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Indications of Factors Determining Corn Farmers' Behavior in Miomaffo Barat District, North Central Timor Regency, Indonesia

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Abstract. Corn farmers on the RI–RDTL border frequently face limited resources in developing their agricultural potential, despite continuous government efforts to provide support and facilitation. Addressing this issue requires an understanding of both internal and external factors related to farmers, innovative characteristics, the role of information media, and the involvement of extension workers. This study aims to examine the determinants influencing maize farmers' practices in West Miomaffo District, North Central Timor Regency. Data were collected through a survey of 161 corn growers and analyzed using Structural Equation Modeling with Partial Least Squares (SEM-PLS). The analysis revealed that communication efficacy and farmer-related external factors significantly influence behavioral changes, with critical ratio values exceeding the threshold (CR > 1.96). Conversely, internal farmer factors, innovation characteristics, and the role of extension workers did not have a significant effect on practice changes. These findings highlight that strengthening external support systems and improving communication strategies are more decisive for behavioral transformation among maize farmers in the border area than internal or innovation-driven factors.

Keywords: behavior; corn farmers; determining factors; indications

INTRODUCTION

Economic development in North Central Timor Regency still relies on the agricultural sector because ± 80% of the people of North Central Timor still work in agriculture (Taena et al., 2023), one more thing: out of twenty-one different kinds of businesses in North Central Timor Regency, the agriculture sector accounts for the most significant percentage at 40.23 percent of the regional gross domestic product (GRDP), followed by the government administration sector, defense, insurance (16, 63%), construction (9.97), and education services (7.06%), information and communication (5.59%), and wholesale and retail trade (5.56%). The GRDP of North Central Timor Regency in 2021 was 4222.69 billion rupiah (Badan Pusat Statistik (BPS, 2024).

The agricultural sector, particularly food crops, is currently one of the primary programs of the regional government aimed at accelerating economic growth (Sumartono, 2021). Corn is one of the food crops developed by the regional government as a superior regional product (Amir, 2022). BPS TTU data (2022) indicate that corn productivity in North Central Timor Regency, across 24 sub-districts, averages 2.3 tons/ha. This productivity level is significantly lower than the corn productivity of East Nusa Tenggara Province, which is 2.5 tons/ha, and nationally, in 2021, with an average of 5.5 tons/ha (BPS NTT, 2022).

The low productivity of corn farmers in the RI–RDTL border region, particularly in the West Miomaffo District, is influenced by several structural and contextual factors, including an unfavorable climate, limited financial capital, and suboptimal farm management practices. These challenges were further exacerbated by the Covid-19 pandemic, which intensified socioeconomic vulnerability and contributed to persistent poverty in the region. According to BPS, the poverty rate in TTU Regency reached 22.62 percent in 2021, equivalent to 58.33 thousand people, with a poverty line of IDR 394,818

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per capita per month (BPS NTT, 2022).

Previous studies have emphasized the role of empowerment programs in reducing rural poverty. Qu (2022) noted that rural empowerment initiatives share standard features, including village-based implementation, community group participation, access to agricultural and non-agricultural capital, and the establishment of microfinance institutions, often supported by extension workers and facilitators (Mulyani et al., 2024). Empirical evidence from Maulu et al. (2021) demonstrates that agricultural extension interventions have a significant impact on farmer group behavior, with a constant B value of 7.253 and an extension worker role coefficient (B = 0.165), indicating that stronger extension involvement enhances empowerment outcomes. Similarly, Antwi-Agyei & Stringer (2021) emphasized the importance of farmer communication in improving knowledge, skills, and farming practices.

Despite these insights, a limited understanding remains of the specific determinants shaping corn farmers' behavioral changes in the border areas of East Nusa Tenggara, where poverty rates are among the highest in Indonesia. Most prior studies have examined empowerment broadly, without sufficient attention to localized contexts characterized by geographical remoteness, climate adversity, and borderland vulnerabilities. Therefore, this study addresses this research gap by investigating the determining factors of corn farmer behavior in West Miomaffo District, North Central Timor Regency, using a structural modeling approach. The novelty of this research lies in its focus on a border district with unique socioeconomic challenges, combined with its methodological rigor in identifying behavioral determinants.

This study is significant as it provides evidence-based insights for policymakers and development practitioners to design targeted interventions that not only improve agricultural productivity but also contribute to poverty alleviation and regional development in one of Indonesia's most vulnerable border regions.

METHODS

Coverage

This study focuses on identifying the factors that support the empowerment of corn producers in the RI–RDTL border region. It specifically examines both internal and external factors that shape the practices and outcomes of corn growers in this unique geographic and socioeconomic setting.

Location

The research was conducted in six villages: Sallu, Noepesu, Fatuneno, Suanae, Fatunisuan, and Lemon, which are known for their food crops, horticulture, and livestock production. These villages are geographically located between 124°16'24.6"E and 124°19'01.2"E, and 9°30'06.3"S and 9°33'27.8"S, at an elevation of approximately 1,100 m above sea level, which provides favorable conditions for grain cultivation. The fieldwork was conducted from January to March 2023, involving interviews and observations with household heads who cultivate corn as their primary respondents.

Types of Data and Data Collection Techniques

Primary data were obtained through structured interviews and questionnaires, while secondary data were collected from the Central Statistics Agency (BPS), the Ministry of Agriculture, and the Department of Agriculture of NTT Province and TTU Regency. The total population consisted of 8,143 officially registered farmer group members in the e-RDKK system of North Central Timor Regency, with a specific focus on those cultivating corn.

The sampling followed the guidelines by Oliveira & Pirscoveanu (2021), which suggests that for large populations, a sample of 10–30 percent is sufficient to represent the population. Based on this, 161 farmers were selected using a purposive sampling approach. This method was deemed appropriate because it allowed the

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researchers to choose farmers deliberately who were consistently active in corn cultivation and farmer group activities, ensuring that the sample reflected the characteristics most relevant to the study's objectives. The rationale for the sample size was that it fell within the acceptable range for large populations, provided sufficient statistical power for Structural Equation Modeling (SEM), and remained manageable within the study's logistical and resource constraints.

Data analysis

This study employed a mixed-methods design, integrating the philosophical paradigms of positivism and post-positivism by combining quantitative and qualitative approaches (Creswell, 2017), Quantitative data were analyzed using Structural Equation Modeling (SEM) with Generalized Structured Component Analysis (GSCA) and SmartPLS software, which is suitable for both small samples (30–50) and larger samples (above 250) (Ghozali, 2020). Qualitative data from interviews and observations were analyzed descriptively to provide context and support for the quantitative findings. While this approach offers a more comprehensive understanding of the research problem, its limitation lies in the potential imbalance between the depth of qualitative insights and the breadth of quantitative generalizations. Additionally, integrating two forms of data requires careful alignment, which may pose challenges in interpretation.

Ethical Considerations

Ethical protocols were followed throughout the study. Participation was voluntary, and informed consent was obtained from all respondents prior to the interviews and questionnaire distribution. Farmers were assured of confidentiality, and their responses were anonymized to protect privacy. The research adhered to ethical guidelines for social science research, ensuring that respondents were not exposed to harm or coercion during data collection.

RESULTS AND DISCUSSION

Behavior Determining Factors Farmer J Agung in the District of West Miomaffo, North Central Timor Regency

A SEM-GSCA analysis of the variables impacting the actions of maize farmers in the Miomaffo Barat District, North Central Timor Regency. If the correlation between the two variables is linear, then the linearity test is appropriate. To test the linearity assumption, researchers use SPSS. If the test's significance result is lower than alpha (5%/0.05), we say that the two variables' correlation is linear. Table 1 presents the test results.

Table 1. Linearity test results

"Relationship Pattern ' Variables"				
Var. Exogen	-->	Var.Endogen	P-Value Linearity	Conclusion
Internal Factors of Farmers (X1)	-->	Farmer Behavior (Y2)	0.000	Linear
External Factors of Farmers (X2)	-->	Farmer Behavior (Y2)	0.000	Linear
Innovation Characteristics (X3)	-->	Farmer Behavior (Y2)	0.000	Linear
The Role of Information Media (X4)	-->	Farmer Behavior (Y2)	0.000	Linear
Role of Extension Workers (X5)	-->	Farmer Behavior (Y2)	0.000	Linear

Source: Processed Primary Data, 2022

The results of the linearity test, used to determine the suitability of the SEM-GSCA

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model, are shown in Table 1. According to the test results, every single causative variable has a significant impact on the effect variable. This demonstrates that the SEM-GSCA model is effective for this study. If the t-value of the factor loading is greater than or equal to 1.96and/or the standard factor loading is greater than or equal to 0.50. The variable in question has significant validity with respect to its construct or latent variable. Utilizing Construct Reliability (CR ≥ 0.70) and Average Variance Extracted (AVE ≥ 0.50), the reliability of the measuring model in GSCA can be evaluated. Using Confirmatory Factor Analysis (CFA), we move on to examine the measurement model. According to Table 2, all loading factor values and AVE values are valid, as they are all equal to or greater than 0.50. Additionally, reliability calculations have determined that all Cronbach's Alpha (α) values are ≥ 0.70, indicating high reliability. So, it's safe to assume that there are good indicators for all exogenous latent variables.

Table 2. Evaluation of the measurement model (outer model) variables exogenous

Latent Variables	Observed Variables	Partial Validity (Per-Indicator) (LF>0.5=Valid)		Rank	Overall Validity (Per-Construct) (AVE>0.5=Valid)		Cronbach Reliability (CR > 0.7)	
		Outer Loading	Note		AVE	Conclusion	CR	Note.
Internal Factors of Farmers (X1)	X1.1	0.838	Valid	1	0.629	Valid	0.877	Reliable
	X1.2	0.708	Valid	6				
	X1.3	0.729	Valid	5				
	X1.4	0.832	Valid	2				
	X1.5	0.824	Valid	3				
	X1.6	0.817	Valid	4				
External Factors of Farmers (X2)	X2.1	0.845	Valid	3	0.726	Valid	0.801	Reliable
	X2.2	0.850	Valid	2				
	X2.3	0.862	Valid	1				
Innovation Characteristics(X3)	X3.1	0.830	Valid	2	0.596	Valid	0.82	Reliable
	X3.2	0.815	Valid	3				
	X3.3	0.831	Valid	1				
	X3.4	0.691	Valid	4				
	X3.5	0.678	Valid	5				
The Role of Information Media (X4)	X4.1	0.885	Valid	1	0.727	Valid	0.874	Reliable
	X4.2	0.877	Valid	2				
	X4.3	0.779	Valid	4				
	X4.4	0.866	Valid	3				
Role of Extension Workers(X5)	X5.1	0.710	Valid	6	0.619	Valid	0.893	Reliable
	X5.2	0.679	Valid	7				
	X5.3	0.815	Valid	4				
	X5.4	0.743	Valid	5				
	X5.5	0.846	Valid	3				
	X5.6	0.847	Valid	2				
	X5.7	0.848	Valid	1				

Source: Processed Primary Data, 2022

To isolate the most critical factors that influenced the latent exogenous construct. With a maximum loading factor of 0.838, X1.1 (Age) is the best indication for the Internal Factor variable for Farmers (X1), which is X1. X2.3 (Access to capital) has the most significant factor loading of 0.862 and is thus the most critical indicator for the External Factor of Farmers (X2). X3.3 (Complexity) has the highest factor loading

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of 0.831 and is thus the most significant indicator for the Innovation Characteristics (X3) variable. X4.1 (Availability of information) has the most significant factor loading of 0.885 and is thus the most important indication for the Role of Information Media (X4) variable. With a factor loading of 0.848, X5.7 (Educator) stands out as the most significant indicator for the Role of Extension Workers (X5) variable.

According to the measurement model analysis, the method used is Confirmatory Factor Analysis (CFA), and the endogenous variables are listed in Table 3.

Table 3. Evaluation of the Measurement Model (Outer Model) endogenous variables

Latent Variables	Observed Variables	Partial Validity (Per Indicator) (LF > 0.5=Valid)		Rank	Overall Validity (Per Construct) (AVE > 0.5=Valid)		Cronbach Reliability (CR > 0.7)	
		Outer Loading	Note		AVE	Conclusion	CR	Description
Effectiveness (Y1)	Y1.1	0.747	Valid	5	0.658	Valid	0.895	Reliable
	Y1.2	0.785	Valid	4				
	Y1.3	0.841	Valid	3				
	Y1.4	0.893	Valid	1				
	Y1.5	0.876	Valid	2				
	Y1.6	0.708	Valid	6				
Farmer Behavior (Y2)	Y2.1	0.831	Valid	2	0.681	Valid	0.765	Reliable
	Y2.2	0.805	Valid	3				
	Y2.3	0.839	Valid	1				

All loading factors are valid (≥0.5), as indicated in the table, and the average variance extracted (AVE) is also valid (≥0.5), as stated in the table. Furthermore, all Cronbach's alpha values (CR) are ≥ 0.70, indicating dependability, according to the reliability calculations. It follows that there are suitable and practical indicators for each of these endogenous latent variables. Y1.4 (method) has a maximum factor loading of 0.893 and is thus the best indication for the Communication Effectiveness measure (Y1). With a factor loading of 0.839, Skills (Y2.3) is the most critical component in determining Farmer Behavior (Y2). After that, it is need to draw a route layout after analyzing the tracking data using measurement and structural model design. To determine the effect of every part. In ***Figure 1***, we can see the correlation between the structural model's coefficient path and the measurement model's specified weight factor of manifest variables.

There are several steps involved in the model testing process. The first step is to create structural models, and the second is to create a measurement model. Building a path diagram is the third step, and then turning it into equations is the fourth. Goodness-of-fit testing takes place in step six, while parameter estimation is the focus of stage five. Testing hypotheses is the last step. Step seven involves completing the tasks and ensuring the results are satisfactory enough to test the model. As shown in Table 4, the results of the Goodness of Fit model are reported.

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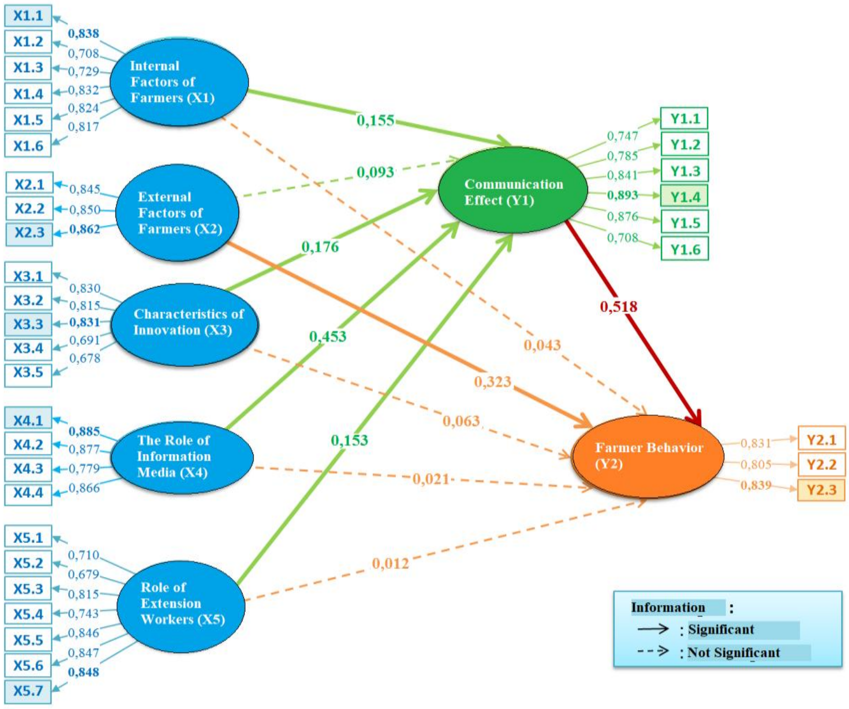

Figure 1. Influence between Structural Model Research Variables

The findings of the model compatibility assessment, also known as Goodness of Fit (GOF), were conducted to evaluate the overall degree of compatibility between the data and the model used. The compatibility test for the entire model pertains to the study of GOF statistics produced by the software, specifically GSCA. Utilizing the GOF size standards and GOF statistical results, a compatibility analysis can be conducted. The complete model is presented in Table 4.

Table 4. Goodness of Fit Index Results (Inner Model)

Goodness of fit index	Cut of Value	Results	Information
' FIT '	>0.500	0.585	Good fit model
' AFIT '	>0.500	0.578	Good fit model
' GFI '	>0.900	0.933	Good fit model
' SRMR.	<0.080	0.423	Marginal fit model

FIT is 0.585, indicating that the created model can account for all known variables with a magnitude up to 0.585. This suggests that the exogenous variable explains 58.5% of the variation, while the remaining 41.5% is due to other factors. Similarly, the AFIT score is 0.578, meaning that the model explains 57.8% of the variation, with the remaining 42.2% attributed to external factors. A Goodness of Fit Index (GFI) of 0.933 indicates a good fit, as values greater than or equal to 0.9 are considered adequate (Diamantopoulos, 2000, in Ghozali, 2005). However, the Standardized Root Mean Square Residual (SRMR) is 0.423, which exceeds the threshold of 0.08, suggesting that the model exhibits only a marginal fit. The Goodness of Fit Test, as described earlier, has shown that three of the four Model Accuracy Tests are suitable, or good fits. One possible interpretation of the results is that they provide a comprehensive structural

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framework, as illustrated in a Path Diagram, by integrating multiple connected theories; this framework might be considered either a novel scientific finding or a viable grand theory at present.

A causal relationship is being established through the testing of the hypothesis, which is currently underway. Almost nothing if at the 0.05 level of significance, the critical ratio (CR) value is between -1.96 and 1.96. The structural model's critical ratio and result estimation were both made easier by the GSCA program application. **Table 5** displays the calculated coefficients.

Table 5. Estimation and Testing Results of Variable Study

Influence between latent variables			Hypothesis	Path Coefficient	CR	p-value	Conclusion
Var. Exogen	-->	Var. Endogen					
Internal Factors of Farmers (X1)	-->	Farmer Behavior(Y2)	H 6	0.04	0.9	0.369	Not Significant
External Factors of Farmers (X2)	-->	Farmer Behavior(Y2)	H 7	0.32	3.61	0,000	Significant
Innovation Characteristics(X3)	-->	Farmer Behavior(Y2)	H 8	0.06	1.06	0.291	Not Significant
The Role of Information Media (X4)	-->	Farmer Behavior(Y2)	H 9	0.02	0.24	0.811	Not Significant
Role of Extension Workers(X5)	-->	Farmer Behavior(Y2)	H 10	0.01	0.17	0.865	Not Significant
Communication Effectiveness(Y1)	-->	Farmer Behavior(Y2)	H 11	0.51	5.86	0,000	Significant
R square Y1					0.91		
R square Y2					0.88		

* Significance at $\alpha = 0.05$

According to Table 5, farmer behavior is significantly influenced by effective communication (Y1) and external factors. Evaluating the hypothesis by comparing the mark coefficient track with the critical ratio, using the conditions of a vital ratio value exceeding 1.96 and a p-value below α 0.05. In general, a mathematical structural model equation is presented in Equation 1.

$$Y2 = 0.51*Y1 + 0.31*X2,\ R\ 2 = 0.88\ ...\ (1)$$

According to the equation above, the second variable in the behavioral model is 0.88. This indicates that the model accounts for 88% of the variance in the farmer's behavior, with the remaining 12% attributed to variables not included in the model.

A comprehensive explanation of each component that determines Effective Communication and Change Behavior in relation to Farmer Corn, supported by data from interviews and observations, further substantiates the explanation.

The results of the SEM-GSCA analysis reveal that only two variables exerted a significant direct effect on farmer behavior (Y2): External Farmer Factors (X2) (path coefficient = 0.323; CR = 3.61; $p < 0.001$) and Communication Effectiveness (Y1) (path coefficient = 0.518; CR = 5.86; $p < 0.001$). Other constructs, namely Internal Farmer Factors (X1), Innovation Characteristics (X3), Role of Information Media (X4), and Role of Extension Agents (X5), did not demonstrate statistically significant direct effects (CR < 1.96; $p > 0.05$). The measurement model satisfied reliability and validity requirements (outer loadings ≥ 0.50, AVE ≥ 0.50, CR ≥ 0.70). The structural

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model explained a substantial proportion of the variance (R^2 Y1 = 0.91; R^2 Y2 = 0.88). However, the global model fit presented mixed evidence, with a GFI of 0.933 (acceptable) but an SRMR of 0.423 (indicating residual misfit). These findings warrant cautious interpretation and suggest potential areas for model refinement.

Table 5 explains the factors that influence the real (significant) behavior of farmers (Y2) in farming corn in the District of West Miomaffo, East Timor Regency, North Central, which includes Effectiveness of Communication (Y1) and External Factors Affecting Farmers (X2). Testing hypothesis with compare mark coefficient track with CR value with criteria CR value > 1.96 at the level of significance 0.05. In mathematics, a structural model equation can be written as Equation 2.

$$Y2=0.51(Y1)+0.32(X2), R2=0.88 \ldots\ldots (2)$$

The Influence of Internal Factors on the Behavior of Farmer Corn in Miomaffo Barat District, North Central Timor Regency

Figure 1 and Table 5 present the results of the structural model analysis, which indicate that the internal factors of the farmers (X1) have a positive impact on their behavior (Y2). A CR value of 0.9 is associated with a path coefficient of 0.043. The H0 hypothesis is accepted since the CR value is smaller than the critical value (0.9 < 1.96), indicating that the Internal Farmer Factor variable (X1) has no significant impact on the Farmer Behavior variable (Y2). Findings. This is supported by Suh & Molua (2022), who found that the characteristics of individual cocoa farmers are related to their behavior in applying BP3T fertilizer technology within farmer groups in the Regency of Fifty Cities. There is no relationship at the 90% level. Generally, characteristics of farmers do not relate to the behavior of farmers in applying farming corn in the District West Miomaffo, North Central Timor Regency. According to Rigg et al., (2020) and (Mariyono et al., 2021) that characteristics farmers like age, level education, experience farming, and wide land no forever relate with adoption of innovation, but are supported by other factors such as social in groups and communities, and social status participate influence adoption an innovation (Coppock et al., 2022). Considering the internal aspects of farmers, such as age, formal education, non-formal education, agricultural experience, extensive land cultivation, and cosmopolitanism, there is no enduring connection with the conduct of farmers. Fundamentally, the application of technological packages constitutes an endeavor. maize in the District of West Miomaffo, North Central Timor Regency (Mariyono et al., 2021).

Influence of External Factors to the Behavior of Farmer Corn Plant Uses Based on Local Wisdom

Analysis of the results indicates that External Factor Variables for Farmers (X2) positively influence Farmer Behavior (Y2). With a CR value of 3.61 and a path coefficient of 0.323, it can be inferred that there is a correlation between an increase in the recognition of external factors (X2) and an improvement in farmer behavior (Y2). The hypothesis test rejects H0 because the CR value is greater than the threshold value (3.61 > 1.96), indicating that X2 is an external factor variable that has a considerable impact on Y2 in the context of farmers' behavior. Research results. This is supported by Jalil et al. (2021), who found that external factors influencing farmers are highly relevant to the role of farmers in the effort to prevent fires in peatland areas, which involves their involvement in farmer groups.

Influence Characteristics Innovation on Farmer Behavior in Miomaffo Barat District, North Central Timor Regency

Results show that X3, Characteristics Innovation, has a beneficial effect on Y2, Farmer Behavior. A CR value of 1.06 is associated with a direct path coefficient of

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0.063. Hypothesis 0 is accepted since the CR value is less than the important value (1.06 < 1.96), indicating that the variable Characteristics Innovation (X3) has an insignificant influence on the variable Behavior Farmers (Y2), according to the hypothesis statistics. In line with the results of Effendy et al. (2021) and Rizzo et al. (2024), innovative qualities are positively and significantly associated with farmers' behavioral changes regarding the deployment of Salibu rice technology in Tanah Datar Regency, West Sumatra. Farmers who consistently obtain the necessary information for their business will make more significant changes to their behavior.

The Influence of the Role of Information Media on Farmer Behavior in Miomaffo Barat District, North Central Timor Regency

The analysis of the structural model (Figure 1 and Table 5) demonstrates that the Role of Information Media (X4) positively influences Farmers' Behavior (Y2). The Path coefficient is 0.021, with a corresponding CR value of 0.24. Since the CR value is below the crucial threshold (0.24 < 1.96), the hypothesis test endorses the acceptance of H0, suggesting that the variable Role of Information Media (X4) has a minimal impact on the variable Behavior of Farmers (Y2). This is in line with the study's results (Wang & Zhang, 2023), which indicate that the characteristics of BP3T technology (Bacteria Rooting Driver Plant Growth) fertilizer pens relate to the real behavior of farmers. For applying the technology mentioned in the land of cocoa. Likewise, according to Skaalsveen et al. (2020) and Rizzo et al. (2024), the characteristics of innovation relate to the behavior of farmers in the adoption and implementation of innovations for sustainability.

Influence of the Role of Extension Workers to Farmer Behavior Corn in Miomaffo Barat District, North Central Timor Regency

The analysis of the structural model (Figure 1 and Table 5) reveals that the Role of Extension Workers (X5) positively influences Farmer Behavior (Y2), with a path coefficient of 0.012 and a CR value of 0.17. The CR value is smaller than the critical value (0.17 < 1.96), indicating that the null hypothesis (H0) is accepted, which signifies that the variable Role of Extension Workers (X5) has an insignificant influence on the variable Behavior of Farmers (Y2). Research results. This is compared to a backward study (Asprooth et al., 2023), which found that the role of extension workers in agriculture has a significantly influential impact on the behavior of farmers in Pekanbaru City.

Influence Effectiveness Communication to Behavior Farmer Corn in Miomaffo Barat District, North Central Timor Regency

Farming corn is a human need that can be met by utilizing completely new ideas and innovations, as well as available resources, where the decision is the best choice from the actions carried out by individual farmers planting corn previously. The CR value is 5.86, the path coefficient is 0.518, and the standardized beta coefficient is 0.298. Since 5.86 > 1.96 is greater than the critical value, the hypothesis statistics show that H0 is rejected, meaning that Y1, the variable for Effectiveness Communication, significantly affects Y2, the variable for Behavior of Farmer corn. Yue et al. (2023) stated that pattern communication, like direction communication, channels, methods, and targets effective communication, has a positive and significant influence on changing the behavior of barn members. The behavior in question related to the openness and participation of farmers in barn activities. Based on six indicator gauge effectiveness communication farming corn that is communicator (Y1.1), message (Y1.2), media/ channel (Y1.3), method (Y1.4), recipient (Y1.5), effect/impact (Y1.6), all have positive and real influence on forming variable behavior in farmers. The factor loading value for indicator method Y1.4 is the

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highest at 0.893. Consequently, if management aims to enhance the value of the Communication Effectiveness variable (Y1), the statistical advice is to prioritize the technique indication (Y1.4) for improvement. According to the study's results on the effectiveness of communication-related methods, counseling needs to be improved and enhanced to increase the likelihood of behavioral change among farmers in sustainable corn farming development (Wasono et al., 2024). Asprooth et al. (2023) state that farmers who have access to information, training, courses, internships, and counseling in real-world settings (such as demonstration plots or gardens) can increase their ability to change their behavior. Figure 1 and Table 5 illustrate that the internal factors of farmers, characteristics of innovation, the influence of information media, and the function of extension workers are significant. No direct and significant influence on the conduct of farmers cultivating corn in the West Miomaffo District, North Central East Timor Regency. All CR values are less than the critical value (CR < 1.96).

Determinants of Corn Farmer Behavior and Their Implications for Poverty Alleviation in Miomaffo Barat District

The productivity of corn farmers in North Central Timor Regency continues to face considerable challenges, primarily due to climate variability, limited access to financial capital, and suboptimal management of agricultural practices. These structural constraints have been further exacerbated by the socioeconomic disruptions caused by the COVID-19 pandemic, which collectively contribute to the persistence of poverty in rural areas of the region. According to BPS TTU (2022), the poverty rate in TTU Regency reached 22.62 percent in 2021, equivalent to 58.33 thousand individuals, with the poverty line recorded at 394,818 rupiah per capita per month (BPS NTT, 2022). Such figures underscore the severity of rural deprivation and the urgent need for effective interventions that directly address both agricultural productivity and household welfare.

Previous studies have emphasized the role of empowerment programs as critical instruments in poverty alleviation strategies in rural settings. Qu (2022) argues that empowerment initiatives are particularly effective because they share several common features, including a village-based approach, implementation through community groups, provision of agricultural and non-agricultural business capital, establishment of microfinance institutions at the village level, and continuous guidance by extension workers. Similarly, Mulyani et al. (2024) highlight that empowerment interventions grounded in local community structures have proven sustainable in addressing rural poverty. These insights suggest that structured empowerment efforts can significantly enhance the resilience of farming communities.

Empirical findings further reinforce the importance of extension services in farmer empowerment. Maulu et al. (2021) demonstrated that socio-economic empowerment of farmer groups through agricultural extension interventions leads to notable behavioral changes. Their analysis revealed a constant B value of 7.253, indicating that, in the absence of extension worker involvement, empowerment among farmer groups remains relatively limited. Conversely, the role of extension workers carries a B value of 0.165, signifying that every incremental increase in the effectiveness of extension activities contributes to a measurable improvement in empowerment outcomes. Complementing these findings, Antwi-Agyei & Stringer (2021) assert that strengthening farmer communication fosters not only improvements in knowledge and skills but also enhances farmers' ability to adopt more effective agricultural practices. These studies collectively highlight the critical role of social and institutional support in transforming farmer behavior.

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Despite this growing body of literature, research gaps remain in understanding the specific determinants of farmer behavior in localized contexts. While previous studies provide valuable evidence on the role of empowerment and extension services more broadly, few have explored these dynamics in districts such as Miomaffo Barat, which present unique climatic, economic, and sociocultural conditions. This contextual specificity is essential, as local variations may significantly shape both the constraints and opportunities for farmer empowerment. Addressing this gap, the present study aims to investigate the determinants of corn farmer behavior in Miomaffo Barat District, North Central Timor Regency, thereby contributing to both academic discourse and policy formulation.

The urgency of this study lies in its direct relevance to regional development and poverty alleviation strategies. Given that corn farming constitutes a primary livelihood for many households in North Central Timor, improving farmer behavior and decision-making processes has the potential to enhance productivity, strengthen household resilience, and reduce poverty incidence. Furthermore, by situating the analysis within the broader framework of empowerment and extension services, this study provides insights into how tailored interventions can be designed to address the specific needs of corn farmers in this district. The novelty of this research lies in its focus on the localized determinants of farmer behavior, offering an empirical contribution that bridges the gap between general empowerment theories and their practical application in a distinct regional setting.

Table 6. Indirect influence between latent variables

Indirect Influence	Calculation	Results	CR	p-value	Information
Internal Factors of Farmers (X1) towards Farmer Behavior (Y2) through Communication Effectiveness (Y1)	0.155 x 0.518	0.080	2,663	0.009	Significant
External Factors of Farmers (X2) on Farmer Behavior (Y2) through Communication Effectiveness (Y1)	0.093 x 0.518	0.048	1,471	0.143	Not Significant
Innovation Characteristics (X3) on Farmer Behavior (Y2) through Communication Effectiveness (Y1)	0.176 x 0.518	0.091	3,376	0.001	Significant
The Role of Information Media (X4) on Farmer Behavior (Y2) through Communication Effectiveness (Y1)	0.453 x 0.518	0.235	3,979	0,000	Significant
The Role of Extension Workers (X5) on Farmer Behavior (Y2) through Communication Effectiveness (Y1)	0.153 x 0.518	0.079	2,221	0.028	Significant

Source: Processed Primary Data, 2022

Based on the calculation, the influence of No direct between variables in Table 6 shows

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that the influence of the No direct Internal Farmer Factor variable (X1) on Behavior Farmers (Y2) through Effectiveness Communication (Y1) is as large as 0.080 with a t-statistic of 2.663 (significant). The influence of No Direct External Factors (X2) on the Behavior of Farmers (Y2) through Effective Communication (Y1) is as big as 0.048 with a t-statistic of 1.471 (not significant). Influence of No direct Characteristics Innovation (X3) towards Behavior Farmers (Y2) through Effectiveness Communication (Y1) is as big as 0.091 with a t-statistic of 3.376 (significant). The influence of No Direct Role of Information Media (X4) on Behavior of Farmers (Y2) through Effectiveness of Communication (Y1) is as large as 0.235 with a t-statistic of 3.979 (significant). The influence of No Direct Role of Extension Workers (X5) on Behavior of Farmers (Y2) through Effective Communication (Y1) is as large as 0.079 with a t-statistic of 2.221 (significant).

Thus, it can be explained that Information Media Role Variables have the greatest influence on variable Behavior Farmer through effective communication in farming corn. The next influence is characteristics innovation, which encompasses internal factors of farmers, the role of extension workers, and external factors affecting farmers.

CONCLUSION

The study concludes that the behavior of maize farmers in Miomaffo Barat District, North Central Timor Regency, is significantly influenced by both individual and contextual factors. Among these, external factors such as access to capital and institutional support, as well as the effectiveness of communication, play a dominant role in shaping farmers' behavioral responses to innovation and agricultural practices. These findings confirm that internal characteristics do not solely determine farmer behavior but are also shaped by the interaction between external conditions, communication effectiveness, and institutional mechanisms that facilitate information exchange and learning processes.

Future research is recommended to expand this analysis through comparative studies across various districts or provinces to evaluate whether similar behavioral determinants persist under different socio-economic and agro-ecological conditions. Longitudinal and mixed-method approaches, such as participatory or qualitative inquiry, would also be valuable in capturing the dynamic evolution of farmer behavior and providing deeper insights into motivational and perceptual factors underlying behavioral change in rural agricultural settings.

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