Farmers' Strategic of the Sustainability of Corporate-Based Cassava Farming: A Study of Technology Adoption on Farming Performance

Nur Muttaqien Zuhri[1,*]*, Ali* Khamdi[1] , *Wahyu* Imam Santoso[1] , *Nun* Maulida Suci Ayomi[1] , *Nurul* Puspita[1] , *Suharti* Suharti[2] , *Edy* Purwanto[2] , *Agusnawan* Linu Ibrahim[3] , *Nurulia* Dimitha[3] and *M Danil* Furqansyah[3]

[1]Department of Agribusiness, Faculty of Economics and Business, Universitas Muhammadiyah Semarang, Indonesia

[2]Department of Management, Faculty of Economics and Business, Universitas Muhammadiyah Semarang, Indonesia

[3]Department of Agribusiness, Faculty of Economic, Universitas Muhammadiyah Aceh, Indonesia

Abstract. Technology adoption is crucial for agribusiness growth, enabling farmers to meet competitive market demands. Rural farmers need to adopt technology to improve their businesses and lives. This study aims to identify the most prominent factors that influence the adoption of corporate-based cassava farmer technology on farming performance. Using a quantitative method, the study was conducted in Puntukrejo Village, Karanganyar Regency, Indonesia. In this study, which included 65 respondents, structural equation modelling (SEM-PLS) based on WARP-PLS was used to identify the critical features that yield the best agricultural performance. The results showed that creativity, annual income, education, and land suitability affect technology adoption. The creativity variable had the most significant path coefficient, indicating that farmers' success will be significantly influenced by their level of creativity. The study suggests that enhancing land suitability, annual income, and education could significantly encourage the community to embrace technology for sustainable cassava farming.

1 Introduction

Developing Farmer Business Corporations is a comprehensive agricultural endeavor [1]. The initiative is an example of community empowerment to address food insecurity and reduce poverty [2]. The operation supports farmer groups by providing certified seeds, organic fertilizer, non-subsidized NPK fertilizer, herbicides, and technology. In summary, the farmers will utilize obvious tactics in distributing agricultural resources [3]. Even as farmers try to balance surplus and limited essential resources, such as labor, money, technology, and management, agriculture remains a highly diversified industry. Although some farmers may have a low school education, technology utilization has emerged as the most crucial aspect of agriculture [4,5]. It is predicted that innovative technologies will be

---

* Corresponding author: nurmuttaqien@unimus.ac.id

critical to economic success, and the use of these technologies by the agricultural sector will improve food security [6].

Farmers are the main actors receptive to technology [7], yet their role has yet to be fully used. It is a fact that actions related to cultivation methods are not the only factors that influence farmers' ability to achieve excellent farming performance [7,8]. However, the abilities, attitudes, knowledge, and skills farmers practice in managing their farm business also play a role [9,10]. Applying agricultural technology is critical to the success of market-focused enterprises [11].

Similarly, another viewpoint states that farmers' business development aims to enable them to develop their operations into modern and sustainable enterprises through cutting-edge technology [7,12,13]. Technology is critical to agribusiness growth, as farmers must master technology to meet the demands of a competitive market [2,14]. One of the strategic requirements for farmers running local resource-based micro-enterprises in rural areas is technology adoption [15]. Optimization of the technology adoption function is needed to intervene against globalization's impact on farmers' lives in rural areas. Technology adoption is expected to encourage behavior that leads to better business, better living, and better agriculture.

Although the adoption of cultivation technologies has been the subject of several studies, only a few have addressed adopting sustainable cultivation technologies for cassava. These studies have only identified economic aspects. This study's novelty is identifying factors that include social and economic characteristics. In addition, the samples used are farmers who are partners of the company in cassava cultivation. This study aims to examine the impact of the adoption of technology elements on farmers' views on sustainable corporate-based cassava farming. Adopting technology can increase current value and stimulate farmers' laborproductivity and inventiveness.

2 Research method

2.1 Respondents and Sampling

The study included sixty-five farmers who collaborated with a cassava plantation company. Non-probability sampling was utilized for this research. Surveys and interviews were conducted to gather primary data in November and December 2023. The research was conducted in Puntukrejo Village, Ngargoyoso District, Karanganyar Regency. This area is the leading producer of cassava and serves as a model for cultivation through corporate partnerships.

2.2 Data Analysis

The data analysis method utilized in this study was Partial Least Square via the WARP-PLS application [10,16]. The approach of analyzing data using Structural Equation Modeling, Partial Least Square (SEM-PLS), effectively establishes the relationships between specific parameters and farmers' adoption of new technologies. This study focuses on the performance of farming as the dependent variable (Y). It was influenced by various factors, represented by the independent variables examined for their potential impact. These variables were based on crucial farmer attributes, including creativity ($X1$), annual income ($X2$), education ($X3$), and land suitability ($X4$). Therefore, these attributes could influence farming performance and were included as independent variables in the analysis.

3 Results and Discussion

3.1 The Attributes of the Participants

In this study, 54.73% of the farmers were male and 45.27% were female. Most of them fall into the elderly category. The proportion of those above 55 years old is 33.51%, while the proportion of those between 46 and 55 years old is 28.15%. The third rank is occupied by the 36-45 age range, representing 25.27% of the total. Finally, 13.07% of farmers are aged between 26 and 35.

The education level of 33.87% of the participants was high school or vocational graduation, followed by junior high school graduates (30.14%), primary school graduates (27.3%), and those who never attended school or did not finish primary school (30.7%). These statistics show that most farmers have the primary education required to use technology.

3.2 Examining the Outer Model

3.2.1 Test of Validity

To assess the survey's legitimacy using SEM-PLS, it is necessary to determine if the markers satisfy the requirements for combined legitimacy in the unlikely event that the p-esteem is less than 0.001 and the stacking factor esteem is more than 0.5. When assessing legitimacy, the concurrent validity test can be established by using the Average Variance Extracted (AVE) after eliminating random fluctuations for each variable in the model. If the Average Variance Extracted (AVE) value, which indicates the variance captured by the construct, exceeds 0.50, the test is deemed significant. The outcomes of factor loading and indicator weights for both reflective and formative measurement models of each variable indicator can help assess the appropriateness of the initial outer model test. It is important to emphasize that a factor loading of 0.30 and a p-value of less than 0.001 in the reflective indicator model are crucial signs of acceptable validity. This is how validity tests are measured. The factor-loading findings are displayed in Table 1 below. Creativity ($X1$), annual Income ($X2$), education ($X3$), and land suitability ($X4$) are some of the factors included in the inner model.

Table 1. Combined Loading - Transverse Loading

	X.1	X.2	X.3	X.4	Y.1	Classify	P.value
X.1-1	.863	.308	.273	.007	-.173	Reflecting	< .001
X.1-2	.667	-.273	.982	-.178	-.126	Reflecting	< .001
X.1-3	.797	-.391	-.078	.163	-.063	Reflecting	< .001
X.1-4	.582	.388	-1.872	.052	.683	Reflecting	< .001
X.2-1	-.078	.872	-.075	-.470	.273	Reflecting	< .001
X.2-2	.098	.895	-.274	-.025	-.135	Reflecting	< .001
X.2-3	.017	.481	.498	.628	-.094	Reflecting	< .001
X.3-1	-.172	.193	.881	-.037	-.065	Reflecting	< .001
X.3-2	.152	-.188	.940	-.129	.172	Reflecting	< .001
X.3-3	-.088	-.044	.886	.352	-.048	Reflecting	< .001
X.4-1	-.038	-.204	.005	.908	.044	Reflecting	< .001
X.4-2	-.126	.295	-.694	.890	.027	Reflecting	< .001
X.4-3	.152	-.167	.473	.815	.006	Reflecting	< .001
Y.1-1	-.046	.076	-.083	-.078	.925	Reflecting	< .001
Y.1-2	.032	-.078	.031	.066	.892	Reflecting	< .001

The loading factor value for this study is 0.30 using the information in Table 1, which indicates that discriminant and convergent validity are met. The p-value of each indicator is less than 0.001, which suggests that all indicators fulfil the criteria and are considered genuine.

In the following discriminant validity test, the correlation coefficients of additional variables are compared with the square root value of the average variance extracted (AVE). In cases where the average variance of each study variable is more than 0.5, the discriminant validity test is observed. The AVE results, used to assess the survey's authenticity discriminantly, are presented next.

Table 2. Square Root of AVE Value

Var-AVE	X.1	X.2	X.3	X.4	Y
X.1	0.726	-0.273	-0.687	-0.482	0.192
X.2	-0.287	0.752	0.522	0.222	0.310
X.3	-0.619	0.528	0.892	0.591	0.445
X.4	-0.572	0.241	0.578	0.852	0.397
Y	0.216	0.377	0.420	0.408	0.946

In Table 2, it can be observed that the square root of the AVE value is higher than the correlation value with the other categories within the same column. If the value of AVE exceeds 0.5, it suggests that at least 50% of the variance of the measure can be sufficiently accounted for. This is a significant finding as it indicates that the condition for discriminant validity is met, which is a crucial aspect of our research model.

3.2.2 Reliability Test

The variables considered capable of explaining the data from these variables are tested using the composite reliability test. To demonstrate the stable nature of the survey used in this examination, the combined reliability and Cronbach Alpha values should be more than 0.7 and 0.6, respectively. The effects of Cronbach alpha and composite dependability are displayed in Table 3.

Table 3. Reliability Test

Var-Resbility Test	X-1	X-2	X-3	X-4	Y-1
Composite Reliability	0.855	0.831	0.985	0.901	0.841
Cronbach's Alpha	0.703	0.722	0.826	0.882	0.683

According to Table 3, the Alfa Cronbach value is over 0.6, and the composite reliability test results for all research variables are over 0.7. These results indicate that each research variable meets the reliability test requirements and can be considered a reliable basis for testing in the inner model.

3.3 Inner-Model Examination

3.3.1 The determination coefficient

The number of variations of endogenous variables that exogenous variables can explain is represented by the determination coefficient (R^2) value. R^2 values of 0.75, 0.50, or 0.25 for endogenous variables are generally considered good, medium, and bad models. Table 4 shows the determination coefficient.

R-square values interpret the influence of exogenous variables on latent variables. The R-square value for variable *Y* is 0.557 based on the information in Table 4. This figure
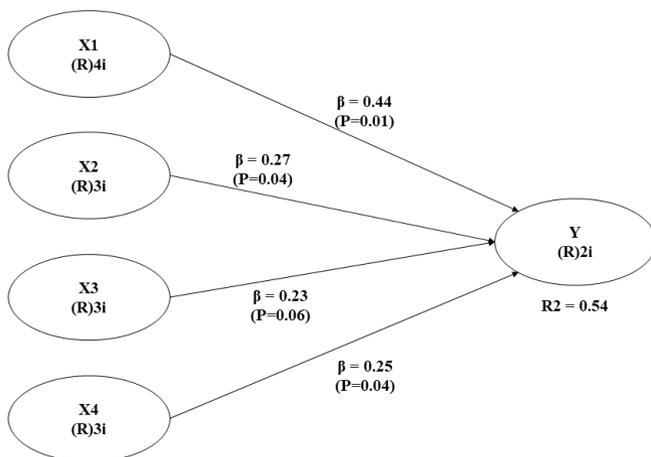
shows that creative factor variants in technology adoption account for 55.7% of *Y* variables. On the other hand, factors not included in the research model take the remaining portion into account. The R-square analysis of the *Y* variable in this study produced more than 0.557 findings, indicating a moderate R-square level.

Table 4. Determination coefficient

	X-1	X-2	X-3	Y-1
R-Square				.557
Adj-R. Square				.482

3.3.2 Path Coefficient

The relevance between variables that show a link between exogenous and endogenous factors is shown using path coefficients. If the value is less than 0.1, the route coefficient criteria indicate a weak association. A significant association exists if the path coefficient value is near 1.

Fig. 1. Path Coefficient

The route coefficient on all constructions positively and significantly influences the variable Y, as observed from the path coefficient in the Figure. 1. This is shown in the variable *X1*, which substantially affects farming performance (*Y1*) and has a path coefficient value of 0.44, indicating a substantial influence with a p-value of less than 0.001 (P<0.01). Thus, it is possible to conclude that 44% of initiative variables significantly impact and contribute to agricultural success.

3.3.3 Goodness of fit

Examples of fit models that can be used to evaluate Tenenhaus Goodness of Fit (GoF) include Sympson's Paradox Ratio (SPR), R-squared Contribution Ratio (RSCR), Statistical Suppression Ratio (SSR), Average Path Coefficient (APC), Average R-squared (ARS), Average Adjusted R-squared (AARS), Average VIF (AVIF), Average Full Collinearity VIF (AFVIF), and Nonlinear Bivariate Causality Direction Ratio (NLBCDR). The findings from the evaluation are presented in Table 5 to demonstrate their quality.

All conformance and quality index models satisfy the requirements, as Table 5 demonstrates. In summary, the inner model relationship (latent variable) is assumed to have a good goodness index.

Table 5. (GoF) Goodness of Fit Model

Model Similarity and Quality Index	Conformity Criteria	Result	Explanation
(SPR)	Accept if ≥ 0.7, ideal =1	1	Ideal
(NLBCDR)	Accept if ≥ 0.7	1	Acceptable
(AVIF)	Accept if ≤ 5, ideal ≤ 3.3	1.653	Ideal
(AFVIF)	Accept if ≤ 5, ideal ≤ 3.3	2.876	Ideal
(AARS)	($p < 0.05$)	0.488 P<0.001	Fulfilled
(RSCR)	Accept if ≥ 0.9, ideal = 1	1	Ideal
(APC)	($p < 0.05$)	0.258 P=0.010	Fulfilled
(GoF)	Small≥ 0.1, medium ≥ 0.25, large ≥ 0.36	0.876	Large
(SSR)	Accept if ≥ 0.7	1	Acceptable
(ARS)	($p < 0.05$)	0.582 P<0.001	Fulfilled

3.4 SEM-PLS Model

3.4.1 Model of Measurement

When transformed into an equation, the path diagram produces the following outcome.

Table 6. Model of Measurement

Variable Type	Variable	(Equation)
Exogenous	Creativity (X1)	$X10 = 0.787\xi_1 + \delta_1$
		$X11 = 0.647\xi_1 + \delta_2$
		$X12 = 0.795\xi_1 + \delta_3$
		$X13 = 0.582\xi_4 + \delta_4$
	Annual income (X2)	$X20 = 0.842\xi_2 + \delta_5$
		$X21 = 0.871\xi_2 + \delta_6$
		$X22 = 0.503\xi_2 + \delta_7$
	Education (X3)	$X30 = 0.862\xi_3 + \delta_8$
		$X31 = 0.914\xi_3 + \delta_9$
		$X32 = 0.844\xi_3 + \delta_{10}$
	Land Suitability (X4)	$X40 = 0.971\xi_4 + \delta_{11}$
		$X41 = 0.986\xi_4 + \delta_{12}$
		$X42 = 0.865\xi_4 + \delta_{13}$
Endogenous	Farming Performance (Y1)	$Y10 = 0.987\eta_1 + \varepsilon_1$
		$Y11 = 0,933\eta_1 + \varepsilon_2$

* δ: distribution over real numbers
   ξ: distributed random variable

3.4.2 Structural Model (Inner Model)

Assessing an inner model's effectiveness hinges on the R-Square value. This value plays a pivotal role in uncovering whether the external hidden variable exerts a substantial influence on the internal hidden variable. The equation provided below neatly encapsulates the R-squared values obtained from the three approaches.

$$\eta1= -0{,}41\xi1 + 0{,}24\xi2 + 0{,}21\ \xi3 + 0{,}23\ \xi4 + \zeta \qquad (1)$$

3.4.3 Hypothesis Test Result

This study's central hypothesis is to evaluate how adopting sustainable technologies affects farming performance. WarpPLS software programs are used to test this hypothesis. The hypothesis testing decision rule is used if a p-value of 0.10 is found. When the p-value is less than 0.05, it is considered statistically weak; when it is greater than 0.05, it is considered highly significant.

Table 7. Hypothesis Test Result

Hypothesis	Factor	Path-Coefficients	p-values	Result
H.1	(X-1) – (Y)	0.462	< 0.001	Received, highly significantly
H.2	(X-2) – (Y)	0.270	0.042	Received, significantly
H.3	(X-3) – (Y)	0.222	0.058	Received, significantly
H.4	(X-4) – (Y)	0.296	0.046	Received, significantly

Table 7's hypothesis testing results show that every variable substantially impacts company success. This is evident from the significance criteria, which state that a p-value of less than 0.1 (alpha 10%) indicates significance. This category shows the degree of correlation between variables. With a p-value of less than 0.001, creativity ($X1$) is the variable that significantly and positively affects farming performance. Its path coefficient is 0.462. Farmers who are creative in their approach will swiftly integrate widely accepted technology, which will also likely pave the way for future success. For instance, demonstrating innovation frequently entails modifying technology to boost output and seize chances others would pass over. Being proactive means making things happen instead of merely waiting to see what occurs, which is what creativity entails [11]. A further observation from the conversation is that corporate-oriented farms aim to maximize earnings in market-oriented cassava farming while boosting sustainable cassava output. Therefore, farmers that fall into these categories are seen to have higher incomes and present chances for company expansion. For these two reasons, this attribute is highly relevant to farming success, as most farmers are incredibly aware of their aims connected to sustainable agriculture.

In Puntukrejo village, corporate-based cassava farmers have used innovative technologies to address issues like biodiversity loss, soil erosion, and climate change and meet their customers' evolving demands and preferences. This may be exhibited by: 3. Investing in agricultural production; 4. Adopting and learning new technologies; and 5. They are adopting agriculture and marketing technology so the market can broadly embrace it.

Moreover, the factors that noticeably and significantly influence these outcomes are the suitability of the land ($X4$), which has a path coefficient of 0.296 and a p-value of 0.046, and annual income ($X2$), which has a path coefficient of 0.270 and a p-value of 0.042. In the agriculture industry, flexibility is crucial since income directly affects innovation, efficiency, and output. Considering how expensive agriculture is to run, it becomes natural that income significantly impacts prospects for technology adoption. Farmers who have worked hard to cultivate rough land would naturally be reluctant to accept new technology regarding land adaptability. Corporate mentoring can result in improved work results and a better bottom line. Group work is essential to the firm.

Meanwhile, additional factors with the highest p-value of 0.058 include education ($X3$), which has positive and significant path-coefficient of 0.222. Farmers often have to contend with distinct operational situations in these regions. Farmer access to, processing of, and use of information pertinent to technology adoption is enhanced by higher education levels. Agriculturalists can improve their farming performance sustainably by acquiring the

necessary skills via education [6]. A business cooperation method evaluated economically, socially, and environmentally with a favorable effect on farmers is corporation-based cassava farming in the study region. Applying technology in Cassava farming and marketing helps farmers grow their enterprises and maximize their potential for well-being.

4 Conclusion and recommendation

Creativity, annual income, education, and land appropriateness were factors that influenced the adoption of technology. Among the other factors, the creative variable had the most significant path coefficient, indicating that a farmer's success would be significantly influenced by their level of creativity. Furthermore, the annual income of farmers and the appropriateness of their land for cultivation may sustain or even enhance agricultural productivity. The level of education that farmers possess can also improve the performance of the farming industry, however not to a greater extent than other variables. Therefore, corporate efforts to promote farmer collaboration with farmer organizations and farmer self-awareness are required to increase the adoption of this technology for improved farming performance. The government's participation will considerably help farmers by offering marketing support and coaching to improve the efficiency of cassava growing.

References

1. E. F. P. Muñoz, P. A. Niederle, B. C. de Gennaro, and L. Roselli, Sustain. **13**, 1 (2021)
2. Y. Istaitih, S. Alsadi, A. Elrashidi, M. Kanan, A. Al-Sartawi, and J. Asad, Inf. Sci. Lett. **12**, 2241 (2023)
3. Y. Gao, D. Zhao, L. Yu, and H. Yang, J. Rural Stud. **76**, 173 (2020)
4. G. W. Norton and J. Alwang, Appl. Econ. Perspect. Policy **42**, 8 (2020)
5. R. Sun, S. Zhang, T. Wang, J. Hu, J. Ruan, and J. Ruan, Sustain. **13**, (2021)
6. S. Ruzzante, R. Labarta, and A. Bilton, World Dev. **146**, 105599 (2021)
7. S. B. Peles and D. Kerret, Clim. Dev. **13**, 922 (2021)
8. N. Ray, G. Clarke, and P. Waley, J. Rural Stud. **86**, 127 (2021)
9. K. Takahashi, R. Muraoka, and K. Otsuka, Agric. Econ. (United Kingdom) **51**, 31 (2020)
10. P. K. Sarma, M. J. Alam, and I. A. Begum, GM Crop. Food **13**, 327 (2022)
11. J. P. Chavas and C. Nauges, Appl. Econ. Perspect. Policy **42**, 42 (2020)
12. M. Kernecker, A. Knierim, A. Wurbs, T. Kraus, and F. Borges, Precis. Agric. **21**, 34 (2020)
13. M. Marie, F. Yirga, M. Haile, and F. Tquabo, Heliyon **6**, (2020)
14. I. Jan, Environ. Sci. Pollut. Res. **28**, 20690 (2021)
15. M. Han, R. Liu, H. Ma, K. Zhong, J. Wang, and Y. Xu, Agric. **12**, 1 (2022)
16. R. A. Z. Tama, M. M. Hoque, Y. Liu, M. J. Alam, and M. Yu, Agric. **13**, (2023)