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Considering Bali's Agricultural Policies in Implementing the Development of MDA-Path Analysis

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ABSTRACT. *The agricultural sector plays a vital role in Bali's economy, culture, and food security, particularly in rice production. However, challenges such as land conversion and fluctuating farmer incomes have led the Bali government to implement various agricultural policies. Farmers' welfare is a critical factor in ensuring national food security, as prosperous farmers can improve production and maintain food stability. This study employs Discourse Network Analysis (DNA) to identify key factors affecting farmers' welfare in Bali and integrates MDA-Path Analysis to examine the relationships between exogenous variables and farmers' economic conditions. A mixed-method approach (qualitative and quantitative) is used to explore farmers' inclusivity and validate the MDA-Path Analysis model. Data is collected through in-sample validation using surveys conducted among farmers who are members of farmer groups in Bali. The results of this study indicate that human resource quality has the most significant impact on farmers' welfare, followed by price volatility and ease of technology use. The MDA-Path Analysis model demonstrates high classification accuracy, as reflected in sensitivity values exceeding 80%, confirming its effectiveness in distinguishing between different income and welfare categories. These findings provide valuable insights for strategic policy-making, enabling data-driven decision-making to enhance farmers' welfare and economic stability in Bali.*

Keywords: *Agricultural Policy, Discourse Network Analysis, Farmers' Welfare, Food Security, MDA-Path Analysis*

INTRODUCTION

The agricultural sector plays a crucial role in the economy, culture, and food security of Bali. As an island with a rich agricultural tradition, Bali has long relied on rice cultivation, livestock farming, and horticulture to meet the needs of its population and the rapidly growing tourism industry. The development of the agricultural sector in supporting food and nutrition in Bali is closely related to the realization of food security, as emphasized in Food Law No. 7 of 1996 and Government Regulation No. 68 of 2002 concerning Food Security. Food security is a condition that includes the availability, access, and utilization of adequate food to meet the food and nutritional needs of each individual in achieving optimal health and well-being [1]. Therefore, by strengthening resilience, it can support the achievement of community health and welfare and support the realization of state development. This is because nutritious food is needed to meet the most important basic needs in the implementation of quality human resources (HR) for a country.

However, in recent years, agricultural sustainability has become a major concern due to land conversion, fluctuations in farmers' incomes, and changes in climatic conditions. To address these challenges, the Bali government has implemented various agricultural policies aimed at improving farmers' welfare and strengthening food security, such as the development of organic farming, controlling land-use conversion for tourism purposes, and other strategic agricultural plans. Understanding the effectiveness of these policies requires a strong analytical framework to evaluate the direct and indirect impacts of various factors on farmers' welfare.

Farmers as holders of an important role in maintaining food security, are vulnerable to food instability that depends on the welfare of farmers. Prosperous farmers will ensure availability in meeting the needs of farmers, so that they can increase food security [2]. Prosperous farmers are able to manage their businesses more effectively and with quality. Thus, the welfare of farmers indirectly contributes to maintaining national food security. In addition, the welfare of farmers is also supported by farmers' income. Adequate income allows farmers to better meet the needs of farmers [3]. Income from both agricultural and non-agricultural activities is a farmer's strategy to improve welfare [4]. Therefore, increasing farmers' income can improve their welfare, so that it has a good impact on national food security. The welfare of farmers can be supported by several factors that can be obtained through the variable mining process with Discourse Network Analysis (DNA).

Discourse Network Analysis (DNA) is an analysis to study the relationship and interaction between institutions, actors, and discourse on certain policy issues based on validated sources such as television, radio, newspapers, magazines, or social media platforms [5]. DNA can process unstructured text data, extracting key elements and variables that support farmers' welfare in Bali. The results of DNA will then be used to determine which factors are most significant in distinguishing farmer welfare categories and whether farmers' income categories also play a role in their welfare through MDA-Path Analysis, which is the primary objective of this study.

As far as existing research, there has been no development of MDA-Path Analysis, which is a novelty in this research. Multiple Discriminant Analysis (MDA) is one part of the discriminant analysis. MDA and discriminant analysis have differences that lie in the number of categories of response variables. In the discrimination analysis, the number of response variable categories is only one to two, while MDA has a number of response variable categories more than two. Discrimination analysis is one of the multivariate analyses that functions to explain the differentiators between groups by understanding exogenous variables that have a significant effect on distinguishing categorical groups in endogenous variables [6].

MDA has one of the drawbacks in dealing with the relationship between endogenous and exogenous variables that are directly and indirectly observed. This makes MDA need to be approached with path analysis. Path analysis is a statistical technique used to analyze the direct or indirect relationship between exogenous variables and endogenous variables[7]. With the development of MDA-Path Analysis, it can be used to see the direct and indirect relationship of exogenous variables to endogenous variables that have more than two categories. The development of MDA-Path Analysis is an MDA algorithm that is integrated with Path Analysis.

Therefore, this study aims to develop an MDA-Path Analysis algorithm to assess its performance in analyzing farmers' welfare data. The integration of these methods will help identify the most influential factors in differentiating levels of farmers' welfare in Bali. Furthermore, this study seeks to evaluate classification accuracy and goodness of fit, which are key considerations in determining the best differentiators in MDA-Path Analysis. The findings of this research are expected to provide early warnings for farmers and companies in making policy decisions from the perspective of statistical advancements.

RESEARCH METHODS

The approach used to achieve this goal is a mixed method (qualitative and quantitative). The qualitative approach lies in variable mining carried out in the literature on strengthening the inclusivity of farmers in supporting the creation of a sustainable economy through Discourse Network Analysis (DNA). Meanwhile, the quantitative approach lies in the validity and interpretation of MDA-Path analysis modeling based on statistics and computing.

Data Source

This research process was conducted using in-sample validation. In-sample validation refers to the process of analyzing real primary data obtained from the field. The population consists of farmers who are members of farmer groups in Bali Province, within the operational area of a state-owned fertilizer company, totaling 477,439 individuals across 12,323 farmer groups. These farmers are members of farmer groups, landowners, and have at least a senior high school education or its equivalent. The sample used for this study was rounded to 176 farmer groups. The primary data was collected through surveys using questionnaires and the judgment sampling method. Judgment sampling is a form of convenience sampling, where population elements are selected based on the researcher's judgment. The researcher, based on expertise and careful consideration, selects the elements to be included in the sample, ensuring that they represent or align with the population under study [8].

The Proposed Method

Big Data exploration for variable mining with a focus on this research problem uses Discourse Network Analysis (DNA). Discourse Network Analysis is an analysis to study the relationship and interaction between institutions, actors, and discourse on certain policy issues based on validated sources such as television, radio, newspapers, magazines, or social media platforms. DNA can process unstructured text data so that data can be processed and conclusions can be obtained. DNA produces variables and indicators that will be used in research.

Discourse Network Analysis (DNA) Procedure

Big Data exploration for variable mining with a focus on this research problem uses Discourse Network Analysis (DNA). Discourse Network Analysis is an analysis to study the relationship and interaction between institutions, actors, and discourse on certain policy issues based on validated sources such as television, radio, newspapers, magazines, or social media platforms. DNA can process unstructured text data so that data can be processed and conclusions can be obtained. DNA produces variables and indicators that will be used in research.

Multiple Discriminant Analysis (MDA) Method

The results of DNA are used as data collection to describe the inclusivity of farmers. The data obtained is carried out Explanatory Factor Analysis to adjust the eigenvalues that make up X Factors. Exploratory Factor Analysis (EFA) is a statistical technique that aims to identify the latent factor structure or dimension of a set of variables that are correlated with each other [6]. By grouping related variables into specific factors or components, EFA simplifies complex data and helps identify patterns in relationships between variables. EFA plays an important role in understanding the latent dimension in data, namely factors that cannot be directly measured but affect the observed variables [9]. EFA is usually performed when the researcher does not have a specific hypothesis regarding the number or nature of the factors underlying the data. The two main procedures in EFA are factor extraction and factor rotation, which help to produce data structures that are easier to interpret [10].

From X Factors will be formed p Exgenous Variables. For Endogenous Variables, cluster anlaysis is performed. Each Endogen is analyzed clusters, so that k-categories are formed in each endogenous. Cluster analysis is a statistical technique that aims to group objects based on similarity characteristics into homogeneous groups, where objects in one group are more similar to each other than objects in another group [11]. The process of cluster analysis is to group data which is carried out by two methods, namely hierarchical methods and non-hierarchical methods. The difference between hierarchical methods and non-hierarchical methods lies in determining the number of clusters. In the non-hierarchical method, the number of clusters has been determined in advance, while the hierarchical method of the number of clusters is determined based on the results of the analysis.

In the hierarchical cluster analysis, it is considered that initially each object is a separate cluster, then the two closest objects or clusters are combined to form a smaller cluster [12]. Hierarchical cluster analysis has several algorithms used to form clusters, namely single linkage, complete linkage and average linkage [11].

1) Single Linkage (Nearest Neighbor)

In this method, the distance between two clusters is determined by the closest distance between members in both clusters as formulated in equation (1).

$$d_{(AB)C} = \min(d_{AC}, d_{BC}) \quad (1)$$

wich:

$d_{(AB)C}$: average distance between cluster AB an cluster C

d_{AC} : distance between object A in cluster C

d_{BC} : distance between object B in cluster C

2) Complete Linkage (Farthest Neighbor)

The distance between clusters is determined by the farthest distance between members in both clusters, resulting in a more compact group with the formula as in equation (2).

$$d_{(AB)C} = \max(d_{AC}, d_{BC}) \quad (2)$$

wich:

$d_{(AB)C}$: average distance between cluster AB and cluster C

d_{AC} : distance between object A in cluster C

d_{BC} : distance between object B in cluster C

3) Average Linkage

Combining clusters based on the average distance between members of both clusters, offsetting single and complete linkage and producing groups that tend to be more balanced is shown based on the results of the formula calculation in equation (3).

$$d_{(AB)\mathrm{C}} = \frac{\sum_A \sum_B d_{AB}}{N_{(AB)} N_C} \quad (3)$$

wich:

$d_{(AB)\mathrm{C}}$: Average distance between cluster AB and cluster C

d_{AB} : the distance between object A in cluster C and object B in cluster C

$N_{(AB)}$: number of objects in the cluster (AB)

N_C : number of objects in cluster C

From the above formation, the first model of MDA was carried out gradually involving X_1-X_p to Y_1. The second model involves X_1-X_P and Y_1 to Y_2, but the matrix is comprehensive. The significance test uses sampling, because there is no Path-MDA test yet, the bootstrap and jacknife methods can be done. Compare each possibility that is formed, so as to form the best guess. Multiple Discriminant Analysis (MDA) is one part of the discriminant analysis. The difference between MDA and discriminant analysis lies in the number of response variable categories. In the discrimination analysis, the number of response variable categories is only one to two, while MDA has a number of response variable categories more than two. Discrimination analysis is one of the multivariate analyses that functions to model the relationship between a categorical response variable and one or more quantitative explanatory variables [13]. MDA can be used as a grouping method because it produces a function that has the ability to differentiate between clusters. The function is formed by maximizing the distance between clusters. If the response variable or categorical data consists of only two categories of response variables, it is called the Two-Group Discriminant Analysis model, while if the category of response variables consists of more than two categories, it is called MDA. In this research, MDA was used because the response variables consisted of three categories of response variables. MDA belongs to the multivariate dependence method [12]. The model can be written as in equation (4).

$$Y_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_p X_{pi} \quad (4)$$

wich:

Y_i : The response variable is categorical or nominal data in the ith unit of observation

X_{pi} : The p-th explanatory variable in the ith observation unit

β_p : The coefficient of the function of the p-th crime

i : 1, 2, 3, …, n

Path Analysis Method

While, path analysis is a direct development of multiple regression that aims to provide an estimate of the magnitude and significance of hypothetical causal relationships in a set of variables [14]. Path analysis can be interpreted as a continuation of multiple regression analysis, although path analysis is independent of statistical procedures in determining causal relationships, while linear regression is indeed a statistical procedure used to analyze causal relationships between the variables tested.

There are several objectives of using path analysis, namely to see the relationship between variables based on a priori model, explain the reasons for correlated variables using a temporal model, describe and test a mathematical model with the underlying equation, identify the propagation path of a variable to other variables that it influences, and calculate the influence of a predictor variable on other endogenous dependent variables [15]. There are three types of influence of path analysis, namely [16].

1) Direct effect: The direct influence occurs when exogenous and endogenous do not require other variables as mediation.
2) Indirect effect: Indirect influence occurs when the relationship between exogenous and endogenous requires other variables as intermediaries.
3) Total Effect: Total influence is the sum of direct and indirect influences.

Hybrid of MDA-Path Analysis Method

If given paired data $(X_i, Y_{1i}, Y_{2i})$with $i = 1,2,3,\ldots,n$, which follows the multiple discriminant analysis model which is integrated with path analysis, the form of the function as presented in equation (5) is obtained.

$$\begin{aligned} Y_{1i} &= \beta_{11} X_{1i} + \beta_{12} X_{2i} + \beta_{13} X_{3i} \\ Y_{2i} &= \beta_{21} X_{1i} + \beta_{22} X_{2i} + \beta_{13} X_{3i} + \beta_4 Y_{11i} + \beta_5 Y_{12i} \end{aligned} \quad (5)$$

Before obtaining a model in multiple discriminant analysis which is integrated with path analysis, the model is first obtained from (a) multiple discriminant analysis; (b) Multiple Discriminant Analysis which is integrated with path analysis.

A known model of multiple discriminant analysis with equations (6).

$$Y_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_p X_{pi} \quad (6)$$

where:

Y_i : The response variable is categorical or nominal data in the i-th unit of observation

X_{pi} : The p-th explanatory variable in the ith observation unit

β_p : The coefficient of the function of the p-th crime

i : 1, 2, 3, …, n

Known multiple discriminant analysis model for Y_{1i} as a function of $f(X_i)$, The formation of a multiple discriminant analysis model for Y_{2i} as a function of $f(X_i, Y_{1i})$, where Y_{1i}categorical, so that the *multiple discriminant analysis* model can be used dummy variables on $Y_{2i} = f(X_i, Y_{11i}, Y_{12i})$, with equation (7).

$$\begin{aligned} Y_{1i} &= \beta_{11} X_{1i} + \beta_{12} X_{2i} + \ldots + \beta_{1p} X_{pi} \\ Y_{2i} &= \beta_{21} X_{1i} + \beta_{22} X_{2i} + \ldots + \beta_{2p} X_{pi} + \beta_{p+1} Y_{11i} + \beta_{p+2} Y_{12i} \end{aligned} \quad (7)$$

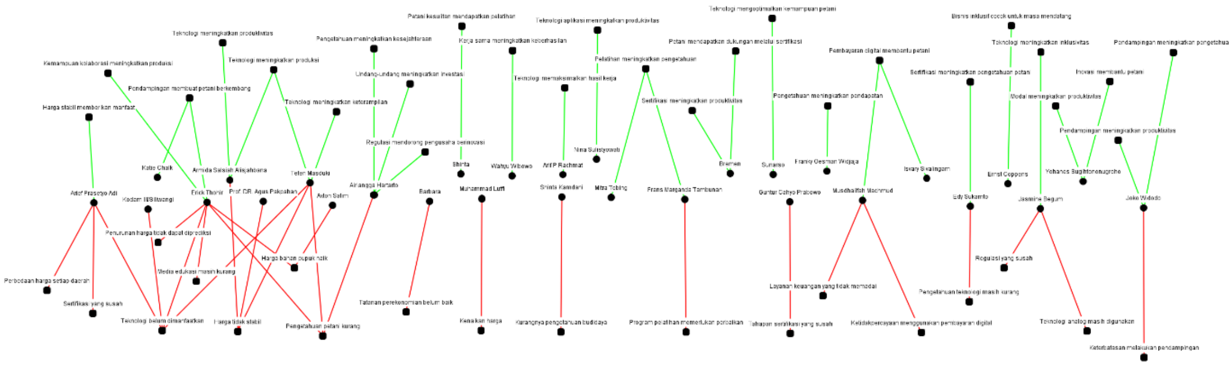

Figure 1. Results of Discourse Network Analysis on Farmer Welfare

Where:

Y_{1i} : The first response variable is categorical or nominal data in the ith unit of observation

Y_{2i} : The second response variable is categorical or nominal data in the ith unit of observation

Y_{11i} : The first response variable of the first category in the i-th observation unit

Y_{12i} : The first response variable of the second category in the i-th observation unit

X_{pi} : The p-th explanatory variable in the ith observation unit

β_p : The coefficient of the function of the p-th crime

i : 1, 2, 3, …, n

RESULTS AND DISCUSSIONS

Results Discourse Network Analysis (DNA)

Exogenous variables in this study were obtained through the variable mining process using the Discourse Network Analysis (DNA) method. In qualitative research, data saturation often occurs after approximately 12–30 data sources, depending on the complexity and homogeneity of the data being analyzed [17]. In this study, 30 news stories with validated sources were used and produced graphic visualization of issues and actors in Figure 1.

Based on the statements of actors and issues in Figure 1, the variables described in Table 1 are obtained

Based on Table 1, the variables obtained from DNA can be explored as factors for farmers' welfare. However, some variables are indicated to be related, such as the Easy to Learn System variable (I1) with the Easy-to-Use System variable (I8). This indicates that an intuitive system with a well-designed interface will be easier to learn and

Table 1. Results of Discourse Network Analysis

Variable	ID
Easy-to-Learn System	I1
Skill Improvement System	I2
Education	I3
Price Stability	I4
On-Demand System	I5
Intellectual Quality	I6
Ease of Price Prediction	I7
Easy-to-use system	I8
Price Variations	I9

use, demonstrating a connection between learnability and usability[18]. Thus, it is necessary to collect variables into common factors based on the relationship between variables through Exploratory Factor Analysis.

Result of Factor Analysis

Exploratory Factor Analysis aims to reduce the dimensions of variables to several common factors while maintaining the diversity of the original variables. The determination of the number of factors formed can be done using the eigenic value and the cumulative proportion of each factor. The following are the results of the calculation of the written eigenvalue in Table 2.

Based on Table 2, it can be seen that there are 9 factors that can represent variables. There are 3 common factors were obtained that had an eigenvalue of more than 1 and had a cumulative diversity greater than 70%. Therefore, 3 common factors can explain the diversity in all variables. Table 3 shows that the results of factor loading on each varimax rotation and quartimax rotation produce almost the same grouping of variables. Through the table, it can be seen that the results of the factor loading values with the rotation of varimax and quartimax on several factors together are used to determine the meaning of each factor

Table 2. Eigenvalues between Factors

Factors	Varimax Rotation			Quartimax Rotation		
	Eigen	Var Prop	Cum Prop	Eigen	Var Prop	Cum Prop
F1	**4.593**	**0.510**	**0.510**	**4.617**	**0.513**	**0.513**
F2	**1.570**	**0.174**	**0.685**	**1.539**	**0.171**	**0.684**
F3	**1.388**	**0.154**	**0.839**	**1.399**	**0.155**	**0.839**
F4	0.434	0.048	0.887	0.147	0.016	0.856
F5	0.309	0.034	0.922	0.188	0.021	0.877
F6	0.216	0.024	0.946	0.219	0.024	0.901
F7	0.213	0.024	0.969	0.256	0.028	0.930
F8	0.139	0.015	0.985	0.296	0.033	0.962
F9	0.139	0.015	1.000	0.336	0.037	1.000

Table 3. Loading Factor

Indicators	ID	Varimax Rotation			Quartimax Rotation			Variables
		F1	F2	F3	F1	F2	F3	
Education	I3	**0.587**	0.043	0.070	**0.640**	0.063	-0.005	Quality of Human Resources (X3)
Intellectual Quality	I6	**0.598**	0.027	-0.037	**0.723**	-0.078	-0.001	
Price Variations	I9	0.053	**0.564**	0.079	0.078	**0.787**	-0.064	Price Volatility (X1)
Price Stability	I4	0.037	**0.671**	0.085	0.088	**0.671**	0.089	
Ease of Price Prediction	I7	0.065	**0.742**	0.038	0.059	**0.528**	-0.059	
Easy-to-Learn System	I1	0.053	0.099	**0.504**	-0.005	0.077	**0.543**	Ease of Use of Technology (X2)
Skill Improvement System	I2	0.083	0.030	**0.547**	-0.044	-0.057	**0.513**	
On-Demand System	I5	-0,010	-0,047	**0,567**	-0,040	0,061	**0,756**	
Easy-to-use system	I8	-0,084	-0,094	**0,590**	0,076	-0,025	**0,612**	

loading value. The naming of factors is based on the characteristics that correspond to the members of each factor.

The Education and Intellectual Quality indicators have a loading value close to 1 in Factor 1, so it can be said that both indicators are reflected in the Human Resource Quality variable in Factor 1. The Price Variation, Price Stability, and Price Predictability indicators have loading values close to the value of 1 on Factor 2, which indicates that the three indicators characterize the Price Volatility variable. Meanwhile, the indicators of Easy to Learn System, Skill Improvement System, On-Demand System, and Easy-to-Use System have a loading value close to 1 on Factor 3, which indicates that the number of indicators illustrates the Variable of Ease of Use of Technology. The formed factor is used as an exogeneous variable in the MDA-Path model.

Results of Cluster Analysis

Before the Path-MDA analysis, category initiation was carried out on endogenous variables through cluster analysis. The endogenous variables used in this study are presented in Table 4.

Cluster analysis with Single Linkage, Average Linkage, and Complete Linkage methods measures the distance from the data object to the center of the cluster. The determination of the optimal number of clusters is carried out based on the Silhoutte Index. An optimal cluster is a group that has the shortest distance between individuals in the cluster and has a long distance from other cluster objects.

The following are the results of the silhoute index value.

Table 4. Endogenous Variable Instruments

Variable	Indicators
Farmer Income (Y1)	Revenue Stability (Y1.1)
	Production Efficiency (Y1.2)
	Diversification of Revenue Sources (Y1.3)
Farmer Welfare (Y2)	Residence (Y2.1)
	Production Facilities (Y2.2)
	Access to Health Facilities (Y2.3)

Based on Table 5, it can be concluded that in the variables Y1 and Y2, clusters of 3 produce the highest values for both Single Linkage, Average Linkage, and Complete Linkage. The following are the results of the grouping.

Based on Table 6, it can be known how many members there are in each group. The naming between groups is based on the score range that each object has with the following criteria on Table 7 [19].

In the Y1 variable, the members of the 2nd group have the most members, namely as many as 40 farmers who have moderate income characteristics. Likewise, in the Y2 variable, members of the 2nd group have as many as 49 farmers who have characteristics of a medium level of welfare. To be more confident of the results of the grouping, a comparative test between groups was carried out using MANOVA. The following are the results of the comparative test between groups presented in Table 8.

Based on the results in Table 8, it shows that the comparison test between the variables X1-X3 to the group results obtained a p-value < 0.05, so it can be said that there is a significant difference between the groups. The income group of farmers based on price volatility, ease of use of technology, and quality of human resources shows that at medium and high levels they have similar values, but have differences with low-income farmer groups. Meanwhile, the farmer welfare group based on price volatility, ease of use, and quality of human resources shows that at low and medium welfare levels have similar values, but have differences with the farmer group with high welfare. This shows that the results of the grouping can be continued on the MDA-Path.

Results of Estimation of MDA-Path Parameters

The results of estimating the parameters of the MDA-Path model based on the simulation results with the best performance to see how much the influence of exogenous variables on endogenous variables using the indication of the average linkage method in cluster analysis and the rotation of varimax in exploratory factor analysis are attached in Table 9 as follows.

Based on Table 9, it can be known that the accuracy of the classification is based on the accuracy and sensitivity values obtained by more than 80%. This indicates that the classification performance is very good. The following model is presented in equation (8) as follows.

$$Y_{1i} = \hat{\beta}_{11}X_{1i} + \hat{\beta}_{12}X_{2i} + \hat{\beta}_{13}X_{3i}$$

$$Y_{2i} = \hat{\beta}_{21}X_{1i} + \hat{\beta}_{22}X_{2i} + \hat{\beta}_{23}X_{3i} + \beta_3 Y_{11i} + \beta_4 Y_{12i}$$

(8)

Table 5. Cluster Validity

Cluster	Variable Y1			Variable Y2		
	Silhoute			Silhoute		
	Single	Average	Complete	Single	Average	Complete
1	0.182	0.233	0.274	0.182	0.183	0.220
2	0.287	0.282	0.283	0.288	0.294	0.297
3	**0.317**	**0.318**	**0.312**	**0.303**	**0.315**	**0.315**
4	0.291	0.291	0.300	0.296	0.299	0.287
5	0.207	0.221	0.245	0.198	0.239	0.257
6	0.183	0.244	0.193	0.225	0.255	0.181
7	0.184	0.213	0.188	0.197	0.243	0.273
8	0.187	0.206	0.256	0.247	0.186	0.247
9	0.202	0.247	0.237	0.263	0.249	0.205

Table 6. Clustering Results

Group	Y1	Y2
Low	25	22
Medium	40	49
High	35	29

Table 7. Grouping Criterion

Average Score	Information
1.00 – 1.50	Very Low
>1.50 – 2.50	Low
>2.50 – 3.50	Medium
>3.50 – 4.50	High
>4.50 – 5.00	Very High

Table 8. MANOVA Comparative Test Results

Gr.	Var.	P-value	Sign	Posthoc		
				Low	Med	High
Y1	X1-X3	0.032	s	a	b	b
Y2	X1-X3	0.003	s	a	a	b

Table 9. Results of Estimation of MDA-Path Analysis Parameters

Exogenous	MDA-Path	
	Income (Y1)	**Welfare (Y2)**
Price Volatility (X1)	0.233	0.663
Ease of Use of Technology (X2)	0.190	0.048
HR Quality (X3)	0.523	0.648
Dummy Y1 (Medium vs High)	-	0.814
Dummy Y1 (Low vs High)	-	0.729
Accuration	**83.52%**	**84.08%**
Sensitivity	**80.47%**	**80.69%**
Spesificity	**60.47%**	**64.36%**

Based on the equation (8), it shows that the coefficients of X1, X2, and X3 to the variables Y1 and Y2 are positive, meaning that the higher the price volatility, ease of use of technology, and quality of human resources can increase farmers' income and welfare. In addition, the variable category Y1 has a positive influence on Y2. This indicates that when farmers have higher incomes, it will also improve the welfare of farmers. Comparison of the influence of farmers' income on the welfare of farmers in the high-income category and low-income category is 0.729. Meanwhile, the effect of comparing high farmers' income with medium farmers' income was 0.814. However, the comparison of the influence of medium farmer income with low income has the highest ratio value, which is 0.896. This indicates that farmers with middle income have the highest influence on farmers' welfare compared to farmers with high income and low income.

Based on these results, it can be known that segmentation based on income categories is important in designing effective agricultural policies in Bali to improve farmers' welfare. According to the development economics literature, middle groups often need different support than low or high groups because they are in a transition phase where rising incomes can significantly affect long-term well-being [20]. By implementing policies focused on productivity enhancement and risk management, middle-class farmers can be empowered to achieve greater economic stability and welfare. Thus, Balinese farmers can benefit from targeted agricultural subsidies and agricultural technology assistance as part of policy implementation.

Theoretically, the increase in income is positively correlated with the improvement of welfare, especially in the context of agriculture. The welfare of farmers does not only depend on the amount of income, but also on the stability and predictability of that income [21]. In this study, the greater influence of middle-income income on welfare compared to high- or low-income categories shows that farmers at the middle-income level can be more stable in managing their finances to meet basic needs and improve the quality of life. This is in line with the basic needs' theory, which states that the fulfillment of basic needs improves welfare and quality of life [22]. Therefore, in Bali's agricultural policy framework, a more inclusive approach is necessary to enhance farmers' economic stability through price stability schemes, agricultural commodity diversification, and farmland protection.

Based on the MDA-Path analysis, biological factors are also crucial in improving farmers' income and welfare, alongside socio-economic factors. To enhance farmers' welfare, better management of seasonal crops like rice, corn, and vegetables, which are susceptible to price fluctuations, should focus on selecting climate-resistant and pest-tolerant varieties. Therefore, Bali's agricultural policies should place greater emphasis on organic farming, as supported by the regional government's agricultural programs.

Additionally, the use of appropriate fertilizers and efficient fertilization methods can improve agricultural yields, thereby stabilizing farmers' income. The Bali Organic Farming program has demonstrated that Balinese farmers rely less on expensive chemical fertilizers, reinforcing policies that support agroecological practices and sustainable farming in Bali.

Beyond biological factors and farm management, easy-to-use agricultural technology also plays a significant role in enhancing productivity. Bali's agricultural policies should further encourage digitalization and the adoption of smart farming technologies, particularly for small- and medium-scale farmers. With more accessible technology, farmers can manage their crops more efficiently, improve product quality, and reduce risks associated with price volatility and extreme weather conditions.

CONCLUSION

The results of the MDA-Path Analysis model estimation indicate that Human Resource Quality (HR Quality) has the most significant impact on both farmers' income and welfare, demonstrating a strong positive contribution to these variables. Additionally, Price Volatility exerts a greater influence on farmers' welfare, while Ease of Use of Technology contributes more significantly to income growth. The analysis further reveals that income category (Y1) plays a crucial role in determining farmers' welfare (Y2), with the greatest influence observed between the medium and high-income groups.

This model exhibits high classification accuracy, with sensitivity values exceeding 80%, although specificity remains relatively lower. These findings confirm that MDA-Path Analysis provides a comprehensive and structured approach for evaluating the interconnections between farmers' welfare, income stability, and policy interventions. The integration of Discourse Network Analysis (DNA) with MDA-Path allows policymakers to identify key determinants of economic stability for farmers while assessing the direct and indirect relationships among various policy-related factors.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the authorship, financial support, or any relationship with the research objects mentioned in this paper.

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