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The effect of the agricultural mechanization assistance model on socio-economic changes of farmer groups in Palopo city, Indonesia

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Abstract
Increasing agricultural productivity through agricultural mechanisation by the Palopo City government of Indonesia is a policy to meet the needs of farmers in developing their agricultural businesses. This study uses innovation and technology adoption variables, variable effectiveness of machinery and agricultural extension as intervening variables to determine effective models to see socio-economic changes in agricultural groups through agricultural mechanisation assistance in Palopo City, Indonesia. This research method used descriptive research techniques with a quantitative analysis approach. Then, all data was collected using a structured questionnaire with closed questions using a Likert scale. The data was tabulated using Microsoft Excel, and then the data collected was analysed by variance-based statistics, namely SEM PLS. According to the study's SEM analysis findings, 34.6 % of socio-economic changes are influenced by innovation and technology adoption, the impact of agricultural extension workers on socio-economic changes obtained by 4.4 %, while the overall influence of variability on socio-economic changes in community results obtained by 16.6 %.

Keywords: machine effectiveness, agricultural economics, innovation, productivity, technology.

Introduction

The development of agricultural mechanisation technology is directed at improving welfare and independence, especially in the farming community (Karmini 2018). It is certain that if suitable agrarian technology has been successfully developed and applied by the farming community, then food security or food self-sufficiency will be achieved, and independence in economic and political terms can be realized (Senyolo et al., 2018).

Alongside technological developments and agricultural modernisation, there is also an increase in the scope of agricultural mechanisation. (Negrete 2019). Currently, mechanisation technology used in the production process until postharvest is not only technology based on mechanical energy but has begun using electronic technology or sensors, nuclear, Image Processing, and even robotic technology (Emmanuel et al. 2016). The use of machinery includes producing, harvesting, and handling or processing agricultural products (Kalita 2018).

Development in the agricultural sector is a strategic activity and is inseparable from the performance of agricultural extension services (Ragasa et al. 2016). Because of this, the growth of the farming industry depends on extension workers acting as a bridge between farmers' methods and the quickly advancing fields of science and technology (Saputri, Anantanyu, and Wjianto 2016). In carrying out extension activities, the success rate requires support from various parties, especially from the extension workers' performance (Elias et al. 2016). An agricultural extension worker can compile a work plan while carrying out extension activities based on the needs of farmers as targets. To implement targets and objectives, an extension worker must be capable and competent (Khalil et al. 2009).

Since agricultural extension workers are at the vanguard of Indonesia's agricultural development, their roles in the modern agricultural sector must include innovation, facilitation, consultation, and communication (Purwatiningsih, Fatchiya, and Mulyandari 2018). Extension workers greatly influence the success of agriculture since they have direct contact with farmers, which enables the government's Agriculture Office to organise programs and deliver them to farmers immediately (Adiwisastra, Vintarno, and Sugandi 2019). Extension agents link national development initiatives and recognise that farmers are becoming more sophisticated, wise, and focused on meeting market demands. The responsibility and function of agricultural extension workers as motivators in their target areas cannot be divorced from these efforts (Agunga 2015).

Indonesia has very little innovation in agricultural mechanisation to boost productivity and production, so investment activities in farmer families must be carefully planned and understood (Elian, Lubis, and Rangkuti 2014). It takes the participation of extension workers as motivator agents, educators, dynamic actors, organisers, communicators, and companions for farmers to influence the absorption of technology and find innovations in running their farms (Darmawan & Mardikaningsih, 2021). Munurut (Managanta 2020) states that one of the primary responsibilities of agricultural extension workers is to help farmers adopt new ideas. Once this is done, extension workers teach farmers how to use production technology, increasing the farm business's productivity (Baig & Aldosari, 2013).

The Positive Impact of socio-economic aspects for farmers with the participation of extension workers with advances in agricultural mechanisation technology is the availability of the facilities and infrastructure needed, such as postharvest tool tractors or called alsintan (agricultural machinery tools) is a significant increase in production (Mbatha &; Consulting, 2020). The community will have options to raise their revenue due to the economic side of the mechanisation assistance investment. The government's financial role as a source of local original income has a favourable impact (PAD) (Purba, F., and Nuryanti 2016).

Table 1. Data on alsintan beneficiary groups
(source Department of Agriculture, Livestock and Plantations Palopo City in 2022)

No	District	Number of recipient groups	
1	Sendana	22	
2	Mungkajang	4	
3	Wara	6	
4	South Wara	13	
5	Eastern Wara	7	
6	Western Wara	19	
7	North Wara	-	
8	Bara	2	
9	Telluwanua	114	
	Sum	**187**	

This study uses innovation and technology adoption characteristics, the efficiency of rural mechanisation machinery, and the function of agricultural extension workers to analyse the farm mechanisation aid model and socio-economic changes in the farming community in Palopo City. Table 1 lists the groups to which the Palopo City Government distributed alsintan rocks in 2022.

Research Methods

Up to 20 % of the population was chosen as the study's sample size. This sample size is predicated on the judgment of (Gay, Mills, and Airasian 2012) that for descriptive research, the minimum sample is 10% of the population. Considering the population representation and the research design (quantitative descriptive research), we chose a sample of 20 % of the population, or 38 farmer groups with two respondents each, for a total of 76 respondents. The Palopo City administration provided alsintan aid to the farmer groups that served as samples in 2022. In June 2023, a closed, structured questionnaire was used to collect data. Descriptive research *explanatory* a quantitative approach designed for this study, it can explain the events obtained by researchers at the research location (Agung and Yuesti 2013; Hermawan and Hariyanto 2022). Researchers also do this to study and analyse the influence between independent and dependent variables. The independent variable consists of innovation and technology adoption (X1), machine effectiveness (X2), and dependent variables, namely socio-economic changes (Y) and agricultural extension workers (Z) as intervening variables.

EXCEL and SPSS were utilised in this study's descriptive statistical analysis. In this work, the Smart PLS program was used to conduct imperative statistical analysis using variance-based Structural Equation Modeling (SEM) approaches. When there are particular issues with variant-based data, limited research samples, missing data (missing value), and multicollinearity, SEM analysts measure multiple regression (Dameria Sinaga 2022).

Based on previous research conducted by (Li et al. 2019), this study obtained three findings, namely: (1) The most critical factor influencing Agricultural Mechanization Level AML is Agricultural Equipment Level (AEL) (2) Benefit factors, demographics, and the degree of economic development all have an impact on AML in China, both directly and indirectly through AEL (3) AEL is only indirectly impacted by the availability of land resources, policy, and environmental conditions. Additional research was carried out (Z. Li et al., 2022). The study's findings included the following: (1) The PLS-SEM model accurately interprets experimental data (2) Elements influencing the degree of development Economic elements carry the most significant weight in Hubei, China's Sustainable Agricultural Mechanization (SAM), while government policy variables are the most crucial for fostering development and environmental factors are the most crucial result factors (3) Because economic and policy issues have an impact on agricultural productivity, they play a significant role in promoting SAM. Therefore, it is essential to research the model of agricultural mechanisation assistance and socio-economic changes in the farming community in Palopo City.

The purpose of this study model is to examine each variable's hypothesis. In the first hypothesis, innovation and technology adoption (X1) have an impact on socio-economic changes (Y); in the second, machine effectiveness (X2) has an impact on socio-economic changes (Y); in the third, innovation and technology (X1) have an impact on socio-economic economic changes (Y) through agricultural extension workers as intervening variables; and in the fourth, machine effectiveness (X2) has an impact on socio-economic economic changes (Y) through agricultural extension workers as intervening variables. Additionally, Figure 1 illustrates the study's conceptual framework in the following way:

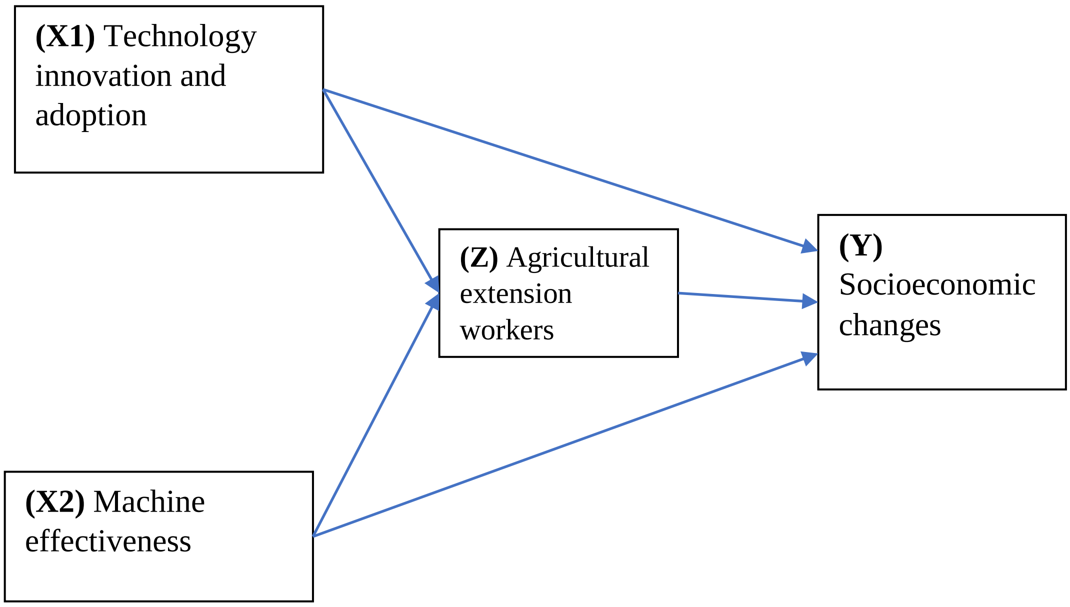

Figure 1. Conceptual framework

Results And Discussion

Analysis of Imperative Statistics

The Smart PLS program and the PLS Algorithm procedure's analysis results evaluate a research model's validity and reliability. The given model is known as the External Model Test (reliability). Figure 2 presents the acquired results. This test aims to identify the relationship between each latent variable and its indicators.

Examine the loading factor value in the latent variable with its indicators to determine the convergent validity of the hypothesis. Table 2 displays the test results.

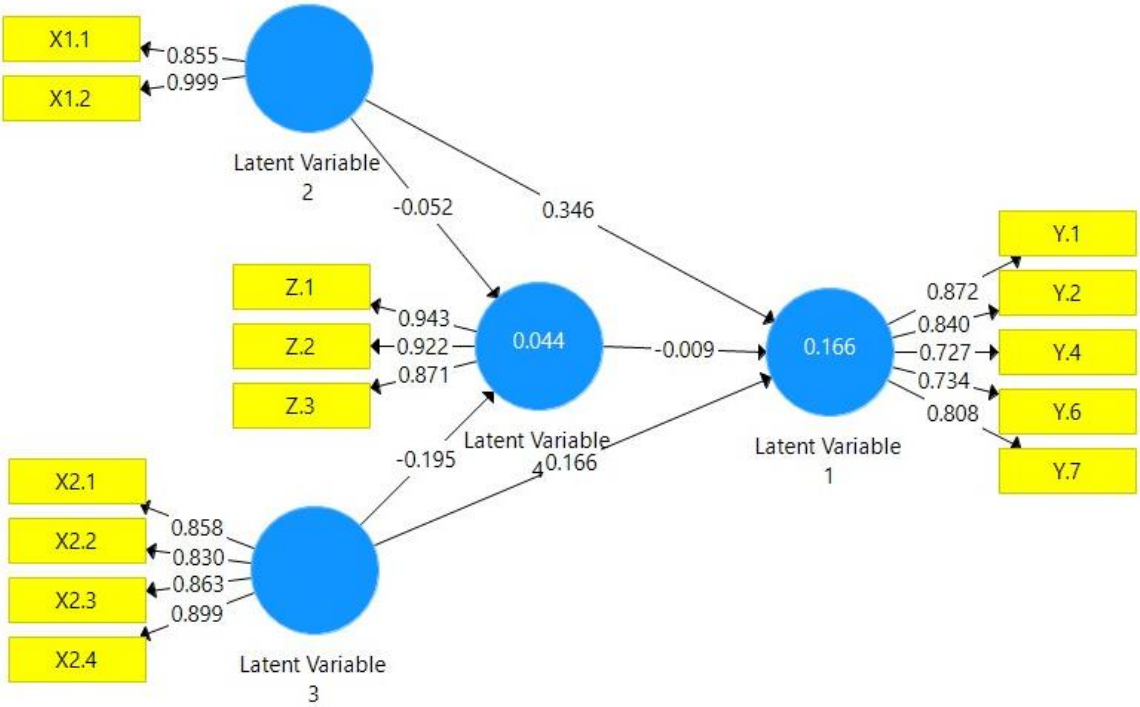

Figure 2. *External Model*

Table 2. *External Loading (Convergent Validity)*

Indicators	Socio-economic Change (Y)	Agricultural extension worker (Z)	Machine effectiveness (X2)	Technology innovation and adoption (X1)
X1.1 Benefits				0,855
X1.2 Complexity				0,999
X2.1 Efficient			0,858	
X2.2 Effectiveness			0,830	
X2.3 Productivity			0,863	
X2.4 Quality of results			0,899	
Z1.1 Visit intensity		0,943		
Z1.2 Quality of information		0,922		
Z1.3 Increased productivity		0,871		
Y1.1 Change in revenue	0,872			
Y1.2 Changes in sources of livelihood	0,840			
Y1.4 Resource access capabilities	0,727			
Y1.6 Ability to manage assets	0,734			
Y1.7 Ability to develop a business	0,808			

The outcomes acquired are the outer loading values on each variable indicator using the external model. The model is deemed valid if the validity value is > 0.7, as indicated in Table 2. The Average Variance Extracted (AVE) size with an expected value of > 0.5 is used to evaluate the indicator's validity level in the reflective model. All of the examined SEM model variables are deemed genuine, as evidenced by Table 3 results, which demonstrate that each variable's AVE value is more than 0.5. The values of Cronbach Alpha (CA) and Composite Dependability (CR) indicate the reliability level of the model. This kind of reliability determines each variable indicator's level of internal dependability. The value deemed trustworthy is.

Table 3. R-Square value of each variable

Variable	CA	CR	AVE
Socio-economic Change (Y)	0,858	0,875	0,897
Agricultural extension worker (Z)	0,899	0,913	0,937
Engine effectiveness (X2)	0,887	0,914	0,921
Technology innovation and adoption (X1)	0,907	8,174	0,927

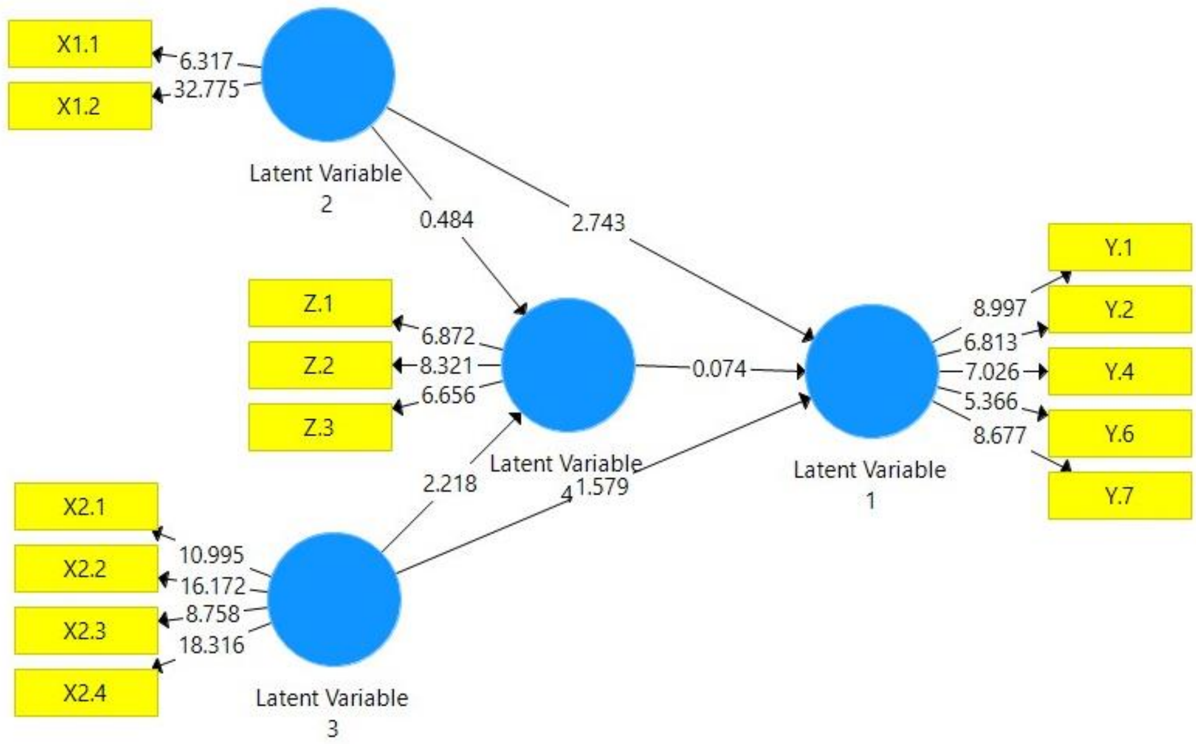

Figure 3. *Inner Model*

Determinant coefficients (R-Square) and T-calculated meters for structural tests or inner model analysis are used in Smart PLS applications. T Calculate determines how much influence one variable has over the others. The results indicate a positive and substantial influence between the variables if the T calculate > T Table value and the P-Value is < 0.05 (as α or cut-off value). A measure of the degree to which the independent variable influences the dependent variable is provided by the inner test of the SEM model, which displays the computed T value and P value. In the Smart PLS application, bootstrapping approaches generate the internal model testing value. The outcomes are shown in Figure 3.

Table 4. T Calculate the independent variable's value concerning the dependent variable.

Variable	T Table	T Calculate	P Values
Technology innovation and adoption (X1) -> Socioeconomic change (Y)	1.66515	2,691	0,007
Technology innovation and adoption (X1) -> Agricultural extension workers (Z)	1.66515	2,218	0,027
Machine effectiveness (X2) -> Socioeconomic change (Y)	1.66515	1,660	0,098
Machine effectiveness (X2) -> Agricultural	1.66515	0,484	0,628

extension workers (Z)			
Agricultural extension workers (Z) -> Socio-economic Change (Y)	1.66515	0,074	0,941
Technology innovation and adoption (X1) -> Agricultural extension workers (Z) -> Socioeconomic change (Y)	1.66515	0,028	0,978
Machine effectiveness (X2) -> Agricultural extension workers (Z) -> Socioeconomic change (Y)	1.66515	0,072	0,943

As can be seen in Figure 3, each independent variable (innovation and technology adoption) has an R-squared value of 2,743, machine effectiveness is 1,579, and the intervening variable (agricultural extension) has a value of 0.074. These results indicate that the model is moderately robust. The independent variable hypothesis test on the dependent variable can be expressed as follows, based on the T-count analysis results displayed in Table 4:

The effect of innovation and technology adoption (X1) on socio-economic Change (Y)

The Palopo City Government provided agricultural mechanisation equipment to farmer groups, and the study of the respondents' replies revealed a high average for the impact of innovation and technology adoption on socio-economic Change. Four outcomes were obtained from the SEM analysis in the table: P values = 0.007 < α = 0.05, Tcalculate value = 2.691 > table T value = 1.66515. This suggests that the agricultural mechanisation rock initiative of the Palopo City Government is positively and significantly impacted by innovation and technology adoption in terms of socio-economic improvements.

The study's conclusions align with the study's (Takahashi et al., 2020) heading, "A Review of the Recent Literature on Technology Adoption, Impact, and Extension in Developing Countries' Agriculture: Where Variability Matters." To significantly reduce the consequences of socio-economic changes in agriculture, it is recommended that technology adoption be utilised in conjunction with an integrated farm management system. This has a positive influence on agriculture. The SEM study also revealed that, at 32,775 %, complexity was the innovation and technology adoption indicator that contributed the most. Profit, at 6,317 %, is, by contrast, the indication of innovation and technology adoption that contributes the least.

The effect of innovation and technology adoption (X1) on agricultural extension workers (Z)

The effect of innovation and technology adoption on agricultural extension workers was found to have a high average among responders to farmer groups obtaining agricultural mechanisation equipment from the Palopo City Government. Four outcomes were obtained from the SEM analysis in the table: P values = 0.027 < α = 0.05, Tcalculate value = 2.218 > table T value = 1.66515. This suggests that agricultural extension workers on the Palopo City Government Agricultural Mechanization Rock are favourably and significantly impacted by innovation and technology adoption.

The study's findings are consistent with a study by Emmanuel et al. (2016) titled "Impact of Agricultural Extension Service on Adoption of Chemical Fertilizer: Implications for Rice Productivity and Development in Ghana," which found that the use of agricultural extension workers had a significant favourable influence on the uptake and productivity of agricultural technology. The SEM analysis also revealed that the indicators of the agricultural extension workers who contributed most to the research showed that the intensity of visits reached 94.7 %. Comparatively, an increase in production (87.1%) is the metric of agricultural extension workers contributing the least.

The effect of machine effectiveness (X2) on socio-economic Change (Y)

The Palopo City Government sent agricultural mechanisation boulders to farmer organisations, and examining the respondents' comments revealed a poor average of machine efficacy. The SEM analysis yielded four outcomes: Tcalculate value = 1.660 < table T value = 1.66515 and P Values = 0.098 > α = 0.05, as shown in the table. This suggests that socio-economic changes in the agricultural mechanisation rocks of the Palopo City Government are not positively and significantly impacted by the machine's efficacy.

Congruent with the same research, Scaling Agricultural Mechanization Services in Smallholder Farming Systems: Case studies from sub-Saharan Africa, South Asia, and Latin America are the findings of this study (Loon et al., 2020) This study highlights a significant unmet need for agricultural mechanisation to assist rural development programs by blurring the lines between large- and small-scale agriculture, given the project's reliance on the private sector as a partner with the government. This is made feasible by the fact that government aid occasionally deviates from the desires of every farmer group member. Usually, moreover, the mechanisation aid they obtain is of low quality, making it unusable.

The effect of machine effectiveness (X2) on agricultural extension workers (Z)

The average low influence of machine effectiveness on agricultural extension personnel is revealed by examining respondents' replies to the recipient farmer group's agricultural mechanisation rocks Palopo City Government. The SEM analysis yielded four findings, shown in the table: T calculate = 0.484 < T table = 1.66515 and P Values = 0.628 > α = 0.05. This suggests that the machine's efficacy has no appreciable beneficial impact on agricultural extension personnel on the Palopo City Government's agricultural mechanisation rocks. The research's findings are consistent with previous studies' findings (Berhanu & Poulton, 2014; Sunartomo, 2016). (Hasan et al., 2017) Whereas the study's conclusions significantly indicated that medium-sized rice producers' competency level was inadequate because

The effect of agricultural extension workers (Z) on socio-economic Change (Y)

Examining respondents' responses to the recipient farmer group's agricultural mechanisation rocks, the Palopo City Government reveals an unsatisfactory average for the influence of agricultural extension workers on socio-economic transformation. Four conclusions from the SEM study are displayed in the table: P Values = 0.941 > α = 0.05 and T Calculate = 0.074 < T table = 1.66515. This suggests that the agricultural extension workers do not have a noteworthy and favourable impact on the agricultural mechanisation goals of the Palopo City Government in terms of economic and social improvements. This is made feasible because beneficiary groups are created according to unique demands. Following help, members disregard group norms, most likely due to agricultural extension workers' lack of oversight, advice, and support.

The effect of innovation and technology adoption (X1) on socio-economic Change (Y) through agricultural extension workers (Z) as intervening variables

The average impact of innovation and technology adoption on socio-economic changes through agricultural extension workers as intervening variables was found to be low, according to an analysis of respondents' responses to farmer groups receiving agricultural mechanisation equipment from the Palopo City Government. The four outcomes of the SEM analysis are T calculate value = 0.028 < table T value = 1.66515 and P Values = 0.978 > α = 0.05 in the table. This suggests that despite adding agricultural extension specialists as intervening variables, innovation and technology adoption do not positively and significantly alter socio-economic improvements in the agricultural mechanisation rocks of the Palopo City Government. Studies reveal that factors related to agricultural extension provide little effect when acting as intermediaries between raising agricultural production and improving farmers' socio-economic status.

The effect of machine effectiveness (X2) on socio-economic Change (Y) through agricultural extension workers (Z) as an intervening variable

The efficiency of agricultural extension workers as an intervening variable was found to be low on average in the replies given by respondents to farmer groups that received agricultural mechanisation rocks from the Palopo City Government. The four outcomes of the SEM analysis are T calculate value = 0.072 < table T value = 1.66515 and P Values = 0.943 > α = 0.05 in the table. This suggests that, despite the diversity of agricultural extension workers serving as an intervening variable, the machine's efficacy does not significantly and favourably affect socio-economic changes in the agricultural mechanisation rocks of the Palopo City Government. Studies reveal that factors related to agricultural extension provide little effect when acting as intermediaries between raising agricultural production and improving farmers' socio-economic status.

Conclusion

The findings of this study, which used SEM analysis, revealed that farmer groups receiving support from the Palopo City government had the following effects on socio-economic changes: 34.6 % showed the influence of innovation and technology adoption, 16.6 % indicated the impact of machine effectiveness, 4.4 % showed the effect of agricultural extension workers, and 16.6 % showed the overall impact of variability on socio-economic changes in the community. The findings demonstrate that, to maximise the growth in innovation and technology adoption and the socio-economic changes brought about by agricultural mechanisation, the Palopo City administration must limit its efforts to the Agriculture Office.

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