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Socioeconomic and contextual determinants of biopesticide adoption among Indonesian farmers

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Abstract. *Istriningsih, Yulianti A, Dewi YA, Hanifah VW, Suryana AT, Triyanti R, Yuniarsih ET, Alfayanti, Dadang, Nugrahapsari RA. 2026. Socioeconomic and contextual determinants of biopesticide adoption among Indonesian farmers. Asian J Agric 10 (1): g100177. https://doi.org/10.13057/asianjagric/g100177.* Despite being more environmentally friendly than synthetic pesticides, biopesticides remain underutilized in Indonesia due to socioeconomic and contextual constraints affecting farmers' adoption decisions. This study employs a Theory of Planned Behavior (TPB)-informed background factor framework to examine the socioeconomic and contextual determinants of biopesticide adoption using survey data from 322 farmers cultivating six major crops across five Indonesian provinces between August and December 2020 and applies a logit regression model. The results indicate that participation in training programs, family size, formal education, and farming experience significantly increase the likelihood of biopesticide adoption, with training emerging as the strongest determinant, raising adoption probability by approximately 18 percentage points. Each additional year of schooling also increases adoption likelihood by about 2.7 percentage points. Adoption is notably higher among shallot farmers than among those cultivating other crops, reflecting crop-specific vulnerability to pest and disease attacks as well as market quality considerations. These findings underline the importance of integrating behavioral insights into agricultural extension policies through targeted training, farmer field schools, and demonstration programs to strengthen farmers' capacity and promote biopesticide adoption in support of sustainable agriculture.

Keywords: Biopesticides, Indonesia, logit model, shallot, technology adoption

INTRODUCTION

The use of synthetic pesticides remains the dominant method for pest and disease control in agriculture due to their broad-spectrum activity, persistence, and rapid action. However, improper application has raised serious concerns, including pest resistance, harmful residues in agricultural products, loss of beneficial organisms, environmental degradation, and health risks for farmers (Macharia et al. 2013; Pengpan et al. 2024; Sajjad et al. 2024). Consequently, biopesticides have gained increasing attention as eco-friendly alternatives that reduce ecological disruption and support safer agricultural production systems (Bhattacharjee and Dey 2014; Ravikumar et al. 2015; Senthil-Nathan 2015; Purwar 2017).

Despite these advantages, the adoption of biopesticides remains limited in many developing countries (Liu et al. 2022), including Indonesia, where farmers continue to rely heavily on synthetic pesticides (Mariyono et al. 2018; Istriningsih et al. 2022). Previous studies suggest that adoption of agricultural technologies and sustainable practices is influenced by socioeconomic characteristics such as age, education, family size, farming experience, land ownership status, farm size, and participation in training programs (Baumgart-Getz et al. 2012; Kamarulzaman et al. 2012; Liu et al. 2016; Adusumilli and Wang 2019; Despotović et al. 2019; Khan et al. 2020; Nyangau et al. 2020; Josue-Canacan 2022; Diana et al. 2024). Beyond socioeconomic factors, contextual farming conditions including crop type (Pingali 2001; Mrema et al. 2017), pesticide cost share (Thomas et al. 2018), and pest and disease types may further shape farmers' pest management decisions. Collectively, these studies indicate that adoption behavior is shaped not only by farmers' characteristics, but also by farming context and resource conditions. However, few studies jointly examine socioeconomic and crop-specific contextual drivers of biopesticide adoption across multiple commodities in Indonesia using a behavioral framework.

Although extensive literature exists on agricultural technology adoption, studies examining biopesticide adoption in Indonesia remain fragmented, often focusing on particular commodities or technical constraints, with limited integration of behavioral theory and contextual farming conditions. Consequently, empirical understanding of adoption behavior across diverse commodities and agroecological settings remains insufficient. This gap is particularly relevant given Indonesia's heterogeneous agroecological conditions, diverse commodities, and predominance of smallholder farming, which may shape adoption behavior differently across regions and commodities.

To address this gap, this study employs a Theory of Planned Behavior (TPB)-informed framework. TPB explains intention and behavior through three interrelated constructs: attitudes toward the behavior, subjective norms, and perceived behavioral control (Ajzen 1991). These constructs are shaped by behavioral, normative, and control beliefs, respectively. Ajzen (2005) further argues that background factors, such as socioeconomic and contextual conditions, influence intention and behavior indirectly through these beliefs structures. In line with this view, this study positions socioeconomic and contextual variables as TPB-informed background factors, rather than directly measuring the core TPB constructs. This approach aligns with previous studies that extended TPB by integrating socioeconomic and contextual determinants to explain behavioral intentions across different settings (Darabi et al. 2017; Nguyen 2018; Saragih 2023; Fantaye et al. 2025; Usman et al. 2025).

In this study, socioeconomic characteristics may shape farmers' knowledge, social interaction, resources, and perceived capacity to adopt environmentally friendly pest management practices. Meanwhile, contextual farming conditions may influence adoption decisions through differences in pest pressure, production risk, input dependency, and perceived need for alternative pest management strategies. Farmers cultivating different commodities may therefore exhibit different adoption behaviors, while higher pesticide expenditure and greater pest and disease diversity may strengthen incentives to adopt biopesticides. Understanding these contextual differences is important for designing more targeted strategies to promote biopesticide adoption. This study advances existing research by moving beyond intention-based analyses to examine actual adoption behavior, incorporating both socioeconomic and contextual determinants within a TPB-informed framework and employing a logit regression approach to generate policy-relevant insights into farmers' adoption decisions.

Based on this framework, the following hypotheses are proposed: (H_1) Younger farmers are more likely to adopt biopesticides. (H_2) Farmers with higher education levels are more likely to adopt biopesticides. (H_3) Farmers with larger household sizes are more likely to adopt biopesticides. (H_4) Farmers with longer farming experience are more likely to adopt biopesticides. (H_5) Landowner farmers are more likely to adopt biopesticides. (H_6) Farmers with larger farm sizes are more likely to adopt biopesticides. (H_7) Farmers who participate in training programs are more likely to adopt biopesticides. (H_8) Farmers cultivating different types of commodities are likely to differ in their likelihood of adopting biopesticides. (H_9) Farmers with a higher pesticide cost share are more likely to adopt biopesticides. Lastly, (H_{10}) Farmers experiencing a higher number of pest and disease types are more likely to adopt biopesticides.

MATERIALS AND METHODS

Data collection

This study was conducted during the rainy season from August to December 2020 using individual surveys and face-to-face interviews. Respondents were asked to report their pest management practices during the most recent planting season within the survey period, ensuring a consistent temporal reference across all commodities included in the study. Enumerators received two days of training prior to data collection to ensure a consistent understanding of the questionnaire. Permission to conduct the study was obtained from the district, sub-district, and village authorities, and all respondents provided informed verbal consent after being informed about the study objectives, interview duration, and their right to withdraw at any time. Consent was obtained once prior to each interview and recorded by enumerators. The study ensured strict confidentiality of respondents' identities and responses throughout the research process.

The survey covered five provinces in Indonesia (Table 1). Provinces and districts were selected using convenience sampling based on accessibility, field familiarity, and budget constraints. Within each selected district, villages and farmer respondents were selected using simple random sampling from official farmer lists provided by local agricultural extension agents. This sampling design constitutes a limitation of the study, as the findings are analytically generalizable to similar contexts but do not provide nationally representative estimates. Although initial site selection was non-random, random sampling at the village and respondent levels helps mitigate selection bias within the sampled areas and strengthens internal validity. A total of 322 farmers were surveyed, of whom 128 (39.75%) had applied biopesticides during the most recent planting season, while 194 (60.25%) had not. Table 2 summarizes the main commodities cultivated by respondents, reflecting the diversity of farming systems included in the analysis.

Model specifications

This study analyzes biopesticide adoption as a binary outcome and examines how socioeconomic and context-specific factors influence adoption decisions within the framework of the Theory of Planned Behavior. Given the dichotomous nature of the dependent variable, a binary logit regression model was employed to estimate the probability of biopesticide adoption as a function of farmer characteristics, farm attributes, and contextual conditions (Table 3). The expected signs of the explanatory variables are grounded in the adoption and behavioral economics literature. Age is expected to have a negative effect, as older farmers tend to be less open to new technologies, while education is expected to positively influence adoption by shaping farmers' attitudes, decision-making, and ability to evaluate new practices. Family size and farming experience are anticipated to increase adoption by improving labor availability and enhancing awareness of the long-term risks associated with intensive synthetic pesticide use. Land ownership and farm size are also expected to have positive effects, as landowners have stronger incentives to invest in long-term sustainability, and larger farms generally possess greater resources and risk exposure that encourage the adoption of cost-effective pest management strategies. Participation in training is expected to positively influence adoption by improving knowledge, skills, and peer learning. Crop type is assigned an ambiguous sign (+/–) due to differences in pest and disease pressure and market incentives across commodities. A higher share of pesticide costs and a greater diversity of pests and diseases are expected to increase adoption as farmers seek more economical and sustainable pest management strategies.

We estimated a logistic regression model in which inference based on robust standard errors was prioritized, as the number of clusters was insufficient to reliably implement cluster-robust standard errors. For completeness, results using cluster-robust standard errors are also reported in Supplementary 1.

The logit regression model captures the adoption of biopesticides and its determinants. The probability of farmers adopting biopesticides ($Y = 1$) is a function of the cumulative standard logistic distribution function evaluated at $z = \beta_0 + \beta_1 X$, which can be expressed as follows (Stock and Watson 2020; Thapa et al. 2021):

$$Pr\ (Y = 1|\ X) = F(\beta_0 + \textstyle\sum_{i=1}^{n} \beta_i X_i\ ) \qquad [1]$$

This can be expressed in logarithmic form as follows: $\log\left(\frac{Pr}{1-Pr}\right) = \text{logit (Y)};$

$$\text{logit (Y)} = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + \beta_7X_7 + \beta_8X_8 + \beta_9X_9 + \beta_{10}X_{10} \qquad [2]$$

Where, **Y** denotes the probability of farmers adopting biopesticides; β_0 represents the intercept; β_{1-10} represent the regression coefficients to be estimated; X includes age, formal education, family size, farming experience, land ownership, farm size, participation in training, cultivated commodity type, pesticide cost share, and number of pest and disease types.

Table 1. Study sites in Indonesia

Provinces	Number of respondents	%
West Java	78	24.224
Central Java	128	39.752
Banten	26	8.075
Lampung	43	13.354
North Sumatera	47	14.596
Total	322	100

Table 2. Commodities cultivated by respondents

Commodities	Number of respondents	%
Rice	82	25.466
Maize	55	17.081
Shallot	59	18.323
Red chili	50	15.528
Potato	50	15.528
Oil palm	26	8.075
Total	322	100

Table 3. Dependent and explanatory variables used in the logit regression model

Variables	Description	Expected sign
Dependent Variable:		
Y = Biopesticide adoption	Whether farmers had applied biopesticides on their farmland during the most recent planting season, regardless of user status (new or long-term). (1 = Yes, 0 = No)	
Explanatory Variables:		
X_1 = Age	Farmer's age (years)	-
X_2 = Formal education	Years of formal education (years)	+
X_3 = Family size	Number of household members (persons)	+
X_4 = Farming experience	Years of farming experience (years)	+
X_5 = Land ownership	Land tenure status (1 = Landowner, 0 = Tenant)	+
X_6 = Farm size	Cultivated land area (hectares)	+
X_7 = Participation in training	Attendance in pesticide-related training (1 = Yes, 0 = No)	+
X_8 = Cultivated commodity type	The main crop cultivated by farmer (1 = Shallot, 2 = Red chili, 3 = Maize, 4 = Potato, 5 = Rice, 6 = Oil palm)	+/-
X_9 = Pesticide cost share	Percentage of pesticide costs relative to total farming expenses per hectare (%)	+
X_{10} = Number of pest and disease types	Number of pest and disease types affecting the farm	+

Note: The cultivated commodity variable was included in the regression as a set of dummy variables, with shallot serving as the reference category. Shallot is selected as the reference crop as it is widely cultivated and typically requires intensive pesticide application (Dirgayana et al. 2026), allowing other commodities to be compared against a crop with relatively high input intensity. The number of pest and disease types was elicited from farmers' open-ended responses during the survei

RESULTS AND DISCUSSION

Demographic characteristics

Most respondents were within the productive age group, had moderate formal education levels, and possessed considerable farming experience. The sample was predominantly composed of male landowners with household sizes of three to four members. More than half of the respondents had participated in agricultural training programs. Farm size, pesticide cost share, and pest and disease exposure varied across respondents, indicating heterogeneous farming conditions. Detailed respondent characteristics are presented in Supplementary 3.

Table 4 presents the mean and proportion difference tests between biopesticide users and non-users. Biopesticide users had significantly higher levels of formal education, larger household sizes, and longer farming experience than non-users. Participation in training programs was also significantly higher among biopesticide users. A marginal difference was observed between tenant farmers and landowners in biopesticide use. Differences in biopesticide use were also observed across commodity types, with higher proportions among shallot farmers and lower proportions among maize and oil palm farmers. In addition, biopesticide users reported significantly higher numbers of pest and disease types affecting their crops. No significant differences were observed for age, farm size, and pesticide cost share.

Farmers' knowledge of and access to biopesticides

The mean difference tests reported in the previous section (Table 4) provide exploratory comparisons between adopters and non-adopters, while the regression analysis forms the basis for statistical inference by accounting for multiple covariates simultaneously. More than half of the respondents were familiar with biopesticides, and approximately 40% reported having applied them, with adoption patterns varying across commodities due to differences in production systems and pest pressures (Supplementary 4). Farmers used both commercial and self-produced biopesticides. Commercial products included biological agents such as *Bacillus thuringiensis, Beauveria, Pseudomonas, Trichoderma, Metarhizium*, and *Paenibacillus* sp. Meanwhile, many farmers produced biopesticides using locally available materials, including animal urine, fermented organic mixtures, liquid smoke, and plant-based ingredients. Knowledge and skills related to self-produced biopesticides were acquired through local knowledge, training programs, and peer-to-peer learning. These findings indicate that farmers' adoption of biopesticides is influenced not only by product availability, but also by access to knowledge, local resources, and technical capacity for preparation and application.

Among biopesticide users only 41 farmers (32%) used commercial biopesticides, while the majority relied on self-produced alternatives. As summarized in Table 5, commercial biopesticides were mainly accessed through farmer groups and local kiosks, followed by agricultural programs and informal farmer networks. This suggests that limited market availability and distribution channels may constrain access to commercial biopesticides and encourage reliance on self-produced alternatives.

Table 4. Mean and proportion differences test between biopesticide users and non-users

Variables	**Users (N = 128)**	**Non-users (N = 194)**	**p-value**
Age (years), mean (SD)[a]	47.883 (10.466)	46.747 (11.529)	0.370
Formal education (years), mean (SD)[a]	9.328 (3.665)	8.624 (3.194)	0.069*
Family size (persons), mean (SD)[a]	4.180 (1.503)	3.716 (1.203)	0.002***
Farming experience (years), mean (SD)[a]	20.898 (12.359)	17.479 (11.639)	0.012**
Land ownership, proportion (%)[b]			0.075*
Landowner	37.097 (0.031)	62.903 (0.031)	
Tenant	48.648 (0.058)	51.350 (0.058)	
Farm size (hectares), mean (SD)[a]	1.147 (2.181)	1.119 (1.455)	0.890
Participation in training, proportion (%)[b]			<0.001***
Yes	49.718 (0.038)	50.282 (0.038)	
No	27.586 (0.037)	72.414 (0.037)	
Cultivated commodity type, proportion (%)[b]			<0.001***
Shallot (reference)	59.322 (0.064)	40.668 (0.064)	
Chili	34.009 (0.067)	66.000 (0.067)	
Maize	25.455 (0.059)	74.545 (0.059)	
Potato	40.000 (0.069)	60.000 (0.069)	
Rice	47.561 (0.055)	52.439 (0.055)	
Oil palm	11.538 (0.063)	88.461 (0.063)	
Pesticide cost share (%), mean (SD)[a]	0.274 (0.185)	0.272 (0.200)	0.920
Number of pest and disease types, mean (SD)[a]	4.133 (2.149)	3.655 (2.130)	0.050*

Note: Standard deviations are in parentheses: ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$, [a]: Mean difference tested using t-test, [b]: Proportion difference tested using χ^2 test

Factors influencing the use of biopesticides

The results of the analysis show that biopesticide adoption was significantly influenced by formal education, family size, farming experiences, participation in training, and cultivated commodity type (Table 6). Farmers who attended training exhibited an adoption probability that was 18.1 percentage points higher than those who did not attend training, indicating the important role of extension and capacity-building programs. Each additional household member significantly increased the probability of adoption by approximately 7.9 percentage points, while one additional year of formal education and farming experience increased the probability of adoption by 2.7 and 0.6 percentage points, respectively, ceteris paribus. Adoption also varied significantly across commodity types. Compared with shallot farmers, those cultivating chili, maize, potato, rice, and oil palm showed lower probabilities of adopting biopesticides, with adoption probabilities reduced by 22.5, 35.2, 21.4, 18.8, and 50.9 percentage points, respectively. The remaining determinants did not show significant effects on biopesticide adoption. Accordingly, the empirical findings support H2, H3, H4, H7, and H8, while H1, H5, H6, H9, and H10 are not supported.

Among the significant factors, participation in training emerged as the strongest determinant of biopesticide adoption based on the magnitude of the marginal effects, highlighting the important role of capacity-building and extension services in promoting adoption. This is followed by family size and formal education, while the effect of farming experience is relatively modest. The relatively low pseudo-R^2 suggests that additional behavioral, institutional, or market-related factors influencing biopesticide adoption were not fully captured in the model. Model diagnostic results are presented in Supplementary 2.

Discussion

A logit model was employed to examine the determinants of biopesticide adoption among farmers by integrating socioeconomic and contextual factors. The results indicate that adoption is primarily associated with formal education, family size, farming experience, participation in training, and cultivated commodity types. These findings are discussed below under three thematic aspects: knowledge and capacity, socioeconomic factors, and crop-specific drivers.

Knowledge and capacity

Formal education, participation in training, and farming experience shape farmers' knowledge, attitudes, and perceived ability to implement alternative pest management practices. From a TPB perspective, these factors primarily influence attitudes and perceived behavioral control, which subsequently affect farmers' behavioral intentions toward biopesticide adoption. Among these factors, participation in training appears to play the most important role in strengthening farmers' technical knowledge and application skills related to biopesticides. Training programs facilitate knowledge transfer (Mulugeta et al. 2024), increase farmers' confidence in applying biopesticides effectively, and expose them to recommendations from extension agents and peers. Such interactions may reinforce subjective norms that support environmentally friendly pest management practices. These findings are consistent with Liu et al. (2016) and Wang et al. (2023), who found that training contributes significantly to biopesticide adoption. The widespread use of self-produced biopesticides in this study further highlights the importance of capacity building, as adequate knowledge and technical skills are required to ensure their safety and effectiveness.

Formal education may also increase farmers' awareness of the environmental and health risks associated with synthetic pesticides while improving their ability to evaluate alternative technologies and process technical information. As noted by Mulyaningsih et al. (2018), education influences farmers' attitudes, actions, and decision-making processes related to technology adoption. This finding is consistent with previous studies showing that education positively affects farmers' willingness to pay for and adopt biopesticides (Kamarulzaman et al. 2012; Liu et al. 2016; Abdollahzadeh et al. 2018; Constantine et al. 2020; Huang et al. 2022). Within the TPB framework, education may strengthen positive beliefs regarding the expected outcomes of biopesticide use, thereby fostering favorable attitudes toward adoption.

Table 5. Farm-level distribution channels for commercial biopesticides (n = 41)

	Number of respondents	%
Farmer groups	13	31.707
Local village kiosks	11	26.829
Agricultural program	9	21.951
Outside village kiosks	8	19.512
Fellow farmers	7	17.073
Other farmer groups	3	7.317

Note: Multiple responses allowed

Table 6. Factors influencing farmers to adopt biopesticides

Variables	Coefficient	Marginal effect
Age (years)	-0.005 (0.016)	-0.001
Formal education (years)	0.116** (0.046)	0.027
Family size (persons)	0.338*** (0.104)	0.079
Farming experiences (years)	0.026* (0.014)	0.006
Land ownership (1 = Landowner)	-0.436 (0.299)	-0.104
Farm size (Hectares)	0.056 (0.064)	0.013
Participate in training (1 = Yes)	0.780*** (0.267)	0.181
Cultivated commodity type (ref. = Shallot)		
Chili	-0.915** (0.439)	-0.225
Maize	-1.510*** (0.488)	-0.352
Potato	-0.870** (0.441)	-0.214
Rice	-0.761* (0.403)	-0.188
Oil palm	-2.675*** (0.773)	-0.509
Pesticide cost share (%)	0.856 (0.730)	0.200
Number of pest and disease types	-0.019 (0.063)	-0.004

Note: Robust standard errors are in parentheses. Pseudo-R^2 = 0.1443, Log pseudolikelihood = -185.14953, LR χ^2 = 44.85***. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. Shallot is the reference category for the cultivated commodity type variable

Farming experience may also strengthen farmers' perceived behavioral control by increasing their confidence in managing the risks associated with alternative pest management practices. More experienced farmers are likely to better recognize the long-term limitations of intensive synthetic pesticide use, including pest resistance and declining effectiveness (Daniel 2024), which may encourage consideration of more sustainable alternatives such as biopesticides. This finding is consistent with Liu et al. (2016), who reported that farming experience positively influences biopesticide adoption. Previous studies also suggest that experienced farmers may be more willing to experiment with new practices and technologies (Nyangau et al. 2020; Praneetvatakul et al. 2024).

Socioeconomic factors

Socioeconomic characteristics of farming households also play an important role in shaping biopesticide adoption. Among these factors, household size shows a significant positive association with biopesticide adoption, suggesting that larger households are more likely to adopt biopesticides. This pattern reflects the importance of labor availability, as households with more members tend to have greater capacity to implement alternative pest management practices. From the perspective of TPB, this condition strengthens perceived behavioral control, as farmers with adequate household labor may perceive fewer constraints in implementing biopesticide practices. This interpretation is consistent with Tsegaye et al. (2017), who show that the adoption of technologies for green production, including conservation agriculture, is significantly influenced by household labor size. However, this finding contrasts with Nyangau et al. (2020), who report that larger family sizes in Uganda reduce the likelihood of biopesticide use due to greater household financial pressures and competing consumption needs. This difference may reflect contextual variations in household resource allocation and labor availability. In the present study, larger households may provide additional labor that supports the preparation and application of self-produced biopesticides, whereas under conditions of greater economic pressure, larger household size may instead constrain farmers' capacity to adopt alternative pest management practices.

Interestingly, the mean difference test indicates that tenant farmers are more likely to apply biopesticides, although this factor is not significant in the regression model. This can be understood from the fact that, in the context of local production practices, many farmers rely on self-produced biopesticides made from locally available materials. For tenant farmers, self-produced biopesticides therefore represent a financially accessible option that reduces dependence on purchased synthetic inputs and helps sustain crop protection under limited capital conditions. This finding contrasts with Sklenicka et al. (2015), who report that landowners are generally more likely to adopt conservation practices.

Crop-specific drivers

Crop type plays an important role in shaping farmers' decisions to adopt biopesticides. In this study, shallot cultivation serves as the reference category in the regression model because it is widely cultivated and typically requires intensive pesticide application. Using shallots as the benchmark allows comparison with crops characterized by lower pesticide intensity. The results indicate that biopesticide adoption is relatively more common among shallot farmers. This pattern is closely related to the production characteristics of shallots, which are highly susceptible to pests and diseases and therefore require intensive crop protection (Resiani et al. 2025; Dirgayana et al. 2026). Prolonged reliance on synthetic pesticides under these conditions may increase environmental and health risks (Mahfudz et al. 2019), encouraging farmers to consider safer alternatives such as biopesticides.

Economic considerations may also contribute to this pattern. Shallots are considered a high-value crop (Sahara et al. 2025), making product quality and pesticide residue concerns more important for market competitiveness. Kamardiani and Apriani (2025) report that shallots produced using environmentally friendly practices in Bantul District, Indonesia, are recognized for superior quality and receive higher market prices. Similarly, He et al. (2023) show that food safety concerns and residue awareness influence farmers' preferences for safer pest management strategies. Together, these findings suggest that stronger biopesticide adoption among shallot farmers reflects the combined effects of high pest pressure and market incentives related to product quality and safety. This interpretation is consistent with Nyangau et al. (2020), who find that vegetable farmers show a higher willingness to pay for biopesticides.

Surprisingly, the number of pest and disease types shows a significant mean difference between biopesticide users and non-users, but is not significant in the regression model. This suggests that greater pest and disease diversity may increase farmers' awareness of crop protection problems, but may not be sufficient to encourage a shift from synthetic pesticides to biopesticides. Under conditions of high production risk, farmers tend to prioritize pest control methods that provide rapid and visible results. Synthetic pesticides are widely perceived as more reliable because of their immediate knockdown effects (Oguh et al. 2019). In contrast, biopesticides are often associated with slower action (Rogers et al. 2017; Lazarevic-Pašti et al. 2025). Consequently, high pest and disease pressure may reinforce continued dependence on synthetic pesticides rather than stimulate adoption of biopesticides. This pattern reflects a risk-avoidance strategy in which farmers prioritize short-term effectiveness over long-term sustainability. From a TPB perspective, this may shape farmers' outcome evaluations and lead to more cautious attitudes toward biopesticide adoption despite awareness of environmental benefits.

Overall, the findings of this study are broadly consistent with the TPB-informed framework adopted in this study. However, TPB is used primarily as an interpretive framework rather than being directly operationalized through latent constructs such as attitudes, subjective norms, and perceived behavioral control. Consistent with Ajzen (2005), this study interprets socioeconomic and contextual variables as background factors that may indirectly influence adoption behavior through underlying belief structures. Participation in training, which shows the largest marginal effect in the model, may reinforce subjective norms through interactions with extension agents and fellow farmers that encourage environmentally friendly pest management practices. Training programs also strengthen farmers' technical knowledge and confidence in applying biopesticides effectively. Family size may strengthen perceived behavioral control by increasing labor availability for preparing and applying biopesticides, particularly self-produced alternatives. Formal education may contribute to more favorable attitudes toward biopesticides by improving farmers' understanding of pest management and its environmental and health impacts. Farming experience may also strengthen perceived behavioral control by increasing practical knowledge and confidence in managing the risks associated with alternative pest management practices. These interpretations are consistent with TPB arguments that background factors shape behavioral, normative, and control beliefs, which subsequently influence behavioral intention and adoption behavior. In addition, cultivated commodity type emerges as an important contextual factor influencing adoption behavior. The higher likelihood of adoption among shallot farmers suggests that crop-specific conditions, including pest pressure and market quality considerations, shape farmers' evaluations of the suitability and effectiveness of biopesticides. Thus, adoption decisions are influenced not only by socioeconomic characteristics but also by the production context of the cultivated crop. Meanwhile, the non-significant effect of age suggests that adoption decisions may be more strongly associated with access to information, training opportunities, and other enabling factors than with generational differences among farmers. Similarly, land ownership status does not significantly influence biopesticide adoption, which may reflect relatively similar production practices and input management between owner and tenant farmers in the study area. In addition, the non-significant effect of pest and disease diversity may indicate continued reliance on synthetic pesticides due to their perceived effectiveness, availability, and familiarity among farmers.

Limitations

While the study provides valuable insights, several limitations must be acknowledged. The relatively low pseudo-R^2 indicates that the model used in this study explains only a small portion of the variance in biopesticide adoption. This suggests that, beyond the variables examined, other behavioral and institutional factors may also play a significant role, such as farmers' attitudes toward innovation, perceived risk, biopesticide price, policy incentives, and market access. Future research could incorporate these behavioral and market dimensions and apply longitudinal or experimental approaches to better understand pathways for scaling up biopesticide adoption in Indonesia. Moreover, the sampling approach employed in this study necessitates cautious interpretation of the results, as it may constrain the generalizability of the findings. This study relies on self-reported measures of biopesticide adoption and pest incidence, obtained by asking farmers whether they applied biopesticides and how many pest attacks occurred during the planting period. This approach may increase the risk of response bias. Future studies could improve data reliability through direct field observations or triangulation with field extension agents. In addition, the use of a cross-sectional research design may raise potential endogeneity concerns due to possible reverse causality and the inability to fully control for unobserved heterogeneity, such as farmers' preferences and specific local practices, which are not directly observed but may influence the validity of the findings. The use of panel data may help better capture dynamic behavioral changes over time and reduce potential endogeneity concerns.

In conclusion, this study supports the hypothesis that biopesticide adoption among Indonesian farmers is shaped primarily by socioeconomic capacity and production context rather than by pest pressure alone. The findings indicate that participation in training, family size, formal education, farming experience, and crop type are important factors associated with biopesticide adoption. Among these factors, participation in training emerges as the strongest determinant, highlighting the importance of capacity-building and extension services in promoting environmentally sustainable pest management practices. The results also demonstrate that adoption decisions are influenced not only by individual socioeconomic characteristics but also by crop-specific production and market conditions.

Based on these findings, this study contributes a key behavioral insight that awareness alone does not necessarily lead to behavioral change. Even when farmers face serious pest and disease problems, this condition is not sufficient to encourage a shift from synthetic pesticides to biopesticides. Farmers are more likely to adopt biopesticides when they possess sufficient knowledge, technical skills, and confidence to implement alternative pest control methods. Crop-specific production characteristics also matter, as farmers cultivating high-value and pest-sensitive crops tend to show stronger incentives to adopt safer pest management practices due to higher production risks and market quality considerations. Therefore, efforts to promote wider biopesticide adoption in Indonesia should prioritize strengthening farmer training, extension services, and field-based demonstration activities that provide practical evidence of biopesticide effectiveness. Adoption programs should also incorporate crop-specific approaches and strengthen collaboration between extension institutions and the private sector to improve farmers' access to reliable and affordable biopesticide products.

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Supplementary

Supplementary 1. Logistic regression model with robust and cluster-robust standard errors by district and commodity type

Factors influencing farmers to adopt biopesticides (robust SE)

Variables	Coefficient	Marginal effect
Age (Years)	-0.005 (0.016)	-0.001
Formal education (Years)	0.116**(0.046)	0.027
Family size (persons)	0.338***(0.104)	0.079
Farming experiences (years)	0.026*(0.014)	0.006
Land ownership (1 = Landowner)	-0.436 (0.299)	-0.104
Farm size (Hectares)	0.056 (0. 064)	0.013
Participate in training (1 = yes)	0.780*** (0. 267)	0.181
Cultivated commodity (1 = shallot)[a]		
2 = chili	-0.915** (0.439)	-0.225
3 = maize	-1.510***(0.488)	-0.352
4 = potato	-0.870** (0.441)	-0.214
5 = rice	-0.761* (0.403)	-0.188
6 = oil palm	-2.675*** (0.773)	-0.509
Pesticide cost share (%)	0.856 (0.730)	0.200
Number of pest and disease types	-0.019 (0.063)	-0.004

Note: Robust standard errors in parentheses. Pseudo-R^2 = 0.1443, Log pseudolikelihood = -185.14953, LR chi^2 = 44.85***, ***: p<0.01, **: p<0.05, *: p<0.1, [a]: Base variable for commodities

Factors influencing farmers to adopt biopesticides (clustered SE by district)

Variables	Coefficient	Marginal effect
Age (Years)	-0.005 (0.016)	-0.001
Formal education (Years)	0.116**(0.052)	0.027
Family size (persons)	0.338***(0.059)	0.079
Farming experiences (years)	0.026**(0.011)	0.006
Land ownership (1 = Landowner)	-0.436 (0.272)	-0.104
Farm size (Hectares)	0.056 (0.092)	0.013
Participate in training (1 = yes)	0.790***(0. 270)	0.181
Cultivated commodity (1 = shallot) [a]		
2 = chili	-0.916*(0.532)	-0.225
3 = maize	-1.510***(0.374)	-0.352
4 = potato	-0.870***(0.285)	-0.214
5 = rice	-0.761***(0.245)	-0.188
6 = oil palm	-2.675***(0.694)	-0.509
Pesticide cost share (%)	0.856 (0.802)	0.200
Number of pest and disease types	-0.019 (0.082)	-0.004

Note: Clustered robust standard errors by district in parentheses. Pseudo-R^2 = 0.1443, Log pseudolikelihood = -185.14953, ***: p<0.01, **: p<0.05, *: p<0.1, [a]: Base variable for commodities

Factors influencing farmers to adopt biopesticides (clustered SE by commodity)

Variables	Coefficient	Marginal effect
Age (Years)	-0.005 (0.019)	-0.001
Formal education (Years)	0.116***(0.034)	0.027
Family size (persons)	0.338***(0.076)	0.079
Farming experiences (years)	0.026**(0.011)	0.006
Land ownership (1 = Landowner)	-0.436 (0.368)	-0.104
Farm size (Hectares)	0.056 (0.080)	0.013
Participate in training (1 = yes)	0.790**(0. 363)	0.181
Cultivated commodity (1 = shallot) [a]		
2 = chili	-0.916*(0.151)	-0.225
3 = maize	-1.510***(0.256)	-0.352
4 = potato	-0.870***(0.249)	-0.214
5 = rice	-0.761***(0.171)	-0.188
6 = oil palm	-2.675***(0.475)	-0.509
Pesticide cost share (%)	0.856 (0.776)	0.200
Number of pest and disease types	-0.019 (0.080)	-0.004

Note: Clustered robust standard errors by district in parentheses. Pseudo-R^2 = 0.1443, Log pseudolikelihood = -185.14953, ***: p<0.01, **: p<0.05, *: p<0.1, [a]: Base variable for commodities

We estimated the models using both robust standard error and adjusted for clustering at both the district and commodity levels to account for potential intra-group correlation among farmers. The data cover nine districts and six commodity types, for which we report cluster-robust standard errors. However, given the limited number of clusters, the Wald chi-square statistic is not reported. Therefore, our final model relies on robust standard errors, which yield results similar to those obtained with cluster-robust standard errors, as presented in Supplementary 1.

Supplementary 2. Diagnostic tests and post-estimation results of the logistic regression model

Diagnostic test

Variance Inflation Factor (VIF) Diagnostic Test for Multicollinearity

Variables	**VIF**	**1/VIF**
Age (Years)	1.74	0.574
Formal education (Years)	1.36	0.737
Family size (persons)	1.04	0.962
Farming experiences (years)	1.77	0.564
Land ownership (1 = Landowner)	1.14	0.878
Farm size (Hectares)	1.20	0.830
Participate in training (1 = yes)	1.14	0.877
Cultivated commodity (1 = shallot)[a]		
2 = chili	1.70	0.589
3 = maize	1.84	0.545
4 = potato	1.78	0.562
5 = rice	2.04	0.490
6 = oil palm	1.74	0.575
Pesticide cost share (%)	1.09	0.920
Number of pest and disease types	1.30	0.766
Mean VIF	1.49	

Multicollinearity diagnostics were assessed using Variance Inflation Factors (VIFs). The VIF values for all predictors ranged from 1.04 to 2.04, with a mean of 1.49, which is below the commonly accepted threshold of 5. These results indicate no evidence of problematic multicollinearity among the independent variables.

Logistic model (post estimation)
Classification table

```
               ———————— True ————————
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |        69            33  |        102
     -     |        59           161  |        220
-----------+--------------------------+-----------
   Total   |       128           194  |        322

Classified + if predicted Pr(D) >= .5
True D defined as use_pesticide != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   53.91%
Specificity                     Pr( -|~D)   82.99%
Positive predictive value       Pr( D| +)   67.65%
Negative predictive value       Pr(~D| -)   73.18%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)   17.01%
False - rate for true D         Pr( -| D)   46.09%
False + rate for classified +   Pr(~D| +)   32.35%
False - rate for classified -   Pr( D| -)   26.82%
--------------------------------------------------
Correctly classified                        71.43%
--------------------------------------------------
```

The classification table shows that the model correctly classified 71.4% of cases overall, with a sensitivity of 53.9% and a specificity of 83.0%. The positive predictive value was 67.7%, and the negative predictive value was 73.2%, suggesting that the model performed better at correctly identifying non-users than users.

Goodness-of-Fit Statistics for the Logistic Regression Model
Dependent variable: use_pesticide

Statistic	**Value**
Number of observations	322
Number of covariate patterns	322
Pearson χ^2 (307)	325.99
Prob > χ^2	0.2183

The table collapsed on the quantiles of the estimated probabilities

Group	**Prob**	**Obs_1**	**Exp_1**	**Obs_0**	**Exp_0**	**Total**
1	0.1347	3	2.7	30	30.3	33
2	0.1932	11	5.4	21	26.6	32
3	0.2689	7	7.5	25	24.5	32
4	0.3298	3	9.7	29	22.3	32
5	0.3848	9	11.3	23	20.7	32
6	0.4418	13	13.6	20	19.4	33
7	0.5096	16	15.4	16	16.6	32
8	0.5757	19	17.3	13	14.7	32
9	0.6712	23	20.0	9	12.0	32
10	0.9354	24	25.1	8	6.9	32

Statistic	**Value**
Number of observations	322
Number of groups	10
Hosmer–Lemeshow chi2(8)	16.48
Prob > chi2	0.0360

The Pearson goodness-of-fit test suggested that the model fit the data adequately ($\chi^2(307) = 325.99$, $p = 0.2183$). In contrast, the Hosmer–Lemeshow test indicated some evidence of lack of fit between predicted and observed outcomes ($\chi^2(8) = 16.48$, $p = 0.036$). Nevertheless, the model exhibited acceptable discriminative ability, with an area under the ROC Curve (AUC) of 0.75 (N = 322), as shown in Figure S1, indicating that it can reasonably distinguish between biopesticide users and non-users.

lroc test

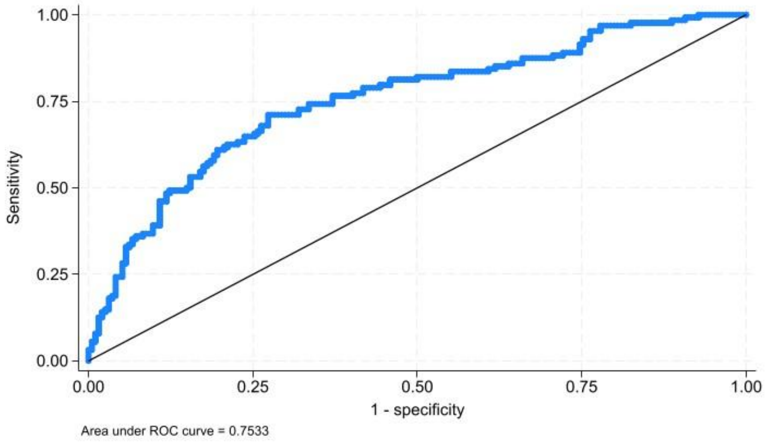

Figure S1. ROC Curve and Area Under the Curve (AUC) for Logistic Regression

Supplementary 3. Respondents' characteristics

Respondents' characteristics	**Number of respondents**	**%**	**Average**
Age (years):			
– 20 - 35 years old	44	13.7	
– 36 - 64 years old	255	79.2	
– > 64 years old	23	7.1	
Total	322	100	47.2

Respondents' characteristics	Number of respondents	%	Average
Formal education (years):			
– Never attended school	6	1.9	
– 2-6 years (elementary school)	124	38.5	
– 9 years (junior high school)	75	23.3	
– 12 years (senior high school)	96	29.8	
– > 12 years (higher education)	21	6.5	
Total	322	100	8.9
Gender:			
– Male	309	96	
– Female	13	4	
Total	322	100	-
Family size (persons):			
– 1 family member	6	1.9	
– 2 family members	41	12.7	
– 3-4 family members	184	57.1	
– 5-6 family members	83	25.8	
– > 6 family members	8	2.5	
Total	322	100	4
Land ownership:			
– Landowner	248	77	
– Tenant	74	23	
Total	322	100	-
Farming experience (years):			
– 1-5 years	49	15.2	
– 6-10 years	53	16.5	
– 11-15 years	39	12.1	
– 16-20 years	78	24.2	
– 21-25 years	28	8.7	
– > 25 years	75	23.3	
Total	322	100	18.8
Farm size (hectare):			
– 0.01-0.25 Ha	69	21.4	
– 0.26-0.50 Ha	84	26.1	
– 0.51-1.00 Ha	93	28.9	
– 1.01-2.00 Ha	42	13.0	
– 2.01-4.00 Ha	22	6.8	
– > 4.00 Ha	12	3.7	
Total	322	100	1.1
Participation in training:			
– Yes	177	55	
– No	145	45	
Total	322	100	-
Pesticide cost share (%):			
– 1-20%	148	46	
– 21-40%	113	35.1	
– 41-60%	41	12.7	
– 61-80%	13	4	
– > 80%	7	2.2	
Total	322	100	27
Number of pest and disease types:			
– None	3	0.9	
– 1 type	43	13.4	
– 2 types	52	16.1	
– 3 types	57	17.7	

Respondents' characteristics	Number of respondents	%	Average
– 4 types	60	18.6	
– 5 types	41	12.7	
– 6 types	19	5.9	
– 7 types	23	7.1	
– 8 types	19	5.9	
– 9 types	3	0.9	
– 10 types	1	0.3	
– 11 types	1	0.3	
Total	322	100	4

Supplementary 4. Farmers knowledge on biopesticides

	Number of respondents	%
Farmers who possess knowledge about biopesticides:		
– Yes	181	56.2
– No	141	43.8
Total	322	100
Farmers who have experience using biopesticides:		
1. Rice	39	30
2. Maize	14	11
3. Shallot	35	27
4. Red chili	17	13
5. Potato	20	16
6. Oil palm	3	2
Total	128	
Farmers who do not have experience using biopesticides:		
1. Rice	43	22
2. Maize	41	21
3. Shallot	24	12
4. Red chili	33	17
5. Potato	30	15
6. Oil palm	23	12
Total	194	