Determinants of Palaycheck System Adopter Category among Rice Farmers in Northern Mindanao, Philippines: Evidence from an Ordered Logit Model

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ABSTRACT

This study quantitatively examines the determinants of the Palay Check System adopter category among rice farmers in selected provinces of Northern Mindanao, Philippines. Using a cross-sectional survey of 271 Palay Check-trained farmers, the study employs descriptive statistics and an ordered logit model to estimate the association between socioeconomic, institutional, and farm-level factors and the adopter category, measured on a five-point ordinal scale (laggards to innovators).

Descriptive results indicate a mean adopter category level of 3.454 (SD = 1.157), meaning in the early majority adopter category, with substantial variation across farmers. The ordered logit model is jointly significant (LR $\chi^2 = 95.48$, $p < 0.001$) with a pseudo R^2 of 0.121. Institutional membership exerts a strong and statistically significant positive effect on being in the higher adopter categories ($\beta = 1.371$, $p < 0.001$), increasing the probability of being in the innovator category by 20.41 percentage points. In contrast, tenure insecurity emerges as a binding constraint; tenants ($\beta = -0.910$, $p < 0.01$), leaseholders ($\beta = -1.412$, $p < 0.01$), and farmers under other tenure arrangements ($\beta = -1.304$, $p < 0.01$) exhibit farmers in the lower adopter categories, with reductions in the probability of being in the innovator category of up to 19.81 percentage points.

Non-farm income is negatively associated with the adopter categories ($\beta = -0.000009$, $p < 0.001$), consistent with opportunity cost effects. Education shows a weak negative relationship ($\beta = -0.066$, $p < 0.10$), while age, household size, farm income, and farming experience are not statistically significant.

The findings indicate that variation in adopter category among trained farmers is primarily driven by institutional access, land tenure conditions, and livelihood diversification rather than demographic characteristics. These results highlight the importance of strengthening farmer organizations, improving tenure security, and designing extension programs that accommodate non-farm employment dynamics to enhance adopter intensity in rice-based systems.

Keywords: Palay Check System; technology adoption; ordered logit; rice farming; Philippines

INTRODUCTION

Background of the study

Agriculture serves as a foundation of national development by providing essential food supplies, industrial raw materials, and rural employment opportunities. In the Philippines, a vibrant agricultural sector is critical for accelerating economic recovery, enhancing food security, and alleviating rural poverty (World Bank, 2020). Within this context, agricultural extension services play a central role in bridging the gap between research innovations and farmers, facilitating the adoption of productivity-enhancing technologies (FAO, n.d.). Effective advisory systems not only promote sustainable resource management but also enhance climate resilience in agricultural production (Alam et al., 2024). Consequently, modern extension and advisory systems are essential in enabling smallholder farmers to access appropriate innovations, information, and services necessary for sustainable agrifood systems (FAO, 2020). By translating complex scientific knowledge into practical and actionable recommendations, extension services strengthen farmers' decision-making capacity, improve farm management, and support the adoption of improved agricultural practices (Bridging the Gap, 2023).

In the Philippine context, these initiatives are reinforced by national policies such as the National Rice Program and the Rice Tariffication Law (Republic Act No. 11203, 2019), which established the Rice Competitiveness Enhancement Fund (RCEF) to support mechanization, seed systems, credit access, and extension services. Notably, a portion of the fund is allocated specifically to strengthening rice extension services, implemented through key institutions such as the Agricultural Training Institute (ATI), Technical Education and Skills Development Authority (TESDA), and the Philippine Rice Research Institute (PhilRice). These institutional arrangements is an evidence of the government's commitment to enhancing farmers' capacity to adopt improved technologies and practices, particularly in rice-based systems where productivity gains remain uneven.

Within this policy environment, ATI-accredited Learning Sites for Agriculture (LSAs) and TESDA Farm Schools are an important platforms in promoting peer-to-peer knowledge exchange and strengthen farmers' technical and managerial capabilities (ATI, 2019). Central to these initiatives is the PalayCheck System, developed by PhilRice, which serves as a science-based, participatory rice crop management framework organized around key production checks (PhilRice, 2023). Delivered primarily through Farmer Field Schools (FFS) reinforced with demonstration farms the system enables farmers to integrate knowledge and practice, facilitating more efficient and sustainable rice production. Empirical evidence suggests that such participatory and extension-driven approaches are effective in enhancing learning and adoption, particularly in smallholder contexts where information constraints are binding (Campenhout, 2021).

Despite these extensive institutional efforts, the adoption of improved agricultural practices remains heterogeneous across farmers. A substantial body of empirical literature demonstrates that adoption is influenced by a combination of socioeconomic, institutional, and farm-level factors rather than exposure alone. For instance, education, access to extension, irrigation, and machinery ownership have been shown to significantly influence the adoption of modern rice technologies in the Philippines (Mariano et al., 2012). Similarly, institutional participation and access to information networks play a critical role in facilitating adoption by reducing uncertainty and transaction costs (Addai et al., 2022; Chang et al., 2024). At the same time, structural constraints such as land tenure insecurity and limited access to resources may hinder adoption even when technologies are available (Nguyen, 2020; Paltasingh, 2018;). Furthermore, livelihood diversification, particularly through non-farm income, introduces opportunity costs that may reduce farmers' engagement in agricultural innovation (Shen et al., 2023).

From an economic perspective, these patterns are consistent with the notion that adoption is a utility-maximizing decision under constraints, where farmers evaluate expected benefits relative to risks, resource availability, and competing livelihood opportunities. As emphasized in the theoretical framework, adoption is not a binary outcome but an ordered and incremental process, reflecting varying degrees of farmers' decisions on adoption. This implies that even among farmers with uniform access to training, differences in socioeconomic conditions, institutional access, and farm characteristics lead to differences in adoption timing ranging from laggards to innovators.

Given this context, a critical gap remains in understanding the determinants of adopter category among farmers who have already been exposed to agricultural innovations. Evaluating adopter categories is important because it helps identify differences in adoption behavior, enabling targeted extension strategies that accelerate technology diffusion, reduce adoption gaps, and improve the effectiveness of innovation promotion (Ayisi et al., 2022). Further, understanding adopter categories is important in diffusion research because it explains differences in farmers' adoption behavior and enables targeted extension interventions that improve technology dissemination, policy targeting, and adoption efficiency across heterogeneous groups (Ojiako-Chigozie, 2024). Much of the existing literature focuses on binary adoption decisions or access to technology, with limited attention to the gradation and heterogeneity of adoption behavior. This gap is particularly relevant for integrated systems such as PalayCheck, where adoption involves multiple practices implemented progressively rather than a single discrete decision.

Accordingly, this study addresses this gap by examining the following research question: What factors influence the innovation adoption spectrum as measured by the adopter category of the PalayCheck System among rice farmers trained through Learning Sites for Agriculture (LSAs) and TESDA Farm schools in Northern Mindanao? Specifically, the study analyzes how socioeconomic, institutional, and farm-level characteristics are associated with the adopter category using an ordered logit framework. By focusing on trained farmers, the analysis isolates differences in adoption behavior that arise from constraints and incentives, thereby providing more precise insights into the drivers of technology utilization in rice-based systems.

Scope and Delimitation of the study

This study focuses on examining the determinants of PalayCheck System adoption among rice farmers in selected provinces of Northern Mindanao, Philippines. Specifically, the analysis covers farmers who have undergone formal PalayCheck training through Learning Sites for Agriculture (LSAs), Rice Competitiveness Enhancement Fund (RCEF)–supported farms, and Technical Education and Skills Development Authority (TESDA) programs conducted during the period 2019–2020. By restricting the sample to trained farmers, the study isolates variation in the level of adoption category, rather than differences in access to training or exposure to the technology.

Geographically, the study is limited to four provinces—Bukidnon, Lanao del Norte, Misamis Occidental, and Misamis Oriental—where PalayCheck training activities were implemented. Camiguin was excluded due to the absence of training programs during the reference period. These selected areas provide a heterogeneous but analytically coherent setting characterized by differences in agroecological conditions, institutional access, and farming systems, which are relevant for explaining adoption behavior.

The study employs a quantitative cross-sectional design, using primary data collected from 271 rice farmers through structured face-to-face interviews. The analysis is confined to variables captured in the survey instrument, including socioeconomic and demographic characteristics such as age, education, household size, income, and farming experience; institutional factors such as membership in farmer organizations; and farm-level characteristics such as farm size, tenure status, production system, and location. The dependent variable is the level of PalayCheck adoption, measured as an ordinal variable reflecting the intensity of compliance with recommended practices.

Methodologically, the study is limited to the application of descriptive statistics and an ordered logit model to estimate the association between explanatory variables and adoption levels. The analysis assumes the proportional odds condition inherent in the ordered logit framework and focuses on statistical associations rather than causal inference. As such, the findings should be interpreted as correlational rather than causal relationships.

Several delimitations are acknowledged. First, the study does not include untrained farmers; therefore, it does not assess access to training or compare adopters versus non-adopters. Second, the cross-sectional nature of the data limits the ability to capture dynamic adoption behavior over time or learning effects. Third, the study relies on self-reported survey data, which may be subject to recall bias or measurement error. Fourth, institutional variables are proxied primarily through membership indicators and may not fully capture the quality or intensity of extension services. Finally, the geographic focus on Northern Mindanao limits the generalizability of the findings to other regions with different institutional, economic, and agroecological contexts.

Despite these limitations, the study provides robust insights into the factors associated with adoption category among trained farmers and contributes to a more nuanced understanding of technology adoption behavior in rice-based systems

Theoretical Framework

This study is anchored in a synthesis of neoclassical microeconomic theory, innovation diffusion theory, specifically within Rogers' Diffusion of Innovations. The framework conceptualizes adoption as a utility-maximizing decision under constraints, wherein farmers' timing of adoption (adopter category) is based on expected returns, risk exposure, and resource availability. Such decisions are inherently heterogeneous, reflecting variation in socioeconomic characteristics, institutional access, and farm-specific endowments. This integrated perspective is widely supported in the empirical literature on agricultural technology adoption, which emphasizes both economic incentives and structural constraints (Feder et al., 1985; Foster & Rosenzweig, 2010; Jack, 2013).

t its core, the analysis draws on Microeconomic Theory, particularly the random utility maximization (RUM) framework, which assumes that individuals are assigned to the adopter category that yields the highest expected utility given their socioeconomic and farm characteristics. In the context of agricultural innovation diffusion, this approach can be used to model farmers' classification into ordered adopter categories ranging from laggards to innovators (Train, 2009; Asfaw et al., 2012). Let UijU_{ij}Uij denote the latent utility derived by farmer iii from belonging to adopter category jjj, where j=1,2,…,Jj = 1,2,\dots,Jj=1,2,…,J represents ordered categories of adoption behavior (e.g., laggard, late majority, early majority, early adopter, innovator). The utility function is specified as:

At its core, the analysis draws on Microeconomic Theory, particularly the random utility maximization (RUM) framework, which assumes that individuals choose the the adopter category that yields the highest expected utility. In the context of agricultural technology adoption, this approach has been extensively applied to model farmers' categories into ordered adopter categories ranging from laggards to innovators (Train, 2009; Asfaw et al., 2012). Let U_{ij} denote the utility derived by farmer i from belonging to PalayCheck system adopter category j, where $j=0,1,\dots,J$ represents ordered adopter categories (laggard, late majority, early majority, early adopter, and innovator). The utility function is specified as:

$$U_{ij} = V_{ij}\left(X_{i,}, Z_i\right) + \varepsilon_{ij}$$

Within the random utility framework of Microeconomic Theory, the term U_{ij} denotes the latent (unobserved) utility that farmer iii derives from being classified into adopter category j. It is a theoretical construct that captures the overall preference given the level of innovativeness or adoption behavior, integrating both measurable and unobservable determinant that influence the likelihood of belonging to a specific adopter category.

The utility function is decomposed into two components. The first, $V_{ij}\left(X_{i,}, Z_i\right)$, represents the systematic or observable component of utility, which is a function of farmer-specific characteristics $X_{i,}$ (such as age, education, and farm size) and institutional or environmental factors Z_i (including access to extension services, input markets, and infrastructure). This component reflects the portion of utility that can be explained by observable variables and is therefore amenable to econometric estimation. In empirical applications, V_{ij} is typically specified as a linear index allowing the researcher to quantify how changes in these factors shift the utility associated with different adopter categories.

The second component, ε_{ij}, captures unobserved heterogeneity—factors influencing adopter categories that are not measured in the dataset, such as farmer ability, risk preferences, expectations, or measurement error. The inclusion of this stochastic term acknowledges that decision-making is not fully deterministic and justifies the probabilistic nature of discrete choice models.

Importantly, U_{ij} itself is not directly observable. What is observed is the farmer's chosen adopter category, which is assumed to be the outcome of a utility-maximizing process. Specifically, farmer i selects adopter category j if and only if it yields the highest utility among all feasible alternatives. Thus, observed adopter category reveals the ranking of utilities, rather than their absolute values.

In the context of ordered adopter category outcomes, the utility framework implies that higher levels of adopter category (towards innovator category) correspond to higher latent utility. Consequently, adopter category can be modeled as a discrete choice over ordered alternatives, where the probability of observing a particular adopter category depends on how the explanatory variables $X_{i,}$ and Z_i shift the underlying utility distribution. This provides the theoretical justification for employing ordered logit, where the latent utility U_{ij} is mapped into observable categories through threshold mechanisms.

In sum, U_{ij} serves as the conceptual bridge between economic theory and empirical modeling, linking farmers' decision-making behavior to observable adopter category outcomes through a structured, probabilistic framework.

Innovation Diffusion and Learning Dynamics

The decision of the timing of adoption is supported by Diffusion of Innovations Theory, which posits that technology uptake is a dynamic and cumulative process rather than an instantaneous choice. Farmers gradually adjust their adoption behavior as they acquire information, update beliefs, and observe outcomes from both personal experience and social interactions. In this context, PalayCheck adoption in terms of the adopter category is shaped not only by expected profitability but also by perceived risk, compatibility with existing practices, and ease of implementation.

Empirical evidence underscores the importance of learning mechanisms and social interactions in agricultural technology adoption. Farmers rely on peer networks and extension systems to reduce uncertainty about new practices, particularly when technologies are complex or knowledge-intensive (Conley & Udry, 2010; Krishnan & Patnam, 2014). Exposure to demonstration farms, training programs, and farmer organizations enhances information flows and accelerates learning, leading to adoption over time. Moreover, experiential learning allows farmers to update subjective expectations regarding productivity and risk, reinforcing continued adoption (Foster & Rosenzweig, 2010). Thus, adoption is a sequential and path-dependent process, best understood in terms of the adoption timing across the "laggard-to- innovator" spectrum where information diffusion and learning dynamics play a central role.

Agricultural Household Behavior under Market Imperfections

The framework also builds on the Agricultural Household Model, which recognizes that smallholder farmers operate under imperfect or missing markets. In such environments, production and consumption decisions are jointly determined, implying that adoption choices cannot be analyzed independently of household preferences and constraints.

Under market imperfections, households face binding constraints in labor, credit, and insurance markets, which influence both their ability and willingness to adopt new technologies. Even when PalayCheck practices are expected to be profitable, liquidity constraints, land fragmentation, and labor shortages may limit adoption, thus will adopt later or sooner (de Janvry et al., 1991; Dillon & Barrett, 2017). Risk considerations further complicate decision-making, as farmers may avoid early adoption with uncertain outcomes despite potentially higher returns. Risk considerations further complicate decision-making, as farmers may avoid early adoption with uncertain outcomes despite potentially higher returns (Kahan, 2016). Empirical studies confirm that credit access, asset ownership, and labor availability significantly affect technology adoption decisions in smallholder systems (Kassie et al., 2015; Wossen et al., 2017).

Consequently, adoption behavior reflects not only expected economic gains but also the household's capacity to mobilize resources, manage risk, and smooth consumption, highlighting the importance of incorporating household-level constraints into the analysis.

Institutional and Information Constraints

Consistent with Institutional Economics, the framework emphasizes that institutional environments play a critical role in shaping adoption outcomes. Institutions influence access to information, reduce uncertainty, and lower transaction costs associated with acquiring and implementing new technologies.

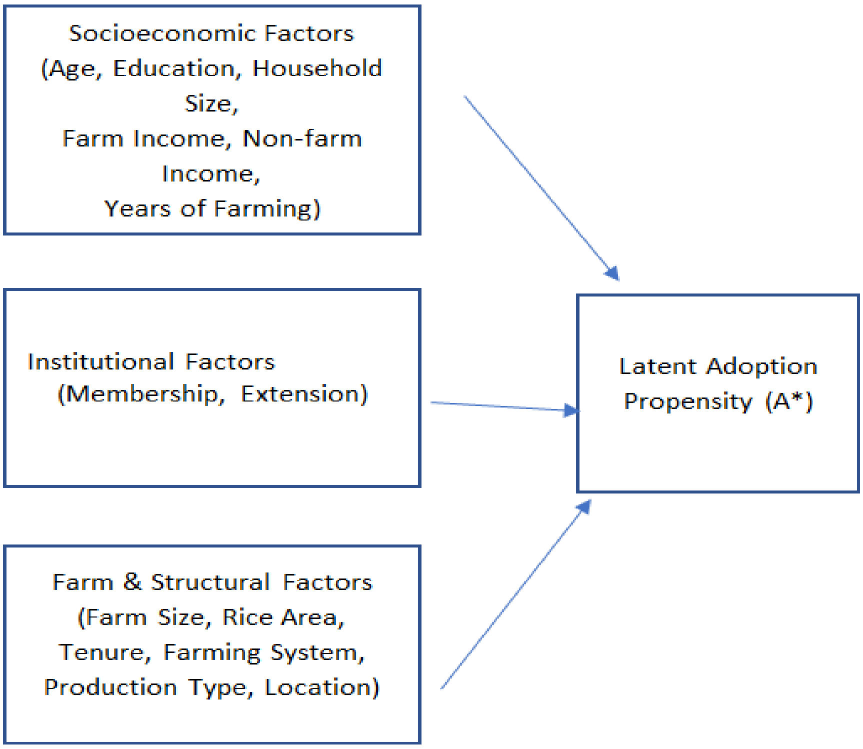
Extension services, farmer organizations, and government programs function as key intermediaries that facilitate knowledge dissemination and enhance farmers' capabilities. Empirical evidence demonstrates that access to extension and institutional support significantly increases the likelihood and timing of adoption by reducing information asymmetry and improving access to inputs and markets (Asfaw et al., 2012; Krishnan & Patnam, 2014). Conversely, weak institutional support may result in coordination failures and persistent inefficiencies, leading to non-adoption of technology. Thus, institutional quality and accessibility are critical determinants of technology diffusion in agricultural systems.

Conceptual Framework

This study conceptualizes the adopter categories of the PalayCheck System as an ordered behavioral outcome influenced by a set of socioeconomic, institutional, and farm-level factors, consistent with the random utility framework of Microeconomic Theory. Farmers are assumed to select their adoption category based on expected benefits and constraints, where in the higher adopter categories reflect greater utility derived the PalayCheck system training.

The dependent variable is the PalayCheck adopter category (A*), measured on an ordinal scale ranging from "1=not yet adopted PalayCheck practices (Laggard) 2= recently adopted PalayCheck after many others (Late majority), 3 = adopted PalayCheck after most others in my community (Early majority), 4=adopted PalayCheck shortly after others in my community (Early adopter), and 5 = first in my community to try PalayCheck (Innovator) capturing the increasing level of adopter innovativeness observed in the sample. This ordered structure reflects incremental adoption behavior rather than a binary decision.

Figure 1. The schematic diagram of the study



The explanatory variables are grouped into three major components, consistent with the empirical specification. First, socioeconomic and demographic characteristics include age, years of education, household size, farm income, non-farm income, and years of farming. These variables capture human capital, labor availability, income diversification, and experience, which influence farmers' capacity to process information, allocate resources, and engage in agricultural innovation. For instance, the presence of non-farm income reflects opportunity costs that may reduce the intensity of farm-level adoption, while education and experience shape decision-making and technical understanding.

Second, institutional factors are represented primarily by membership in farmer organizations, along with related access to extension services and training. In line with Institutional Economics, these variables capture the role of institutions in facilitating access to information, inputs, and support systems. Institutional participation reduces uncertainty and enhances the ability of farmers to adopt the PalayCheck system early on, as reflected in the strong empirical association between membership and higher adoption levels.

Third, farm-level and structural characteristics include total farm size, rice farm size, tenurial status, farming system and location. These variables reflect the resource base, production environment, and structural constraints faced by farmers. In particular, land tenure plays a critical role, as secure ownership provides incentives for long-term investment, while tenancy and leasing arrangements may discourage adoption due to uncertainty and limited control over land use.

Consistent with the Agricultural Household Model, these factors jointly influence the farmer's latent adoption propensity, which reflects the underlying utility associated with the adoption timing (adopter categories). This latent propensity is not directly observable but is expressed through ordered categories of adoption intensity. Accordingly, the relationship is modeled using an ordered logit framework, where explanatory variables shift the probability of farmers being in higher or lower adoption categories.

Objective of the Study

This study aims to analyze the determinants of PalayCheck System adoption among farmers in selected provinces of Northern Mindanao.

Specifically, it aims to:

1. Describe the socioeconomic, demographic, and farm characteristics of farmers, and examine the distribution and variability of key variables relevant to PalayCheck adopter category; and
2. Estimate the association of socioeconomic, institutional, and farm-level factors with the level of PalayCheck adopter category using an ordered logit model.

Hypotheses of the Study

Consistent with the study's objective of examining the determinants of PalayCheck System adopter category using an ordered logit framework, the hypotheses are formulated within the random utility and latent variable structure, where higher levels of adoption reflect greater underlying utility derived from the timing of adoption. The hypotheses focus on the direction and statistical significance of the association between explanatory variables and the ordered level of adopter category.

H_0 (Null Hypothesis): Socioeconomic, institutional, and farm-level characteristics have no statistically significant association with the level of PalayCheck System adopter category among rice farmers in Northern Mindanao.

H_1 (Alternative Hypothesis): At least one socioeconomic, institutional, or farm-level characteristic is significantly associated with the level of PalayCheck System adopter category among rice farmers in Northern Mindanao.

REVIEW OF RELATED LITERATURE

A substantial body of empirical literature examines the determinants of agricultural technology adopter category and adoption, emphasizing the roles of socioeconomic, institutional, and farm-level factors in shaping farmers' decision-making behavior. In rice-based systems, adoption is increasingly viewed as a multidimensional and context-dependent process influenced by information access, resource constraints, and incentive structures rather than mere exposure to technology.

Institutional Membership and Adoption

The results indicate that membership in farmer organizations significantly increases the likelihood of belonging to PalayCheck higher category adopters. This finding is strongly supported by empirical literature emphasizing the role of institutional participation in facilitating technology uptake. For instance, Mariano et al. (2012) demonstrate that extension-related variables and capacity-enhancement activities exert the largest positive effects on the adoption of modern rice technologies in the Philippines. Similarly, Addai et al. (2022) find that

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participation in farmer organizations improves access to inputs, information, and training, thereby significantly increasing adoption rates among rice farmers. Evidence from Southeast Asia further confirms that institutional support systems—particularly extension services and farmer networks—are among the most consistent determinants of adoption (Chang et al., 2024).

These findings are consistent with the present study, where institutional membership substantially increases the probability of higher adoption levels, reinforcing the argument that information access, coordination, and collective action mechanisms are central to agricultural technology diffusion.

Land Tenure and Adoption Behavior

The negative and statistically significant effects of tenancy and lease arrangements on adoption are consistent with the property rights literature. Empirical evidence shows that secure land tenure strengthens incentives for long-term investment in productivity-enhancing technologies. For example, Nguyen (2020) finds that secure land rights significantly increase the adoption of improved rice varieties in Vietnam, while Paltasingh (2018) reports similar findings in India, where tenure security enhances the adoption of modern rice technologies. Rogers (2003) suggests that innovators and early adopters possess a greater willingness to assume risk and invest in uncertain technologies, whereas laggards are more constrained by insecurity.

Conversely, farmers operating under insecure tenure arrangements face reduced incentives to adopt due to uncertainty over future returns. Kehinde et al. (2021) further confirm that weak property rights limit investment behavior among rice farmers. These findings align with the present results, where tenants and leaseholders exhibit significantly lower adoption intensity, consistent with the theoretical prediction that tenure insecurity discourages investment in improved agricultural practices.

Non-Farm Income and Opportunity Cost Effects

The negative effect of non-farm income on adoption supports the opportunity cost hypothesis, which posits that off-farm activities divert labor and managerial attention away from agricultural production. Empirical evidence across rice-based systems substantiates this relationship. Fernandez-Cornejo et al. (2005) show that off-farm income can reduce the likelihood of adopting new agricultural technologies due to competing labor demands and resource allocation trade-offs.

More recent studies reinforce this conclusion. Shen et al. (2023) demonstrate that off-farm employment reduces engagement in rice production decisions, while Anang and Yeboah (2019) show that households with diversified income sources allocate less effort to farm-level innovation. Similarly, Do (2026) finds that the expansion of off-farm employment opportunities negatively affects the adoption of improved rice production practices.

Education and Human Capital

The negative association between education and adoption observed in the results contrasts with the conventional expectation that education enhances adoption. However, this finding is not entirely inconsistent with the empirical literature. Mariano et al. (2012) suggest that education may influence adoption indirectly through profit orientation and access to alternative income opportunities. More educated farmers may diversify into non-farm employment, thereby reducing their engagement in agricultural activities.

This interpretation is supported by Glover et al. (2020), who show that technology adoption decisions are shaped not only by knowledge and awareness but also by economic incentives and livelihood strategies. Thus, the negative effect of education observed in this study may reflect opportunity cost dynamics and labor reallocation effects rather than a deficiency in technical capacity.

Farm Size and Resource Endowments

The results indicate that farm size variables are not statistically significant, although they exhibit economically meaningful patterns. This is consistent with the mixed evidence in the literature. De Souza Filho et al. (1999) find that adoption of sustainable technologies may decrease with farm size under certain conditions, particularly when technologies are labor-intensive and better suited to smallholder systems. Conversely, Yamano et al. (2016) report that larger farms may benefit from economies of scale, facilitating adoption through improved access to capital and inputs.

In the Philippine context, Mariano et al. (2012) emphasize that small farm size can constrain adoption due to limited access to resources. The lack of statistical significance in the present study suggests that farm size alone may not be a decisive determinant, but rather interacts with institutional access, resource availability, and production conditions.

Social Learning and Information Diffusion

The importance of institutional membership serves as a proxy for extension access in this study is further supported by literature on social learning and diffusion processes. Palis (2006) demonstrates that farmer field schools enhance learning and adoption through experiential and peer-based approaches. Similarly, Campenhout (2021) provides experimental evidence that improved access to information significantly increases adoption by reducing uncertainty and improving decision-making.

Adopter category

These findings reinforce the interpretation that technology adoption is a dynamic and socially embedded process, driven by information flows, learning mechanisms, and peer interactions, consistent with the diffusion of innovations framework. Empirical studies further confirm that farmers differ systematically in their adopter categories, with variations in access to information, risk preferences, and exposure to extension services shaping their position from laggards to innovators. For instance, Rogers' diffusion framework continues to be widely validated in agricultural contexts, where adopter categorization explains heterogeneity in the speed and intensity of technology uptake (Rogers, 2003; Ojiako-Chigozie, 2024). Recent evidence by Ayisi et al. (2022) also shows that identifying adopter categories among smallholder farmers improves understanding of adoption behavior and helps tailor extension strategies to specific groups. Similarly, Tey and Brindal (2021) highlight that peer effects and social learning significantly influence movement across adopter categories, particularly in rice-based farming systems. Collectively, these studies underscore that adopter categories are not merely descriptive classifications but essential analytical tools for understanding and promoting technology diffusion in agriculture.

Therefore, the empirical literature strongly supports the main findings of this study. Institutional participation and tenure security emerge as the most robust determinants of adoption, while non-farm income introduces trade-offs that reduce engagement in agricultural innovation. Human capital and farm characteristics exhibit more nuanced and context-dependent effects.

By aligning closely with both Philippine-specific and international evidence, the results of this study contribute to the broader literature on agricultural technology adoption in rice-based systems, while providing new insights into the role of institutional access, tenure security, and livelihood diversification in shaping adoption intensity.

METHODOLOGY

Research Design

This study employs a quantitative cross-sectional research design utilizing both descriptive analysis and inferential statistics to examine PalayCheck System adopter category among rice farmers in selected provinces of Northern Mindanao.

The descriptive analysis is used to summarize and characterize the sample through measures of central tendency and dispersion (e.g., mean, standard deviation, minimum, and maximum) as well as frequency distributions for categorical variables. This provides a detailed profile of farmers' socioeconomic, demographic, and farm characteristics, and captures the extent of variability and heterogeneity within the sample.

The inferential analysis is conducted using an ordered logit model, which is appropriate given the ordinal nature of the adoption variable. This approach estimates the statistical association between explanatory variables—such as socioeconomic, institutional, and farm-level factors—and the level of PalayCheck adopter category. The model allows for the examination of how these factors are associated with shifts in the probability of farmers being in higher or lower adoption categories, thereby addressing the study's objective of identifying key determinants of being in a certain spectrum of adopter category.

Research Locale

This study was conducted in Northern Mindanao, Philippines, a key agricultural region characterized by diverse agroecological conditions and significant rice production activity. The region covers approximately 2,049,602 hectares and consists of five provinces: Bukidnon, Camiguin, Lanao del Norte, Misamis Occidental, and Misamis Oriental. However, consistent with the study's focus on PalayCheck System adoption, only provinces with active PalayCheck training and extension interventions from 2019 to 2020 were included—namely Bukidnon, Lanao del Norte, Misamis Occidental, and Misamis Oriental—while Camiguin was excluded due to the absence of training activities during the reference period.

The selection of Northern Mindanao provides a suitable empirical context due to its heterogeneous production environments, varying levels of institutional support, and diversity in farming systems, all of which are central to explaining adoption behavior. The presence of Agricultural Training Institute (ATI)-accredited learning sites and PalayCheck training providers across the region enables the examination of how access to extension services, training, and farmer networks influences adoption intensity.

Bukidnon, the largest province in the region, is widely regarded as the "food basket of Mindanao" due to its substantial agricultural output. Its agroecological diversity—ranging from highland areas to irrigated lowland rice systems—provides an appropriate setting for analyzing variation in adoption across different production conditions. According to the Philippine Statistics Authority, the province has a population of 1,601,902 (PSA, 2025). The province hosts multiple ATI-accredited learning sites and demonstration farms, which play a critical role in facilitating farmer training and technology dissemination. In addition, the coexistence of commercial plantations and smallholder farms allows for the analysis of adoption behavior across different farm structures and resource endowments.

Lanao del Norte presents a contrasting environment, characterized by both coastal and upland agricultural systems. As of the 2020 Census, it has a population of 722,902 (PSA, 2021). The coexistence of farming and fishing livelihoods makes it particularly relevant for examining the effects of income diversification and non-farm income on technology adoption. The presence of PalayCheck training providers in both inland and coastal municipalities provides an opportunity to assess adoption behavior under varying institutional and economic conditions.

Misamis Occidental, a narrow coastal province with fertile plains and a central mountain range, has a population of 602,126 (PSA, 2020). Its economy is supported by both agriculture and fisheries, with major crops including rice, corn, and coconut. The presence of PalayCheck training providers across municipalities and cities enables the analysis of institutional access in a coastal-agricultural context. Its diversified production systems provide a relevant setting for examining how farm diversification influences adoption decisions.

Misamis Oriental serves as a regional economic and logistical hub, with a population of 956,900 excluding its highly urbanized capital, Cagayan de Oro City (PSA, 2021). Its mix of agricultural production, commerce, and infrastructure development makes it suitable for analyzing how market access and institutional connectivity affect adoption behavior. The presence of accredited farm schools and training centers further supports the study's focus on institutional determinants of adoption.

Lasly, the selected provinces provide a diverse yet analytically coherent setting, capturing variation in agroecological conditions, institutional access, land tenure arrangements, and livelihood strategies. This diversity strengthens the study's ability to identify the determinants of PalayCheck adoption and enhances the external validity of the findings.

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Sample Design

The sample size for this study was determined using a standard approach for estimating proportions in survey research, followed by a finite population correction to account for the bounded population of PalayCheck-trained farmers.

The initial sample size was computed using the formula:

$$n_o = \frac{Z^2 p(1-p)}{e^2}$$

where n_o is the initial sample size, Z is the critical value at the 95% confidence level (1.96), p is the assumed population proportion (0.5), and e is the margin of error (0.05). Substituting these values:

$$n_o = \frac{(1.96)^2(0.5)(0.5)}{(0.05)^2} = 384.16 \approx 384$$

Since the population of PalayCheck-trained farmers is finite, the sample size was adjusted using the finite population correction (FPC)**:**

$$n = \frac{n_o}{1 + \frac{n_o - 1}{N}}$$

where where N represents the total population. Based on available administrative records, the estimated population of trained farmers included in the study areas is approximately:

$$N \approx 919$$

Substituting into the formula:

$$n = \frac{384}{1 + \frac{384-1}{919}} = \frac{384}{1.417} \approx 271$$

Thus, the required sample size after applying the finite population correction is approximately 271 respondents.

Following data collection, survey responses were subjected to standard data screening and validation procedures, including checks for completeness, logical consistency, and extreme values. Observations with substantial missing data or implausible responses were excluded to ensure the reliability of the dataset. As a result, the final number of valid observations retained for analysis was 271 respondents, which is consistent with the statistically derived sample size.

The achieved sample size is considered adequate for the estimation of an ordered logit model, as it provides sufficient variation across adoption levels and explanatory variables while maintaining statistical precision. Moreover, the use of a finite population adjustment ensures that the sample appropriately reflects the size and structure of the underlying population of PalayCheck-trained farmers.

Participants

This study utilized a survey-based approach, with respondents consisting of rice farmers who have undergone formal training on the PalayCheck System in Northern Mindanao. Consistent with the study's objective of analyzing the determinants of adoption, the survey targeted farmers with prior exposure to PalayCheck training to capture variation in the adopter category.

The survey respondents were rice farmers who participated and completed the PalayCheck training conducted through Learning Sites for Agriculture (LSAs) and TESDA Farm Schools This training is embedded in the TESDA TVET qualification title "FFS on Production of High Quality Inbred Rice and Seed during the period 2019–2020. The list of trained farmers was obtained from training providers and TESDA offices and was cross-validated using records from the Department of Agriculture–Agricultural Training Institute (DA-ATI Region 10) to ensure data accuracy and consistency. The training is considered a "season-long" training with a total of 14 sessions complemented with hands on training at the demonstration farms.

The selection of training providers followed complete enumeration meaning all fifteen (15) LSAs that conducted PalayCheck training in 2019 and 2020 were included in the study. The use of this cohort allows sufficient time for farmers to adopt and implement PalayCheck practices, thereby enabling the observation of variation in adopter category at the time of the survey.

Focusing on trained farmers ensures that all respondents share a common baseline exposure to the PalayCheck System. This allows the analysis to examine differences in adoption intensity, rather than access to training, and ensures that variation in the dependent variable reflects differences in socioeconomic characteristics, institutional access, and farm-level conditions. The survey instrument was designed to capture these dimensions, including farmer demographics, farm characteristics, institutional participation, and the level of compliance with PalayCheck recommendations.

Method of data collection

Primary data for this study were collected through a structured survey administered via face-to-face interviews with rice farmers who had undergone PalayCheck System training in Northern Mindanao. This data collection approach is consistent with the study's quantitative cross-sectional research design, which aims to examine the determinants of adopter category using observable socioeconomic, institutional, and farm-level variables.

Prior to data collection, ethical clearance was secured from the Research Ethics Committee (REC) of the CMU Institutional Ethics Review Committee (IERC). Formal letters of permission were submitted to the Municipal Mayors and Municipal Agriculture Offices (MAOs) of the selected municipalities across Bukidnon, Lanao del Norte, Misamis Occidental, and Misamis Oriental. Coordination with local government units and agricultural offices facilitated access to lists of PalayCheck-trained farmers and ensured the orderly conduct of the survey. These preparatory activities were undertaken from the last week of December 2025 to the first week of January 2026.

The survey instrument was designed to generate data consistent with the study's conceptual and econometric framework, capturing variables included in the ordered logit model. Specifically, the questionnaire collected information on: (1) socioeconomic and demographic characteristics (e.g., age, education, household size, income, and farming experience); (2) institutional factors (e.g., membership in farmer organizations and access to extension services); and (3) farm-level characteristics (e.g., farm size, tenure status, production system, and location). In addition, the instrument measured the level of PalayCheck adopter category as an ordinal variable reflecting the level of adopter category from laggard to innovator.

Before participation, respondents were informed about the purpose and scope of the study, and informed consent was obtained through signed consent forms in accordance with ethical research standards. Interviews were conducted in locations convenient to the respondents, such as their homes or farms, and were administered in the local language to ensure accurate comprehension and reliable responses. Each interview lasted approximately 45 minutes.

The survey was conducted from the second week of January to the second week of March 2026, covering approximately three months. Trained enumerators assisted in data collection under the supervision of the researcher to ensure consistency in survey administration. Completed questionnaires were reviewed regularly to verify completeness and internal consistency, and necessary clarifications were made during the data collection process when feasible.

This survey-based data collection procedure ensured the generation of a high-quality cross-sectional dataset suitable for estimating the determinants of PalayCheck adoption using an ordered logit model, as it captures both the explanatory variables and the ordinal structure of adopter category among trained farmers.

Method of Data Analysis

This study employed a two-stage analytical framework aligned with its objectives to examine the determinants of PalayCheck System adoption among farmers in selected provinces of Northern Mindanao.

For the first objective, descriptive statistical analysis was conducted to characterize the socioeconomic, demographic, and farm-level attributes of the respondents. Continuous variables—including age, years of education, household size, farm income, non-farm income, total farm size, rice farm size, and years of farming—were summarized using the mean, standard deviation, minimum, and maximum values to capture central tendency and dispersion. Categorical variables—such as membership status (member_cat), gender (gender_cat), civil status (civil_cat), farming system (diversified), tenure (tenurial_cat), production type (prod_cat2), and location (prov_cat)—were described using frequency and percentage distributions. This stage provides a comprehensive overview of the distribution and variability of key variables relevant to adopter category.

For the second objective, an ordered logit (proportional odds) model was employed to estimate the association between explanatory variables and the adoption cetegory. The dependent variable, adopter category, is measured on a five-point ordinal 1=not yet adopted PalayCheck practices (Laggard) 2= recently adopted PalayCheck after many others (Late majority), 3 = adopted PalayCheck after most others in my community (Early majority), 4=adopted PalayCheck shortly after others in my community (Early adopter), and 5 = among the first in my community to try PalayCheck (Innovator), making the ordered logit model appropriate as it preserves the ordinal nature of the outcome and models transitions across ordered categories.

Econometric Model

Given that PalayCheck adopter category is inherently ordinal—reflecting increasing levels of compliance with recommended practices—the theoretical model is operationalized using a latent variable approach consistent with discrete choice theory. Let A_i^*denote the unobserved propensity of farmer i when to adopt:

$$A_i^* = X_i\beta + Z_i\gamma + \varepsilon_i$$

where X_i and Z_i are vectors of explanatory variables, β and γ are parameters to be estimated, and $\varepsilon_i$is a stochastic error term capturing unobserved influences. The latent variable A_i^*represents the underlying utility-based propensity for adopter category.

The observed adopter category $A_i$is determined by threshold crossings of this latent variable:

$$A_i = j \; if \; \mu_{j-1} < A_i^*$$

where μ_j are unknown cut points to be estimated. This formulation is consistent with the ordered logit model, which assumes a logistic distribution of the error term and the proportional odds assumption across outcome categories (Greene, 2018; Wooldridge, 2010). Empirical applications in agricultural economics frequently employ this framework to model adoption category when technologies are implemented in stages rather than as binary choices (Kassie et al., 2015; Melesse et al., 2021).

Interpretation of Coefficients and Marginal Effects

The estimated coefficients represent the effect of explanatory variables on the latent adoption propensity, not directly on probabilities. A positive coefficient indicates an increase in the likelihood of being in higher adopter categories, while a negative coefficient indicates a shift toward lower adopter categories.

To facilitate economic interpretation, marginal effects were computed for each outcome category. These measure how a change in an explanatory variable affects the probability of being in a specific adopter category, holding other variables constant.

Diagnostic Tests and Model Validation

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

Variance Inflation Factors (VIF) were computed to assess the degree of linear correlation among explanatory variables. Values below conventional thresholds indicate absence of serious multicollinearity.

Model Specification Test. A linktest was performed to evaluate model specification. A statistically significant predicted value (_hat) combined with an insignificant squared term (_hatsq) indicates correct model specification and absence of omitted variable bias.

Robustness Check. To account for potential heteroskedasticity, the model was re-estimated using robust standard errors. Consistency in coefficient signs, magnitudes, and significance levels confirms the stability of the results.

Ethical Considerations

To uphold the confidentiality of the gathered data, the researcher adhered to several ethical considerations. The researcher obtained approval from the Institutional Ethics Review Committee (IERC) prior to conducting the study. Before data collection, the researcher sought permission from the participants, ensuring that they were provided with clear and understandable information about the study's purpose and their rights. Respondents were given the freedom to decline participation at any point in the study without facing any negative consequences. The privacy of participants were safeguarded, with their personal information treated as strictly confidential. Furthermore, the researcher handled the collected data in accordance with data protection regulations, ensuring secure storage, use limited only to the intended purposes, and retention for an appropriate period. These ethical measures collectively ensured the protection and respect of participants' rights and the confidentiality of their data. Proper entry protocols were also observed, such as writing formal letter of permission to all the Municipal Mayors and Municipal Agriculturist. Courtesy visits to all the municipalities involved were also done.

RESULTS AND DISCUSSION

This section presents the empirical findings, beginning with the descriptive profile of farmers and farm characteristics, followed by the econometric analysis of the determinants of PalayCheck System implementation. The descriptive statistics outline the socioeconomic and structural conditions of farmers, while the ordered logit model examines how these factors influence adopter category. Together, the results provide both statistical and economic insights into the drivers of being in a particular adopter category.

Descriptive Profile Of Farmers And Farm Characteristics

Distribution and Variation in Farmers’ Socioeconomic and Farm Characteristics

The Table 2 summarizes the descriptive statistics of the continuous variables, providing a quantitative profile of farmers’ socioeconomic conditions, resource endowments, and level of PalayCheck adoption. These statistics are essential for understanding both the central tendencies and the degree of heterogeneity within the sample.

Table 2. Descriptive statistics of the continuous variables of the study

Variable	Mean	SD	Min	Max
Adopter category	3.454	1.157	1.000	5
Age	49.72	11.433	22.000	76

educ years	11.063	3.476	6.000	20
householdsize	4.118	1.513	1.000	12
farmincom	60401.638	53373.032	5000.000	350000
nonfarmincom	48486.347	48232.635	0.000	276000
totalfarmsize	1.119	.947	0.010	7
ricefarmsize	.894	.791	0.010	7
yearsoffarming	20.761	12.402	1.300	63

The adopter category variable has a mean of 3.454 (SD = 1.157), indicating that on average, farmers fall between early majority and early adopters of the PalayCheck system. This can be describes as farmers are moderate adopters – willing to adopt after the social validation of the practice. However, the full range from min = 1 to max = 5 suggests substantial variation ranging from laggards to innovators, which implies that while some farmers are already towards the innovator category, others remain in the laggard category, reflecting uneven diffusion of the technology.

The average age of farmers is 49.72 years (SD = 11.43), with a range from 22 to 76 years. This indicates a predominantly middle-aged to older farming population, a common feature in developing-country agriculture. The relatively wide dispersion suggests generational diversity, which may translate into differences in risk preferences, openness to innovation, and responsiveness to extension services.

In terms of human capital, farmers have an average of 11.06 years of education (SD = 3.48), roughly corresponding to completion of secondary education. The range (6 to 20 yea) reveals notable variation, with some farmers having minimal formal education and others attaining higher levels. This heterogeneity is important, as education enhances the ability to understand and adopt improved farming practices.

The average household size is 4.12 members (SD = 1.51), indicating moderately sized households. The variation (1 to 12 members) reflects differences in family structure and labor availability. Larger households may have greater labor resources for farm operations but also higher consumption demands, which can influence production and investment decisions.

The income variables reveal significant economic diversity. Mean farm income is approximately ₱60,402 (SD = ₱53,373), while non-farm income averages ₱48,486 (SD = ₱48,233). The large standard deviations relative to the means indicate high income inequality within the sample. The presence of non-farm income, including cases with zero values, suggests that while some households are diversified, others rely solely on agriculture. This dual-income structure is typical in rural economies, where non-farm activities serve as a risk-coping mechanism.

Regarding farm characteristics, the average total farm size is 1.12 hectares (SD = 0.95), and rice farm size averages 0.89 hectares (SD = 0.79). These figures confirm the predominance of smallholder farming systems, consistent with the structure of Philippine agriculture. The wide range (up to 7 hectares) indicates some degree of landholding inequality, although the majority of farmers likely operate on relatively small plots.

Finally, farming experience averages 20.76 years (SD = 12.40), with a range from about 1 to 63 years. This suggests that most farmers possess substantial practical knowledge, although there is considerable variation between relatively new entrants and highly experienced farmers. Such differences may influence both productivity and adoption decisions.

Therefore, Table 2 highlights a heterogeneous farming population characterized by adopter category within the early majority, aging yet experienced farmers, modest educational attainment, small farm sizes, and highly variable income sources. These descriptive patterns provide important context for interpreting the econometric results, particularly in understanding how resource constraints and socioeconomic diversity shape technology adopter category.

Categorical Distribution of Socioeconomic and Farm Characteristics

Table 3 presents the distribution of categorical variables, offering a structural view of institutional participation, demographic composition, production systems, and land tenure arrangements. From an analytical standpoint, these distributions reveal the underlying constraints and enabling conditions that shape farmers' decisions to adopt PalayCheck adoption.

The membership variable shows that 57.56% of farmers are members of an organization, while 42.44% are non-members. This relatively high participation rate suggests that a majority of farmers are embedded in institutional networks, which typically facilitate access to extension services, training, and inputs. However, the sizable proportion of non-members indicates that information asymmetry and exclusion remain relevant, potentially contributing to disparities in adoption outcomes.

In terms of gender, the sample is female-dominated (60.52%), with males accounting for 39.48%. This is a notable finding, as it reflects the increasing feminization of agriculture, often driven by male out-migration or diversification into non-farm employment. From an economic perspective, this has implications for technology adopter category, as gender differences may affect access to credit, extension services, and decision-making authority.

Table 3. Descriptive statics of the categorical variables of the study

Variables	Category	Frequency	Percent (%)
Membership	Non-member	115	42.44
	Member	156	57.56
	Total	271	100.00
Gender	Female	164	60.52
	Male	107	39.48
	Total	271	100.00
Civil Status	Single	42	15.50
	Married	206	76.01
	Widow/Widower	19	7.01
	Others	4	1.48
	Total	271	100.00
Tenurial Status	Owned	159	58.67
	Tenant	65	23.99
	Lease/Rent	22	8.12
	Others	25	9.23

	Total	271	100.00
Province	Bukidnon	153	56.46
	Lanao del Norte	20	7.38
	Misamis Occidental	67	24.72
	Misamis Oriental	31	11.44
	Total	271	100.00

The distribution of civil status indicates that the vast majority of respondents are married (76.01%), followed by singles (15.50%) and widowed individuals (7.01%). This suggests that most farmers operate within stable household units, which can enhance labor availability and risk-sharing mechanisms. Married households may be better positioned to adopt innovations earlier due to pooled resources and shared decision-making.

With respect to tenurial status, 58.67% of farmers own their land, while 23.99% are tenants, 8.12% lease/rent, and 9.23% fall under other arrangements. The predominance of owner-operated farms is significant, as secure property rights are strongly associated with higher investment in productivity-enhancing technologies. Conversely, the presence of tenants and renters suggests that a non-negligible share of farmers may face tenure insecurity, which can discourage long-term investments such as improved farming practices.

Finally, the geographic distribution reveals that more than half of the respondents are from Bukidnon (56.46%), followed by Misamis Occidental (24.72%), Misamis Oriental (11.44%), and Lanao del Norte (7.38%). This uneven distribution suggests that the sample is geographically concentrated, which may reflect differences in program implementation, agro-climatic suitability, or accessibility. From an econometric perspective, this reinforces the need to control for location effects, as regional characteristics can significantly influence adopter category.

In synthesis, Table 3 highlights a farming population characterized by moderate institutional integration, female participation, marital stability, smallholder ownership, and a strong reliance on monocropping and conventional production systems. These structural features provide important insights into both the opportunities (e.g., high membership and land ownership) and constraints (e.g., limited diversification and unequal institutional access) that shape the adopter categories.

Table 4. Provincial Mean Adoption Category of PalayCheck Farmers in Northern Mindanao

PROVINCE	MEAN ADOPTION CATEGORY	STANDARD DEVIATION	N
Bukidnon	3.569	1.196	153
Lanao del Norte	3.850	1.089	20
Misamis Occidental	3.119	1.008	67
Misamis Oriental	3.355	1.170	31
Total	3.454	1.157	271

Table 4 reports Provincial variation in PalayCheck adoption categories was observed across the study areas. Farmers in Lanao del Norte exhibited the highest mean adoption category (Mean = 3.850), indicating that respondents in the province generally belonged between the Early Majority and Early Adopter groups. This was followed by Bukidnon (Mean = 3.569), Misamis Oriental (Mean = 3.355), and Misamis Occidental (Mean = 3.119). The overall mean adoption category of 3.454 suggests that, on average, farmers were situated between the Early Majority and Early Adopter categories, indicating substantial diffusion of the PalayCheck System among trained rice farmers in Northern Mindanao.

Determinants Of Palaycheck System Implementation

Table 5 reports the ordered logit estimates and marginal effects for the determinants of PalayCheck System adoption category, where adopter category is categorized from laggard to innovator, providing both statistical and economic interpretations level of adopter category. The model is jointly significant (LR $\chi^2 = 95.48$, $p < 0.001$), indicating that the explanatory variables collectively influence the latent propensity adopter category, consistent with the ordered logit framework where coefficients reflect shifts in an unobserved adoption category index across thresholds.

Continous variables

Age ($\beta = -0.009$, $p = 0.554$) is not statistically significant, and its marginal effects are negligible across all adopter category levels (e.g., +0.10% for “late majority” and −0.14% for “innovators”). This indicates that life-cycle effects do not play a decisive role in shaping adoption behavior, suggesting that both younger and older farmers face similar incentives and constraints, consistent with findings in rice adoption studies (Mariano et al., 2012).

Education ($\beta = -0.066$, $p < 0.10$) exhibits a weakly significant negative effect. The marginal effects indicate that additional years of schooling increase the probability of being in the lower adopter categories (e.g., +0.76%) while reducing the likelihood of being in the higher adopter category “innovator” (−1.04%). This suggests that the higher is the educational attainment, the less likely they are to adopt certain technologies because possibly they are more cautious in terms of adoption. This pattern is consistent with labor reallocation mechanisms, whereby more educated farmers diversify into non-farm activities, thereby reducing the intensity of engagement in farm-level innovations (Shen et al., 2023).

In contrast, non-farm income ($\beta = -0.000009$, $p < 0.001$) is negative and highly significant, which indicates that farmers with higher non-farm income are less likely to be early adopters or innovators. Although marginal effects are numerically small, they consistently shift probabilities away from higher adopter category levels. This provides strong evidence for the opportunity cost hypothesis, whereby engagement in off-farm employment reduces the time and managerial effort allocated to improved agricultural practices (Shen et al., 2023; Anang & Yeboah, 2019).

Table 5. Determinants of PalayCheck System Implementation (Ordered Logit Estimates with Marginal Effects)

Variables	B	P-value	Laggard (1)	Late Majority(2)	Early Majority(3)	Early Adopter(4)	Innovator (5)
Age	-0.009	0.554	0.02%	0.10%	0.05%	-0.03%	-0.14%
Education (years)	-0.066*	0.064	0.15%	0.76%	0.36%	-0.23%	-1.04%
Household size	0.044	0.571	-0.10%	-0.51%	-0.24%	0.15%	0.70%
Farm income	-0.000002	0.561	0.00%	0.00%	0.00%	0.00%	0.00%
Non-farm income	-0.000009***	0.000	0.00%	0.00%	0.00%	-0.00%	-0.00%
Total farm size	0.371	0.215	-0.87%	-4.28%	-2.02%	1.30%	5.86%
Rice farm size	-0.436	0.214	1.02%	5.02%	2.38%	-1.53%	-6.89%
Years of farming	-0.015	0.238	0.04%	0.18%	0.08%	-0.05%	-0.24%

Membership (Non-member)							
Member	1.371***	0.000	-3.16%	-17.50%	-5.81%	6.06%	20.41%
Gender (ref. Female)							
Male	0.067	0.776	-0.16%	-0.77%	-0.37%	0.23%	1.07%
Civil Status (Ref: Single)							
Married	0.059	0.861	-0.15%	-0.70%	-0.28%	0.23%	0.89%
Widow/Widower	1.021*	0.079	-1.70%	-10.48%	-7.24%	1.64%	17.78%
Others	0.394	0.666	-0.85%	-4.51%	-2.26%	1.26%	6.36%
Tenurial Status (Ref: Owned)							
Tenant	-0.910***	0.003	1.84%	11.31%	5.15%	-4.08%	-14.21%
Lease/Rent	-1.412***	0.002	3.67%	18.69%	4.88%	-7.43%	-19.81%
Others	-1.304***	0.002	3.21%	17.08%	5.14%	-6.69%	-18.74%
Location (Ref: Bukidnon Province)							
Lanao del Norte	0.828*	0.086	-1.21%	-8.05%	-6.72%	0.84%	15.13%
Misamis Occidental	-0.614*	0.057	1.66%	7.60%	2.63%	-2.91%	-8.98%
Misamis Oriental	0.001	0.998	0.00%	0.00%	0.00%	0.00%	0.00%
model statistic	Value		cut point	Estimate	std. error	95% confidence interval	
Observations	271		Cut 1	-5.684	1.044	[-7.729, -3.639]	
Log-likelihood	-345.950		Cut 2	-2.849	0.961	[-4.733, -0.966]	
LR χ^2	95.48		Cut 3	-1.032	0.950	[-2.895, 0.831]	
Prob > χ^2	0.000		Cut 4	0.054	0.946	[-1.800, 1.908]	
Pseudo R^2 (McFadden)	0.121						

However, household size ($\beta = 0.044$, $p = 0.571$) and farm income ($\beta = -0.000002$, $p = 0.561$) are not statistically significant, with marginal effects showing only minor and or zero. This suggests that household labor endowment does not constitute a binding constraint for adopting PalayCheck practices earlier, consistent with evidence that labor availability alone does not guarantee technology adoption without complementary resources (Yamano et al., 2016). Further, result implies that internal farm earnings alone are insufficient to induce adoption timing, possibly due to limited variation or because liquidity constraints are not the primary barrier, consistent with studies emphasizing institutional and informational constraints over income effects (Chang et al., 2024).

Farm Characteristics and Experience

Total farm size (β = 0.371, p = 0.215) is not statistically significant; however, its marginal effects suggest an economically meaningful pattern. Larger farms reduce the probability of being in the lower adopter categories - laggard or late majority (e.g., −4.28% for "late majority") and increase the likelihood of being in the innovator category level (+5.86%). This simply implies that farm size alone is a weak predictor of innovation (Ma, W. et al. 2018; Lowder, S. K., Skoet, J., & Raney, T. 2016).

Rice farm size (β = −0.436, p = 0.214) is likewise not statistically significant, but its marginal effects reveal the opposite tendency; it increases the probability of being in the lower adopter categories (e.g., +5.02% for "late majority") and reduces being in the innovator category level (−6.89%). This contrast suggests heterogeneity in land-use allocation, where specialization in rice production may constrain flexibility or increase risk exposure, consistent with adoption trade-offs in specialized systems (Glover et al., 2020).

Years of farming (β = −0.015, p = 0.238) is not significant, and marginal effects are small (e.g., +0.18% for "late majority" and −0.24% for "innovators"). This indicates that accumulated experience does not necessarily translate into being in the higher adopter category level, possibly reflecting persistence of traditional practices or diminishing returns to experience. This aligns with evidence that experience may reinforce traditional practices rather than encourage innovation (Manda, J. et al., 2020).

Using land ownership as the reference category, tenure status emerges as a critical determinant. Tenants (β = −0.910, p < 0.01), leaseholders (β = −1.412, p < 0.01), and other tenure arrangements (β = −1.304, p < 0.01) all exhibit significantly in the lower adopter category, laggard to early majority. Marginal effects are economically large, with leaseholders experiencing a 19.81% reduction in the probability of being in the innovator category. This is consistent with the property rights hypothesis, where secure land tenure increases incentives for long-term investment in agricultural technologies (Nguyen, 2020; Paltasingh, 2018).

Institutional and Demographic Factors (with Reference Categories)

Using non-members as the reference category, membership (β = 1.371, p < 0.001) significantly increases adoption intensity. The marginal effects are substantial; membership is associated with a probability of being in the lower adoption categories (−17.50% for "late majority") and increases the likelihood of being in the innovators (+20.41%). This implies that members of organizations are more likely to be in the earlier adopter category than non-members. This indicates that non-members face structural constraints, while institutional participation enhances access to information, inputs, and extension services, thereby reducing uncertainty and transaction costs (Addai et al., 2022; Campenhout, 2021).

With female farmers as the reference group, gender (male) is not statistically significant (β = 0.067, p = 0.776), and marginal effects are minimal. This suggests that adoption decisions are not systematically differentiated by gender, consistent with mixed evidence in the literature (Achukwu et al., 2023).

Using single farmers as the reference category, civil status shows limited effects. Married farmers (β = 0.059, p = 0.861) and those in other categories (β = 0.394, p = 0.666) do not differ significantly from singles, indicating that single farmers provide a baseline adoption pattern. However, widowed farmers (β = 1.021, p < 0.10) exhibit a higher likelihood of adoption, with marginal effects indicating a 17.78% increase in the innovator probability. This may reflect differences in household autonomy or decision-making structures, as suggested in behavioral adoption studies (Ghimire & Huang, 2016).

Location Effects (with Reference Categories)

Using Bukidnon as the reference province, spatial heterogeneity is evident. Farmers in Lanao del Norte (β = 0.828, p < 0.10) are more likely to adopt, with a 15.13% increase in the higher adopter category probability, suggesting relatively stronger institutional or agroecological conditions. In contrast, farmers in Misamis Occidental (β = −0.614, p < 0.10) are less likely to adopt, with an 8.98% decrease in full adoption probability, meaning farmers are more likely in the lower adoption categories. Misamis Oriental (β = 0.001, p = 0.998) does

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not differ significantly from Bukidnon, indicating comparable adoption conditions, which are widely recognized as critical determinants of adoption (Chang et al., 2024).

Threshold Parameters and Latent Index Partitioning

The estimated cut points are strictly increasing ($-5.684 < -2.849 < -1.032 < 0.054$), confirming the internal consistency of the ordered logit specification. The differences between adjacent thresholds—2.835, 1.818, and 1.086—indicate how the latent adoption index is partitioned into observed categories. The relatively larger spacing between the first two thresholds suggests that a wider range of the latent index is associated with the lowest adopter category compared to higher adopter categories, where transitions across adoption levels depend on shifts in the latent utility index relative to threshold parameters (Ambong, 2022).

Within the ordered logit framework, outcome probabilities depend on the relative position of the latent index $X\beta$ with respect to these thresholds. Thus, while the threshold spacing does not directly measure behavioral "difficulty," it implies that transitions out of the lowest category require larger shifts in the latent index compared to transitions among higher adopter categories, holding covariates constant.

Importantly, the interpretation of these thresholds must remain conditional on the covariates, as the probability of crossing any threshold is determined by $\tau j - X\beta$. Therefore, the observed pattern of decreasing threshold intervals is best understood as reflecting the distribution of the latent adoption propensity rather than structural costs alone. Nevertheless, when considered alongside the estimated coefficients—particularly those capturing institutional access and tenure security—the results are consistent with an adoption process in which initial movement away from laggard is more demanding than subsequent improvements in adoption intensity.

Test of Multicollinearity

Table 6 reports variance inflation factors (VIF) and their reciprocals (tolerance = 1/VIF) for all regressors. Overall, the evidence indicates no serious multicollinearity concerns. The mean VIF of 1.82 is well below conventional thresholds, suggesting that, on average, the explanatory variables exhibit low linear dependence. Most continuous variables show modest VIF values (approximately 1.1–2.2), implying stable coefficient estimation and reliable inference. The only relatively higher values are observed for total farm size (VIF = 5.33) and rice farm size (VIF = 5.71), which is expected given their structural relationship, as rice area is a component of total farm size. However, these values remain below critical levels and do not indicate problematic multicollinearity, although they may slightly inflate standard errors and warrant cautious interpretation when considered jointly. All categorical (dummy) variables likewise exhibit low VIFs, confirming that the inclusion of multiple factor variables does not introduce redundancy. Overall, the diagnostics suggest that the estimated effects are not driven by multicollinearity, and the model retains sufficient independent variation to support robust and credible econometric inference.

Table 6. Multicollinearity Test

Variables	VIF	1/VIF
Continuous Variables		
Age	2.15	0.464
Education (years)	1.20	0.831
Household Size	1.14	0.880
Farm Income	1.86	0.537
Non-farm Income	1.15	0.867

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Total Farm Size	5.33	0.187
Rice Farm Size	5.71	0.175
Years of Farming	2.01	0.497
Categorical Variables (Dummy Variables)		
Membership (Member)	1.12	0.896
Gender (Male)	1.05	0.948
Civil Status: Married	1.68	0.595
Civil Status: Widow/Widower	1.66	0.601
Civil Status: Others	1.15	0.871
Diversification (Diversified)	2.00	0.501
Tenurial: Tenant	1.31	0.760
Tenurial: Lease/Rent	1.14	0.881
Tenurial: Others	1.19	0.839
Production (Organic)	1.15	0.870
Location: Lanao del Norte	1.22	0.821
Location: Misamis Occidental	1.58	0.633
Location: Misamis Oriental	1.43	0.700
Mean VIF	1.82	

Linktest for model specification

The linktest results in Table 7 provide a diagnostic assessment of model specification by examining whether additional nonlinear combinations of the predicted values contribute explanatory power.

The coefficient on the predicted value (_hat) is positive and statistically significant ($\beta = 0.702$, $p = 0.002$), indicating that the model contains relevant explanatory information and is appropriately capturing systematic variation in the dependent variable. In contrast, the squared predicted term (_hatsq) is not statistically significant ($\beta = -0.099$, $p = 0.137$), suggesting no evidence of major specification error such as omitted nonlinearities or incorrect functional form. This combination—significant _hat and insignificant _hatsq—is consistent with a correctly specified model.

Table 7. Result from the Linktest for model specification

Variable	Coefficient (β)	Std. Error	z-value	P-value	95% Confidence Interval
_hat	0.702	0.223	3.14	0.002	[0.265, 1.140]
_hatsq	-0.099	0.067	-1.49	0.137	[-0.230, 0.031]

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Cut Point	Estimate	Std. Error	95% Confidence Interval	
Cut 1	-5.729	0.494	[-6.698, -4.760]	
Cut 2	-2.769	0.258	[-3.275, -2.262]	
Cut 3	-0.931	0.195	[-1.313, -0.549]	
Cut 4	0.142	0.186	[-0.222, 0.507]	
Model Statistic		Value		
Number of observations		271		
Log-likelihood		-344.867		
LR χ^2 (df = 2)		97.64		
Prob > χ^2		0.000		
Pseudo R^2		0.1240		

The reported cut points remain monotonically increasing ($-5.729 < -2.769 < -0.931 < 0.142$), confirming the internal consistency of the ordinal structure and indicating that the latent adoption index is properly partitioned into ordered categories. Model fit statistics further support the adequacy of the specification: the likelihood ratio statistic (LR $\chi^2 = 97.64$, $p < 0.001$) indicates that the model is jointly significant, while the pseudo R^2 of 0.124 suggests moderate explanatory power for cross-sectional adoption behavior.

Therefore, the linktest results provide no indication of misspecification, reinforcing the robustness of the ordered logit estimates. The absence of a significant _hatsq term implies that the model does not omit key nonlinear relationships, and the specification is therefore suitable for interpreting the determinants of PalayCheck System adoption.

Robustness Check of the Ordered Logit Estimates

Table 8 presents the ordered logit estimates with robust standard errors to assess the sensitivity of the baseline results (Table 4) to potential heteroskedasticity. Overall, the results are broadly consistent, as the signs, magnitudes, and general patterns of statistical significance are largely preserved. The model remains jointly significant (Wald $\chi^2 = 101.74$, $p < 0.001$), and the pseudo R^2 (0.121) is unchanged, indicating that the overall fit of the model is not affected by the use of robust standard errors.

For continuous variables, the results remain similar to the baseline specification. Age, household size, farm income, total farm size, rice farm size, and years of farming continue to be statistically insignificant, suggesting that their estimated effects are not sensitive to heteroskedasticity. Education retains a weak negative association with adoption ($\beta = -0.066$, $p = 0.076$), closely aligned with the baseline estimate ($p = 0.064$), indicating that its marginal significance is not driven by variance assumptions. Non-farm income remains negative and statistically significant ($\beta = -0.000009$, $p < 0.001$), with a slightly stronger z-value, suggesting that its estimated effect is stable under alternative variance specifications.

Table 8. Robustness Check: Determinants of PalayCheck System Implementation (Ordered Logit with Robust Standard Errors)

Variables	Coefficient (β)	Robust SE	z-value	p-value
Age	-0.009	0.015	-0.59	0.556
Education (years)	-0.066*	0.037	-1.78	0.076

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Household Size	0.044	0.073	0.60	0.546
Farm Income	-0.000002	0.000003	-0.56	0.577
Non-farm Income	-0.000009***	0.000002	-4.03	0.000
Total Farm Size	0.371	0.376	0.99	0.324
Rice Farm Size	-0.436	0.393	-1.11	0.267
Years of Farming	-0.015	0.014	-1.11	0.269
Membership (Ref: Non-member)				
Member	1.371***	0.270	5.07	0.000
Gender (Ref: Female)				
Male	0.067	0.242	0.28	0.781
Civil Status (Ref: Single)				
Married	0.059	0.323	0.18	0.856
Widow/Widower	1.021*	0.627	1.63	0.104
Others	0.394	0.772	0.51	0.610
Farming sytem (Ref: Monocropping)				
Diversified	0.527	0.450	1.17	0.242
Tenurial Status (Ref: Owned)				
Tenant	-0.910***	0.334	-2.72	0.006
Lease/Rent	-1.412***	0.459	-3.08	0.002
Others	-1.304***	0.424	-3.08	0.002
Production (Ref: Non-organic)				
Organic	-0.018	0.462	-0.04	0.969
Location (Ref: Bukidnon)				
Lanao del Norte	0.828	0.527	1.57	0.116
Misamis Occidental	-0.614*	0.314	-1.96	0.051
Misamis Oriental	0.001	0.464	0.00	0.998
Model Statistic		Value		
Observations		271		
Wald χ^2		101.74		

Prob > χ^2		0.000		
Log pseudolikelihood		-345.950		
Pseudo R^2		0.121		

Key institutional and structural variables also show consistent results. Membership remains positive and highly significant ($\beta = 1.371$, $p < 0.001$), with no meaningful change in magnitude. Similarly, tenure variables continue to exhibit negative and statistically significant coefficients: tenants ($\beta = -0.910$, $p = 0.006$), leaseholders ($\beta = -1.412$, $p = 0.002$), and other arrangements ($\beta = -1.304$, $p = 0.002$). The similarity of these estimates to the baseline suggests that the relationship between tenure status and adopter categories is not sensitive to heteroskedasticity.

For other categorical variables, the general pattern is also maintained. Gender, most civil status categories, farming system, and production type remain statistically insignificant. The coefficient for widowhood becomes less precisely estimated ($p = 0.104$ compared to $p = 0.079$), indicating some sensitivity to the choice of standard errors, although the direction of the effect is unchanged. Location effects are qualitatively similar: Misamis Occidental remains marginally significant ($p = 0.051$ vs. 0.057), while Lanao del Norte becomes statistically insignificant ($p = 0.116$ vs. 0.086), suggesting that these spatial effects are somewhat sensitive to variance adjustments.

Taken together, the comparison between Tables 4 and 8 indicates that the main empirical patterns are not materially altered when robust standard errors are used. While some coefficients exhibit minor changes in statistical significance, particularly among weaker predictors, the key variables—such as membership, tenure status, and non-farm income—remain consistent in both sign and inference. This suggests that the baseline results are reasonably stable with respect to heteroskedasticity, although caution remains warranted in interpreting variables with marginal significance.

SUMMARY, CONCLUSION, AND RECOMMENDATION

Summary

This study examined the determinants of the PalayCheck System adopter category among 271 rice farmers in selected provinces of Northern Mindanao using descriptive statistics and an ordered logit model. The average adoption level was 3.454 (SD = 1.157), indicating that farmers fall between the early majority (3) and early adopter (4) categories, which implies that farmers adopt the PalayCheck system after it has been adopted by other farmers in their locality. However, the relatively large standard deviation also shows substantial variation, meaning that the sample still includes farmers across all five categories—from those who have not yet adopted (Laggards) to those who were among the first adopters (Innovators). The model is jointly significant (LR $\chi^2 = 95.48$, $p < 0.001$) with a pseudo R^2 of 0.121, suggesting that the included variables account for a meaningful share of variation in the latent adoption index.

The results indicate that institutional and structural variables are more strongly associated with adopter categories than demographic characteristics. Membership in farmer organizations is positively and highly significant ($\beta = 1.371$, $p < 0.001$), with marginal effects indicating a 20.41 percentage-point increase in the probability of being in the higher adopter category. In contrast, tenure insecurity is negatively associated with adopter categories: leaseholders ($\beta = -1.412$, $p < 0.01$), tenants ($\beta = -0.910$, $p < 0.01$), and other arrangements ($\beta = -1.304$, $p < 0.01$) exhibit in the lower adopter categories, with reductions in higher adopter category probability of up to 19.81%. Non-farm income is also negatively associated with adopter category ($\beta = -0.000009$, $p < 0.001$), consistent with opportunity cost considerations. Most demographic and farm-level variables are not statistically significant, while education shows a weak negative association. Robustness checks using heteroskedasticity-consistent standard errors confirm that these patterns are stable.

Conclusion

This study aimed to (1) describe the socioeconomic, demographic, and farm characteristics of rice farmers and (2) estimate the association of these factors with the PalayCheck System adopter category level in selected provinces of Northern Mindanao. The descriptive results reveal a heterogeneous farming population characterized by farmers in the early majority and early adopter categories (mean = 3.454), smallholder production systems, and diverse income sources, including substantial participation in non-farm activities. These patterns indicate that farmers operate under varying resource endowments and institutional conditions, which shape their innovation adoption category.

The econometric analysis shows that the adopter category is more strongly associated with institutional and structural factors than with demographic characteristics. Membership in farmer organizations is positively associated with higher levels of adoption, while insecure tenure arrangements—such as tenancy and leasing—are negatively associated with adoption. Non-farm income is also negatively associated with adoption, suggesting that competing livelihood activities may reduce engagement in improved farming practices. In contrast, variables such as age, household size, and farming experience do not exhibit statistically significant associations, while education shows only a weak relationship.

Therefore, the findings suggest that variation in PalayCheck adopter reflects differences in institutional access, tenure conditions, and livelihood structures, rather than purely individual characteristics. The presence of moderate average adoption alongside substantial variability indicates that all five adopter categories are present, spreading unevenly- progressing through early majority while co-existing with both laggards and innovators.

Recommendation

Grounded in the empirical results, the following recommendations are directed to the appropriate authorities in Northern Mindanao to improve PalayCheck adoption:

1. Expand Institutional Access and Farmer Organization Support

The Department of Agriculture Philippines (DA), Agricultural Training Institute (ATI), and Local Government Units (LGUs) should strengthen support for farmer organizations, given the strong positive association between membership and PalayCheck adoption. This can be achieved through expanded capacity-building programs, cluster-based extension approaches, and targeted incentives to increase membership participation. ATI may enhance the quality and reach of training delivery, while LGUs can play a key role in facilitating local organization, coordination, and sustained farmer engagement.

2. Address Tenure-Related Constraints

The Department of Agrarian Reform (DAR), Department of Agriculture Philippines (DA), and Local Government Units (LGUs) should address tenure-related constraints that are associated with lower levels of PalayCheck adoption. Strengthening tenure security through improved land documentation and integration of beneficiaries into support programs is essential. At the same time, DA and LGUs should ensure that tenants and leaseholders are systematically included in extension services and subsidy programs to reduce barriers to technology adoption.

3. Adapt Extension Strategies to Diversified Livelihoods

The Department of Agriculture Philippines – Regional Field Office 10, Agricultural Training Institute (ATI), and Local Government Units (LGUs) should adapt extension delivery mechanisms in response to the negative association between non-farm income and adoption. Extension services need to be more flexible and accessible through modular training schedules, mobile or digital platforms, and localized farmer field schools that accommodate the time constraints of farmers engaged in off-farm activities. Such adjustments can improve participation and enhance the effectiveness of technology dissemination among part-time and diversified farmers.

4. Implement Location-Specific Interventions

The Department of Agriculture, Philippines – Regional Field Office 10 and Provincial LGUs in Bukidnon, Lanao del Norte, Misamis Occidental, and Misamis Oriental should design location-specific interventions in response to observed spatial variation in PalayCheck adoption. In coordination with DA, provincial governments should tailor programs based on local agroecological conditions, infrastructure availability, and institutional capacity to ensure that extension strategies are context-appropriate and more effective in addressing region-specific constraints.

5. Strengthen Inclusive and Practical Knowledge Dissemination

The Agricultural Training Institute (ATI), Department of Agriculture Philippines (DA), Local Government Units (LGUs), and State Universities and Colleges (SUCs) should enhance inclusive and accessible extension strategies to address heterogeneity in education and access among farmers. Training programs should prioritize practical and easily understood approaches, including demonstration farms, peer learning, and farmer-led extension methods. SUCs can further support these efforts by strengthening research–extension linkages and facilitating technology validation to ensure that recommended practices are locally appropriate and readily adoptable.

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