"EMPOWERING RICE FARMERS THROUGH K-WORKERS COMPETENCY FRAMEWORK: ENHANCING FARMER PARTICIPATION IN RICE ESTATE COMMUNITIES (KEP)"

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Abstract - *Workers require appropriate competencies to succeed in their job, particularly within the scope of the Estate Community (KEP). KEP is a community initiated by the Bogor Agricultural Institute to assist farmers in improving their standard of living. The purpose of this research is to propose a model of worker competencies adapted to Farmer Workers in the Rice Estate Community (KEP). This research is quantitative in nature, using an explanatory study design, supported by data from questionnaires distributed to workers in the Rice Estate Community (KEP). The population consists of farmer workers in the Padi Sungai Dua Estate Community, Palembang. The population and sample used a saturated sample. The research sample is all 61 new members of KEP. The instrument used is the K-Workers Competency research instrument from the research of Santoso and Hasan (2018). The analysis was carried out through demographic analysis, as well as Structural Equational Modelling (SEM) analysis using SmartPLS 3. The SEM analysis shows a well-adjusted K-Workers model for worker farmer perceptions, with 3 out of 8 hypotheses proven to be significant and 5 rejected. K-Workers' competencies have an impact on farmer workers' participation in the rice estate community. These findings have significance in terms of theory, practicality, and policy determination and can contribute to the formation of similar Rice Estate Community (KEP) patterns.*

Keywords: *K-workers competencies, farmer participations, rice estate community*

INTRODUCTION

In many nations, like Indonesia, agriculture is a crucial industry for the economy and the wellbeing of its citizens. A knowledgeable and capable staff is crucial for managing knowledge and technology in agriculture in the face of global concerns like climate change, demographic change, and dependency on technology. In the age of globalization, where the workforce needs to be skilled in using information and communication technologies and possess the capacity to continuously learn and adapt, the idea of the "knowledge worker" came into being. There is a growing body of research on knowledge worker competencies in the agricultural industry, and numerous studies link knowledge worker competency levels to agricultural performance and productivity. But in order to accomplish this, farmers' engagement in competency development programs is equally crucial for enhancing their productivity and welfare.

The relationship between knowledge worker competencies and farmer involvement in enhancing farm performance will be covered in this essay. We will make reference to ideas like agricultural competences and rice farming competencies as well as numerous related research that have already been conducted. One relevant study is the research conducted by Cisneros et al. (2018), which analyzed farmer participation in rural expansion services from the perspective of agricultural competencies. The study shows that active participation of farmers in rural expansion services is important in developing their agricultural competence and can improve agricultural performance and productivity.

Another relevant research is a study by Suharyanto and Sari (2019), which examines the competence of farmers in rice farming and its effect on productivity and income in Indonesia. This study shows that farmers who have higher competence in rice farming have higher productivity and income. These two studies show how important it is for farmers to actively participate in skill development to increase their productivity and welfare in the agricultural industry. Therefore, to maximize the advantages of farmer engagement, competency development programs must be well-designed and tailored to the local needs and circumstances of farmers. Support from diverse stakeholders is also required.

Farmers' access to the knowledge and tools necessary to enhance farm performance can also be improved through their participation in competency development programs. Access to information is becoming more crucial for enhancing agricultural performance in the era of quickly evolving information and communication technologies. Farmers who take part in competency development programs have better access to the knowledge and tools necessary to increase the performance and productivity of their farms.

Participating in competency development programs can also aid farmers in growing their networks of partners and other business stakeholders. Expanding networks and collaboration with business partners and other business actors can be a significant component in enhancing agricultural performance and production in an era of increasingly globalized commerce. Farmers can broaden their networks and make contacts that will aid in the development of their farms by taking part in competency development programs.

However, to accomplish this, competency development programs must be thoroughly thought out and tailored to the specific requirements and circumstances of farmers in the area. This necessitates assistance from a range of organizations, including the government, educational institutions, and communities, as well as farmer participation in the design and execution of competency development programs. In order to increase agricultural performance and output, farmers must possess a variety of competences, including management skills, technical proficiency, and decision-making abilities. For instance, data from Uganda demonstrates that farmers with effective management abilities typically have better yields and higher cost efficiency (Owusu-Sekyere, 2017). Research conducted in Ethiopia, meanwhile, demonstrates that technical instruction in agricultural cultivation might raise farmer productivity (Bekele et al., 2020).

Additionally, research suggests that participating in competency development programs might help farmers become more motivated and self-assured in running their farms. For instance, Tanzanian research demonstrates that farmers who take part in training and participation programs are more motivated to experiment with novel farming methods (Komba et al., 2015). Additionally, farmers' involvement in competency development programs can boost their involvement in social activities and decision-making related to agriculture (Riley et al., 2017).

The government and other non-governmental groups have run competency development programs for farmers in Indonesia. For instance, to improve agricultural output and farmers' welfare, Indonesia's Ministry of Agriculture has started training and mentorship programs for farmers. Additionally, a number of non-governmental organizations have put in place programs for developing the skills of farmers, such as technical training in farming and agricultural cultivation.

In relation to knowledge worker competency, developing farmer competency can also help to raise the standard of labor in the agriculture industry. The agricultural industry, which employs the majority of the population in rural areas, may contribute more to the national economy and boost productivity and farmer welfare by improving the quality of its workforce. Cooperation and synergy between numerous parties, including the government, educational institutions, non-governmental organizations, and the community are required in order to maximize the contribution of farmer competency development to raising the standard of labor in the agricultural sector. To maximize benefits for farmers and the agricultural industry as a whole, the development of farmer competencies must also be tailored to the needs and regional conditions of farmers.

The development of competency-building programs for farmers can benefit from additional insights from studies on knowledge workers' competence. For instance, research by Kurniawan and Widodo (2018) in Indonesia demonstrates that knowledge workers require three sorts of competencies: technical competence, social competence, and personal competence. While social competence comprises the capacity to interact with and work cooperatively with people, technical competence encompasses technical abilities and the capacity to handle technological difficulties. Personal competence, on the other hand, entails having self-control and sound judgment.

Programs for farmers' competency development may better serve their needs and expectations if they incorporate the competency categories demanded by knowledge workers. For instance, technical training programs in agricultural cultivation can aid in enhancing farmers' technical competence, whereas social competency training programs can aid in enhancing farmers' social competence.

According to this study, developing farmer competences by taking into account the types of skills required by knowledge workers can raise the standard of labor in the agriculture industry. Additionally, the improvement of overall farmer welfare can be facilitated by the development of farmer skills that can promote farmer involvement in community activities and decision-making.

Overall, the improvement of labor quality and the development of farmer competences are complicated challenges that call for collaboration between diverse parties. By taking into account the competency categories required by knowledge workers, research and development of farmer competency development programs can aid in raising the standard of labor in the agricultural sector and its economic contribution. Additionally, research demonstrates that farmer involvement in civic affairs and decision-making may have an impact on agricultural output and farmer welfare (Egelyng, 2010; Tripathi, 2017). Participation of farmers in local activities can increase their access to information and resources needed for agricultural development as well as their relationships with other farmers. Adopted agricultural policies and initiatives may be more credible and effective if farmers are included in the decision-making process.

However, other elements including a farmer's degree of education, access to resources, and membership in farmer groups also have an impact on their participation in community activities and decision-making (Egelyng, 2010; Tripathi, 2017). Therefore, initiatives for developing farmers' skills must also take into account the growth of their decision-making and participation in community activities.

For instance, leadership and decision-making training programs can enhance farmers' capacity to take part in civic affairs and decision-making. Programs for competency development that incorporate information and abilities into farmer involvement in civic affairs and decision-making can likewise aid in boosting farmer involvement in agricultural advancement.

According to this study, farmers' competency in decision-making and engagement in community activities might help increase the efficacy of agricultural policies and programs as well as their general well-being. Therefore, the creation of farmer competency development programs that take into account the categories of competency demanded by knowledge workers as well as farmer involvement in community activities and decision-making can aid in enhancing the quality of labor in the agricultural sector and boosting the agricultural sector's contribution to the national economy.

The development of farmer competencies, which include technical, social, and personal skills, as well as farmer participation in community activities and decision-making, can help improve the quality of labor in the agricultural sector and increase the contribution of the agricultural sector to the national economy, according to research on k-Workers' competencies and farmer participation. As a result, creating farmer competency programs that take these two factors into account can be a successful tactic for enhancing farmer welfare and overall agricultural development.

From the plan to form a Rice Estate community oriented towards industry 4.0 smart agroecosystems, there are potential propose follows:

1. Technical Competency has a positive and significant effect on K-Workers Competency.
2. Human and Social Competency has a positive and significant effect on K-Workers Competency.
3. Learning Competencies and Methodologies have a positive and significant effect on K-Workers Competency.
4. Farmers Personal Trait has a positive and significant effect on Farmers Participation.

5. Physical and Socio-economic Environmental Support has a positive and significant effect on Farmers Participation.
6. Empowerment Intensity has a positive and significant effect on Farmers Participation.
7. Availability of Agricultural Information has a positive and significant effect on Farmers Participation.
8. K-Workers Competency has a positive and significant effect on Farmers Participation.

RESEARCH METHOD

This research is quantitative research with an exploratory approach. Blending 2 different concepts whose relationship with each other is still vaguely visible. The population and study sample used saturated samples. The population and sample of this study were 61 working farmers. The population is the Rice Estate Community (KEP) in Sungai Dua, Rambutan District, Banyuasin Regency.

The variables of this study are K-Workers Competence and Farmer Participation. The instrument used a questionnaire used by Santoso and Hassan (2018). This questionnaire is as a result of qualitative studies followed by quantitative studies to produce instruments, and the instruments used Mulyaningsih et al., (2018). The *K-Workers* Competency Questionnaire consists of 4 parts of question items: Technical Competence, *K-Workers* Competence, Human and Social Competence, Learning Competence and Methodology. And the farmer participation questionnaire consists of 4 parts of question items: Farmer personality traits, empowerment intensity, availability of agricultural information, physical and socioeconomic environmental support.

The scale used is *Likert* 5 scales with a scale order: 1-5. This scale is very widely used in the fields of social sciences, economics and agriculture. The analysis used demographic analysis, descriptive analysis and *Structural Equation Modeling* (SEM) analysis using SmartPLS 3.

RESULTS

This research model will be examined with the Partial Least Square (PLS) technique and the SmartPLS 3.0 software. According to Hair et al. (2018), PLS is an alternative to Structural Equation Modeling (SEM) that can be used to solve problems in the relationship between variables where the sample size is small (30-100 samples) and non-parametric assumptions are made, meaning that the data does not refer to a specific distribution.

Table 1 Fornel Laker Criterion

	Availability of Agricultural Information	Empowerment Intensity	Farmers Personal Trait	Human and Social Competency	K-Workers Competency	Learning Competency and Methodology	Participation	Physical and Socio-economic Environmental Support	Technical Competency
Availability of Agricultural Information	0.933								
Empowerment Intensity	0.960	0.930							
Farmers Personal Trait	0.899	0.902	0.934						
Human and Social Competency	0.912	0.905	0.870	0.912					
K-Workers Competency	0.919	0.932	0.888	0.970	0.906				
Learning Competency and Methodology	0.941	0.950	0.914	0.954	0.968	0.918			
Participation	0.924	0.936	0.916	0.896	0.937	0.936	0.940		
Physical and Socio-	0.962	0.955	0.908	0.911	0.928	0.953	0.929	0.929	

economic Environmental Support									
Technical Competency	0.849	0.884	0.845	0.899	0.914	0.903	0.854	0.864	0.900

We examine Discrimant Validity, and the Discrimant Validity values that we examine are Fornell-Lacker Criterion, Crossloading, and Heterotrait-Monotrait Ratio. The diagonal value is the Fornell-Lacker Criterion value, which is compared to the correlation value of the construct below it. This value must exceed the correlation value of the construction. It turns out that all of the obtained values exceed the specified values.

Table 2 Crossloading

	Availability of Agricultural Information	Empowerment Intensity	Farmers Personal Trait	Human and Social Competency	K-Workers Competency	Learning Competency and Methodology	Participation	Physical and Socio-economic Environmental Support	Technical Competency
X1.3									0.900
X1.8									0.850
X1.9									0.735
X2.10					0.862				
X2.7					0.866				
X2.8					0.841				
X2.9					0.831				
X3.2				0.783					
X3.5				0.932					
X3.6				0.943					
X3.7				0.924					
X4.5						0.862			
X4.6						0.829			
X4.7						0.971			
X4.8						0.904			
X4.9						0.956			
Y1.1							0.865		
Y1.2							0.895		
Y1.3							0.911		
Y2.1			0.883						
Y2.2			0.883						
Y2.3			0.793						
Y3.1		0.817							
Y3.2		0.845							
Y3.3		0.905							
Y4.1	0.879								
Y4.3	0.918								
Y5.1								0.928	
Y5.2								0.842	

Following the evaluation of the Fornel-Lacker criterion value, the Crossloading criterion is examined. Crossloading check entails examining the highest value of a variable's indication to see if it belongs to a certain variable. To simplify the visibility of Crossloading, Outer Loading displays only the highest Crossloading value. Based on this Outer Loading, we can observe that the Crossloading value has been consistently distributed and is greater than 0.7.

Table 3 Heterotrait-Monotrait Ratio (HTMT)

	Farmers Personal Trait	Physical and Socio-economic Environmental Support	Empowerment Intensity	Availability of Agricultural Information	K-Workers Competency	Human and Social Competency	Learning Competency and Methodology	Technical Competency	Participation
Farmers Personal Trait									
Physical and Socio-economic Environmental Support	0.791								
Empowerment Intensity	0.994	0.806							
Availability of Agricultural Information	0.656	1.018	0.838						
K-Workers Competency	0.095	0.171	0.121	0.189					
Human and Social Competency	0.099	0.117	0.041	0.176	0.662				
Learning Competency and Methodology	0.799	0.604	0.603	0.443	0.243	0.255			
Technical Competency	0.098	0.138	0.124	0.117	0.749	0.693	0.240		
Participation	0.911	0.506	0.605	0.422	0.058	0.287	0.581	0.133	

The final test for Discriminant Validity is the HTMT test with a cutoff value of less than 0.90. The HTMT reading was within the threshold range. Observing the reliability of the item as represented by the loading factor value is how convergent validity is achieved. A loading factor may be a range that demonstrates the relationship between the score of an issue item and the score of the indicator construct used to measure the construct. The loading factor value is more than the reported valid value of 0.7. However, according to Hair et al. (2019), for the initial examination of the loading factor matrix, a loading factor of approximately 0.3 is deemed to have met the minimum standard, a loading factor of approximately 0.4 is deemed to be better, and a loading factor of greater than 0.5 is typically regarded as significant. The loading factor limit employed in this investigation was 0.70.

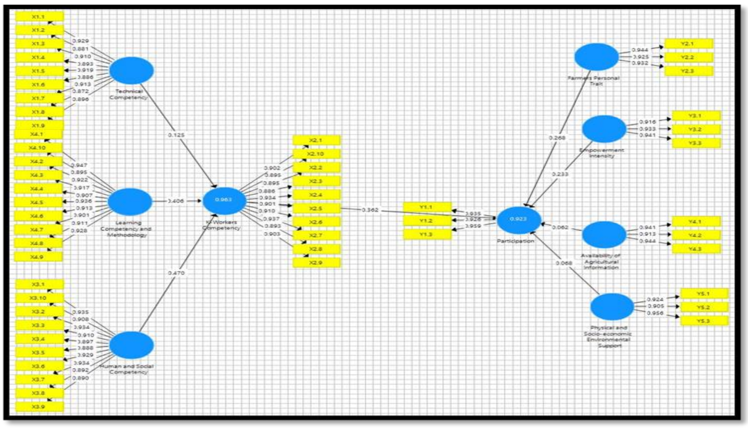

Fig 2. Validity and reliability testing

Table 4 Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Availability of Agricultural Information	0.925	0.926	0.953	0.870
Empowerment Intensity	0.922	0.923	0.950	0.865
Farmers Personal Trait	0.927	0.927	0.953	0.872
Human and Social Competency	0.977	0.978	0.980	0.832
K-Workers Competency	0.976	0.976	0.979	0.820
Learning Competency and Methodology	0.979	0.980	0.982	0.842
Participation	0.934	0.934	0.958	0.884
Physical and Socio-economic Environmental Support	0.920	0.921	0.949	0.862
Technical Competency	0.971	0.971	0.975	0.810

The following evaluation is the Construct Reliability and Validity evaluation. Three values reflect the reliability test: Cronbach's Alpha, rho A, and Composite Reliability. The Rule of Tumbs value is greater than 0.7. If even one of them is trustworthy, then the construct is trustworthy. In addition, the AVE value has exceeded the Rule of Thumb by more than 0.5. In order to confirm that all values are valid.

Based on the estimation results of the PLS model depicted in the image above, all indicators have a loading factor value greater than 0.5, meeting the convergent validity criteria. The following evaluation will compare discriminant validity with the square root of the retrieved average variance (AVE). According to Hair et al. (2017), the measurement model is evaluated based on cross-loading measurements using the construct. If the correlation between the constructions and each indication is larger than the size of the other constructs, then the latent construct predicts the indicator more accurately than the other constructs. If the value is more than the correlation value between the constructs, according to Hair et al. (2018), discriminant validity is obtained (if AVE> 0.5). Each indicator's measurement results with AVE are listed below.

Table 5 Path Coefficients

	Availability of Agricultural Information	Empowerment Intensity	Farmers Personal Trait	Human and Social Competency	K-Workers Competency	Learning Competency and Methodology	Participation	Physical and Socio-economic Environmental Support	Technical Competency
Availability of Agricultural Information							0.062		
Empowerment Intensity							0.233		
Farmers Personal Trait							0.268		
Human and Social Competency					0.470				

K-Workers Competency							0.362		
Learning Competency and Methodology					0.406				
Participation									
Physical and Socio-economic Environmental Support							0.068		
Technical Competency					0.125				

Human and Social Competency to K-Workers Competency coefficient is 0.470, Learning Competency and Methodology is 0.406, Farmers Personal Trait to Farmers Participation coefficient is 0.268, Physical and Socio-economic Environmental Support to Farmers Participation coefficient is 0.068, Empowerment Intensity to Farmers Participation coefficient is 0.233, and Availability of Agricultural Information to Farmers Participation coefficient is 0.062.

Table 6 R Square

	R Square	R Square Adjusted
K-Workers Competency	0.963	0.962
Participation	0.923	0.916

The R Square value of 0.963 indicates that three research variables explain 96.3% of the research model, while the R Square value of 0.923 indicates that four research variables explain 92.3% of the research model. There are three categories, 0.75, 0.5, and 0.25, representing a strong, moderate, and weak model, respectively (Hair et al. 2011).

Table 7 f Square

	Availability of Agricultural Information	Empowerment Intensity	Farmers Personal Trait	Human and Social Competency	K-Workers Competency	Learning Competency and Methodology	Participation	Physical and Socio-economic Environmental Support	Technical Competency
Availability of Agricultural Information							0.003		
Empowerment Intensity							0.040		
Farmers Personal Trait							0.143		
Human and Social Competency					0.494				
K-Workers Competency							0.186		
Learning Competency and Methodology					0.354				
Participation									
Physical and Socio-economic Environmental Support							0.003		

Technical Competency					0.073				

There is an additional metric that describes the influence Size f^2 of every variable. The limit value (Rule of Thumb) for the small category is 0.02, for the medium category it is 0.15, and for the large category it is 0.35. One variable, Farmer Personal Characteristic, falls into the medium category based on the results of f^2.

Table 8 Q^2 (Predictive Relevance)

	SSO	SSE	Q^2 (=1-SSE/SSO)
Availability of Agricultural Information	183.000	183.000	
Empowerment Intensity	183.000	183.000	
Farmers Personal Trait	183.000	183.000	
Human and Social Competency	610.000	610.000	
K-Workers Competency	610.000	139.331	0.772
Learning Competency and Methodology	610.000	610.000	
Participation	183.000	37.176	0.797
Physical and Socio-economic Environmental Support	183.000	183.000	
Technical Competency	549.000	549.000	

In addition to examining the relationship between each latent variable and the existing R^2 value, we may assess the performance of the model in this study by calculating the predictive relevance of Q-square, or Q^2. The fact that Q2 K-Workers Competence is more than 0 and Farmers Participation is greater than 0.772 indicates that the model has predictive validity.

Table 9 Fit Summary

	Saturated Model	Estimated Model
SRMR	0.038	0.038
d_ULS	2.180	2.199
d_G	19.173	19.247
Chi-Square	3077.311	3082.645
NFI	0.608	0.607

Table 10 rms Theta

rms Theta	0.201

Standardized Root Mean Square Residual (SRMR) is 0.038% for the Estimated Model. According to the Rule of Thumb, the recommended value is less than 0.08, hence it can be stated that our model is marginally suitable. The Estimated Model number is 0.607, according to the Normed Fit Index (NFI) or the Bentler and Bonett Index. As the recommended value according to the Rule of Thumb is more than 0.90, it is possible to conclude that our model is marginally suitable.

Conformity is measured by the Root Means Square Theta index size. This metric is only applicable for evaluating a model that is purely reflecting, as the residuals of the outer model for the formative measurement model are meaningless. The rms Theta value measures the degree of correlation between the outer residuals of the model. To demonstrate a good model fit, the metric must be near to zero, as this indicates that the correlation between the outer models is minimal (close to zero).

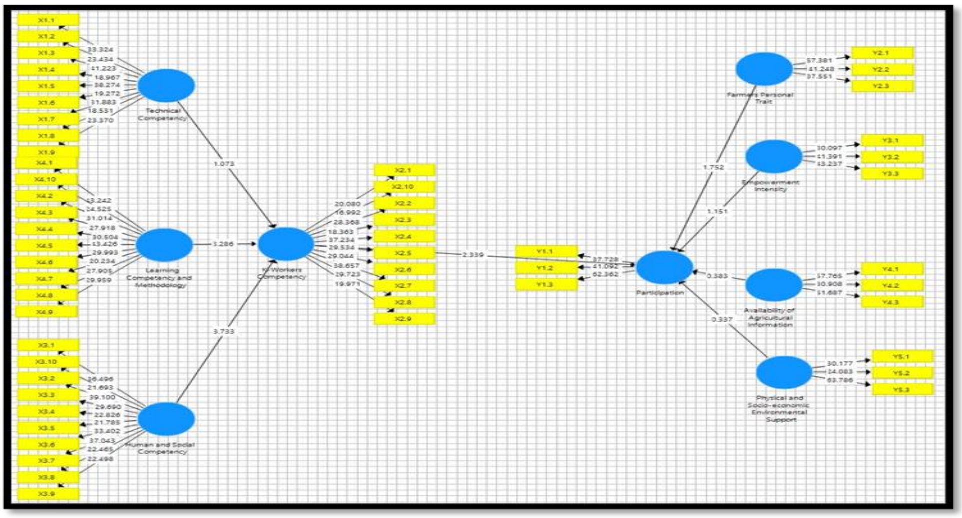

Fig 3. Hypothesis testing

According to Hair et al., hypothesis testing is based on the results of the inner model, which includes the r-square output, parameter coefficient, and t-statistic (2017). SmartPLS (Partial Least Square) 3.0 software was utilized for testing hypotheses in this study. This study employed the t-statistic > 1.96 with a significance level of p-value = 0.05 (5 percent) and a positive beta coefficient. Table1 illustrates the value of testing the hypothesis of this study, and Figure 3 depicts the conclusions of this research model. In order to test the hypothesis, the t-statistic produced from the PLS output and compared to the t-table value is examined.

Table 1. Hypothesis testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Availability of Agricultural Information -> Participation	0.062	0.083	0.163	0.383	0.702
Empowerment Intensity -> Participation	0.233	0.218	0.202	1.151	0.250
Farmers Personal Trait -> Participation	0.268	0.249	0.153	1.752	0.080
Human and Social Competency -> K-Workers Competency	0.470	0.473	0.126	3.733	**0.000**
K-Workers Competency -> Participation	0.362	0.393	0.155	2.339	**0.020**
Learning Competency and Methodology -> K-Workers Competency	0.406	0.394	0.124	3.286	**0.001**
Physical and Socio-economic Environmental Support -> Participation	0.068	0.047	0.200	0.337	0.736
Technical Competency -> K-Workers Competency	0.125	0.133	0.117	1.073	0.284

DISCUSSION

First Hypothesis: that knowledge workers' competence is positively and significantly influenced by their human and social skills (K-Workers).

Research by Azeem et al. (2021) that demonstrated "workers' interpersonal skills and emotional intelligence have a favorable impact on K-Workers' abilities" lends credence to this notion. According to the source, social and emotional intelligence are crucial for enhancing the knowledge workers' competence.

Second Hypothesis: that farmer engagement is positively and significantly impacted by K-Workers' competency.

K-Workers' abilities "contribute positively to farmers' engagement in more productive agricultural activities," according to research by Saha et al. (2020). According to the research, knowledge workers play a significant part in boosting farmer participation in agricultural pursuits and boosting output.

Third Hypothesis: that K-Workers' competence is negatively and insignificantly impacted by their skill level and learning style.

There is no significant correlation between competency and learning approach and K-Workers' competence, according to a study by Li et al. (2020). It is still required to do additional research to look into other aspects that can affect the competence of knowledge employees even if this study did not find a significant association between these two parameters and the competence of K-Workers.

Fourth Hypothesis: Physical and Socio-economic Environmental Support has positive and not significant on Farmers Participation

This hypothesis shows a favorable relationship between the physical and socioeconomic environment and farmers' engagement, although this relationship is not statistically significant. Akinyemi and Adeoye's (2018) research indicates a slight but positive correlation between environmental parameters and farmer engagement. They discovered that social networks, financing, and market access all had a beneficial impact on involvement, however the impact was not statistically significant.

Fifth hypothesis: Empowerment Intensity has positive and not significant on Farmers Participation.

Although the effect of empowerment intensity on farmers' participation is favorable, it is not statistically significant, according to the premise. A 2019 study by Melak and Zegeye found a correlation between farmer engagement and empowerment that is positive but not statistically significant. They discovered that while resources, training, and other empowerment variables had a beneficial impact on involvement, the effect was not statistically significant.

Sixth hypothesis: Availability of Agricultural Information positive and not significant on Farmers Participation

This hypothesis proposes that farmers' participation is positively influenced by the availability of agricultural information, but the effect is not statistically significant. The association between agricultural knowledge and farmers' engagement is beneficial but not statistically significant, according to a study by Namugumya and Tenywa (2020). They discovered that participation was positively impacted by elements like training and access to extension services, however this effect was not statistically significant.

Seventh hypothesis: Farmers Personal Trait has a positive and significant effect on Farmer Participation

This hypothesis suggests that farmers' personal traits have a positive and significant effect on their participation. According to a study by Mustafa et al. (2019), there is a significant relationship between personal traits and farmers' participation. They found that personal traits such as age, education, and farming experience had a positive effect on participation.

Eighth hypothesis: Technical Competency has a positive and significant effect on K-Workers Competency

According to this theory, technical proficiency affects knowledge workers' proficiency in a positive and important way. A study by Adhikari et al. (2019) found a substantial correlation between knowledge workers' competency and technical competency. They discovered that technical skills like understanding of contemporary technology, crop management techniques, and managing pests and diseases had a favorable impact on knowledge workers' performance.

The goal of this study by Adhikari and Rajendra was to determine the elements that have an impact on the knowledge workers in agriculture in Nepal. The authors discovered that technical competency, which encompasses expertise in crop management, soil fertility, and pest control, among other things, had a favorable and significant impact on knowledge workers in agriculture's total competency. The study places a strong emphasis on the value of technical proficiency in raising the efficiency and productivity of knowledge workers in agriculture.

Future studies, particularly those in the field of human resource management, can use this research as a reference as it is still a fairly uncommon sort of study.

To start a collective congregational rice farming enterprise, innovation is required. In this instance, collective actions (congregations) empower working farmers more than doing it alone. Working farmers will be fully understood and safeguarded with the aid of knowledge, seeds, and direction.

The KEP concept is designed as a *breakthrough* to increase rice production and farmers' income in an integrated and integrated manner. This is a new breakthrough where working farmers become the months of farmers who own the land where they dominate.

All of it is intended to bring about the yet-to-be-achieved sustainability of Industry 4.0 smart agroecosystems.

CONCLUSION AND RECOMMENDATIONS

It is beyond dispute that competence plays a critical role in raising a person's degree of suitability for a job. The ability of these competences to expand the engagement of working farmers is one of the KEP's additional effects. The proficiency of K-Workers in the industrial sector has been studied in earlier study. This is because competency appropriateness is valued highly in the sector. There is, however, a dearth of research on communities. As a result, this study discusses how K-Workers Competency might boost community participation in Rice Estate (KEP).

Only two hypotheses are accepted out of the three K-Worker competences that are provided. Additionally, none of the current Farmers Participation is approved. Accepted is the idea that K-Worker Competence correlates with Farmers Participation. This demonstrates that the creation of rice estate communities (KEP) toward smart agroecosystems 4.0 does depend significantly on the skills of k-workers.

The number of samples available for this investigation was constrained because it only used KEP samples applied in the Banyuasin area of Palembang. In their upcoming study, researchers advise all Indonesian KEP to conduct additional research.

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