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Farmer Perspectives and Intentions in Establishing Palm Oil Processing Plants: Evidence from West Sumatra

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ABSTRACT

The development of downstream palm oil processing at the smallholder level in Indonesia remains limited, despite its potential to enhance farmer welfare and promote equitable value chain participation. Persistent disparities in fresh fruit bunch (FFB) prices, slow progress in smallholder-led industrial initiatives, and farmers' vulnerability to market fluctuations point to the need for inclusive downstream strategies. The study aims to assess farmers' perspectives on the establishment of palm oil processing plants at the farmer level. Simple random sampling was employed in selecting 200 smallholders across Dharmasraya and West Pasaman regencies. The research employs a mixed-method combining Structural Equation Modeling–Partial Least Squares (SEM–PLS) and qualitative analysis using NVivo in data analysis. The findings reveal that farmers' expectations of benefits and their readiness significantly influence their intention to build palm oil processing plants. Mediation analysis further shows that readiness partially mediates the relationship between farmer demographic profiles and their intention to invest in processing infrastructure. Most farmers expressed willingness to establish processing plants if they clearly perceive the benefits, such as increased income, price stability, and employment opportunity. However, they face substantial challenges, particularly limited financial capital and inadequate access to technology. These constraints highlight the need for comprehensive support from various stakeholders, including government agencies, cooperatives, and private sector partners, to enable farmers to participate in downstream processing. Strengthening farmer readiness through informal education, technical assistance, and inclusive financing mechanisms is essential to promote sustainable and equitable development in the palm oil sector.

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1. Introduction

The downstream palm oil industry at the farmer level in Indonesia represents a vital yet often overlooked segment of the value chain. Smallholder farmers contribute approximately 40% of the country's palm oil production, making them essential to the industry. However, their involvement is typically limited to the upstream phase—cultivating and harvesting fresh fruit bunches (FFB), which are then sold to intermediary traders or directly to mills for processing into crude palm oil (CPO).

These farmers are heavily dependent on palm oil mills, most of which are owned by large corporations. During the 2022 export restrictions on Indonesian palm oil, many mills reduced their FFB purchases, causing a sharp decline in farm–level prices. A study [1] found that 91% of farmers continued selling their FFB despite prices falling below variable production costs, as they had no viable alternatives. A smaller group (8%) chose to delay harvesting, which negatively affected FFB quality. In extreme cases, some farmers resorted to selling their oil palm land. This situation highlights the weak bargaining position of smallholders. They remain price takers, capturing only the value of the raw product while bearing the greatest risks and losses along the supply chain. Such dynamics threaten the long-term sustainability of the palm oil industry and its potential to improve farmer welfare.

Smallholder participation in downstream activities—such as refining, processing, and manufacturing—remains limited due to barriers including lack of access to capital, technology, infrastructure, and markets. Nonetheless, initiatives are emerging to integrate farmers into value-added processes. These include small-scale processing units and cooperative models that enable collective ownership and management of downstream operations, allowing farmers to capture more value.

One notable initiative is the Indonesian government's Mini Cooking Oil Factory program (Pabrik Mini Minyak Goreng, or Pamigo). This technological innovation enables the conversion of FFB into cooking oil at the local level. Pamigo aims to boost domestic cooking oil production, expand market access for farmers, and increase the added value of agricultural products. By bringing processing closer to the source of raw materials, the program seeks to empower local economies and enhance farmer welfare.

1.1. Theoretical Framework

However, the success of such initiatives hinges on farmers' behavioral intentions and their readiness to invest in processing infrastructure. To explore these dynamics, this study draws on several behavioral and innovation adoption theories: (a) Theory of Planned Behavior (TPB) [2] examines how attitudes, perceived social norms, and control over resources influence farmers' intentions; (b) Technology Acceptance Model (TAM) [3] emphasizes perceived usefulness and ease of use in technology adoption; (c) Diffusion of Innovations Theory [4] explains how new practices spread within communities, shaped by perceived benefits and social networks; (d) Sustainable Livelihoods Framework (SLF) [5] highlights the role of financial, human, and physical assets in enabling participation in downstream activities; (e) COM-B Model [6] frames behavior as a function of capability, opportunity, and motivation, suggesting that interventions like informal education and inclusive financing can enhance readiness; (f) Theory of Reasoned Action (TRA) [7] underscores the influence of beliefs and social norms on behavioral intentions, reinforcing the importance of community and cooperative support.

In assessing technology adoption, farmers' perceptions of specific attributes are crucial [8]. Research shows that adoption is more likely when technologies are perceived to improve productivity or income [9,10] and carry low risk[11]. Participation in cooperatives has also been shown to enhance understanding of agricultural technologies[12], facilitating knowledge sharing and reducing perceived barriers.

Organizational factors—such as management support, internal capacity, and external conditions like market competition and assistance—play a significant role in adoption decisions[13]. While technological barriers such as cost and complexity may not always show statistical significance, qualitative findings reveal their practical importance. Other influential factors include access to finance[14], extension services, demonstration participation[9], farmer characteristics, innovation attributes, and perceived benefits[15]. Additionally, perceived usefulness, ease of use, social influence, and trust are key drivers of technology uptake[16].

Ultimately, the success of downstream palm oil initiatives at the farmer level depends on the active participation and acceptance of smallholders. Their decisions are shaped by economic opportunities, technological and financial constraints, training needs, and policy support. This study aims to assess oil palm farmers' perceptions of both the opportunities and challenges in developing farmer-level downstream processing industries.

1.2. Research Gap

By identifying the key enablers and barriers to smallholder participation, this research informs targeted policy interventions to enhance farmer welfare and promote sustainable growth in Indonesia's palm oil sector. It contributes to the broader discourse on inclusive agricultural development by offering empirical evidence to support context–specific and equitable strategies for strengthening the palm oil value chain.

While many studies have explored agricultural technology adoption, most focus on upstream production or general innovation uptake. For instance, study on farmers' satisfaction and adoption of Coffee Arabica F1 hybrids[14], wheat technology adoption in Ethiopia[9], farmers' Decision for Adoption and Non-Adoption of Oil Palm Cultivation in Northeast Thailand[17], farmers' perception of sustainable soil management practices[18], adoption of climate-smart agriculture innovations[19], Farmers' willingness to adopt conservation practices[20], and perceptions on the adoption of sustainable agricultural intensification practices[21]. These works emphasize productivity, risk perception, and institutional support but rarely address farmer-led downstream initiatives. In contrast, this study offers a novel contribution by investigating smallholder oil palm farmers' intentions to establish processing plants at the farmer level in West Sumatra—an area where such initiatives are still emerging. The technology is significantly different from what the farmers have been practicing. Farmers only get used to farming activities; they will need new knowledge to run a processing business. Therefore, how farmers perceive running a processing business is a critical factor in further developing such a business at the farmer level. **Figure 1** shows the hypothetical model for this study.

The hypotheses assessed are as follows:

H1. *Information positively influences behavioral intention.*

H2. *Readiness positively influences behavioral intention.*

H3. *Demographic profile influences readiness.*

H4. *Readiness mediates the relationship between demographic profile and behavioral intention.*

H5. *Economic conditions positively influence behavioral intention.*

H6. *Partnership positively influences behavioral intention.*

H7. *Perceived benefits positively influence behavioral intention.*

H8. *Constraints negatively influence behavioral intention.*

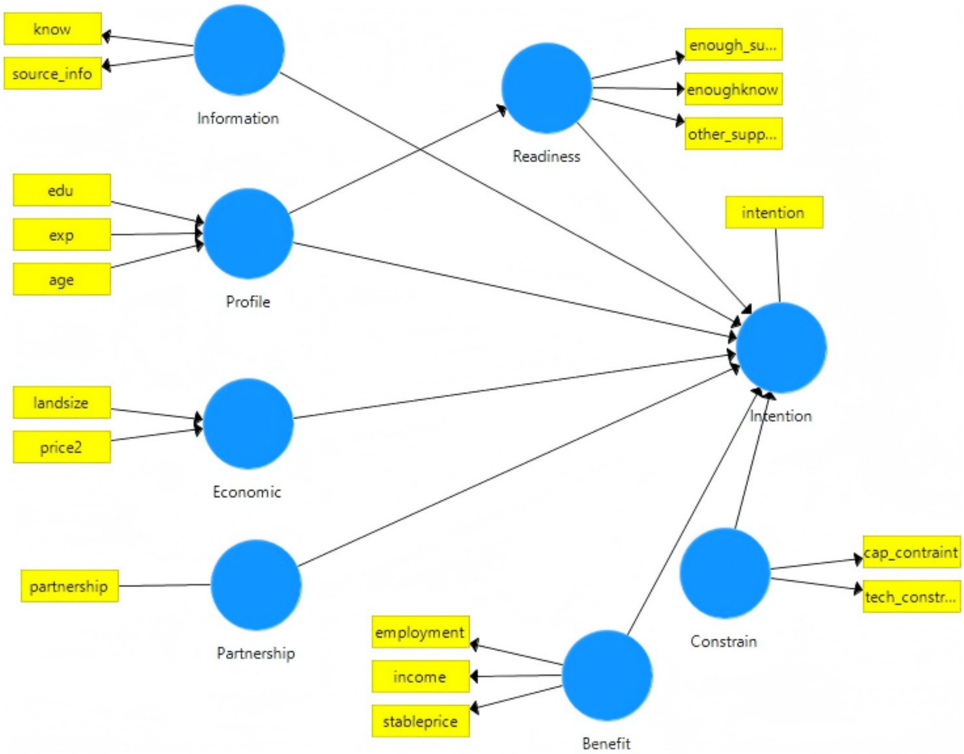

Figure 1. Hypothetical model of intention to establish a palm oil processing plant at the farmer level.

2. Materials and Methods

2.1. Study Area

The study was conducted in two regencies within West Sumatra Province: West Pasaman and Dharmasraya. These areas were purposively selected due to their status as the leading centers of palm oil production in the province, collectively contributing approximately 70% of West Sumatra's total output. As of 2023, West Pasaman encompassed a land area of 127,309 hectares, yielding 372,315.28 tons of palm oil. Dharmasraya, with a total land area of 33,836.20 hectares, produced 120,590.94 tons [22]. In both regencies, oil palm cultivation represents the primary agricultural activity and serves as the main source of income for local farmers. The population of oil palm farmers was recorded at 63,879 in West Pasaman and 17,477 in Dharmasraya.

2.2. Sampling and Data Collection Methods

The sampling design employed a two-stage approach. In the first stage, one cooperative from each regency was selected purposively, based on their operational capacity and expressed interest in developing a palm oil processing facility. The selected cooperatives were Koperasi Produsen Perkebunan Sawit Perintis in West Pasaman, established in 1991 and comprising 506 members, and Koperasi Lubuk Karya in Dharmasraya, established in 1981 with 589 members. In the second stage, a simple random sampling technique was applied to select 100 farmers from each selected cooperative for participation in the study.

Cross-sectional data were used to meet the objective of this study. The data were collected from both primary and secondary sources. The primary data were collected using a structured questionnaire from 200 smallholder farmers who are members of village cooperatives, focusing on their perception of factors influencing their intentions to establish a palm oil processing plant. Secondary data were collected from published documents, such as books, proceedings, and journals, and unpublished documents, like annual reports of different organizations.

The instrument for primary data was developed to ensure alignment with the study's conceptual model (**Figure 1**) and demographical information. Eight variables are involved in the model to assess farmers' perception of establishing a palm oil processing plant. They include information, farmer profile, economic status, partnership, readiness, benefit, constraints, and intention. The definition of the variables is described in **Table 1**. The perception variables are measured on a 5-point Likert scale from "strongly disagree" to "strongly agree".

Table 1. Description of variables and theoretical foundations.

Latent Variable	Indicators	Theoretical Foundations
Intention = the willingness of farmers to establish a processing plant by their cooperative		"intention" in TPB [2]
Readiness = the capacity to establish a processing plant	1. Enough support from the government 2. Having enough knowledge and ability 3. Availability of support from other stakeholders (partnership)	"perceived behavioral control" in TPB [2] and "ease of use" in TAM [3]
The constraints the cooperative will face in establishing a processing plant	1. Capital constraints 2. Technical constraints	"perceived behavioral control" in TPB [2] and "ease of use" in TAM [3]
The benefits farmers can receive if their cooperative establishes a processing plant	1. Increase employment 2. Increase farmers' income 3. FFB price is more stable	"attitude toward the behavior" in TPB [2]; "perceived of usefulness" in TAM [3]; 'perceived advantages" in Diffusion of Innovations Theory [4]
Information farmers receive about the government program on establishing a processing plant at the farmer level	1. Farmers got information on the government program on establishing a processing plant at the farmer level (1 = yes, 0 = no) 2. The source of information (1 = from cooperative, 0 = otherwise)	"social influence" in TRA [7]
Profile of respondents	1. Educational level 2. Experience in palm oil farming (years) 3. Age (years)	"capability" in COM-B Model [6]
Economic condition	1. Size of land holding (ha) 2. Received price of FFB (IDR per kg)	"access to asset" in SLF [5]
Willingness to have a partnership to establish a processing plant		"social influence" in TRA [7]

2.3. Data Analysis

Partial Least Squares SEM (PLS–SEM) was chosen to verify the hypotheses in this study. Observed variables and their associated relationships with latent variables were described by the measurement models. The models were tested in terms of validity and reliability in terms of composite reliability, convergent validity, and discriminant validity. Subsequently, the structural model was tested to verify the proposed hypotheses. Qualitative data were collected through open-ended questions embedded in the same questionnaire to capture the perception of farmers on barriers and required support to build a palm oil processing plant at the farmer level. The qualitative data are analyzed using NVivo, which is expected to enhance the quantitative data.

This study adopts a mixed-methods approach by integrating quantitative analysis using Structural Equation Modeling–Partial Least Squares (SEM–PLS) with qualitative analysis conducted through NVivo. Structural Equation Modelling–Partial Least Squares (SEM–PLS) plays a critical role in this study by enabling the simultaneous analysis of complex relationships among multiple latent variables that influence farmers' intentions to establish palm oil processing plants. Unlike traditional regression techniques, SEM–PLS allows for the assessment of both direct and indirect effects, including mediation pathways—such as the role of readiness in mediating the relationship between farmer profiles and intention. This method is particularly well-suited for exploratory research with relatively small sample sizes and non-normal data distributions, as is often the case in rural development studies. By incorporating measurement and structural models, SEM–PLS ensures the reliability and validity of constructs such as perceived benefits, constraints, and readiness, thereby providing robust empirical evidence to inform policy and intervention strategies in the palm oil sector.

There are two steps in analyzing the data in SEM–PLS. The first step is to evaluate the measurement model. Assessing the measurement model begins with evaluating indicator reliability to ensure that each indicator appropriately reflects its corresponding latent construct. Next, internal consistency reliability is examined using Cronbach's alpha and Composite Reliability, which should meet acceptable thresholds to demonstrate consistency among indicators. Convergent validity is then assessed through the Average Variance Extracted (AVE). Secondly, the structural model is assessed by analyzing path coefficients for significance, typically through bootstrapping procedures. We also examine R^2 values to determine the explained variance of endogenous constructs, and evaluate effect sizes (f^2) and predictive relevance (Q^2) to understand the impact and forecasting ability of the model. **Table 2** shows the criteria to assess the model.

Table 2. Criteria for assessing the model.

Criterion	Acceptable Level
Reflective measurement models	
Reflective indicator loadings	≥0.70, for exploratory research, loadings of 0.60 are acceptable
Internal consistency reliability	Cronbach's alpha > 0.70
Convergent validity	AVE ≥ 0.50
Formative measurement models	
Collinearity (VIF)	VIF < 5
Statistical significance of weights	p-value < 0.05
Structural model	
R^2 value	R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak. R^2 values of 0.90 and higher are typically indicative of over-fitting
Effect size f^2	f^2 values of 0.02, 0.15, 0.35 are considered weak, moderate, strong effects
Q^2 value	Q2 is indicative of predictive relevance; Q^2 Values higher than 0, 0.25, and 0.50 depict small, medium, and large.

Source: Hair et al. [23].

To complement and contextualize these findings, qualitative data were collected through open-ended survey responses and were analyzed thematically using NVivo. This allowed for the identification of nuanced perceptions, constraints, and support needs that may not be fully captured through quantitative indicators. The integration of both methods enhances the validity and depth of the analysis, offering a more comprehensive understanding of the behavioral, institutional, and contextual factors shaping smallholder participation in downstream palm oil processing.

3. Results

3.1. Palm Oil Industry Profile in West Sumatra

Oil palm is a key agricultural commodity in West Sumatra, widely cultivated by both local communities and business entities. Its economic significance is reflected in the substantial production and land area dedicated to its cultivation. Oil palm production reached a total of 715,118.27 tons with the total area of 256,329.51 hectares in 2024, comprising 205,368.57 hectares of mature, productive plantations, 26,734.45 hectares of immature (non-yielding) plantations, and 24,226.49 hectares of old or damaged plantations [24].

Table 3 shows the area and production of oil palm in the last five years. Palm oil production has shown a consistent upward trend, rising from 567,930 tons in 2020 to 715,118.27 tons in 2024, indicating improved yield or processing efficiency. The total plantation area increased significantly from 2020 to 2022, peaking at 251,591 ha. In 2023, there was a notable drop to 203,842.12 ha, possibly due to replanting, land conversion, or data revision. By 2024, the area rebounded to 256,329.51 ha, the highest in the five-year period. Despite the dip in plantation area in 2023, production continued to rise, suggesting either higher productivity per hectare or improved harvesting and processing methods.

Table 3. Oil palm plantation area and production in West Sumatra (2020–2024).

Year	Total Area (ha)	Production (tons)
2020	219,663.00	567,930.00
2021	250,631.00	668,605.00
2022	251,591.00	674,933.00
2023	203,842.12	699,934.62
2024	256,329.51	715,118.27

Source: BPS-Statistics Sumatera Barat Province [25].

Palm oil mills in West Sumatra Province are spread across several regencies/cities, with the highest number located in West Pasaman Regency. The palm oil mills generally produce Crude Palm Oil (CPO); some also process palm kernels. These mills vary in production scale, ranging from medium to large-scale operations. Most of the mills are privately owned companies. As of now, there are no mills owned by farmer organizations.

Figure 2 presents the distribution of palm oil factory capacities ranging from 15.0 to 100.0 tons per hour. A total of 32 factories are represented, with an average capacity of approximately 58.21 tons per hour. The most common capacity is 60.0 tons per hour, associated with the highest number of factories (10). This indicates a strong preference for mid-range capacities among manufacturers. While capacities like 45 tons/hour also show notable representation (5 factories), higher capacities such as 90 and 100 tons/hour are less frequent, suggesting they may be less economically or operationally viable for most producers.

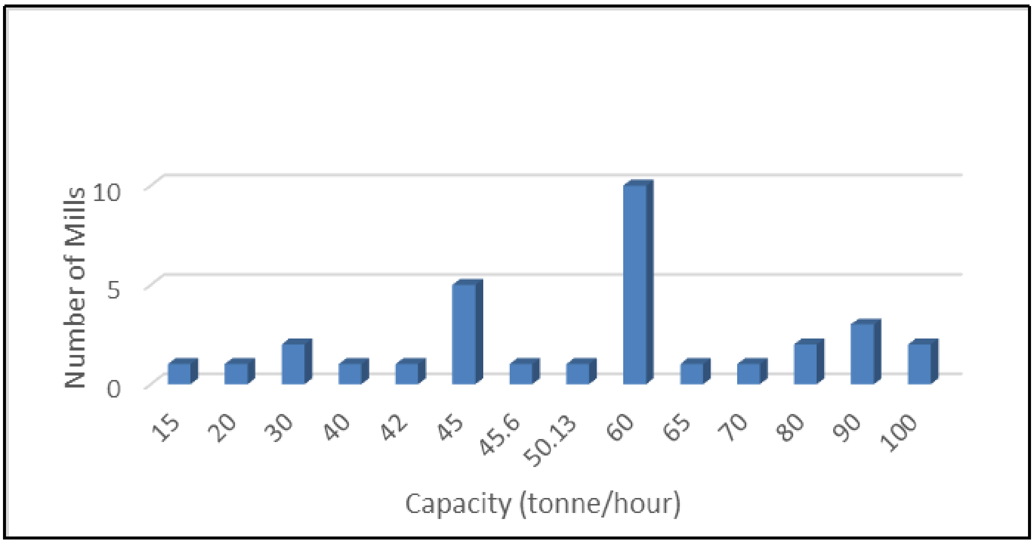

Figure 2. The distribution of palm oil factory capacities in West Sumatra.

Source: Dinas Perkebunan Tanaman Pangan dan Hortikultura Provinsi Sumatera Barat [26].

3.2. The Profile of Oil Palm Smallholders

Table 4 describes the profile of oil palm farmers. The demographic profile of the participants was diverse, reflecting a wide range of socio-economic and farming contexts. The majority of respondents are between 41 and 65 years old, with the highest concentration found in the 51–65 age group (34%). This suggests that the oil palm farming sector in West Sumatra is largely sustained by middle-aged to older adults, who likely possess substantial experience and knowledge of agricultural practices. However, this age profile also raises concerns about generational continuity and the future sustainability of the workforce, especially if younger individuals are not entering the sector. The presence of individuals over 65 years old, particularly more prevalent in Pasaman Barat (10.5%) compared to Dharmasraya (5%), may reflect regional differences in labor availability, retirement norms, or economic necessity. In Pasaman Barat, older individuals may continue working due to limited pension access or strong cultural ties to farming. This aging demographic could have implications for technology adoption, policy planning, as well as health and productivity. Older farmers may be less inclined to adopt digital or mechanized farming tools. There may be a need for targeted programs to encourage youth participation and succession planning. Aging workers may face physical limitations, affecting overall productivity and requiring health support services.

Table 4. Profiles of respondents.

Description	Dharmasraya (%) N = 100	West Pasaman (%) N = 100	Total (%) N = 200
Age (years)			
20–30	4.00	0.50	4.50
31–40	16.00		
41–50	15.00	15.00	30.00
51–65	17.00	17.00	34.00
>65	5.00	10.50	15.50
Education			
Elementary school	13.50	11.00	24.50
Junior high school	18.00	7.00	25.00
Senior high school	13.50	22.00	35.50
Diploma 3	1.00	1.00	2.00
Diploma	0.50	0.00	0.50
Undergraduate	3.50	9.00	12.50
Experience (years)			
1–10	12.50	9.00	21.50
11–20	6.50	12.00	18.50
>20	31.00	29.00	60.00
Number of dependents (persons)			
1–5	44.50	47.50	92.00
6–10	5.50	2.50	8.00
Oil palm area (hectares)			
<2	19.00	0.00	19.00
2.1–5	28.50	50.00	78.50
>5	2.50	0.00	2.50

In terms of educational attainment, most respondents have completed senior high school (35.5%), followed by junior high school (25%). Dharmasraya shows a higher proportion of junior high school graduates, whereas Pasaman Barat has more respondents with senior high school and undergraduate qualifications. The data suggests a moderate level of formal education. This may influence the adoption of agricultural innovations and access to formal employment opportunities. The regional contrast—Dharmasraya with more junior high school graduates and Pasaman Barat with more senior high school and undergraduate holders—could reflect differences in educational infrastructure, socioeconomic conditions, or access to higher education.

Regarding farming experience, a significant portion of respondents (60%) have experience for over 20 years, indicating a predominance of experienced farmers or laborers in both regions. This depth of experience may contribute to stable production practices and resilience in the face of market or environmental challenges. However, it may also suggest limited generational renewal, raising questions about youth involvement in agriculture and long-term sustainability.

The majority support between one to five dependents (92%), reflecting a moderate level of family responsibility. This demographic structure may influence labor availability, household income allocation, and the need for social support systems. It also reflects the socio-economic reality of rural agricultural communities, where family size and dependency ratios are key factors in livelihood strategies. In terms of land ownership, most respondents possess oil palm plantations ranging from 2.1 to 5 hectares (78.5%), indicating a prevalence of medium-scale farming. This scale is often associated with semi-commercial operations—large enough to generate income but small enough to remain family-managed. Dharmasraya's greater variation in land size suggests a more diverse farming landscape, potentially including both smallholders and larger estates. In contrast, Pasaman Barat's concentration in the 2.1–5 hectare range implies a more uniform farming structure, possibly shaped by land policies or historical settlement patterns.

The data paints a picture of a relatively educated, experienced, and moderately burdened agricultural population engaged in medium-scale oil palm farming. Regional differences in education and landholding hint at localized development dynamics. These insights can inform targeted interventions—such as education programs, land reform, or youth engagement strategies—to enhance productivity and sustainability in West Sumatra's palm oil sector.

Table 5 provides a comparative overview of the yield and economic performance of oil palm farming in Dharmasraya and West Pasaman. The data clearly shows that West Pasaman achieves significantly higher productivity, with an average yield of 26,774.28 tons per hectare per year, compared to 14,492.49 tons per hectare per year in Dharmasraya. This substantial difference in output highlights a notable disparity in farming outcomes between the two regions. One of the primary factors contributing to the lower productivity in Dharmasraya is the recent replanting of oil palm trees by many farmers in the area. Replanting is a common practice aimed at rejuvenating aging plantations and improving long-term yields. However, newly planted oil palm trees typically require several years to reach full maturity and optimal production levels. During this early growth phase, the trees produce significantly less fruit, which directly impacts overall yield figures. As a result, the current productivity in Dharmasraya does not yet reflect the full potential of its plantations. This transitional period is expected to be temporary, and yields are likely to improve as the young trees mature. In contrast, West Pasaman may have a larger proportion of mature plantations, which are already operating at or near peak productivity. This maturity, combined with potentially more intensive input use and better agronomic practices, contributes to the region's superior performance. Understanding these dynamics is crucial for interpreting the data accurately and for planning future interventions. Support for farmers during the replanting phase—such as access to high-quality seedlings, training in best practices, and financial assistance—can help accelerate the recovery of yields in Dharmasraya and ensure long-term sustainability of the sector.

Table 5. Average of production, FFB price, and input cost of oil palm farming of respondents.

Description	Dharmasraya	West Pasaman	Total
Production (tonne/year/ha)	14,492.49	26,774.28	20,633.39
FFB price (IDR/kg)	2,484.30	3,272.41	2,878.36
Fertilizer cost (IDR/year/ha)	3,549,113.86	5,850,000.00	4,699,556.93
Chemical cost (IDR/year/ha)	632,443.37	361,150.00	496,796.69

Figure 3 shows the relationship between the age of oil palm trees and their yield, as modelled from the primary data. The trees bear fruit at around the age of three years. The production ranges from 4.5 to 36 tons/hectare/year. It reaches its peak at 15 years old. The quadratic regression curve shown follows the equation. This equation shows that production increases as the tree ages to a certain point, then decreases, reflecting a common pattern in the oil palm crop productivity cycle.

$$y = -0.115x^2 + 3.591x + 0.825 \tag{1}$$

Farmers in West Pasaman enjoy a distinct economic advantage in the oil palm sector due to higher market prices for Fresh Fruit Bunches (FFB) (**Table 5**). On average, they receive IDR 3,272.41 per kilogram, whereas their counterparts in Dharmasraya earn a lower price of IDR 2,484.30 per kilogram. This notable price gap can be attributed to several underlying factors, including differences in market access, quality control standards, and efficiency within the supply chain. One of the most influential factors affecting FFB pricing is the existence of formal partnerships between farmers and palm oil mill companies. Farmers who are part of these partnerships benefit from structured agreements that often include technical support, guaranteed purchase arrangements, and access to government-regulated pricing mechanisms. As a result, they are able to secure higher and more stable prices for their produce.

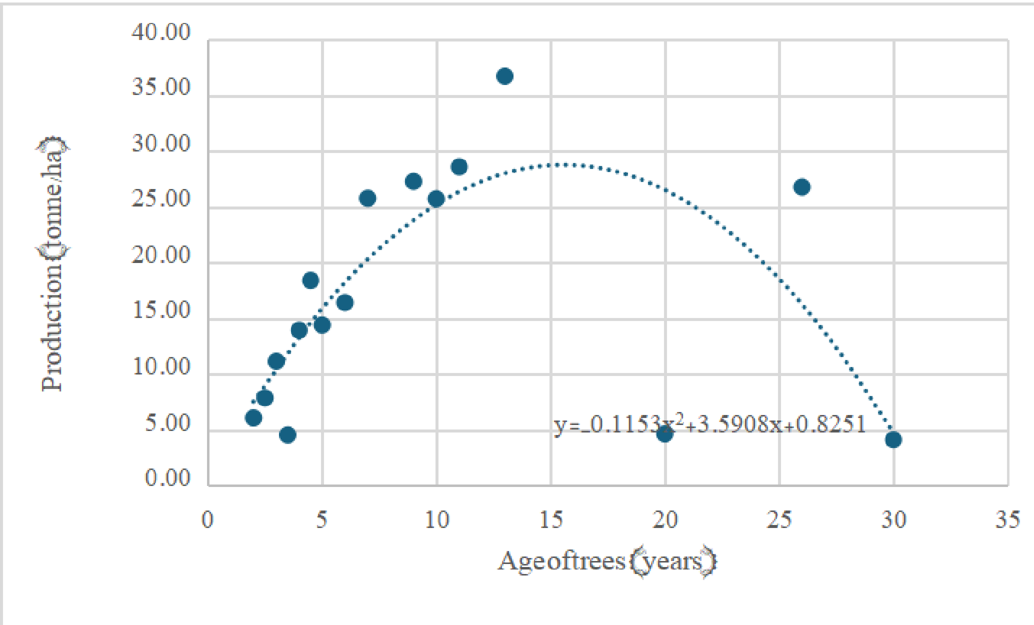

Figure 3. The relationship between oil palm yield and the age of trees.

The provincial government plays a key role in regulating FFB prices, issuing official price determinations on a weekly basis. However, these prices are only applicable to farmers who are affiliated with recognized partner companies. Independent farmers—those who operate outside of formal partnerships—are excluded from this pricing scheme and must negotiate prices individually, often resulting in lower earnings. This system creates a two-tiered market structure, where partnership farmers are economically favored, while independent farmers face greater uncertainty and reduced profitability. The implications of this pricing structure are significant. It encourages farmers to seek partnerships with mills, which can lead to improved farming practices and better access to resources. However, it also highlights the vulnerability of independent farmers, who may lack the bargaining power or infrastructure to compete effectively. Addressing this disparity may require policy interventions aimed at expanding partnership opportunities, improving market transparency, and supporting independent farmers through cooperative models or inclusive pricing frameworks.

West Pasaman incurs higher fertilizer expenses, averaging IDR 5,850,000/year/hectare, compared to IDR 3,549,113.86/year/hectare in Dharmasraya. This could reflect differences in soil fertility, input usage intensity, or pricing. Interestingly, Dharmasraya spends more on chemicals (IDR 632,443.37/year/hectare) than West Pasaman (IDR 361,150.00/year/hectare), possibly indicating greater pest or disease pressure, or differing crop management strategies.

3.3. Farmer Perception of Oil Palm Farmers on Establishing Downstream Industries at the Farmer Level

3.3.1. Measurement Model Assessment

Assessment of the measurement model was conducted using a PLS algorithm for the hypothetical model.

Factor loading and cross-loading were checked as the first step to the measurement model. **Figure 4** illustrates a Structural Equation Model (SEM) that examines the relationships between several latent variables and their influence on farmers' readiness and intention to participate in the development of processing plant (Palm Oil Processing Units) or Pamigo at the cooperative level. The model identifies eight latent constructs: Information, Partnership, Readiness, Intention, Constraint, and Benefit. Latent variables are represented by blue circles and are measured through observed variables (yellow rectangles), with path coefficients indicating the strength and direction of relationships. In **Figure 4**, the values between indicators and latent variables are factor loadings for reflective models and indicator weights for formative models, while p-values are written in brackets.

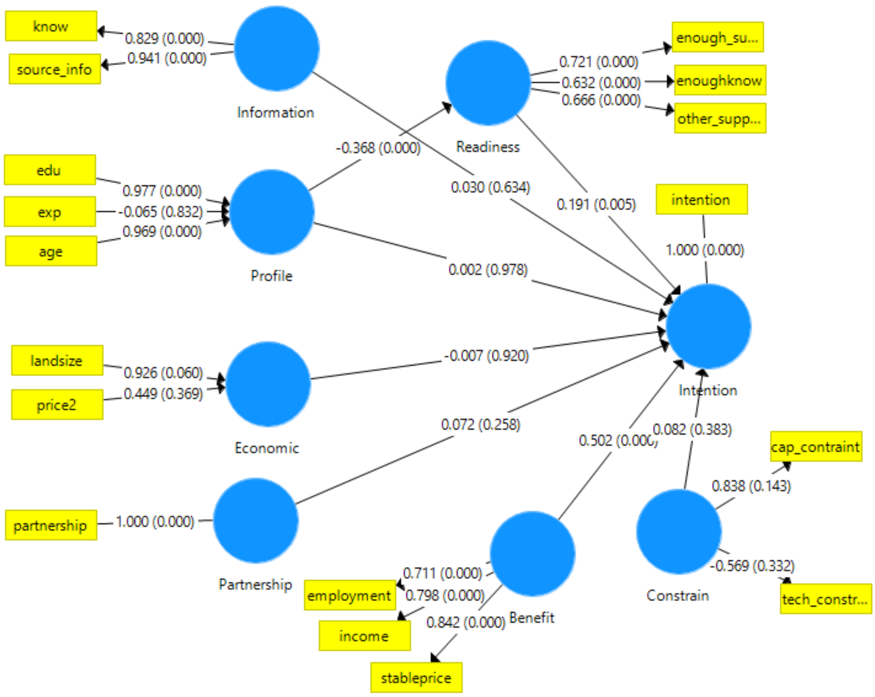

Figure 4. The estimation results of the hypothetical model.

In our study, Information, Profile, Economic, Partnership, Readiness, Intention, Constraint, and Benefit are reflectively measured constructs, while Profile and Economic are formative measured constructs. As this study is an exploratory research, the cut-off point used for factor loadings is 0.60 for the reflective model. The results show that most factor loadings for the reflective measurement model are >0.60. It means that factor loadings are valid. Technological constraint is the only indicator with a factor loading < 0.60; therefore, it is dropped for further analysis. The assessment of Construct Reliability and Validity in **Table 6** shows that the values of Cronbach's Alpha and AVE for Readiness and Constraint are very low. Thus, these two variables need more attention to respecify the model. Other latent variables have the AVE values >0.60.

Table 6. Construct the reliability and validity of the original model.

Variable	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Benefit	0.69	0.71	0.83	0.62
Constraint	−0.05	0.06	0.07	0.51
Information	0.74	0.87	0.88	0.79
Intention	1.00	1.00	1.00	1.00
Partnership	1.00	1.00	1.00	1.00
Readiness	0.42	0.37	0.71	0.45

In the formative model, the result shows that indicator experience (weight = −0.065; ρ = 0.832) is not significant to form construct Profile, while for Economic, indicator price (weight = 0.449; ρ = 0.369). These variables were then dropped from the model.

The second-round estimation was conducted after removing invalid indicators in the model. The second model estimation result is presented in **Figure 5**. All factor loadings are higher than 0.70, and all indicator weights are significant at a 10% significance level. **Table 7** describes that the Final Model is valid based on Construct Reliability and Validity. The values of Cronbach's Alpha are close to 0.70 for one variable and > 0.70 for other variables. The values of Composite Reliability and AVE are > 0.08 and > 0.60, respectively.

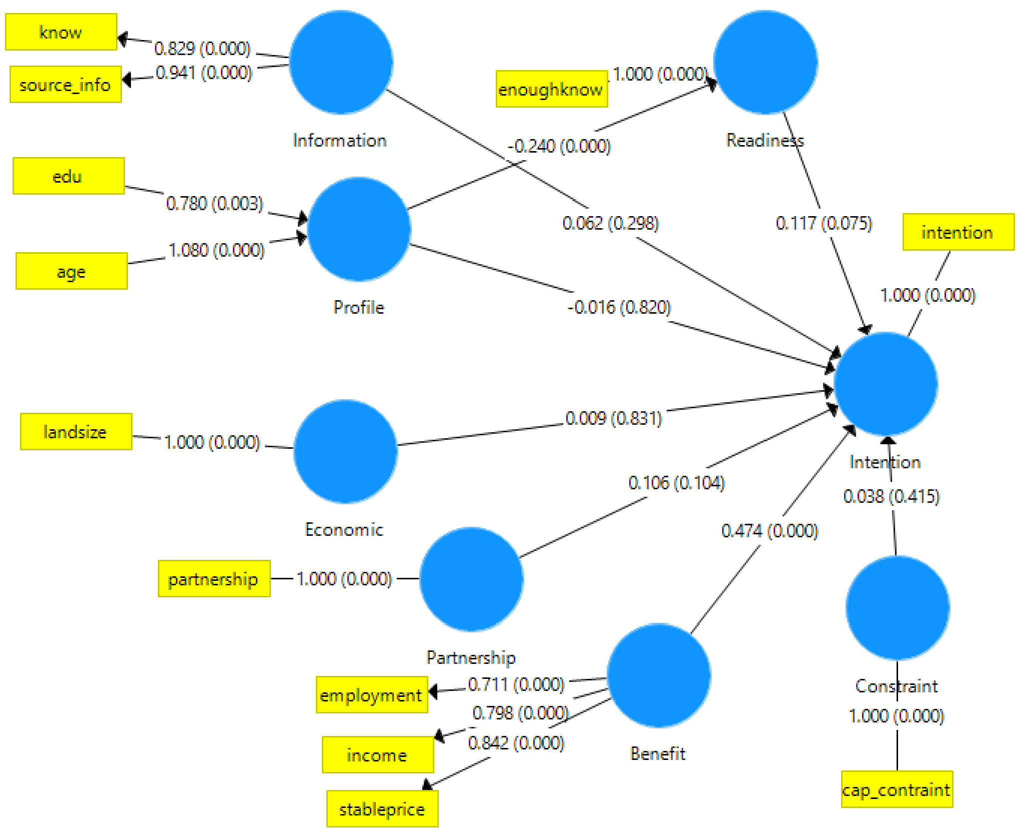

Figure 5. SEM Model of farmers' intention in establishing a processing plant at the farmer level.

Table 7. Construct the reliability and validity of the final model.

Variable	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Benefit	0.691	0.712	0.828	0.617
Constraint	1.000	1.000	1.000	1.000
Information	0.742	0.873	0.880	0.786
Intention	1.000	1.000	1.000	1.000
Partnership	1.000	1.000	1.000	1.000
Readiness	1.000	1.000	1.000	1.000

3.3.2. Structural Model Assessment

Structural model evaluation for endogenous constructs can be measured by R–square. Data analysis using smart–PLS software in the study results in the value R^2 (0.30) for intention is low, meaning that 30% of farmers' intention in establishing a processing plant at the farmer level can be explained by the seven exogenous variables, the remaining 70% is explained by other variables not measured in the study. The R^2 for Readiness is even weaker (0.06), indicating that involving more relevant variables would be more valuable for future research.

Table 8 presents the predictive relevance of–Square value. Q^2 evaluates how well the observed values are reconstructed by the model and its parameter estimates. The result shows that the model has predictive relevance for a particular endogenous construct, with the Q^2 value of 1.88.

Table 8. Predictive relevance of Q^2.

Variable	SSO	SSE	Q^2 (= 1−SSE/SSO)
Benefit	600.000	600.000	
Constraint	200.000	200.000	
Economic	200.000	200.000	
Information	400.000	400.000	
Intention	200.000	162.447	0.188
Partnership	200.000	200.000	
Profile	400.000	400.000	
Readiness	200.000	200.000	

Furthermore, changes in the R–square value are used to assess the effects of certain exogenous latent variables on endogenous latent variables, which can be measured by the value of f^2. Our study found that the perceived benefit has an f^2 value of 0.287 (**Table 9**), indicating that this variable has a moderate influence on farmer' willingness to initiate processing units within their own communities. The effect of Profile on Readiness, and Readiness on Intention are weak with the f^2 values of 0.061 and 0.016, respectively.

Table 9. Path coefficient and hypothesis test.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	*p* Values	f-Square
Benefit -> Intention	0.474	0.472	0.087	5.459	0.000*	0.287
Constraint -> Intention	0.038	0.040	0.046	0.815	0.415	0.002
Economic -> Intention	0.009	0.010	0.041	0.214	0.831	0.000
Information -> Intention	0.062	0.069	0.060	1.041	0.298	0.005
Partnership -> Intention	0.106	0.105	0.065	1.628	0.104	0.014
Profile -> Intention	−0.016	−0.022	0.068	0.228	0.820	0.000
Profile -> Readiness	−0.240	−0.254	0.066	3.628	0.000*	0.061
Readiness -> Intention	0.117	0.112	0.065	1.787	0.075*	0.016

Note: * significant at α = 0.10.

Overall, the model highlights Benefit as a key predictor of Intention, underscoring its central role in influencing farmers' decision-making. The path from Benefit to Intention is both statistically significant and positive (coefficient = 0.474, p = 0.000) as shown in **Table 9**, indicating that the more farmers perceive tangible advantages, the stronger their intention to engage in processing plant development. Readiness, which is measured through an indicator of adequate knowledge about processing operations, has a positive and statistically significant effect on Intention (coefficient = 0.117, p = 0.075). This suggests that when farmers feel adequately supported and informed, they are more likely to develop a strong intention to establish processing facilities.

The profile construct, which includes demographic characteristics such as education level and age, shows a significant negative effect on Readiness (coefficient = −0.240, p = 0.000). This implies that certain demographic groups—possibly older or more formally educated farmers—may feel less prepared or confident in initiating processing activities. Other variables in the model, including Constraints, Economic factors (land size), Information, Partnership, and Profile, do not exhibit significant direct effects on Intention.

The quantitative data are enriched with qualitative data to capture obstacles farmers may face and the support they need to build a palm oil processing plant. The data were analyzed using the NVivo approach. The word cloud in **Figure 6** highlights key terms of constraints associated with establishing a processing plant at the farmers' level. The relative size of each word reflects its frequency or significance within the given context. Among the most prominent terms are Capital, Factory, Land, Location, and Cost, suggesting their central role in discussions around the constraints. Additionally, other notable words such as Licensing, Administrative, Membership, Insufficient, and Regulation further emphasize themes.

Figure 6. Constraints in establishing a palm oil processing plant at the farmer level.

Table 10 presents word frequencies and their weighted percentages, highlighting the most commonly mentioned. The word "capital" stands out significantly, appearing 124 times and accounting for 22.71% of the total, indicating its central importance in the context—likely referring to financial resources or investment. "Factory" follows with 59 mentions (10.81%), suggesting a strong focus on industrial infrastructure. Other frequently occurring terms include "land" (34 mentions, 6.23%), "location" (31 mentions, 5.68%), and "cost" (17 mentions, 3.11%), all of which are critical factors in developing a palm oil processing plant at the farmer level.

Table 10. The main constraints in establishing an oil palm processing plant at the farmer level.

Word	Count	Weighted Percentage (%)
capital	124	22.71
factory	59	10.81
land	34	6.23
location	31	5.68
cost	17	3.11
licensing	15	2.75
administrative	13	2.38
membership	13	2.38
insufficient	12	2.2
regulation	12	2.2

Less frequent but still notable are terms like "licensing" (2.75%), "administrative" and "membership" (both 2.38%), and "insufficient" and "regulation" (each 2.2%). These words suggest concerns or considerations around governance, access, and policy constraints. Overall, the distribution of these terms reflects a thematic emphasis on financial investment, industrial setup, land use, and regulatory frameworks.

Figure 7 and **Table 11** show key terms of farmers' expectations regarding the support to establish an oil palm processing plant at the farmers' level. In line with the main constraint, the most prominent concern is capital, which accounts for 23.12% of the mentions. This suggests that access to financial resources is a major issue, possibly indicating difficulties in securing funding for operations, investments, or growth. Following this, assistance is the second most frequently mentioned term at 10.57%, highlighting a strong need for support—whether in the form of technical guidance, advisory services, or institutional aid.

Figure 7. Expected support in establishing a palm oil processing plant at the farmer level.

Table 11. The main expected support in establishing an oil palm processing plant at the farmer level.

Word	Count	Weighted Percentage (%)
capital	129	23.12
assistance	59	10.57
licensing	31	5.56
price	29	5.2
fertilizer	24	4.3
regulation	15	2.69

Other notable terms include licensing (5.56%) and regulation (2.69%), which point to bureaucratic or legal challenges that may be hindering progress. These could involve complex procedures, unclear requirements, or restrictive policies. The mention of price (5.2%) reflects concerns about the price stability of FFB at the farmer level, which is expected through establishing an oil palm processing plant by farmer institutions. Lastly, fertilizer (4.3%) suggests that agricultural inputs are a specific area of concern, possibly due to supply chain issues or rising costs in the farming sector.

Overall, the data indicates that financial and operational support are top priorities, while regulatory and market-related challenges also play a significant role. These insights can inform targeted interventions, such as financial aid programs, regulatory reforms, and support for agricultural inputs.

4. Discussion

Understanding farmers' perceptions is central to the success of agricultural innovation [27] and downstream engagement. According to Ajzen [28], a farmer's expectations about the outcomes of a technique significantly influence their decision to accept or reject it. Insufficient consideration of farmers' perspectives may result lack of adoption of certain farming methods [19,29]. Studies by Mulyono et al. [30] and Omara et al. [31] highlight that how quickly and widely technologies are adopted depends largely on farmers' perceptions of associated risks, costs, and benefits. The literature consistently highlights that farmer perception is not a peripheral issue but a central factor in the success or failure of agricultural programs. Programs that fail to consider farmers' views, experiences, and local contexts risk low adoption rates. Therefore, engaging farmers early, addressing misconceptions, and building trust through effective extension services are essential strategies for enhancing adoption and ensuring long-term sustainability. In this light, we examined how oil palm farmers perceived on program to involve farmers at the downstream.

4.1. The Effect of Perceived Benefit on Intention

The adoption of new technologies is often influenced by users' perceptions of the economic benefits they may gain. Perceived economic benefit refers to the belief that using a particular technology will result in financial or resource–related advantages, such as cost savings, increased productivity, increased income, and community welfare improvement. This perception plays a critical role in shaping behavioural intentions toward technology adoption, especially in sectors where return on investment is a key consideration.

Our study revealed that the Benefit construct encompasses perceived improvements in employment opportunities, income generation, and price stability—factors that highly influenced the intention to build such a facility. The strong support from its indicators suggests that farmers view the establishment of processing plants, such as Pamigo, as a practical strategy for enhancing their economic resilience and market control. This finding aligns with research by Kule et al.[21] in Eastern Uganda, which showed that farmers who adopted Sustainable Agricultural Intensification Practices (SAIPs) had a more favourable perception of their benefits compared to non–adapters. Non–adopters often viewed these practices as risky and expensive, underscoring the critical role of perception in shaping adoption behaviour. The study highlighted that positive perceptions, along with access to extension services and proximity to markets, were key drivers of adoption.

Similarly, Meshesha et al.[19] found that favourable views on the benefits of climate-smart agriculture—particularly improved productivity—led to higher adoption rates in Ethiopia. Nyairo et al.[32] also emphasized that perceived economic advantages were central to their decision-making. However, even when farmers held positive views of these technologies, adoption was often limited by inadequate access to information and a lack of trust in extension agents. Furthermore, evidence from Tanzania indicated that local perceptions and sustainability concerns significantly influenced the scaling-up of fertilizers, improved seeds, and irrigation technologies[33].

In rural development, the adoption of technology is increasingly recognized as a catalyst for economic transformation, improved livelihoods, and sustainable growth. A critical factor influencing this adoption is the perceived economic benefit—the belief that using a particular technology will lead to tangible financial or productivity gains. This perception significantly shapes the intention of rural populations, particularly farmers and small-scale entrepreneurs, to embrace technological innovations.

Recent studies underscore that when rural users perceive clear economic advantages—such as increased crop yields, reduced production costs, or better market access—they are more likely to adopt agricultural technologies[34,35]. In Nigeria, Nnanna et al.[36] emphasized that technological interventions in rural areas—such as mobile platforms for market access or precision farming tools—are more readily adopted when communities understand their economic implications. However, the study also noted that adoption is moderated by factors such as infrastructure, education, and institutional support, which can either amplify or dampen the perceived benefits.

4.2. The Effect of Perceived Capital Constraint on Intention

Capital constraints are a major barrier to technology adoption in agriculture and rural development—not just due to actual financial limitations, but also perceived ones. Farmers may view new technologies as too costly or risky, even when subsidies or financing are available. These perceptions often stem from limited financial literacy, distrust in institutions, or uncertainty about returns, leading to risk-averse behavior.

Although quantitative analysis showed capital constraints didn't significantly affect intentions to build processing plants, qualitative data revealed it as a major concern. This highlights how risk attitudes shape adoption decisions. For example, Patil and Veettil [37] found risk-seeking farmers in India favored mechanization, while risk-averse ones preferred low-cost, stress-tolerant crops. Ahmed, Correa, and Sitko [38] emphasized that capital-intensive practices improve resilience and income, while labor-intensive strategies vary by context. Brewer and Featherstone [39] showed that while debt can reduce costs, it may also lower efficiency due to agency costs.

Access to finance is crucial for productivity and development, especially among marginalized rural populations. Yadav et al. [40] proposed a pro-poor subsidy model involving banks, suppliers, and the government to improve energy access. Formal savings boost investment and income, while broader financial inclusion and green finance enhance productivity [41,42]. Studies by Villalba, Venus, and Sauer [43], Adong et al. [44], and Maurya and Mohanty [45] highlight structural barriers in agricultural value chains and advocate for inclusive financial reforms.

4.3. The Effect of Economic Condition on Intention

The economic status of farmers, as measured by land ownership size, was not found to significantly influence their intention to establish processing plants at the farm level. This suggests that landholding size is not a critical determinant for participation in downstream agricultural industries. Consistent with this finding, Cho and Yoon [46] observed that technology adoption is often constrained by non-economic factors. Similarly, Ahmar et al. [47] identified socio-economic and infrastructural conditions as key drivers of renewable energy adoption, emphasizing its potential to alleviate rural energy poverty and enhance socio–economic outcomes.

Singhal et al. [48] demonstrated that marketing strategies, economic conditions, and adoption rates significantly shape the diffusion of digital services. Their model, which outperforms traditional diffusion frameworks, offers telecom operators actionable insights for improving service retention and optimizing market strategies. This underscores the importance of understanding user behavior and market dynamics in the digital transformation of emerging economies.

Further studies highlight the multifaceted nature of technology adoption in rural contexts. Dibbern et al. [49], through bibliometric analysis and case studies, identified economic conditions, technological infrastructure, farmer demographics (e.g., age and education), organizational type, and data privacy concerns as major factors influencing the adoption of digital agriculture technologies. They also noted a lack of standardized indicators for measuring adoption, calling for region-specific and socio-economically tailored policy interventions.

Luna-delRisco et al. [50] explored the socio-economic determinants of household adoption of biodigester systems in rural Colombia. Their analysis incorporated factors such as technology perception, training, investment costs, energy savings, and government incentives. Despite the clear benefits of biogas systems, adoption remains limited due to operational reliability issues, regulatory gaps, and insufficient technical capacity. The authors proposed an economic viability model linked to regional GDP to assess adoption potential and advocated for targeted government support in regions with abundant biomass and favorable economic conditions.

4.4. The Effect of Information Received on Intention

Access to timely, relevant, and context-specific information is widely recognized as a key enabler of agricultural and environmental technology adoption, particularly among smallholder farmers and rural households in developing regions. However, in our study, access to information regarding the palm oil downstream program did not significantly influence farmers' intention to adopt, suggesting that information alone may not be a decisive factor. This finding aligns with broader literature indicating that while information is a necessary condition for adoption, it is not sufficient in isolation. For instance, Moore et al. [51] found that weather and climate information services (WCIS) in Guatemala's Dry Corridor positively influenced the adoption of climate-resilient agricultural practices. Farmers who accessed WCIS were more likely to implement adaptive strategies and experienced reduced food insecurity. Nonetheless, financial and structural barriers—rather than informational deficits—were identified as the primary constraints to broader adoption, underscoring the need for complementary support systems. Similarly, Dibbern et al.[49] emphasized that adoption of digital agriculture technologies is shaped not only by access to technical knowledge but also by economic conditions and trust in technology.

In the energy sector, studies by Luna-delRisco et al.[50] and Ahmar et al.[47] demonstrated that awareness and understanding of biogas technology significantly influence household willingness to adopt. However, informed households may still refrain from adoption due to concerns about operational reliability, maintenance costs, and insufficient institutional support.

Collectively, these findings suggest that while access to information enhances awareness and intention, actual adoption depends on a broader constellation of socio-economic, infrastructural, and institutional factors. Effective interventions must therefore integrate information dissemination with financial incentives, capacity-building initiatives, and participatory approaches tailored to local contexts.

4.5. The Effect of Perceived Importance of Partnership on Intention

Partnerships play a pivotal role in facilitating the adoption of agricultural and environmental technologies, particularly in rural and resource-constrained contexts. Collaborative efforts among key stakeholders—including farmers, financial institutions, government agencies, technology providers, and development organizations—can help address barriers related to access, affordability, and technical capacity. However, findings from the structural equation modeling (SEM) analysis in our study indicate that farmers' perceptions of partnership importance did not significantly influence their intention to establish processing plants. This suggests that while partnerships may offer systemic benefits, they are not always perceived as directly relevant to individual decision-making at the farm level.

In contrast, Villalba et al.[43] underscore the critical role of multi-actor partnerships in sustaining credit systems for smallholder farmers. Their framework illustrates how collaboration among banks, agribusinesses, and development organizations can reduce transaction costs and mitigate market risks, thereby improving access to finance and enabling the adoption of climate-resilient practices. Similarly, Yadav et al.[40] propose a contractual partnership model to enhance the delivery of solar home system subsidies in rural India. By linking rural banks, suppliers, and government agencies, their approach ensures that financial support reaches below-poverty-line households, facilitating energy transitions that would otherwise remain inaccessible.

Moore et al.[51] highlight the value of participatory partnerships in the dissemination of weather and climate information services (WCIS) in Guatemala, demonstrating how inclusive engagement improves the relevance and uptake of adaptive agricultural practices. In the renewable energy sector, Ahmar et al.[47] and Luna-delRisco et al.[50] emphasize the importance of integrated partnerships involving households, technical experts, and local institutions. These collaborations support training, resource sharing, and infrastructure development, reducing dependency on subsidies and enhancing long-term sustainability.

Across these studies, a consistent theme emerges: partnerships are essential for bridging gaps between information, resources, and implementation. Whether through financial collaboration, participatory governance, or technical integration, partnerships serve as a foundational mechanism for enabling inclusive and effective technology adoption in rural development contexts.

4.6. The Effect of Farmer Profile on Intention

The initial hypothesis posited that farmers' demographic characteristics—specifically age and educational attainment—would significantly influence their intention to establish palm oil processing facilities. This assumption was grounded in the notion that younger and more educated individuals are generally more receptive to innovation, investment opportunities, and value-added agricultural ventures. Contrary to expectations, however, empirical analysis yielded no statistically significant relationship between these demographic variables and the intention to develop processing plants. This finding suggests that other determinants—such as financial capacity, access to markets, institutional support mechanisms, and perceived profitability—may exert a more substantial influence on farmers' decision-making processes in this context.

In related literature, Dibbern et al.[49] identify age and technical knowledge as salient demographic factors affecting the adoption of digital agricultural technologies. Their findings indicate that younger farmers are typically more inclined to embrace innovation and possess greater proficiency with digital tools, whereas older farmers may exhibit resistance due to unfamiliarity or skepticism. Similarly, Moore et al.[51] report a positive correlation between educational attainment and both access to weather and climate information services (WCIS) and the implementation of climate-resilient agricultural practices in Guatemala. Educated farmers are more likely to comprehend and act upon technical information, thereby enhancing their adaptive capacity in the face of climate variability.

Furthermore, Arranhado et al.[52] underscore the significance of gender-based disparities in education as a critical determinant of multidimensional poverty in Benin. These disparities indirectly constrain the adoption of agricultural technologies, particularly among women. Limited access to education and financial services among female farmers restricts their ability to engage with and benefit from innovative agricultural practices, thereby perpetuating cycles of poverty and technological exclusion.

4.7. The Effect of Farmer Profile on Readiness

The initial hypothesis posited that farmers' demographic characteristics—particularly age and educational attainment—would positively influence their readiness in terms of knowledge. It was assumed that older and more educated farmers would be better equipped to understand available resources. Contrary to this expectation, the empirical findings revealed a negative correlation between these demographic factors and readiness. Specifically, younger and less formally educated farmers reported greater perceived access to sufficient knowledge to establish palm oil processing facilities. This suggests that the knowledge required for such ventures is often acquired through informal channels rather than formal education, thereby diminishing the relevance of traditional educational attainment in this context.

This unexpected outcome can be attributed to several interrelated factors. Informal knowledge networks—such as peer-to-peer learning, community-based exchanges, and social media platforms—play a critical role in disseminating practical, context-specific information within agricultural communities. Younger farmers, in particular, are more likely to engage with these networks and demonstrate higher levels of digital literacy, enabling them to access agricultural advice, market information, and government programs through online platforms. These capabilities allow them to compensate for the lack of formal education and navigate support systems more effectively.

While previous studies have established that demographic variables such as age and education influence the adoption of agricultural innovations, the relationship is often complex and context-dependent. For instance, Rizzo et al.[53] found that although education and age can facilitate innovation adoption, other factors—such as perceived complexity and institutional support—are equally influential. Similarly, Burton[54] argued that demographic characteristics are frequently used to model farmers' environmental behavior, yet the causal relationships remain inconsistent due to cultural and generational dynamics. Ashraf and Qasim[55] further demonstrated that informal learning—such as knowledge transmitted through familial or community networks—can significantly enhance farmers' decision-making and income, particularly when technical agricultural education is limited.

Moreover, recent shifts in the outreach strategies of government and non-governmental organizations have prioritized youth and marginalized groups, often through simplified procedures and youth-oriented training programs. While these initiatives have improved access for younger farmers, they may inadvertently exclude older or more traditionally educated individuals who rely on formal institutions. Additionally, younger farmers often exhibit greater entrepreneurial orientation and risk tolerance, making them more inclined to pursue innovative ventures such as processing plant development. Importantly, the type of education also matters: while formal education may not directly equip farmers with the skills necessary for processing plant establishment, informal and vocational training often provides more relevant and applicable knowledge. Thus, in this context, readiness is shaped more by access to informal learning opportunities, digital tools, and targeted support mechanisms than by age or formal educational attainment.

4.8. The Effect of Readiness on Intention

Readiness in this study refers to a farmer's perceived knowledge, confidence, access to resources, and the availability of support systems. This sense of readiness mitigates perceived risks and enhances motivation to act. A systematic review by Rosário et al.[56] underscores the importance of sociopsychological factors—particularly perceived behavioral control, knowledge, and access to support systems—in influencing farmers' decisions to adopt sustainable agricultural innovations. These findings are consistent with the present study, which suggests that readiness is not solely determined by formal education or age, but rather by a farmer's perceived capacity and the enabling environment in which they operate.

Enhancing readiness through targeted policy interventions, capacity-building programs, and multi-stakeholder collaboration may therefore serve as a strategic lever to promote farmer-led processing initiatives. In the palm oil sector, smallholder farmers who perceive themselves as ready are demonstrably more inclined to invest in processing infrastructure. This is supported by findings from the World Bank and FSG[57], which highlight that access to training, extension services, and market linkages are critical enablers for smallholders to ascend the value chain—from raw material suppliers to processors.

Additionally, Yaseen et al.[17] found that younger farmers with access to training and extension services were more likely to adopt oil palm cultivation and expand into value-added activities. This suggests that readiness, particularly when supported by targeted training and institutional mechanisms, is closely associated with entrepreneurial behavior in the palm oil sector. Therefore, readiness should be conceptualized as a multidimensional construct shaped by experiential learning, institutional support, and by farmers' awareness of business sustainability, and long-term resource management—rather than being solely determined by demographic characteristics.

5. Conclusion

This study investigated the factors influencing smallholder farmers' intentions to establish palm oil processing plants in West Sumatra, Indonesia. Using a mixed-methods approach, the findings reveal that perceived economic benefits and farmer readiness are the most significant predictors of intention. In contrast, demographic characteristics (such as age and education), economic conditions (e.g., land size), and access to information or partnerships did not show a direct influence on intention. Notably, readiness was found to mediate the relationship between demographic profiles and intention, with younger and less formally educated farmers demonstrating higher perceived readiness.

These findings both align with prior studies (e.g., Rosário et al.[56]; World Bank and FSG[57]), and the results affirm that perceived benefits and support systems are critical to technology adoption and entrepreneurial behavior in agriculture. However, the lack of significance for demographic and economic variables contrasts with traditional assumptions that older or more educated farmers are more likely to adopt innovations. This divergence highlights the growing importance of informal learning, digital engagement, and targeted institutional support—especially among younger farmers who are more digitally literate and entrepreneurial.

Based on these insights, several recommendations emerge: (1) Strengthen farmer readiness through informal education, vocational training, and digital literacy programs tailored to local contexts; (2) Demonstrate economic value by showcasing successful farmer-led processing initiatives, conducting cost-benefit analyses, and facilitating peer-to-peer learning; (3) Promote inclusive support systems that engage women, youth, and marginalized groups, ensuring equitable access to resources and opportunities; (4) Address structural barriers by improving access to finance (e.g., microcredit, cooperative funding), simplifying licensing procedures, and streamlining regulatory frameworks to encourage local enterprise development. Encourage multistakeholder collaboration among government agencies, cooperatives, NGOs, and the private sector to provide integrated support for downstream development.

Ultimately, fostering farmer-led processing initiatives requires a shift from focusing solely on demographic or economic conditions to enhancing perceived benefits and readiness. This approach can contribute to more inclusive, sustainable, and resilient agricultural value chains.

Author Contributions

Conceptualization, H.H., M.N., R.F., and D.A.; methodology, H.H. and M.N.; investigation, H.H., M.N., R.F., and D.A.; writing—original draft preparation, H.H.; writing—review and editing, M.N., R.F., and D.A. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare that there is no conflict of interest.

References

[1] Hasnah, H., Azriani, Z., 2022. Analysis of the Impact of Palm Oil Trade Policy on Farmers' Welfare and the Rural Economy in West Sumatra. 4/UN. 16/MWA/PTN-BH/2021. Universitas Andalas: Padang, Indonesia. pp. 1–25. DOI: https://doi.org/10.13140/RG.2.2.26918.59204 (in Indonesian)

[2] Ajzen, I., 1991. The Theory of Planned Behavior. Organizational Behavior and Human Decision Processes. 50(2), 179–211. DOI: https://doi.org/10.1016/0749-5978(91)90020-T

[3] Davis, F.D., 1989. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly. 13(3), 319–340. DOI: https://doi.org/10.2307/249008

[4] Rogers, E.M., 2003. Diffusion of Innovation, 5th ed. The Free Press: New York, NY, USA.

[5] DFID, 1999. Sustainable Livelihoods Guidance Sheets. DFID: London, UK.

[6] Michie, S., van Stralen, M.M., West, R., 2011. The Behaviour Change Wheel: A New Method for Characterising and Designing Behaviour Change Interventions. Implementation Science. 6(1), 42. DOI: https://doi.org/10.1186/1748-5908-6-42

[7] Fishbein, M., Ajzen, I., 1975. Belief, Attitude, Intention, and Behavior: An Introduction to Theory and

Research. Addison-Wesley: Reading, MA, USA.

[8] Adesina, A.A., Zinnah, M.M., 1993. Technology Characteristics, Farmers' Perceptions and Adoption Decisions: A Tobit Model Application in Sierra Leone. Agricultural Economics. 9(4), 297–311. DOI: https://doi.org/10.1111/j.1574-0862.1993.tb00276.x

[9] Siyum, N., Giziew, A., Abebe, A., 2022. Factors Influencing Adoption of Improved Bread Wheat Technologies in Ethiopia: Empirical Evidence from Meket District. Heliyon. 8(2), e08876. DOI: https://doi.org/10.1016/j.heliyon.2022.e08876

[10] Case, S.D.C., Oelofse, M., Hou, Y., et al., 2017. Farmer Perceptions and Use of Organic Waste Products as Fertilisers – A Survey Study of Potential Benefits and Barriers. Agricultural Systems. 151, 84–95. DOI: https://doi.org/10.1016/j.agsy.2016.11.012

[11] Kiggundu, M., Kigozi, A., Walusimbi, K.H., et al., 2021. Farmers' Perception of Calf Housing and Factors Influencing Its Adoption on Dairy Cattle Farms in Uganda. Scientific African. 12, e00805. DOI: https://doi.org/10.1016/j.sciaf.2021.e00805

[12] Wang, G., Xu, M., 2025. Effect of Cooperative Membership on Farmers' Technology Adoption Based on the Mediating Effects of Technology Cognition. Heliyon. 11(2), e42130. DOI: https://doi.org/10.1016/j.heliyon.2025.e42130

[13] Nautwima, J.P., Obrenovic, B., Asa, A.R., et al., 2025. Determinants of Technology Adoption in Small and Medium-Sized Enterprises. Sustainable Futures. 10, 100919. DOI: https://doi.org/10.1016/j.sftr.2025.100919

[14] García, T.N., 2022. Farmers' Perceptions and Adoption of Coffea arabica F1 Hybrids in Central America. World Development Sustainability. 1, 100007. DOI: https://doi.org/10.1016/j.wds.2022.100007

[15] Zulfitriyana, Z., Syarfi, I.W., Hasnah, H., 2020. The Application of UPSUS PAJALE Program Technology on Rice. European Journal of Agriculture and Food Sciences. 2(3), 1–9. DOI: https://doi.org/10.24018/ejfood.2020.2.3.23

[16] Ramadan, E., Abdalla, S., Ahbabi, A.A., et al., 2025. Towards Sustainable Urban Agriculture in the Arid GCC States: Drivers of Technology Adoption Among Small-Scale Farmers. City and Environment Interactions. 28, 100222. DOI: https://doi.org/10.1016/j.cacint.2025.100222

[17] Yaseen, M., Thapa, N., Visetnoi, S., et al., 2023. Factors Determining the Farmers' Decision for Adoption and Non-Adoption of Oil Palm Cultivation in Northeast Thailand. Sustainability. 15(2), 1598. DOI: https://doi.org/10.3390/su15021595

[18] Sharna, S.C., Marasni, T., Pede, P.O., et al., 2025. How Farmers' Perceptions About Sustainable Soil Management Practices Affect Their Behaviour Towards Future Adoption of the Practices in Climate Hazardous Location? Soil & Tillage Research. 249, 1–18. DOI: https://doi.org/10.1016/j.still.2025.106482

[19] Meshesha, A.T., Birhanu, B.S., Ayele, M.B., 2022. Effects of Perceptions on Adoption of Climate-Smart Agriculture Innovations: Empirical Evidence From the Upper Blue Nile Highlands of Ethiopia. International Journal of Climate Change Strategies and Management. 14(3), 293–311. DOI: https://doi.org/10.1108/IJCCSM-04-2021-0035

[20] McCollum, C., Bergtold, J.S., Williams, J., et al., 2022. Perceived Benefit and Cost Perception Gaps Between Adopters and Non-Adopters of In-Field Conservation Practices of Agricultural Producers. Sustainability. 14(19), 11803. DOI: https://doi.org/10.3390/su141911803

[21] Kule, E.K., Obia, A., Agole, D., et al., 2025. Farmer Perceptions and Their Implications for Adoption of Sustainable Agricultural Intensification Practices. Discover Sustainability. 6(1), 45–62. DOI: https://doi.org/10.1007/s43621-025-00929-z

[22] BPS-Statistics Sumatra Barat Province, 2024. Sumatera Barat Province in Figures 2024. Available from: https://sumbar.bps.go.id/en/publication/2024/02/28/1b9d2796de6ef7fdcac6ae79/sumatera-barat-province-in-figures-2024.html (cited 16 June 2024).

[23] Hair, J.F., Ringle, C.M., Sarstedt, M., 2013. Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. Long Range Planning. 46(1–2), 1–12. DOI: https://doi.org/10.1016/j.lrp.2013.01.001

[24] BPS-Statistics Sumatera Barat Province, 2025. West Sumatra Province in Figures 2025. Available from: https://sumbar.bps.go.id/id/publication/2025/02/28/a757962d2ef9b6ce8943ed73/provinsi-sumatera-barat-dalam-angka-2025.html (cited 21 July 2025). (in Indonesian)

[25] Central Bureau of Statistics, 2023. Available from: https://sumbar.bps.go.id/id (cited 22 July 2025). (in Indonesian)

[26] West Sumatra Provincial Office of Plantation, Food Crops, and Horticulture, 2022. List of Land Use Rights Permits, Nucleus and Plasma Land Area, Factory Capacity, and Company Names of Private Plantation Companies and State-Owned Plantation Companies for Palm Oil, Cocoa, and Tea in West Sumatra Province in 2022 (unpublished data). West Sumatra Provincial Office of Plantation, Food Crops, and Horticulture: Padang, Indonesia. (in Indonesian)

[27] Senger, I., Borges, J.A.R., Machado, J.A.R., 2017. Using the Theory of Planned Behavior to Understand the Intention of Small Farmers in Diversify-

ing Their Agricultural Production. Journal of Rural Studies. 49, 32–40. DOI: https://doi.org/10.1016/j.jrurstud.2016.10.006

[28] Ajzen, I., 2019. Constructing a Theory of Planned Behaviour Questionnaire. Available from: https://www.researchgate.net/publication/235913732_Constructing_a_Theory_of_Planned_Behavior_Questionnaire (cited 21 July 2025).

[29] Meijer, S.S., Catautan, D., Ajayi, O.C., et al., 2014. The Role of Knowledge, Attitudes and Perceptions in the Uptake of Agricultural and Agroforestry Innovations Among Smallholder Farmers in Sub-Saharan Africa. International Journal of Agricultural Sustainability. 13(1), 40–54. DOI: https://doi.org/10.1080/14735903.2014.912493

[30] Mulyono, J., Suryana, A.T., Suryana, E.A., 2021. Perception and Innovativeness Level of Farmers on the Integration System of Rice and Cattle Farming. IOP Conference Series: Earth and Environmental Science. 892, 012026. DOI: https://doi.org/10.1088/1755-1315/892/1/012026

[31] Omara, H., Odongo, W., Kule, E.K., 2021. Adoption of Environmentally Friendly Agricultural Technologies Among Smallholder Farmers: The Case of Rocket Barn Technology in Flue-Cured Tobacco Curing in Uganda. Land Degradation & Development. 32(2), 965–974. DOI: https://doi.org/10.1002/ldr.3765

[32] Nyairoa, N.M., Pfeiffer, L., Spaulding, A., et al., 2022. Farmers' Attitudes and Perceptions of Adoption of Agricultural Innovations in Kenya: A Mixed Methods Analysis. Journal of Agriculture and Rural Development in the Tropics and Subtropics. 123(1), 147–160. DOI: https://doi.org/10.17170/kobra-202204216055

[33] Jha, S., Kaechele, H., Lana, M., et al., 2020. Exploring Farmers' Perceptions of Agricultural Technologies: A Case Study from Tanzania. Sustainability. 12(3), 998. DOI: https://doi.org/10.3390/su12030998

[34] Geng, W., Liu, L., Zhao, J., et al., 2024. Digital Technologies Adoption and Economic Benefits in Agriculture: A Mixed-Methods Approach. Sustainability. 16(11), 4431. DOI: https://doi.org/10.3390/su16114431

[35] Thompson, N.M., Bir, C., Widmar, D.A., et al., 2018. Farmer Perceptions of Precision Agriculture Technology Benefits. Journal of Agricultural and Applied Economics. 51(1), 142–163. DOI: https://doi.org/10.1017/aae.2018.27

[36] Nnanna, U.A., Abubakar, T.T., Mohammed, A.U., et al., 2025. The Role of Technology in Transforming Rural Social Systems: An Insightful Review. Journal of Nutrition and Food Processing. 8(1), 1–8. DOI: https://doi.org/10.31579/2637-8914/281

[37] Patil, V., Veettil, P.C., 2024. Farmers' Risk Attitude, Agricultural Technology Adoption and Impacts in Eastern India. Agriculture & Food Security. 13(1), 50. DOI: https://doi.org/10.1186/s40066-024-00497-x

[38] Ahmed, H., Correa, J.S., Sitko, N.J., 2025. Climate Adaptation, Perceived Resilience, and Household Wellbeing: Comparative Evidence from Kenya and Zambia. Ecological Economics. 235, 108611. DOI: https://doi.org/10.1016/j.ecolecon.2025.108611

[39] Brewer, B., Featherstone, A.M., 2017. Agency Cost of Debt: Evidence from Kansas Farm Operations. Agricultural Finance Review. 77(1), 111–124. DOI: https://doi.org/10.1108/AFR-03-2016-0023

[40] Yadav, P., Davies, P.J., Abdullah, S., 2018. Reforming Capital Subsidy Scheme to Finance Energy Transition for the Below Poverty Line Communities in Rural India. Energy for Sustainable Development. 45, 11–27. DOI: https://doi.org/10.1016/j.esd.2018.04.001

[41] Flory, J.A., 2018. Formal Finance and Informal Safety Nets of the Poor: Evidence from a Savings Field Experiment. Journal of Development Economics. 135, 517–533. DOI: https://doi.org/10.1016/j.jdeveco.2018.07.015

[42] Iddrisu, A.G., Donkor, G.N.A., Abor, J.Y., 2025. Green Finance, Financial Inclusion and Agricultural Productivity in Africa. Development and Sustainability in Economics and Finance. 7, 100060. DOI: https://doi.org/10.1016/j.dsef.2025.100060

[43] Villalba, R., Venus, T.E., Sauer, J., 2023. The Ecosystem Approach to Agricultural Value Chain Finance: A Framework for Rural Credit. World Development. 164, 106177. DOI: https://doi.org/10.1016/j.worlddev.2022.106177

[44] Adong, A., Ambler, K., Bloem, J.R., et al., 2025. The Unmet Financial Needs of Intermediary Firms within Agri-Food Value Chains in Uganda and Bangladesh. Food Policy. 132, 102838. DOI: https://doi.org/10.1016/j.foodpol.2025.102838

[45] Maurya, P., Mohanty, P.C., 2019. What Restricts Credit to Women Enterprises? Evidence from India's Informal Sector. International Journal of Social Economics. 46(7), 920–937. DOI: https://doi.org/10.1108/IJSE-08-2018-0422

[46] Cho, S., Yoon, H., 2025. Evaluating the Economic and Environmental Benefits of Rice–Soybean Diversification in South Korea. Agricultural Systems. 224, 104258. DOI: https://doi.org/10.1016/j.agsy.2024.104258

[47] Ahmar, M., Ali, F., He, C., et al., 2025. Understanding the Role of Socio-Economic, Demographic, Environmental, Infrastructural, and Institutional Attributes in the Uptake of Biogas Technology in Pakistan: Proposing and Implementing a Novel Step-Wise Framework. Energy Economics. 148, 108699.

DOI: https://doi.org/10.1016/j.eneco.2025.108699
[48] Singhal, S., Bano, Y., Singh, O., 2025. Investigating the Role of Customers' Disadoption and Dynamic Shifts in Mobile Cellular Diffusion: Evidence from Emerging Economies. Technological Forecasting and Social Change. 219, 124252. DOI: https://doi.org/10.1016/j.techfore.2025.124252
[49] Dibbern, T., Romani, L.A.S., Massruhá, S.M.F.S., 2024. Main Drivers and Barriers to the Adoption of Digital Agriculture Technologies. Smart Agricultural Technology. 8, 100459. DOI: https://doi.org/10.1016/j.atech.2024.100459
[50] Luna-del Risco, M., Gonzalez, C.A., Hernandez, S.M., et al., 2025. Evaluating the Socio-Economic Drivers of Household Adoption of Biodigester Systems for Domestic Energy in Rural Colombia. Sustainable Energy Technologies and Assessments. 73, 104146. DOI: https://doi.org/10.1016/j.seta.2024.104146
[51] Moore, M., List, G., Mauerman, M., et al., 2025. Assessing Disparities in Access, Use, and Potential Benefits of Weather and Climate Information Services Among Farmers in Guatemala's Dry Corridor. Climate Services. 38, 100573. DOI: https://doi.org/10.1016/j.cliser.2025.100573
[52] Arranhado, E., Barbosa, L., Bastos, J.A., 2025. Multidimensional Poverty in Benin. Socio-Economic Planning Sciences. 99, 102181. DOI: https://doi.org/10.1016/j.seps.2025.102181
[53] Rizzo, G., Migliore, G., Giorgio, S., et al., 2024. Key Factors Influencing Farmers' Adoption of Sustainable Innovations: A Systematic Literature Review and Research Agenda. Organic Agriculture. 14(1), 57–84. DOI: https://doi.org/10.1007/s13165-023-00440-7
[54] Burton, R.J.F., 2014. The Influence of Farmer Demographic Characteristics on Environmental Behaviour: A Review. Journal of Environmental Management. 135, 19–26. DOI: https://doi.org/10.1016/j.jenvman.2013.12.005
[55] Ashraf, M., Qasim, M., Gul, F., 2019. Impact of Education on Farmers' Earning: A Household Survey Data Analysis. International Research Journals. 10(1), 200–213.
[56] Rosário, J., Madureira, L., Marques, C., et al., 2022. Understanding Farmers' Adoption of Sustainable Agriculture Innovations: A Systematic Literature Review. Agronomy. 12(11), 2879. DOI: https://doi.org/10.3390/agronomy12112879
[57] FSG Social Impact Advisors, n.d. Improving the livelihoods of palm oil smallholders: The role of the private sector. Available from: https://www.fsg.org/resource/improving-livelihoods-palm-oil-smallholder/ (cited 24 July 2025).