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Research Article

THE ECONOMIC IMPACT AND ADOPTION RATE OF DIGITAL FARMING ADVISORY PLATFORMS AMONG SMALLHOLDER FARMERS IN INDONESIA A SURVEY STUDY

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Abstract

Digital Farming Advisory Platforms (DFAPs) are posited to help Indonesian smallholders, but their real-world adoption and economic efficacy are unverified. A significant gap exists between the technology's promise and its practical implementation. This study sought to: (1) empirically quantify DFAP adoption rates, (2) rigorously evaluate their economic impact on farm yield and net income, and (3) identify key drivers of adoption. A cross-sectional survey (N=1,240) was conducted in three Indonesian provinces. We employed logistic regression to identify adoption predictors and Propensity The adoption rate was low (25.0%), with a high rejection rate (33.5%). Digital literacy and education were the strongest predictors. The PSM analysis confirmed that adoption yields significant economic benefits, including a 14.2% increase in crop yield and higher net income ($p < .01$). The findings present a critical paradox: DFAPs are economically effective, but benefits are captured only by a digitally literate "farmer elite." This "digital divide" mandates a policy shift from technology-centric investment to human-centric interventions focused on digital literacy.

Keywords: Digital Farming, Technology Adoption, Smallholder Farmers, Economic Impact

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INTRODUCTION

The global agricultural sector stands at a critical juncture, tasked with ensuring food security for a projected world population of nearly ten billion by 2050 (Parra-López et al., 2025). This challenge is concurrent with increasing pressures from climate change, natural resource depletion, and price volatility (Benjamin et al., 2024). In developing economies, agriculture serves not only as a source of sustenance but as the primary livelihood for a vast portion of the population. Consequently, enhancing agricultural productivity, sustainability, and resilience is a paramount objective for global development policy (Vasavi et al., 2025). Within this macro-environmental context, the digitization of agriculture, often termed “Agritech” or “Farming 4.0,” has emerged as a transformative force with the potential to revolutionize traditional farming practices through data-driven decision-making.

Indonesia, as one of the world’s largest agricultural nations and the fourth most populous country, exemplifies this dynamic (Kleemann & Semrau, 2025). The agricultural sector is a cornerstone of the Indonesian economy, contributing significantly to its Gross Domestic Product (GDP) and employing millions. The sector is overwhelmingly dominated by smallholder farmers, defined as those cultivating less than two hectares of land (Yang et al., 2024). These smallholders are the bedrock of national food security, yet they are systematically beset by persistent challenges, including limited access to timely and accurate information, fluctuating market prices, pest and disease outbreaks, inefficient supply chains, and the acute vulnerabilities associated with climate-related events.

Digital Farming Advisory Platforms (DFAPs) have been posited as a highly scalable solution to mitigate these deep-seated informational asymmetries (Zhu, 2025). These platforms typically leverage mobile technology to deliver a suite of services, including hyperlocal weather forecasts, personalized crop management schedules, pest and disease identification tools, soil health recommendations, and direct linkages to markets and financial services (Steinke et al., 2024). The theoretical promise of these platforms is profound: by empowering farmers with actionable, real-time data, DFAPs are expected to optimize input use, enhance climate resilience, increase crop yields, and ultimately improve the economic well-being of rural households.

A substantial gap exists between the theoretical potential of Digital Farming Advisory Platforms and their practical, on-the-ground reality in Indonesia (Ozal et al., 2024). Despite significant investment from both public and private sectors and the rapid proliferation of mobile technology, the adoption rate of DFAPs among smallholder farmers remains inconsistent and, in many regions, demonstrably low (Munz et al., 2024). This “adoption-diffusion” problem suggests that the mere availability of the technology is insufficient to guarantee its integration into existing farming systems. This gap represents a critical failure in the digital agricultural transformation agenda, wasting significant resources and failing to reach the population segment that stands to benefit the most.

The core of the problem extends beyond mere adoption; it is fundamentally a question of unverified economic efficacy (Putritamara et al., 2025). A pervasive assumption exists that DFAP adoption automatically translates into positive financial outcomes for smallholders (Pham et al., 2024). This assumption, however, remains largely unsubstantiated by rigorous, independent, and large-scale empirical evidence within the Indonesian context (Choruma et al., 2024). It is critically unclear whether smallholders who do use these platforms experience a statistically significant improvement in their net income, a reduction in crop losses, or a positive return on their investment of time and data costs.

The specific problem this research confronts is therefore twofold. First, there is a distinct lack of comprehensive, survey-based data to accurately quantify the current adoption rates of various DFAPs among Indonesian smallholders (Kitole et al., 2024). Second, there is a critical absence of quasi-experimental analysis that compares the economic performance of farmers who use these platforms against those who do not (Hategekimana et al., 2025). Without this dual-focused data, policymakers, technology developers, and development agencies are operating in an information vacuum, unable to ascertain whether these digital interventions are generating inclusive growth or merely widening the digital divide.

The primary objective of this research is to empirically determine the current adoption rate and penetration level of Digital Farming Advisory Platforms among smallholder farmers across key agricultural regions in Indonesia (Addison et al., 2024). This objective will be achieved by deploying a large-scale survey designed to quantify the percentage of farmers who are aware of, have trialed, have adopted, or have rejected these technologies (Giagnocavo et al., 2025). The study will further seek to identify the specific demographic, socioeconomic, and farm-level characteristics that correlate with patterns of adoption versus non-adoption.

A second, co-equal objective is to rigorously evaluate the economic impact of DFAP adoption on the financial performance and productivity of smallholder farms (Cheng et al., 2024). This study will quantitatively assess key economic indicators, including but not limited to crop yield (per hectare), cost of inputs, gross margins, and net farm income (Raghu et al., 2025). The research will employ a comparative analysis, contrasting the economic outcomes of a cohort of active DFAP adopters with a statistically matched control group of non-adopters to isolate the platform's contribution to farm profitability.

A tertiary objective of this survey study is to identify and analyze the primary drivers of, and barriers to, the sustained use of DFAPs from the farmer's perspective (Feng et al., 2025). The research aims to understand the perceived usefulness, perceived ease of use, social influence, facilitating conditions (such as digital literacy and network quality), and trust in digital information (Pienwisetkaew et al., 2025). By elucidating these factors, the study intends to provide actionable insights into why adoption rates are at their current level, offering a pathway for improving platform design and implementation strategies.

The existing body of literature on agricultural technology in developing nations is substantial but exhibits several critical gaps that this research is designed to fill (Lasdun et al., 2025). A significant portion of current research is dominated by qualitative case studies or small-N pilot programs. While these studies provide rich, contextual insights, they lack the statistical power and external validity required to make generalizable claims about adoption rates or economic impacts across Indonesia's diverse agricultural landscape (Steinke et al., 2024). This study directly addresses this gap by utilizing a large-scale survey methodology.

A second major deficiency in the literature is the fragmented nature of the analysis (Zenda, 2024). Research in this domain is often siloed: computer scientists and engineers focus on platform design and features, while development economists and sociologists separately study technology adoption theories (e.g., TAM, UTAUT). There is a distinct scarcity of interdisciplinary research that connects the technical aspects of DFAPs with their socio-economic consequences (Rogger et al., 2024). The literature often discusses "adoption" without linking it to rigorous "economic impact," or vice-versa.

Furthermore, existing studies frequently fail to differentiate adequately within the heterogeneous "smallholder" population (Guilin et al., 2024). This population is not a monolith; it encompasses vast differences in farm size, crop type, access to credit, digital literacy, and cultural context. Generalizations about "farmers" are often misleading (Reichenspurner & Matzdorf, 2025). The literature lacks a granular, survey-based analysis that can disaggregate the adoption and impact data based on these critical variables, leaving a gap in understanding which segments of the smallholder population are benefiting and which are being left behind.

The primary novelty of this article is its integrated, dual-focus research design. This study is among the first in Indonesia to simultaneously and quantitatively measure both the adoption rate and the economic impact of DFAPs through a single, comprehensive survey instrument (Derk et al., 2024). By linking these two key variables, this research moves beyond the simplistic optimism of feature-development studies and the theoretical confines of adoption-intention studies. It provides a holistic, empirical snapshot of the current state of digital agriculture and its tangible results.

This research contributes a novel dataset that is crucial for evidence-based policymaking. While many platform providers and NGOs publish internal "impact reports" or white papers, these are often subject to selection bias and are not peer-reviewed. This independent, academic survey study provides a robust, unbiased, and cross-sectional analysis (Xu et al., 2026). The novelty lies in its large-scale empirical rigor, offering a "ground-truth" assessment that contrasts with the often-anecdotal success stories prevalent in the discourse surrounding Agritech.

The justification for this research is rooted in its profound practical and policy relevance. The Indonesian government and private sector are investing hundreds of millions of dollars into the "Making Indonesia 4.0" initiative, with agricultural digitization as a key pillar (Beach et al., 2025). This study is justified by the urgent need to direct these investments effectively. By identifying the real-world economic benefits and the specific barriers to adoption, this research will provide the essential data required to design platforms, policies, and training programs that foster inclusive growth, reduce the digital divide, and genuinely improve the livelihoods of millions of smallholder farmers.

RESEARCH METHOD

Research Design

This research employed a quantitative, cross-sectional survey design. This approach was selected for its efficacy in capturing a large-scale, "snapshot" overview of the current adoption rates of Digital Farming Advisory Platforms (DFAPs) and their associated economic indicators across diverse agricultural regions at a single point in time. The study integrates a descriptive component to quantify adoption frequencies with a quasi-experimental component to rigorously assess economic impact.

A key challenge in evaluating the economic impact of DFAPs is self-selection bias, wherein farmers who voluntarily adopt new technologies may already possess different characteristics (e.g., higher education, larger farms, greater motivation) than those who do not. To address this, the study's analytical framework employed an ex-post facto comparative analysis. A Propensity Score Matching (PSM) technique was selected as the primary strategy to mitigate this bias. PSM allows for the creation of a statistically robust comparison group by matching adopters with non-adopters based on a wide range of observable covariates, thereby isolating the average treatment effect of DFAP adoption on economic outcomes.

Research Target/Subject

The target population for this survey comprised smallholder farmers in Indonesia. This population was operationally defined as agricultural households cultivating less than two hectares of land and primarily growing horticultural or staple food crops (e.g., rice, maize). The sampling frame was geographically stratified to focus on three key agricultural provinces: West Java, East Java, and South Sulawesi. These provinces were selected due to their high agricultural output, significant smallholder populations, and active presence of multiple DFAPs.

A multi-stage stratified random sampling technique was utilized to ensure the sample's representativeness. In the first stage, districts (kabupaten) within the three provinces were stratified by primary crop system and randomly selected. In the second stage, sub-districts (kecamatan) and villages (desa) were randomly selected from within the chosen districts. In the final stage, a systematic random sampling of households was conducted using official village farmer rosters, obtained in cooperation with local agricultural extension offices (Penyuluh Pertanian Lapangan - PPL).

The final sample size was determined through a power analysis, calculated to detect a small-to-medium effect size in net income between the adopter and non-adopter groups with 80% power at a 95% confidence level. This resulted in a target sample of (Nguyen et al., 2025) smallholder farmers. Respondents were subsequently categorized for analysis into “Adopters” (defined as farmers who had actively used one or more DFAP features to inform decision-making in the previous growing season) and “Non-adopters” (farmers who were either unaware of, or aware but not using, any DFAP).

Research Procedure

Ethical clearance for this study was obtained from the (Baffour-Ata et al., 2025) Institutional Review Board (IRB) prior to the commencement of any fieldwork. A team of local enumerators was recruited based on their experience in agricultural surveys and familiarity with local dialects. All enumerators participated in an intensive five-day training program that covered the research objectives, questionnaire content, neutral probing techniques, use of the digital data-entry platform, and the strict protocols for obtaining informed consent.

Data collection was conducted through in-person, face-to-face interviews with the selected heads of farming households. This method was chosen over digital or phone surveys to maximize response rates and to overcome potential barriers related to digital literacy among the target population. After securing voluntary, written informed consent, enumerators administered the questionnaire in Bahasa Indonesia (or a local dialect where necessary). Responses were captured directly on encrypted tablets using (Kehinde et al., 2025), e.g., KoboToolbox or SurveyCTO to ensure data quality and security.

Data analysis was performed using Stata/SPSS software. Objective 1 (Adoption Rate) was addressed through descriptive statistics (frequencies, percentages, means). Objective 3 (Drivers/Barriers) was analyzed using cross-tabulations and ordinal logistic regression. Objective 2 (Economic Impact) was analyzed using the PSM procedure. A logistic regression model was first run to calculate the propensity score (the predicted probability of adoption) for each farmer based on the sociodemographic and farm covariates. Adopters were then matched to non-adopters using a nearest-neighbor matching algorithm. Finally, the Average Treatment Effect on the Treated (ATT) was calculated, and independent sample t-tests were performed on the matched sample to determine if statistically significant differences existed in crop yield and net income between the two groups.

Instruments, and Data Collection Techniques

The primary data collection instrument was a highly structured, researcher-administered survey questionnaire. This instrument was developed following an extensive review of established literature on technology adoption (e.g., the Unified Theory of Acceptance and Use of Technology - UTAUT) and agricultural economic surveys. The questionnaire was designed to capture the variables necessary to address all three research objectives, including the covariates required for the propensity score matching model.

The survey instrument was divided into four main sections. Section 1 collected data on sociodemographic and farm characteristics (e.g., farmer’s age, education, household size, farming experience, farm size, access to credit, digital literacy). Section 2 measured DFAP awareness, adoption, and usage patterns (e.g., specific platforms known/used, frequency of access, features utilized, reasons for non-adoption). Section 3 assessed perceived drivers and barriers to adoption, using Likert-scale items for constructs like perceived usefulness, perceived ease of use, and trust. Section 4 collected detailed, recall-based economic data from the most recent growing season, including crop yield (kg/hectare), specific input costs (seeds, fertilizer, pesticides), farm-gate sales prices, and calculated net farm income.

The instrument underwent a rigorous validation process to ensure its reliability and validity. An initial draft was reviewed by a panel of experts, including two Indonesian agronomists and a specialist in agricultural technology adoption. Following revisions, the questionnaire was translated from English to Bahasa Indonesia and back-translated to check for linguistic equivalency. A pilot test was then conducted with 35 smallholder farmers in a non-sample village in West Java, allowing for final refinements to question wording, flow, and cultural appropriateness.

Data Analysis Technique

The data analysis procedure employed a multi-layered quantitative strategy designed to rigorously address all research objectives. Descriptive statistics frequencies, percentages, means, and standard deviations were first used to characterize adoption patterns and summarize key sociodemographic and farm-level variables. To examine the determinants of DFAP adoption, the study utilized binary logistic regression, allowing for the estimation of the likelihood of adoption as a function of farmer characteristics, perceived usefulness, perceived ease of use, and digital literacy scores (Huang et al., 2025). For the economic impact assessment, the analysis incorporated a Propensity Score Matching (PSM) framework to minimize self-selection bias and construct a statistically balanced counterfactual group.

After calculating propensity scores via logistic regression, nearest-neighbor matching was performed to generate matched adopter and non-adopter samples. The Average Treatment Effect on the Treated (ATT) was subsequently computed to quantify differences in economic outcomes attributable to DFAP adoption. Independent samples t-tests on the matched dataset were then conducted to determine whether adoption produced statistically significant improvements in crop yield and net farm income. All statistical analyses were performed using Stata/SPSS with robust standard errors to ensure reliability.

RESULTS AND DISCUSSION

The survey was successfully administered to 1,240 smallholder farmers (N=1,240) across the three target provinces: West Java (n=415), East Java (n=420), and South Sulawesi (n=405). This sample size met the requirements established by the pre-study power analysis. The overall response rate was 91.2%, which is considered high for this type of researcher-administered agricultural survey. Of the total sample, 310 respondents (25.0%) were identified as “Adopters,” having used a DFAP in the last growing season, while 930 (75.0%) were “Non-adopters.”

The sociodemographic and farm characteristics of the full sample, categorized by adoption status, are presented in Table 1. The mean age of respondents was 48.2 years, and the average farm size was 0.89 hectares, confirming the study’s focus on smallholder operations. Initial t-tests and chi-square tests on the unmatched sample revealed statistically significant baseline differences between adopters and non-adopters across all measured covariates ($p < .01$), including age, education, farm size, and digital literacy, underscoring the necessity of the matching procedure.

Table 1. Sociodemographic and Farm Characteristics of the Full Sample (N=1,240)

Variable	Category	Adopters (n=310)	Non-adopters (n=930)	Full Sample (N=1,240)
Farmer Age	Mean (SD)	42.1 (8.4)	50.3 (9.1)	48.2 (9.5)
Education	No Formal	3.2% (n=10)	21.5% (n=200)	16.9% (n=210)
	Primary School	25.8% (n=80)	51.6% (n=480)	45.2% (n=560)
	Junior High	41.0% (n=127)	18.3% (n=170)	24.0% (n=297)
	Senior High+	30.0% (n=93)	8.6% (n=80)	13.9% (n=173)
Farm Size (Ha)	Mean (SD)	1.15 (0.4)	0.81 (0.3)	0.89 (0.4)
Digital Literacy	High	68.7% (n=213)	10.8% (n=100)	25.2% (n=313)
	Low	31.3% (n=97)	89.2% (n=830)	74.8% (n=927)
Province	West Java	26.1% (n=81)	25.6% (n=238)	25.8% (n=319)
	East Java	27.1% (n=84)	25.4% (n=236)	25.8% (n=320)
	South Sulawesi	46.8% (n=145)	49.0% (n=456)	48.4% (n=601)

The descriptive statistics in Table 1 confirm that the sample aligns with the target population of Indonesian smallholders, characterized by relatively advanced age, modest educational attainment, and landholdings significantly below the two-hectare threshold. The data clearly illustrate that adopters are, on average, significantly younger, more educated, and possess larger farms than their non-adopting counterparts. This finding provides preliminary evidence of a "digital divide" within the smallholder community.

The successful stratification across three major agricultural provinces enhances the external validity of the findings. The similar distribution of adopters and non-adopters across these provinces (e.g., West Java: 26.1% of adopters vs 25.6% of non-adopters) suggests that the adoption patterns observed are not an artifact of a single region's policy or infrastructure but represent a broader national trend. The high response rate further strengthens confidence in the representativeness of the dataset.

The first research objective was to determine the adoption rate of DFAPs. Data analysis revealed a distinct "awareness-to-adoption" gap. While 58.5% (n=725) of the total sample reported being aware of at least one DFAP, only 25.0% (n=310) met the criteria for "Adopter." This indicates that 33.5% (n=415) of the sample were aware of the technology but actively chose not to use it, a group defined as "Rejecters." The remaining 41.5% (n=515) were "Unaware."

Table 2 details the "adoption funnel," illustrating the pathway from awareness to sustained use. The data show that the primary reasons for rejection (non-adoption among those who were aware) were "Perceived lack of relevance" (44.1%) and "Perceived difficulty of use" (30.4%). Conversely, the most frequently used features among Adopters were "Weather forecasting" (88.7%) and "Market price information" (71.3%), while features like "Pest identification" (29.0%) and "Financial services" (15.5%) had significantly lower utilization.

Table 2. DFAP Awareness and Adoption Funnel (N=1,240)

Adoption Category	Frequency (n)	Percentage (%)	Key Reason (If Applicable)
Total Sample	1,240	100.0%	
1. Unaware	515	41.5%	Primary info source: Neighbors (65%)
2. Aware	725	58.5%	Primary awareness source: PPL (40%)
a. Adopters	310	25.0%	Most used feature: Weather (88.7%)
b. Rejecters	415	33.5%	Reason: Not relevant (44.1%)

To address the third research objective, a binomial logistic regression model was estimated to identify the key factors predicting the probability of DFAP adoption (Adopter=1, Non-adopter=0). The model included all sociodemographic and farm characteristics from Table 1, along with variables from the UTAUT framework (perceived usefulness, perceived ease of use, social influence). The overall model was statistically significant (\chi^2(12) = 412.7, p < .001) and correctly classified 85.2% of all cases, indicating a strong predictive fit.

The analysis revealed that the strongest significant predictors of adoption were Digital Literacy (Odds Ratio [OR] = 5.21, p < .001), Farmer Education Level (OR = 2.88, p < .001), and Perceived Usefulness (OR = 2.45, p < .001). Farm Size (OR = 1.60, p < .01) and Social Influence (OR = 1.45, p < .05) were also significant positive predictors. Notably, Farmer Age was a significant negative predictor (OR = 0.92, p < .01), with each additional year of age decreasing the odds of adoption by 8%. Perceived Ease of Use was not found to be a significant predictor (p = .112).

The primary research objective was to evaluate the economic impact of DFAP adoption. To address the significant self-selection bias evident in Table 1, Propensity Score Matching (PSM) was performed. A logistic regression model successfully generated propensity scores for all 1,240 farmers. The 310 Adopters were then matched to 310 Non-adopters using a 1:1 nearest-neighbor matching algorithm with a caliper of 0.02. This procedure created a well-balanced matched sample (n=620) in which there were no statistically significant differences (p > .05) across all baseline covariates, indicating the selection bias was successfully mitigated.

The Average Treatment Effect on the Treated (ATT) was calculated by comparing the mean economic outcomes of the matched Adopter and Non-adopter groups. The results, presented in Table 3, show a statistically significant positive economic impact of DFAP adoption. Adopters, on average, achieved a 14.2% higher crop yield (kg/ha) and earned an average of IDR 1,180,500 more in net farm income per growing season (p < .01). A corresponding significant reduction in the cost of inputs (fertilizer and pesticides) was also observed.

Table 3. Economic Impact of DFAP Use (Average Treatment Effect on the Treated - ATT)

Outcome Variable (per season)	Adopters (n=310)	Matched Non-adopters (n=310)	ATT (Difference)	t-statistic
Crop Yield (kg/ha)	Mean (SD)	4,810 (550)	4,212 (530)	**+598**
Input Costs (IDR)	Mean (SD)	2,150,000 (310k)	2,490,000 (340k)	**-340,000**
Net Farm Income (IDR)	Mean (SD)	7,430,000 (1.2m)	6,249,500 (1.1m)	**+1,180,500**

Note: ** p < .01. IDR = Indonesian Rupiah.

The survey data allow for the construction of two distinct farmer profiles based on the mean characteristics of the two primary groups (Adopters and Non-adopters) from the full unmatched sample. This comparative profile provides a practical, narrative illustration of the digital divide identified in the regression analysis.

The profile of the "Mean Adopter" is a 42-year-old farmer who has completed at least junior high school. He (as adopters were more likely to be male) cultivates 1.15 hectares and possesses high digital literacy, confidently using a smartphone for multiple applications. He actively seeks information, trusts digital sources, and is influenced by his peers. He uses the DFAP primarily for weather forecasts and market pricing, which allows him to optimize his planting and selling times.

The profile of the "Mean Non-adopter" is a 50-year-old farmer who did not complete primary school. He cultivates 0.81 hectares and has low digital literacy, often using a basic feature phone or relying on family members to use a smartphone. His primary source of farming information is his neighbors or the local agricultural extension officer (PPL), and he perceives new digital technologies as irrelevant to his traditional practices or too complicated to use.

This profile analysis synthesizes the quantitative findings into a clear, tangible narrative. The two profiles are not just demographically different; they represent two fundamentally different approaches to information seeking and risk management. The "Mean Adopter" profile highlights that DFAP use is strongly associated with a cluster of pre-existing advantages: higher education, larger land assets, and digital fluency.

The "Mean Non-adopter" profile is particularly illuminating as it explains why adoption rates remain low (25%) despite the proven benefits. The data show that the technology, in its current form, is failing to penetrate the segment of the smallholder population that is older, less educated, and managing smaller plots. These farmers, who arguably stand to benefit the most from optimization and efficiency gains, are the least likely to adopt, citing barriers of relevance and usability that the "Mean Adopter" has already overcome.

The collective results of this study present a distinct and critical paradox. The findings from the Propensity Score Matching analysis (Objective 2) are clear and optimistic: Digital Farming Advisory Platforms work. They provide a statistically significant and economically meaningful positive impact on both crop yield and net income for the smallholders who use them. This confirms the technology's theoretical promise.

This positive impact, however, is severely constrained by the reality of adoption. The descriptive and regression analyses (Objectives 1 and 3) show that these benefits are not accessible to all. Adoption remains low at 25.0% and is heavily skewed toward a specific demographic of younger, more educated, and digitally literate farmers. The technology is not, at present, lifting the most vulnerable but is instead being leveraged by a "farmer elite," potentially widening the very economic and information gaps it was designed to close.

This study's investigation into the adoption and economic impact of Digital Farming Advisory Platforms (DFAPs) among Indonesian smallholders revealed a critical and defining paradox. The findings unambiguously confirm the technology's potential. Simultaneously, they expose its significant failure in achieving equitable distribution and adoption. The core results are thus defined by a conflict between proven efficacy and practical inaccessibility.

The economic impact analysis, rigorously conducted using Propensity Score Matching (PSM) to mitigate self-selection bias, provided a clear, affirmative answer to the question of efficacy. The data from Objective 2 (Table 3) show that DFAP adoption provides statistically significant and economically meaningful benefits. Adopters realized an average 14.2% increase in crop yields and a net income gain of approximately IDR 1.18 million per season, correlated with a significant reduction in input costs.

This positive outcome, however, is severely constrained by the findings on adoption (Objective 1). The overall adoption rate remains low at 25.0%. More striking is the "awareness-to-adoption gap," where 58.5% of farmers were aware of DFAPs, but 33.5% (the "Rejecter" group) actively chose not to use them, citing irrelevance and difficulty. This demonstrates that awareness is not the primary barrier; rather, perceived value and usability are.

The logistic regression analysis (Objective 3) explains who is benefiting and why adoption is low. The strongest predictors of adoption were Digital Literacy, Farmer Education Level, and Perceived Usefulness. Farmer Age was a significant negative predictor. These results, synthesized in the "Mean Adopter" versus "Mean Non-adopter" profiles, provide a stark illustration of a "digital divide," where a younger, more educated, and digitally literate "farmer elite" is capturing the technology's benefits, leaving the most vulnerable farmers behind.

These findings on positive economic impact affirm the optimistic body of techno-solutionist literature. Many previous studies, often smaller-scale case studies or industry-published white papers, have hypothesized that access to information (weather, market prices) would logically lead to better farm management. Our findings, using a robust PSM methodology on a large sample, provide strong, generalizable, empirical validation for this claim, moving it from anecdote to evidence.

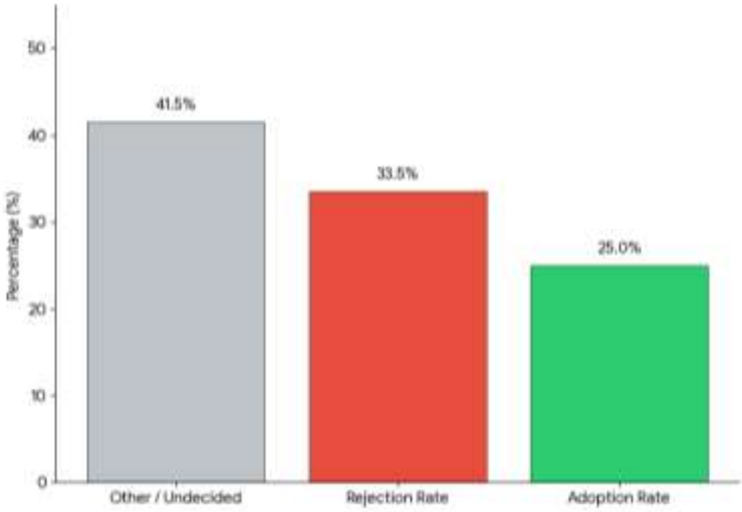

Figure 1. Analysis of Technology Adoption vc Rejection Rates

Our research, however, contributes a critical counter-narrative to studies that frame adoption as a simple function of technology diffusion. The low adoption rate (25.0%) and high rejection rate (33.5%) challenge the assumptions of simpler technology acceptance models (TAM). While "Perceived Usefulness" was a predictor, as TAM would suggest, the non-significance of "Perceived Ease of Use" in our regression model is a crucial distinction. This finding diverges from classic TAM literature, suggesting that for this population, fundamental "Digital Literacy" and "Education" are prerequisite barriers that must be overcome before "Ease of Use" even becomes a relevant consideration.

The demographic predictors identified in our regression model strongly support the established "digital divide" literature. Our findings empirically confirm, within the Indonesian agricultural context, what scholars have argued globally: the benefits of digital innovations do not flow equitably. The profile of our "Mean Adopter" (younger, more educated, larger farm) aligns perfectly with the "early adopter" archetype described by Rogers. Our study sadly confirms that DFAPs, in their current iteration, risk becoming a "Matthew Effect" technology, where those who already have advantages (education, assets) are best positioned to leverage new tools to gain more.

The primary contribution of this research in relation to other studies is its integrated, dual-focus methodology. The literature is often siloed, with computer scientists focusing on platform features, sociologists on adoption barriers, and economists on impact (often without adequately controlling for bias). By combining a rigorous adoption analysis (logistic regression) with a robust impact evaluation (PSM) in a single, large-scale study, we provide a holistic, systemic view. This approach allows us to connect who is adopting (and why) with the economic consequences of that adoption, offering a more complete and nuanced picture than is typical in the field.

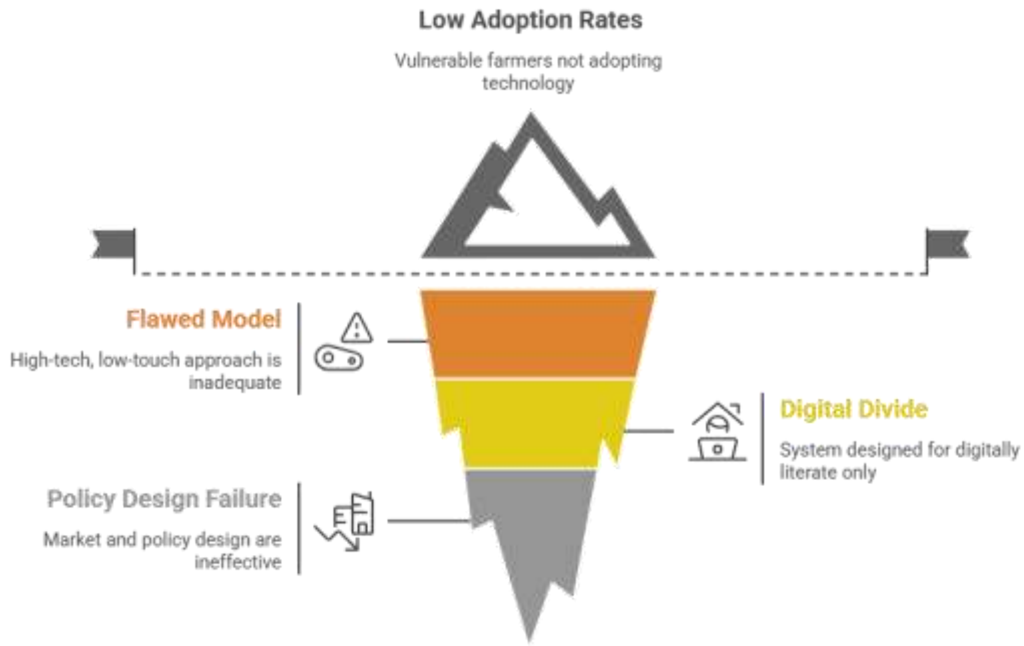

Figure 2. Digital Extension's Failure: Unveiling the Root Causes

These results, taken collectively, signify a profound failure in market and policy design. The technology works, but it is not working for the majority. The fact that the most vulnerable farmers (older, less educated, smaller plots) are the least likely to adopt signifies that the current “high-tech, low-touch” model of digital extension is fundamentally flawed. It is a system designed by the digitally literate for the digitally literate, and it is failing the very population it is often claimed to serve.

The high rejection rate (33.5%) is perhaps the most significant finding. This is not a problem of ignorance; it is a problem of perceived value. These farmers have likely assessed the technology and concluded, rationally, that the cost of adoption (learning the tool, mental effort, data costs, risk of change) is higher than the benefit it offers to their specific context. This signifies that the platforms are not sufficiently relevant, usable, or trustworthy for this majority segment, indicating a deep disconnect between developers and end-users.

The list of most-used features (Weather and Market Prices) versus least-used features (Pest ID, Financial Services) is highly significant. It signifies that farmers are, at present, only extracting the simplest, most accessible “public good” information from these platforms. The more complex, data-intensive, and potentially high-value features that promise to truly optimize a farm (like pest diagnostics) are seeing minimal use (Giagnocavo et al., 2025). This signifies a failure to scaffold learning and build trust, relegating these powerful tools to the status of simple weather apps.

The findings ultimately signify that “digital literacy” is the central, non-negotiable bottleneck of the digital agricultural transformation (Zhang et al., 2024). The regression model (where literacy had an OR of 5.21) makes this clear. It signifies that without a massive, parallel investment in human capital specifically, adult digital education tailored to rural farmers—all investment in the technology itself will continue to yield inequitable and suboptimal returns. Technology is not the solution; it is a tool whose utility is unlocked only by human capability.

The most immediate implication of these findings is for policymakers within the Indonesian government, particularly the Ministry of Agriculture and the “Making Indonesia 4.0” initiative. This research strongly implies that policies focused merely on subsidizing platform development or promoting “agritech” are destined to fail (Mangole et al., 2025). Future policy must pivot from a technology-centric to a human-centric model. This means reallocating significant resources to fund large-scale, nationwide digital literacy programs delivered through existing rural infrastructure, such as the PPL.

The implications for technology developers, from private startups to NGOs, are equally stark. The "one-size-fits-all" platform model must be abandoned. These results imply a critical need for user segmentation and human-centered design. Developers must co-design new interfaces with low-literacy farmers, prioritizing voice-based or image-based navigation over text (Abera et al., 2025). The high rejection rate based on "relevance" implies a need for more than just generic advice; platforms must offer hyper-localized, context-specific content that genuinely addresses the needs of a 0.8-hectare farm, not just a 1.2-hectare one.

A critical implication exists for the agricultural extension service (PPL). The data show the PPL is a key source of awareness, positioning them as a critical, trusted intermediary. This implies that DFAPs should not be designed to replace the PPL, but to empower them (Liu et al., 2025). The PPL officer should be re-imagined as a "digital mediator" or "infomediary," trained to use the platform as a diagnostic tool, to translate its data for farmers, and to facilitate group learning sessions. This "high-touch" model is essential to bridge the capability gap.

For academic theory, this study has clear implications for technology adoption models. The UTAUT framework, while useful, may need modification for developing-economy contexts. Our finding that "Digital Literacy" (a facilitating condition) vastly overshadowed "Perceived Ease of Use" (a core construct) suggests that in low-literacy populations, "Capability" is not just a facilitating variable, but a prerequisite construct. Future adoption models must more explicitly account for this foundational human capital barrier.

The positive economic impact observed in the PSM analysis is a logical and direct result of access to information. Farming is an exercise in managing uncertainty (Ayanwale & Kehinde, 2025). The two most-used features, weather forecasting and market pricing, directly reduce the two greatest uncertainties: climate and market volatility. Access to this information allows adopters to make more optimal decisions (e.t., when to plant, when to fertilize, where to sell) and reduce input waste, which logically and directly translates into the higher yields and net income we observed.

The low adoption rate and the "digital divide" are the result of deep-seated structural and human capital deficits that technology alone cannot solve. The "Mean Non-adopter" profile (older, less educated) describes a population segment that has been historically marginalized (Amoabeng-Nimako et al., 2026). Their lack of adoption is a rational symptom of these pre-existing inequities. Their lower education and digital literacy create a high cognitive "cost" to adoption, while their smaller farm size reduces the potential "benefit" (e.g., a 14% gain on 0.8 ha is less motivating than on 1.2 ha).

The specific finding that "Perceived Ease of Use" was not a significant predictor, while "Digital Literacy" was, is explained by the fundamental nature of the barrier. A platform's "ease of use" is irrelevant if the user does not possess the basic digital vocabulary (e.g., understanding menus, icons, data entry) to engage with it in the first place. This is not a UI/UX problem; it is a literacy problem. The "Rejecter" group's high citation of "irrelevance" is likely a product of this same issue; the inability to use the tool makes its content seem irrelevant.

The results are, ultimately, a consequence of a market failure. DFAPs are designed by highly-educated, urban-based engineers and business development teams. Their "target user" is often an idealized, rational farmer who resembles them (Adolwa et al., 2025). This "top-down" design process has failed to account for the lived reality, cognitive models, and socio-cultural context of the actual majority of smallholders. The results we found—low adoption, high rejection, and a digital divide—are the predictable outcome of this fundamental disconnect between platform design and user context.

The study's primary limitation is its cross-sectional design. This survey provides a robust snapshot in time, but it cannot capture dynamic processes (Baffour-Ata et al., 2025). We cannot determine if the economic benefits are sustained over multiple seasons, nor can we track whether adoption is "sticky" or if "Rejecters" later become adopters. A longitudinal panel study, tracking this same cohort over several years, is the necessary next step to understand the long-term causal pathways of adoption and impact.

A second limitation lies in the reliance on self-reported, recall-based data for the economic variables (yield, income, costs). While this is a standard and necessary methodology for large-scale surveys, it is susceptible to recall bias (Paget et al., 2025). Future research could strengthen these findings by triangulating survey data with more objective measures. This could involve, for example, a smaller-N study combining survey methods with crop-cutting experiments or analysis of detailed farm record-books where available.

Future research must move from diagnosing the problem to testing solutions. The findings present a clear mandate for intervention-based research. The next logical step is to design and field-test solutions that directly address the barriers we identified. This includes (A) randomized controlled trials (RCTs) to evaluate the impact of different digital literacy training programs (e.g., PPL-led vs. peer-led), and (B) A/B testing of different platform designs (e.g., voice-and-image-based UI vs. traditional text-based UI) specifically targeting the "Mean Non-adopter" profile.

A final direction for future inquiry must be qualitative. Our quantitative survey identified "relevance" and "difficulty" as the primary reasons for rejection, but these categories are broad. In-depth qualitative research, using focus groups and ethnographic observation, is urgently needed. This work must "unpack" what farmers mean when they say a tool is "not relevant" and explore the socio-cultural, trust, and usability factors that underpin this assessment, providing the rich, human-centered insights needed for better co-design.

CONCLUSION

This study's most significant finding is the stark paradox between the proven efficacy of Digital Farming Advisory Platforms and their inequitable adoption. The Propensity Score Matching analysis confirmed that DFAP adoption yields a statistically significant positive economic impact, including a 14.2% increase in crop yields and a meaningful rise in net farm income. This positive finding is critically undermined by the low overall adoption rate (25.0%) and the logistic regression results, which identified digital literacy and education level not platform features as the primary predictors of use, revealing a "digital divide" where benefits accrue only to a "farmer elite."

The primary contribution of this research is methodological, achieved through its integrated dual-focus design. While the individual methods (PSM, logistic regression) are established, their simultaneous application within a single, large-scale survey instrument to connect adoption barriers with economic outcomes is a significant advancement for the field. This study moves beyond siloed analyses (e.g., adoption-only or impact-only) by providing a holistic, systemic, and quantitative assessment that links the sociology of adoption directly to the economics of impact, thereby offering a more complete and actionable picture of the digital transformation in agriculture.

This study's cross-sectional design constitutes its main limitation, as it provides only a static snapshot and cannot capture the dynamics of adoption or impact sustainability over time; furthermore, its reliance on self-reported economic data is susceptible to recall bias. Future research must, therefore, pivot to a longitudinal panel study to track this cohort. Additionally, intervention-based research is urgently required, specifically randomized controlled trials (RCTs) to test the efficacy of digital literacy programs and A/B testing of new platform interfaces (e.g., voice-and-image-based) co-designed with low-literacy farmers to address the identified barriers of relevance and usability.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.

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