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# Determinants of Lowland Rice Farmers' Behavior in Food-Insecure Areas in East Nusa Tenggara, Indonesia: A COM-B Model Approach

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**Abstract:** Food security is a critical challenge, especially in regions with environmental and socio-economic constraints. In Indonesia's East Nusa Tenggara (NTT), low agricultural productivity and limited infrastructure hinder food security. This study examines the determinants of farmer behavior in food-insecure regions using the COM-B Model (Capability, Opportunity, Motivation, and Behavior) and a Higher-Order Formative SEM approach. This study evaluates the contributions of agricultural technology (AT), government input support (GIS), agricultural infrastructure (AI), agricultural extension (AE), and farmer groups (FGs) to farmer behavior formation. Data from 202 rice farmers in Kecamatan Lewa, East Sumba show that agricultural infrastructure (AI) and farmer groups (FG) are the strongest contributors, highlighting the importance of physical infrastructure and institutional support. Government input support (GIS) and agricultural extension (AE) also play key roles in improving access to resources, while agricultural technology (AT) has a positive but dependent impact on complementary support systems. This study makes three key contributions: applying the COM-B Model in an agricultural context, integrating five stimulus factors to assess their combined impact, and providing empirical evidence for policy

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Integration-based interventions. The findings offer practical recommendations for improving agricultural sustainability and food security through infrastructure investment, farmer group development, and capacity-building programs. Future research should explore longitudinal studies to assess the lasting effects of these interventions and compare findings across diverse agro-ecological regions to refine policy strategies.

**Keywords:** farmer behavior, COM-B model, agricultural technology, government input support, agricultural infrastructure, agricultural extension, farmer institutions, sustainable farming, food-insecure areas, formative SEM.

# 印度尼西亚东努沙登加拉省粮食不安全地区低地稻农行为的决定因素：COM-B 模型方法

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**摘要:** 粮食安全是一项重大挑战，尤其是在环境和社会经济受到制约的地区。在印度尼西亚的东努沙登加拉省 (NTT)，农业生产力低下和基础设施有限阻碍了粮食安全。本研究使用 COM-B 模型（能力、机会、动机和行为）和高阶形成性 SEM 方法研究了粮食不安全地区农民行为的决定因素。本研究评估了农业技术 (AT)、政府投入支持 (GIS)、农业基础设施 (AI)、农业推广 (AE) 和农民团体 (FG) 对农民行为形成的贡献。来自东松巴省 Kecamatan Lewa 的 202 名稻农的数据显示，农业基础设施 (AI) 和农民团体 (FG) 是最强大的贡献者，突出了物质基础设施和机构支持的重要性。政府投入支持 (GIS) 和农业推广 (AE) 在改善资源获取方面也发挥着关键作用，而农业技术 (AT) 对互补支持系统具有积极但依赖的影响。本研究做出了三个关键贡献：在农业背景下应用 COM-B 模型，整合五个刺激因素以评估其综合影响，并为基于政策整合的干预措施提供实证证据。研究结果为通过基础设施投资、农民团体发展和能力建设计划改善农业可持续性和粮食安全提供了实用建议。未来的研究应探索纵向研究以评估这些干预措施的持久影响，并比较不同农业生态区域的调查结果以完善政策战略。

**关键词:** 农民行为、COM-B 模型、农业技术、政府投入支持、农业基础设施、农业推广、农民机构、可持续农业、粮食不安全地区、形成性 SEM。

## 1. Introduction

Waste Food security remains a critical global challenge, particularly in regions with limited resources and significant environmental constraints on agricultural productivity. In Indonesia, a country with a growing population and diverse agricultural landscapes, food security is a pressing concern, especially in remote areas such as East Nusa Tenggara (NTT). This region faces serious challenges, including low agricultural productivity, inadequate infrastructure, and socio-economic limitations. Therefore, integrated interventions are required to promote more sustainable agricultural practices and enhance food security.

The agricultural sector in East Nusa Tenggara (NTT), particularly in rice farming, is shaped by multiple external factors, including agricultural technology, infrastructure, agricultural extension, farmer groups, and government support. Modern technologies, such as drought-resistant high-yield seeds, play a critical role in stabilizing crop yields in semi-arid regions [1,2]. In addition, agricultural mechanization, including tractors and harvesting machines, has been instrumental in improving farming efficiency by reducing manual labor requirements and minimizing post-harvest losses [3,4]. However, infrastructure limitations, such as restricted access to irrigation systems and poor transportation networks, continue to hinder the development of this sector [5,6].

Agricultural extension (AE) plays a vital role in enhancing farmers' knowledge of sustainable practices, yet it often faces resource shortages and inadequate training for extension workers [7,8]. Farmer groups (FG) contribute to strengthening collaboration among farmers, facilitating knowledge-sharing, and improving access to agricultural inputs and markets [9]. Meanwhile, government support, including subsidies, infrastructure development, and policies promoting sustainability, plays a crucial role. However, its effectiveness is often limited by bureaucratic inefficiencies and implementation challenges [10].

Given these factors, farmer behavior emerges as a key determinant of agricultural sector success. Farmer behavior is not solely influenced by internal characteristics such as knowledge and motivation but is also shaped by external factors, including agricultural technology, government support, infrastructure, agricultural extension, and farmer groups. A comprehensive understanding of farmer behavior is essential for designing effective interventions to enhance farm productivity and sustainability, particularly in food-insecure areas such as Kecamatan Lewa, East Sumba Regency, and East Nusa Tenggara (NTT).

This study applies the COM-B Model (Capability, Opportunity, Motivation, and Behavior) to analyze the formation of farmer behavior in response to agricultural stimuli. Farmers' capabilities, including their knowledge and technical skills, are fundamental in adopting new technologies, such as drought-resistant varieties, which have been proven to enhance food security in environmentally vulnerable areas [12]. Opportunities, encompassing access to irrigation, resources, and institutional support, create an enabling environment for sustainable agricultural practices [11]. Meanwhile, farmers' motivation, influenced by socio-cultural norms and economic incentives, drives the adoption of innovations, including farmer group participation and crop diversification to improve food security [14].

Despite the significant food security challenges in East Nusa Tenggara (NTT), limited research has been conducted to examine how external factors collectively shape farmer behavior using a formative measurement model. Kecamatan Lewa, located in East Sumba Regency, experiences food insecurity due to inadequate infrastructure, limited technological access, and suboptimal institutional and government interventions. Understanding how farmers respond to agricultural stimuli, including technology adoption, input subsidies, agricultural extension, and farmer group participation, is critical for developing targeted strategies to enhance farm productivity, improve farm performance, and support agricultural sustainability.

By employing the COM-B Model (Capability, Opportunity, Motivation, and Behavior) in a Higher-Order Formative SEM approach, this study aims to analyze how multiple external determinants collectively shape farmer behavior in food-insecure areas. The findings are expected to provide valuable contributions to the academic literature and offer practical policy recommendations for stakeholders to enhance agricultural sustainability in similar regions.

Previous studies have analyzed agricultural technology adoption and government support in improving farmer resilience [22,24]. However, limited research has employed the COM-B Model in food-insecure agricultural contexts. This study addresses this gap by integrating multiple agricultural determinants into a Higher-Order Formative SEM model to empirically assess how external interventions shape farmer behavior in resource-constrained environments.

Based on the discussion above, farmer behavior in response to agricultural stimuli is structured by various external factors, including technology, government support, infrastructure, agricultural extension, and farmer groups. This study seeks to empirically examine how these factors contribute to the formation of farmer behavior using a formative measurement model within the COM-B framework. Accordingly, the following hypotheses were developed to test the relationships among these variables:

H1: Agricultural technology (AT) contributes significantly to the formation of farmer behavior (FB).

H2: Government input support (GIS) contributes significantly to the formation of farmer behavior (FB).

H3: Agricultural infrastructure (AI) contributes significantly to the formation of farmer behavior (FB).

H4: Agricultural extension (AE) contributes significantly to the formation of farmer behavior (FB).

H5: Farmer groups (FG) contribute significantly to the formation of farmer behavior (FB).

# 2. Materials and Methods

### 2.1 Study Area and Sampling

This study was conducted in two villages, Kambuhapang and Tanarara, located in Kecamatan Lewa, East Sumba Regency, East Nusa Tenggara Province, Indonesia. These villages were purposively selected because of their significance as key rice-producing areas within the food-insecure region of Kecamatan Lewa. The total agricultural land in these villages consists of 594 hectares of irrigated rice fields and 901 hectares of rainfed rice fields.

The research was conducted between August and November 2024, involving a total population of 408 rice farmers. The sample size was determined using Slovin's formula, resulting in a sample of 202 farmers. To ensure representative sampling, the distribution of respondents across the two villages was carried out through proportional random sampling, considering the number of farmers in each village.

### 2.2 Research Design and Data Collection

This study employed a quantitative research approach using structured questionnaires to collect primary data. The questionnaire was designed to assess farmer behavior in response to agricultural stimuli, focusing on key determinants such as agricultural technology, government support, infrastructure, agricultural extension, and farmer groups, as conceptualized in the COM-B Model.

Secondary data were obtained from relevant sources, including: Government reports from the East Sumba Regency Agriculture Office, Institutional records from the Agricultural, Fisheries, and Forestry Extension Center, Statistical data from the Central Statistics Agency (BPS), academic literature, and published research articles related to agricultural sustainability and food security.

To ensure the validity and reliability of the questionnaire, a pre-test was conducted with a subset of 20 farmers before full-scale data collection. Based on the feedback, minor adjustments were made to improve clarity and relevance.

### 2.3 Research Framework and Methodological Steps

The research followed a systematic methodology, as visually represented in Figure 1. The methodological framework consists of the following key stages:

1. Problem Identification & Research Justification. Defining the research problem based on food security issues in Kecamatan Lewa.
2. Hypothesis Development. developing hypotheses based on the COM-B Model framework.
3. Research Design & Sampling. Select the study area and determine the sample size using Slovin's formula.
4. Data Collection. Conduct structured interviews with selected farmers and obtain secondary data from relevant institutions.
5. Data Processing & Analysis. Using Partial Least Squares-Structural Equation Modeling (PLS-SEM) to analyze the relationships among the study variables in a Higher-Order Formative Model.
6. Results Interpretation. Discussing findings in relation to previous studies and theoretical implications.
7. Conclusions and Policy Recommendations. Providing practical insights for improving agricultural sustainability in food-insecure areas.

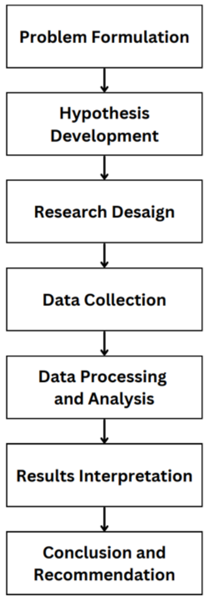


Fig. 1 Research process framework. Source: created by the authors

The methodological framework is illustrated in

Figure 1, providing a step-by-step visualization of the research process. Each stage was carefully structured to ensure the validity, reliability, and robustness of the findings.

Data analysis was conducted using the Structural Equation Modeling-Partial Least Squares (SEM-PLS) method with SmartPLS software. This approach was employed to assess the formative relationships between the exogenous and endogenous variables within a Higher-Order Formative Model framework.

In this study, the endogenous variable was farmer behavior, which was structured on the basis of the COM-B Model components: Capability, Opportunity, and Motivation. The exogenous variables included agricultural technology, agricultural input support, agricultural infrastructure, agricultural extension, and farmer groups, which collectively contributed to the formation of farmer behavior.

Each determinant is measured using multiple indicators that capture the extent to which these factors contribute to shaping farmers' capabilities, opportunities, and motivation in adopting sustainable agricultural practices. The relationships among these variables are illustrated in Fig. 2, which presents the structural model used in this study. The model conceptualizes farmer behavior as a higher-order construct, with external agricultural stimuli acting as formative indicators.

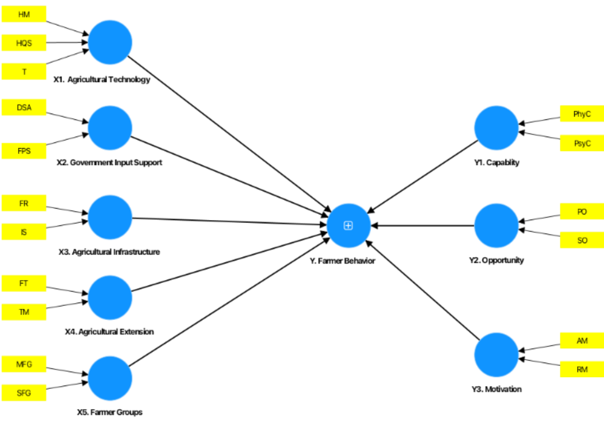


Fig. 2 Higher-Order Formative Structural Model of Farmer Behavior in Food-Insecure Regions. Source: created by the authors

Figure 2 provides an overview of the latent constructs and their respective indicators, serving as the basis for hypothesis testing using Partial Least Squares-Structural Equation Modeling (PLS-SEM).

To validate the formative measurement model, the analysis included: Multicollinearity assessment (Variance Inflation Factor - VIF) to ensure that the indicators were not highly correlated. Weight significance testing to determine the relative contribution of each exogenous variable to the endogenous construct. Path coefficient analysis to examine the structural relationships between the variables.

The SEM-PLS model was used because of its suitability for complex models with hierarchical constructs and small-to-moderate sample sizes. This method enabled a comprehensive examination of the structural relationships among the agricultural determinants of farmer behavior in food-insecure areas.

# 3. Results

## 3.1 Outer Model Evaluation (Formative Model Approach)

This study employs a Higher-Order Formative SEM approach, where the outer model is evaluated at two levels: First-order constructs, which include individual indicators contributing to their respective latent variables. Second-order constructs, where first-order latent variables form the higher-order construct (Farmer Behavior).

Since the model follows a formative approach, its validity is assessed through multicollinearity (VIF), indicator weights, and bootstrapping significance rather than traditional reflective measures such as Average Variance Extracted (AVE) or Cronbach's Alpha.

### 3.1.1 First-Order Outer Model Evaluation

The first-order constructs in this study include: AT, GIS, AI, AE, FG, C, O, and M. Each of these constructs is formed by multiple indicators that uniquely contribute to defining them. The following assessments were performed to evaluate the first-order outer model.

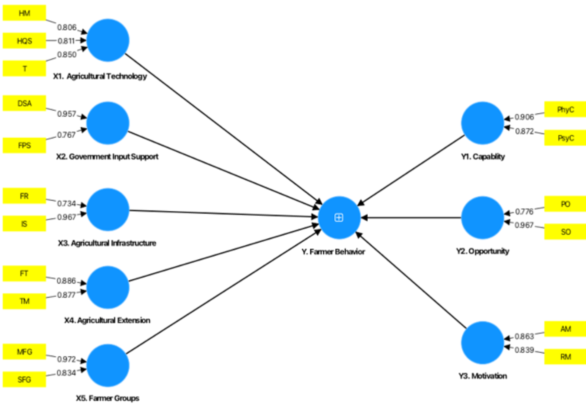


Fig. 3 First-order outer model evaluation in the formative measurement model. Source: created by the authors

### 3.1.2. Multicollinearity Assessment (VIF) – First-Order Constructs

Multicollinearity was assessed using the variance inflation factor (VIF) to determine whether the indicators within each construct were highly correlated. A VIF value below 5 indicates an acceptable level of collinearity

**Tab. 1 VIF values (Processed research data, 2025)**

| First-Order Construct | Indicator | VIF |
|---|---|---|
| AT | High-Quality Seeds (HQS) | 1.545 |
| | Tractors (T) | 1.522 |
| | Harvesting Machines (HM) | 1.560 |
| GIS | Fertilizers and Pesticides Subsidy (FPS) | 1.427 |
| | Direct Seed Assistance (DSA) | 1.427 |
| AI | Farm Roads (FR) | 1.403 |
| | Irrigation Systems (IS) | 1.403 |
| AE | Frequency of Training (FT) | 1.442 |
| | Training Materials (TM) | 1.442 |
| FG | Membership in Farmer Groups (MFG) | 1.871 |
| | Support from Farmer Groups (SFG) | 1.871 |
| C | Physical Capability (PhyC) | 1.515 |
| | Psychological Capability (PsyC) | 1.515 |
| O | Physical Opportunity (PO) | 1.535 |
| | Social Opportunity (SO) | 1.535 |
| M | Reflective Motivation (RM) | 1.589 |
| | Automatic Motivation (AM) | 1.787 |

The outer model evaluation includes three key assessments: Outer Loadings: measures how strongly each indicator is associated with its construct. Outer Weights: indicates the relative contribution of each indicator within its construct.

T-Values and P-Values: assess the statistical significance of each indicator within the model.

Table 2 presents the outer model results for the first-order constructs, showing that all indicators significantly contribute to their respective constructs.

**Tab. 2 Outer loadings, outer weights, and significance testing for first-order constructs (Processed research data, 2025)**

| First-Order Construct | Indic-ator | Outer Loading | Outer Weight | T-Value | P-Value |
|---|---|---|---|---|---|
| AT | HQS | 0.811 | 0.379 | 6.098 | 0.000 |
| | T | 0.850 | 0.456 | 5.537 | 0.000 |
| | HM | 0.806 | 0.378 | 4.809 | 0.000 |
| GIS | FPS | 0.767 | 0.347 | 4.463 | 0.000 |
| | DSA | 0.957 | 0.767 | 12.520 | 0.000 |
| AI | FR | 0.734 | 0.303 | 6.818 | 0.000 |
| | IS | 0.967 | 0.804 | 23.812 | 0.000 |
| AE | FT | 0.877 | 0.578 | 8.151 | 0.000 |
| | TM | 0.886 | 0.558 | 8.497 | 0.000 |
| FG | MFG | 0.972 | 0.754 | 12.307 | 0.000 |
| | SFG | 0.834 | 0.320 | 4.490 | 0.000 |
| C | PhyC | 0.839 | 0.602 | 13.948 | 0.000 |
| | PsyC | 0.808 | 0.521 | 11.007 | 0.000 |
| O | PO | 0.700 | 0.316 | 5.893 | 0.000 |
| | SO | 0.873 | 0.781 | 17.458 | 0.000 |
| M | RM | 0.715 | 0.565 | 10.206 | 0.000 |
| | AM | 0.736 | 0.609 | 11.456 | 0.000 |

The results indicate that all indicators exhibit substantial outer loading values, with the lowest recorded outer loading at 0.700, indicating a strong association between the indicators and their respective constructs. This validates their effectiveness in measuring the intended latent variables. Furthermore, the outer weight values highlight the relative significance of each indicator, demonstrating their distinct contribution to shaping the constructs. The T-values and P-values provide further statistical validation, confirming that all indicators significantly influence their constructs at $p < 0.05$, reinforcing the robustness and reliability of the model.

### 3.1.3 Second-Order Outer Model Evaluation

The second-order construct (FB - Y) is formed by the following first-order latent variables: C (Y1), O (Y2), M (Y3) Tab. Figure 3 presents the results of the second-order construct evaluation, showing how capability, opportunity, and motivation contribute to the formation of farmer behavior.

In evaluating the second-order construct (FB), we examined the multicollinearity (VIF), outer loadings, outer weights, T-values, and P-values to assess its validity and significance.

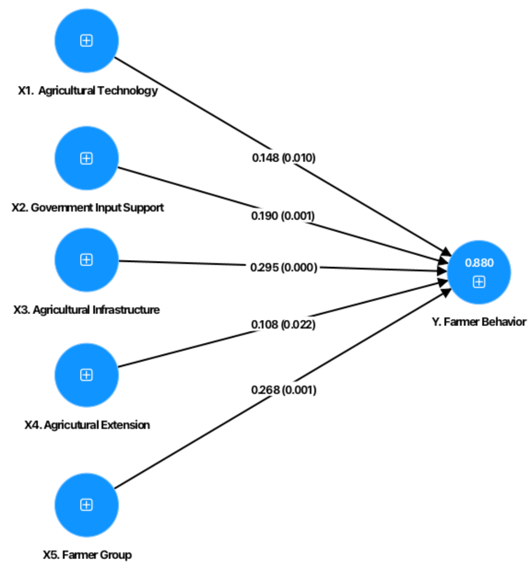


Fig. 4 Second-Order Outer Model Evaluation in the Formative Measurement Model. Source: created by the authors

Multicollinearity was analyzed to determine whether the first-order constructs forming the second-order latent variable (FB) were highly correlated. A VIF value below 5 is considered acceptable, indicating that multicollinearity is not a concern.

The outer loading values were all above 0.700, with C (0.939) and O (0.934) showing the strongest contributions to FB (Table 3). The outer weights indicate that O (0.484) makes the highest contribution, followed by C (0.469). M (0.138) has the lowest contribution but remains statistically significant.

**Tab. 3 Second-Order Outer Model Results (Processed research data, 2025)**

| Second-Order Construct | VIF | Outer Loading | Outer Weight | T-Value | P-Value |
|---|---|---|---|---|---|
| C → FB | 3.012 | 0.939 | 0.469 | 8.238 | 0.000 |
| O → FB | 2.585 | 0.934 | 0.484 | 10.529 | 0.000 |
| M → FB | 2.066 | 0.777 | 0.138 | 3.123 | 0.002 |

The T-values and P-values confirm the statistical significance of all second-order constructs, with $p < 0.05$, ensuring that these dimensions are valid components of FB.

These results suggest that FB is primarily shaped by the availability of opportunities and farmers' capabilities, while motivation, although significant, plays a relatively smaller role in forming farmer behavior.

## 3.2 Inner Model Test Results

The inner model evaluation measures the structural relationships between the latent variables in the research model. The PLS-SEM inner model test includes several key aspects: $R^2$ values, $f^2$ effect sizes, path coefficients, $Q^2$ (predictive relevance), and model fit assessment.

### 3.2.1 Coefficient of Determination ($R^2$)

The R-square ($R^2$) value is used to determine the extent to which the independent variables in the model explain the dependent variable. The $R^2$ values range from 0 to 1, with the following interpretation: 0.19 (weak), 0.33 (moderate), and 0.67 (strong) the relationships within the model.

**Tab. 4 Coefficient of determination test results (Processed research data, 2025)**

| Dependent Variables | R-Square | R-Square Adjusted |
|---|---|---|
| FB | 0.880 | 0.877 |

According to the results in Tab. 4, the $R^2$ value for FB (Y) is 0.880, indicating that 88.0% of the variance in farmer behavior is explained by the independent variables in the model. This value suggests that the model has a strong predictive power.

Furthermore, the adjusted $R^2$ value of 0.877 confirms the model's robustness, demonstrating that the explained variance remains stable even with variations in the number of predictors.

### 3.2.2 Effect Size ($f^2$)

The $f^2$ effect size measures the contribution of each independent variable to the dependent variable.

**Tab. 5 Effect size test results ($f^2$) (Processed research data, 2025)**

| Independent Variable | $f^2$ Effect Size | Interpretation |
|---|---|---|
| AT | 0.037 | Small |
| GIS | 0.081 | Moderate |
| AI | 0.098 | Moderate |
| AU | 0.031 | Small |
| FG | 0.114 | Moderate |

Table 5 summarizes the effect size ($f^2$) for each independent variable on FB (Y). The interpretation follows the Cohen's (1988) guidelines, where 0.02 is considered small, 0.15 moderate, and 0.35 large. The results indicate that FG has the highest effect sizes, while AE has the smallest effect on FB [23].

### 3.2.3 Path Coefficients and Significance Testing

Path coefficients indicate the direction and strength of the relationships between the latent variables. Their significance was tested using T-values and P-values obtained through bootstrapping.

**Tab 6. Path Coefficients and Significance Testing (Formative Model) (Processed research data, 2025)**

| Relationship | Path Coefficient | T-Value | P-Value |
|---|---|---|---|
| AT → FB | 0.148 | 2.563 | 0.010 |
| GIS → FB | 0.190 | 3.232 | 0.001 |
| AI → FB | 0.295 | 3.592 | 0.000 |
| AE → FB | 0.108 | 2.289 | 0.022 |
| FG →FB | 0.268 | 3.472 | 0.001 |

Based on Table 6, the path coefficient results confirm that AI ($\beta = 0.295$, $p < 0.001$) has the highest contribution to FB, indicating that well-developed farm roads and irrigation systems significantly influence farmers' actions. FG ($\beta = 0.268$, $p = 0.001$) also plays an important role, highlighting the importance of social networks in shaping agricultural practices.

GIS ($\beta = 0.190$, $p = 0.001$) provides important resources such as subsidies and direct seed assistance, which further enhance sustainable agricultural behavior. AT ($\beta = 0.148$, $p = 0.010$) and AE ($\beta = 0.108$, $p = 0.022$) contributed moderately, emphasizing that access to quality seeds, machinery, and training programs still played a role, although to a lesser extent.

Overall, the findings validate the formative model, which suggests that agricultural infrastructure, farmer groups, and government support are the main drivers of farmer behavior, while technology and extension services act as complementary factors.

### 3.2.4 Predictive Relevance ($Q^2$)

The Q-square ($Q^2$) value assesses the predictive accuracy of the model using the blindfolding technique. A $Q^2$ value > 0 indicates that the model has good predictive relevance.

Based on the analysis results, the $Q^2$ value for FB (Y) is 0.683, which confirms that the model has high predictive relevance to explain farmer behavior.

### 3.2.5 Model Suitability Assessment

The model suitability assessment in the PLS-SEM is based on the standardized root mean square residual (SRMR) and the standardized fit index (NFI). Based on the analysis results, the model suitability indicators are: SRMR = 0.008 (below 0.08, indicating good model suitability) and NFI = 0.995 (approaching 1, indicating a very suitable model). These values confirm that the model shows a high level of suitability with empirical data.

## 4. Discussion

The findings of this study emphasize the significance of understanding farmer behavior in food-insecure areas using the COM-B Model (Capability, Opportunity, Motivation, Behavior) in a formative measurement framework. This approach provides an in-depth analysis of how various agricultural factors contribute to the shaping of farmer behavior. In the context of Kecamatan Lewa, East Nusa Tenggara, these insights are crucial in identifying the key drivers that influence agricultural decision-making and sustainability.

These findings highlight the necessity of assessing farmer behavior using a structured formative model, which allows for a more precise examination of the individual contributions of agricultural stimulus factors to behavioral outcomes. Figure 2 presents the structural model developed in this study, illustrating the relationships between agricultural technology, government input support, agricultural infrastructure, agricultural extension, and farmer groups, and their contributions to Farmer Behavior.

The Structural Equation Modeling-Partial Least Squares (SEM-PLS) analysis provides empirical evidence of the varying contributions of these factors. The results indicate that AI has the highest contribution to FB, followed by FG and GIS. Meanwhile, AT and AE have smaller, yet still significant contributions. These findings suggest that improving infrastructure and strengthening farmer networks plays a more dominant role in shaping sustainable agricultural behavior compared to technology adoption and training programs alone.

The results reinforce the importance of a multi-faceted approach in supporting farmers in food-insecure regions. Policies aimed at enhancing infrastructure, institutional support, and financial access should be prioritized, as these factors have the most substantial contribution to behavior formation. Additionally, while agricultural extension and technology adoption remain relevant, they should be integrated with broader infrastructure development and financial support mechanisms to maximize their effectiveness. These insights validate the COM-B framework as a valuable analytical tool for evaluating farmer behavior in food-insecure areas and guiding policy interventions aimed at improving agricultural sustainability.

### 4.1 Introduction to Hypothesis Testing

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the proposed hypotheses, assessing the contribution of agricultural technology, government input support, agricultural infrastructure, agricultural extension, and farmer groups to the formation of farmer behavior. The significance of these relationships was determined using the path coefficients ($\beta$), T-values, and P-values, ensuring statistical validation of the formative model.

The results confirm the applicability of the COM-B Model in understanding farmer behavior formation in food-insecure regions, particularly in Kecamatan Lewa, East Nusa Tenggara. The findings emphasize that opportunity-related factors, including agricultural infrastructure and farmer groups, play a dominant role in shaping farmer behavior, as they provide essential resources and social support systems that enable sustainable agricultural practices. In contrast, capability factors such as agricultural technology and motivational drivers like agricultural extension services, while significant, exhibit a relatively lower contribution to behavior formation. These insights underscore the importance of integrated policy interventions that prioritize infrastructure development and community-based support while complementing them with technology adoption and farmer education to enhance long-term agricultural sustainability.

### 4.2 Discussion of Each Hypothesis (H1–H5)

**H1: Agricultural Technology (AT) Contributes Significantly to the Formation of Farmer Behavior (FB)**

The results confirm that AT contributes significantly to the formation of FB, with a path coefficient of 0.148 and a p-value of 0.010, supporting Hypothesis H1. While statistically significant, its contribution is relatively lower compared to AI and FG, indicating that external enabling factors play a more dominant role in shaping farmer behavior.

Within the COM-B framework, agricultural technology enhances C by providing essential tools and innovations that simplify farming practices. The outer weight values for HQS (0.379), T (0.456), and HM (0.378) demonstrate that these elements collectively contribute to improving farmers' efficiency and productivity. This aligns with previous studies, which highlight that mechanization reduces labor dependency and post-harvest losses, ultimately improving farm sustainability [4]. Similarly, Wang et al. emphasized that improved seed varieties and modern agricultural equipment contribute to increased yields and better resource utilization in smallholder farming systems [24].

Subsidies for fertilizers and high-yield seeds facilitate farmers' access to technology, while agricultural extension services enhance farmers' skills and understanding of adopting technological innovations [7]. These findings are supported by previous research, which suggests that financial assistance and knowledge dissemination programs significantly improve the adoption rate of agricultural technology [22]. Without these supporting mechanisms, the benefits of agricultural technology may not be fully realized, particularly in food-insecure areas such as Kecamatan Lewa, where infrastructure limitations and economic constraints persist.

Despite its benefits, the adoption of agricultural technology in these regions faces several challenges, including limited infrastructure, high initial costs, and lack of technical knowledge. The findings indicate that technology adoption is more effective when supported by complementary factors, such as GIS and AE. For example, fertilizer and seed subsidies facilitate access to modern agricultural inputs, while extension services provide training and capacity-building to improve farmers' ability to use new technologies effectively.

The implications of these findings suggest that to maximize the impact of agricultural technology, strengthening infrastructure, improving financial accessibility, and expanding farmer education programs are essential. Policies should focus on making mechanized equipment more affordable and enhancing extension programs to improve technology literacy. Additionally, collaborative efforts between the government, private sector, and farmer institutions can bridge technological gaps and promote sustainable agricultural practices in food-insecure regions.

**H2: Government Input Support (GIS) significantly contributes to the Formation of Farmer Behavior (FB)**

The findings confirm that government input support (GIS) significantly contributes to the formation of farmer behavior, with a path coefficient of 0.190 and a p-value of 0.001, supporting Hypothesis H2. Fertilizer subsidies, pesticide subsidies, and direct seed assistance play a crucial role in enhancing farmers' capability (C) and opportunity (O) to improve agricultural productivity. Among these indicators, direct seed assistance (0.767) had the highest outer weight, followed by fertilizer and pesticide subsidies (0.347), indicating the importance of seed availability in improving crop resilience and farm performance.

Government input support addresses limited access to production inputs, a key challenge faced by farmers in food-insecure areas such as the Lewa District. Research [10] confirmed that input subsidies, particularly for fertilizers and pesticides, play a vital role in stabilizing rice production in regions under high environmental pressure. Additionally, as highlighted [1], drought-resistant seed assistance can improve productivity by up to 20% in semi-arid regions, reinforcing its impact on food security.

However, the effectiveness of government input support is often hampered by uneven distribution and bureaucratic delays. As emphasized [11], ensuring transparency and efficiency in subsidy implementation is critical for maximizing its impact. Strengthening the digitalized distribution systems and monitoring mechanisms can enhance accessibility and reduce inefficiencies in government assistance programs.

Government input support also interacts with other factors, such as agricultural extension (AE) and farmer groups (FG). Extension services play a vital role in educating farmers about the effective use of fertilizers and pesticides, while farmer groups facilitate more structured and collective access to government subsidies. As highlighted [9], collective action within farmer groups enhances the impact of government assistance, enabling broader outreach to smallholder farmers.

To maximize the impact of government input support, policies should focus on improving distribution efficiency, integrating digital tracking systems, and involving farmer groups in subsidy management. Additionally, strengthening extension programs to ensure proper input use can further enhance its benefits. With well-structured implementation, government input support can significantly improve farmer productivity and agricultural sustainability in food-insecure regions.

**H3: Agricultural Infrastructure (AI) Contributes Significantly to the Formation of Farmer Behavior (FB)**

The study results indicate that AI plays a major role in shaping FB, with a path coefficient of 0.295 and a p-value of 0.000, making it the most significant contributor among all the independent variables. These findings support Hypothesis H3 and emphasize the role of FR and IS in increasing farmers' access to resources and enhancing productivity. Among the indicators, IS (0.804) had the highest outer weight, followed by FR (0.303), demonstrating the critical importance of water management infrastructure in food-insecure areas.

Adequate infrastructure reduces transportation costs, improves input accessibility, and facilitates market linkages, ultimately increasing farming efficiency. These findings are supported [11], highlighting that improved road access accelerates technology adoption and reduces logistical constraints for farmers in remote areas. Additionally, it was found [1] that irrigation systems can increase agricultural yields by up to 30% in semi-arid regions, ensuring greater resilience against climate variability.

Beyond capability enhancement, agricultural infrastructure creates O by enabling farmers to participate in government programs such as input subsidies and extension services. Well-developed road networks improve extension service accessibility, allowing for more frequent farmer interactions with agricultural advisors [9]. Furthermore, the synergy between infrastructure development and government support policies strengthens farmers' motivation to adopt improved agricultural practices.

However, challenges remain in infrastructure expansion, including insufficient investment, lack of maintenance, and coordination issues among stakeholders. To optimize its impact, infrastructure development programs should be integrated with farmer empowerment initiatives, such as community-based irrigation management. Increased public and private sector investment in rural infrastructure is crucial to improving farm sustainability, productivity, and long-term food security in vulnerable regions.

**H4: Agricultural Extension (AE) Contributes Significantly to the Formation of Farmer Behavior (FB)**

The results confirm that AE significantly contributes to the formation of FB, with a path coefficient of 0.108 and a p-value of 0.022, supporting Hypothesis H4. AE enhances C and M by improving farmers' knowledge and skill sets. Among the indicators, FT (0.578) had the highest outer weight, followed by TM (0.558), highlighting the importance of both accessibility and content quality in extension programs.

Extension services play a crucial role in knowledge transfer, skill development, and the adoption of sustainable agricultural practices. As emphasized [7], technology-based extension programs (e.g., digital platforms and interactive learning) improve farmer engagement and training effectiveness. Moreover, it was found [8] found that localized, participatory extension models enhance farmers' willingness to adopt innovative practices, especially in resource-constrained environments.

Although extension services contribute positively, their impact is lower than that of infrastructure or farmer groups. This may be due to limited extension agent-to-farmer ratios, inadequate funding, and logistical constraints in remote areas. As highlighted [11], extension activities are more effective when complemented by improved infrastructure, such as well-maintained farm roads, which enable easier access for extension agents.

To maximize the role of agricultural extension, policies should focus on expanding training programs, improving the quality of extension materials, and integrating digital learning platforms. Strengthening the capacity and mobility of extension agents is also necessary to ensure consistent farmer outreach. Moreover, synergizing extension services with input support programs and farmer group networks will create a more holistic approach to agricultural development, particularly in food-insecure areas.

**H5: Farmer Groups (FG) Contribute Significantly to the Formation of Farmer Behavior (FB)**

The results confirm that FG significantly contributes to the formation of FB, with a path coefficient of 0.268 and a p-value of 0.001, supporting Hypothesis H5. FG enhances O and M by providing farmers with access to resources, training, and collective decision-making support. Among the indicators, MFG (0.754) has a higher outer weight than SFG (0.320), indicating that active participation in these groups plays a more significant role in shaping FB.

Farmer groups serve as platforms for collective action, enabling members to access input subsidies, adopt technology, and participate in extension programs more effectively. Well-structured farmer groups provide stronger institutional support, improving farmers' ability to engage in government programs and input distribution networks [9]. Moreover, it was emphasized [20] that social networks within farmer groups foster knowledge sharing, increase risk management capacity, and improve the adoption of sustainable practices.

The role of farmer groups extends beyond economic benefits to social empowerment, where peer influence and community support encourage the adoption of modern agricultural techniques. As suggested [21], horizontal coordination within community-based organizations enhances farmers' resilience to market and environmental shocks, promoting more adaptive and sustainable farming behaviors. Furthermore, farmer group leadership and governance play a crucial role in strengthening collaboration among members and stakeholders.

However, challenges persist in ensuring effective farmer group management. Issues such as low participation rates, weak leadership structures, and limited financial resources hinder the overall effectiveness of these groups. As noted [11], weak institutional frameworks can reduce the efficiency of input distribution and diminish the benefits of government agricultural support programs. Addressing these challenges requires capacity-building initiatives focused on leadership development, financial management, and governance training for farmer group leaders.

To maximize the impact of farmer groups, policies should focus on strengthening institutional frameworks, increasing farmer participation, and integrating farmer groups into broader agricultural development strategies. Governments and stakeholders should encourage active participation through training programs, financial incentives, and networking opportunities. Additionally, synergizing farmer groups with extension services and government assistance programs will create a more structured and sustainable support system, ensuring long-term benefits for smallholder farmers in food-insecure regions.

# 5. Conclusions

This study provides empirical evidence on the determinants of farmer behavior in food-insecure areas using the COM-B Model approach. The findings highlight that capability (C), opportunity (O), and motivation (M) significantly shape farmers' behavioral formation, particularly in the adoption of sustainable agricultural practices. Using PLS-SEM analysis, the study confirms that all five key factors, AT, GIS, AI, AE, and FG, contribute significantly to FB.

Among these factors, AI and FG emerged as the strongest contributors, emphasizing the importance of a well-developed physical infrastructure and strong social institutions in enabling sustainable farming. GIS and AE also play critical roles, particularly in improving farmers' access to essential resources and knowledge. Although AT contributes positively, its effectiveness is contingent on complementary support systems such as extension services and financial assistance.

Furthermore, this study presents several innovative contributions to the academic literature. First, it applies the COM-B model within an agricultural context, an area that remains underexplored in prior research. Second, it integrates five key stimulus factors to comprehensively assess their simultaneous contribution to farmer behavior formation. Third, it provides empirical evidence that policy integration-based interventions are more effective in enhancing the sustainability of farming systems. These findings serve as a valuable reference for policymakers in designing adaptive agricultural development strategies that align with the actual needs of farmers.

In particular, this study highlights the critical role of infrastructure and institutional support in shaping sustainable farming behavior. Policymakers should prioritize investments in rural infrastructure and strengthen farmer organizations to enhance resource accessibility and resilience in food-insecure areas. Additionally, agricultural extension services must be restructured to provide targeted training that aligns with the technological and financial constraints of smallholder farmers.

Future research could explore longitudinal studies to assess the long-term impact of these interventions, as well as comparative studies across different food-insecure regions to further refine the application of the COM-B Model in agricultural behavior analysis. By addressing these challenges, agricultural policies and programs can be better tailored to support smallholder farmers in achieving sustainable and productive farming practices.

## 6. Limitations of the Study and Future Research Directions

Despite its significant contributions, this study has several limitations. First, the research is cross-sectional, meaning it captures farmer behavior at a single point in time. A longitudinal approach in future studies would provide deeper insights into how behavioral changes can evolve in response to agricultural interventions. Second, while this study incorporates five key stimulus factors, other potential determinants of farmer behavior, such as climate variability, socio-cultural influences, and market dynamics, were not explicitly analyzed. Future research should explore these aspects to provide a more holistic understanding of farmer decision-making processes. Third, the study relies primarily on self-reported data, which may be subject to social desirability bias or recall errors. Employing mixed-method approaches that integrate qualitative data from farmer interviews and case studies could enhance the robustness of future findings. Fourth, the study focuses on a specific food-insecure region (Kecamatan Lewa, East Sumba, Indonesia), which may limit its generalizability to other agricultural settings. Future research should conduct comparative studies across multiple regions and countries to examine whether the findings hold true in different socio-economic and environmental contexts.

Finally, while PLS-SEM analysis effectively assesses causal relationships, incorporating experimental or quasi-experimental designs in future studies would help establish stronger causal inferences regarding the impact of agricultural policies and interventions on farmer behavior.

Addressing these limitations in future research will contribute to a more comprehensive understanding of the factors shaping sustainable agricultural practices and improve the effectiveness of policy interventions in food-insecure regions.

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## Author Contributions

A.M.L. served as the principal investigator and was responsible for research conceptualization, data collection, data analysis, and primary manuscript writing. B.S., A.S.H.W., and R.A. contributed to the research design, implementation, and data validation, provided supervision throughout the study, and assisted in the formulation of policy recommendations.

## Conflict of Interest Declaration

The authors declare that they have no affiliations with or involvement in any organization or entity with any financial interest in the subject matter or materials discussed in this manuscript.

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