the determinants of rice cultivation technology adoption among farmers in Pinrang District, South Sulawesi, Indonesia. The findings revealed that the majority of farmers (63.9%) demonstrated moderate adoption levels, while 24.1% achieved high adoption and 12.0% remained at low adoption levels. Ordinal logistic regression analysis identified six significant predictors of adoption: duration of formal education (positive), number of information sources (positive), intensity of extension contact (positive), distance from home to farmland (positive), participation in non-formal education (positive), and household income (positive). Notably, the positive effect of distance from home to farmland diverges from conventional expectations and appears to be mediated by the spatial distribution of agricultural service centers. Conversely, farming experience, age, and land area did not significantly influence adoption levels. This study makes an important methodological contribution by employing an ordinal classification approach to capture variation in adoption intensity, rather than the binary (adopted/not adopted) framework commonly used in previous studies. Furthermore, this is among the first studies in Indonesia to comprehensively examine rice technology adoption across the entire production cycle-from land preparation through harvesting, incorporating seven distinct technologies: tractors, transplanters, drones, electric sprayers, certified seeds, the jajar legowo planting system, and combine harvesters.

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